

# AI-Powered Improvement in Inventory Management for E-Commerce Supply Chains

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## Abstract

Global supply chain issues are a major challenge today given that it is complicated to achieve strategic inventory control, cost and efficient delivery. Many times, conventional approaches can be very much ineffective when it comes to such issues, putting the operation in many problems and added expenses. In line with the research questions, this thesis seeks to determine how AI technologies such as machine learning algorithms like Random Forest and Support Vector Machine (SVM) can be implemented in improving inventory management in e-commerce supply chains. This paper aims to address this argument by pointing out that aspects such as inventory control procedures, lead time, and logistical processes can be addressed through the use of AI to cut carrying costs, improve cash flow, boost delivery effectiveness, and satisfaction levels. Based on the theoretical background and practical applications, as well as the description of specific cases and the results of experiments in the field of the use of artificial intelligence in SCM, this research offers the reader a complete understanding of the opportunities and risks associated with this process. In line with these findings, this paper reveals that AI has significant potential to revolutionize inventory management in contexts pertinent to the current context of small and medium enterprises in the emerging e-commerce market. **Keywords:** Artificial Intelligence, Supply Chain Optimization, Demand Forecasting, Inventory Management, Logistics, Operational Efficiency, Cost Reduction, Data Analysis, Predictive Capabilities, Automation, Innovation in SCM.

## 1 Introduction

Global supply chains are gradually developing into very convoluted systems, with many links and contributors. Typically, the processes within supply chains have not been effectively dealt with through conventional supply chain management practices since they do not consider the complexity of these systems and their integration, resulting in the formation of costs and different inefficiencies Khadem and Keyvanpour 2023. This is especially observable in inventory management in e-commerce supply chains due to fluctuating and constantly growing markets Duan and L. Liu 2019. Due to continuous growth in the e-commerce industry, companies are facing the problem of deficient stock control methods, which include historical sales data and unchanging stock models, and these models hardly depict the current trends in the market leading to overstocking and stock out situations. Currently, Artificial Intelligence (AI) technologies have great potential in improving supply chain functioning as they facilitate real-time data analysis, predictive analyses, and even independent decision-making Haas and Ebner 2019. AI can improve supply chain functions like demand forecasting, inventory, and logistics planning. Through the adoption of AI in inventory control, companies can maintain effective inventory, cut costs on storing inventories, and meet customer satisfaction. The purpose of this research is to shed light on these advantages in the case of e-commerce supply chains for SMEs.

## **Research Question**

How can AI algorithms optimize inventory control procedures, improve lead times, and enhance logistical processes to reduce carrying costs, improve cash flow, enhance delivery efficiency, and increase customer satisfaction in e-commerce supply chains? Additionally, how do these AI algorithms compare to each other in terms of accuracy, efficiency, and scalability?

## **Research Objectives**

1. Investigate the State of the Art in AI Applications for Inventory Management in E-Commerce Supply Chains.

This objective entails a literature search in order to determine current uses of AI in inventory management in e-commerce supply chains. This shall also encompass to establishing the opportunities and limitations of the current AI applications as well as the research holes this study seeks to fill. In this respect, the subject of this research will focus on the specific issues of SMEs operating in the e-commerce industry, which are less examined due to the focus on big companies Choi and Ho 2016. Due to engaging SMEs, this research aims at establishing practical and efficient AI solutions for the independently-owned businesses.

2. Design and Implement AI Models for Optimizing Inventory Management.

This objective is focused on the formulation and creation of AI models for inventory optimization to include the Random Forest as well as Support Vector Machine. Determining suitable features and parameters that relate to inventory control in e-commerce supply chains will be done in the design phase. The implementation phase shall include training these models on previous sales data in order to make accurate inventory forecasts in the future. There should be an improvement in important measures such as stocks, order delivery percentage and cost of holding inventory Duan and L. Liu 2019.

3. Many of the discussed AI models are generally accurate, efficient, and scalable depending on the underlying architecture and algorithms.

This objective is to evaluate the effectiveness of the developed AI models toward the traditional approaches in inventory management. The evaluation will be in terms of such aspects as accuracy of demand forecast, turnover rate of inventory and the capability in handling large data sets. The use of case studies and experiments for verification will be conducted on a sample of SMEs for the purposes of assessing the models' performance. The findings of this research will assist in identifying the realism of these emerging AI solutions in actual e-business settings.

4. Provide Practical Recommendations for Implementing AI-Driven Inventory Management Solutions in SMEs

The last of the goals is to disseminate the research implications to SMEs seeking to implement AI-based inventory management systems. This will include a set of instructions on how to choose suitable models for AI, how integrate the models into the current systems, and how to evaluate the various models' contribution to the supply chain. The above recommendations will be in line with the findings culled from the literature review, the development of the predictive models, and actual empirical validations Haas and Ebner 2019.

## **2 Related work**

### **2.1 AI in Demand Forecasting**

#### **2.1.1 Current State and Importance**

Thus, the demand forecasting is critical when it comes to the stock management to have optimal levels of inventory and timely delivery of products. Popular techniques usually consider only past sales information

and do not take into account such factors as market characteristics at the moment or such influence as promotional. There are similar works of Khadem and Keyvanpour 2023 and Choi and Ho 2016 to show the drawbacks of the methods indicating that while using the static models, it is impossible to provide a fast market adaptation, which causes consequential inventory disequilibrium. These conventional approaches, more often than not, encompass methods like the moving average approach, the exponential smoothing technique, and auto regressive integrated moving average (ARIMA) model which, despite their effectiveness, does not harness the full capability of the analytics systems. Various techniques of demand forecasting have been helpful in the past but prove ineffective in various supply chain situations. Such methods typically presuppose that future demand can be estimated relying on previous sales data only, which is quite insufficient. Industry specific factors like seasonality, trends in the market, and promotional factors have a major influence, and are not fully addressable in traditional systems. This has resulted in over stocking and stock outs; situations that are costly to the supply system Ben-Daya and Alghazi 2019.

### **2.1.2 Machine Learning in Demand Forecasting**

The integration of many external factors and capability of processing big data make the use of machine learning algorithms to provide significant enhancements to the demand forecasting of products. Such mathematical algorithms like Random Forest and SVM showed that the machine learning models are capable to reinterpret the information and give more reliable and timely information compared to the other methods were established by Rafsan and Doe 2024, Rafique and Khan 2023. These models particularly perform very well in giving the true picture and the relationships that exist in the data that standard approaches might not detect.

Scal and SVM are two widely used approaches that have revealed the possibility to improve the demand forecast significantly. Random forest is an ensemble learning technique; in this technique, more than one decision tree is created and then they are combined to get one more accurate and robust model. It can work with large data sets and can work with better dimensions hence, suitable for the demand forecasting model where many variables affect the sales. SVM on the other hand is accurate in high dimensions and mainly applied in regression problem. Through what is known as kernel tricks, it can accommodate non linearities making it ideal for capturing the demand patterns. These capabilities enable the trained models of machine learning to adapt to the newly available data as well as produce more precise and relevant forecasts Gao and W. Wang 2022.

### **2.1.3 Case Studies and Applications**

Some examples are provided of effective integration of AI in the areas of demand forecasting. For example, Procter and Gamble integrates AI into the application to boost the forecast precision based on the sales history, events that are promotional, and social media trends, which helps reduce excessive inventory and saves money by being accurate Khadem and Keyvanpour 2023. The application of using machine learning models in enhancing the forecast and the consequent efficiency in the management of stocks in the retail sector thus enhancing customer satisfaction Haas and Ebner 2019.

There are numerous documented examples that explain how AI is being practically implemented in applied demand forecasting. Large companies such as Procter and Gamble has applied AI in analyzing sales data, company's calendar of promotions and social media activity. Because of such an elaborate data analysis, forecasting has improved and minimized excess inventories as well as made a considerable contribution towards cutting down costs. This is because such improvements not only enable the right inventory to be achieved but also result in the general improvement on the performance of the supply chain. For instance, Bertsimas and Kallus 2016 compared machine learning models' impact on retail

environments and showed that the availability of stock also increases more in parallel with the forecast accuracy of consumer demand. This alignment leads to efficient stock handling and an increased level of satisfaction among the customers.

#### **2.1.4 Limitations and Challenges**

The following are challenges associated with implementing AI in demand forecasting. Data quality is very important although such challenges as sparsity, noise and real-time processing of data pose a problem in the integration of AI models. Furthermore, the AI algorithms are complex and hence the implementation needs large resources both in terms of technology and knowledge in machine learning as well as SCM. Hence, the quality and accessibility of data is determining in driving accurate demand forecasts through application of artificial intelligence. Problems such as data sparsity, noisy data and data quality issues have the potential to provide wrong insights and hence, the poor inventory decision. However, due to highly intricate algorithms used in AI, large amounts of computational resources and memory are required, thus making it a challenge particularly for SMEs. AI for demand forecasting also need data science and machine learning to be done effectively and also understanding of supply chain domain is important as well. To clarify, such interdisciplinary knowledge is required to build and enhance the models to be able to deliver valuable information and enhance the SCM effectiveness Duan and L. Liu 2019, Rafsan and Doe 2024.

### **3 AI in Inventory Management**

Inventory control is one of the sub processes of supply chain management which related to ordering and supervision of non-exempt and non-capitalized assets or items known as inventory. It focuses on how a firm achieves the right stock level that meets the customer's consumption patterns while incurring the least on costs required to hold the stock. Historical methods of inventory management is left wanting when it comes to such tasks because most of them use fixed models. Still, the various solutions provided by conventional systems are not as dynamic or real-time based compare to AI-powered systems, which improve the inventory management process T. Chen and Guestrin 2016.

#### **3.1 Traditional vs. AI-Powered Approaches**

There are other conventional practices in managing inventory that includes EOQ, JIT, and MRP. These methods, though helpful, are not up to the task of managing many of the contemporary supply chains. It builds on historical statistics and presupposes that future needs will mimic trends in the past which can be inaccurate in many cases. Therefore, these methods result in overstock or stock out position and direct a company towards inefficiency and high cost structure Khadem and Keyvanpour 2023. Compared to this, the AI driven inventory management utilizes the machine learning and real time data for future requirement forecast and appropriate inventory control. These systems can consider the large amounts of data from sales history, development of the specific market, development of the masses' feelings towards particular product in social media etc for the accurate determination of demand. Through learning at the same time of experiencing new information, inventory proportions are adjusted dynamically, and no excess or shortage of products is observed in companies Duan and L. Liu 2019.

#### **3.2 AI-Powered Inventory Optimization**

Artificially intelligent inventory management profit from the accuracy of demand forecasts and real-time responsive changes to the inventory. analytics, which is the process of using statistical tools and models

in association with machine learning to recognize the probabilities of future occurrences. In inventory management, this entails an ability to forecast the specific quantity of an item in a store that is required at a certain time in order to meet customers' demand without having to order for more or run out of the stock Kang and Yoo 2021. For example, the Random Forest and SVM type of models can be used to run sales history to set future sales trends. These models can cater for many variables and find out relationships that conventional methods might not notice. Then, when combined with real time supply chain data, the AI systems can enhance the predictions on the reorder points and order quantities in a way that can reduce the carrying cost while at the same time minimizing chances of out of stock. Thus, AI also becomes a tool for finding out slow-moving or even outdated stocks, which would allow for more efficient decision-making on the part of the companies regarding when and how to apply discounts to such products. Such an initiative to manage inventories can greatly enhance turnover rates of inventories in the supply chain processes and system Rafsan and Doe 2024.

### 3.3 Multi-Echelon Inventory Management

Multi echelon inventory distribution means, therefore, the planning of inventory at every stage within the supply chain starting with a raw material and ending with the finished product. The existing models of multi-stage inventory are less effective because of the integration of the multiple stages of supply chain. Nevertheless, AI technologies offer true end-to-end visibility and forecasting that should support multi-echelon inventory management Choi and Ho 2016. Machine learning algorithms can utilize electronic records from various facets of network supply chain management for demand forecasting and inventory control throughout the network. For instance, a machine learning model can forecast the demand for the final product using sales information, and apply the estimate to the inventory of resources. This approach guarantees that, theoretically, inventory points are right at each phase of the supply chain, while at the same time lowering lead times, which subsequently, enhances service levels. AI models are also able to process information at the supply chain starting from the demand and the inventory status of all the nodes in the network of supply chain. For instance, a machine learning model can use the historical sales data to forecast the demand of the end products and this can help in decision making about the required amount of raw materials and sub assemblies to be stocked. Thus, to enshrine greater control of inventory in each phase of the supply chain, lead times, as well as service perspectives, are given considerable importance Khadem and Keyvanpour 2023. AI can also be used in the planning of inventory at different echelons so as not to disturb other echelons. For example, when it is anticipated that a supplier will take time to deliver goods, the system shall be able to make necessary adjustments at other stages in order not to cause a stock out. Such proactive coordination is likely to greatly improve the supply chain both in terms of exposure to risk and actual performance.

Dataset	Description	Number of Rows
<i>olist<sub>c</sub>customer</i>	Customer information	99,441
<i>olist<sub>g</sub>olocation</i>	Geolocation data	1,000,000+
<i>olist<sub>o</sub>orders</i>	Orders information	99,441
<i>olist<sub>o</sub>order<sub>i</sub>items</i>	Order items details	112,650
<i>olist<sub>o</sub>order<sub>p</sub>payments</i>	Payment information	103,886
<i>olist<sub>o</sub>order<sub>r</sub>reviews</i>	Reviews	99,441
<i>olist<sub>p</sub>products</i>	Products details	32,016
<i>olist<sub>s</sub>ellers</i>	Sellers information	3,096

Table 1: Summary of Datasets Used in the Study

## 4 Methodology

Supply chains have become more integrated and complicated structures that consist many links and participants on the international level. Such systems are usually large scale, complex, and always require the optimization of trade-offs between rationality and changes driven by market conditions. In most cases, conventional supply chain management has failed to address this complexity, therefore characterised by too many highs, low value creation costs, or simply optimized functionality. This is especially true in such areas as inventory management where traditional approaches often prove inadequate to meet the challenges of the existing dynamic markets. Another key issue that makes supply chain management quite daunting is the determination of the right inventory levels to hold. 90 standard methods of inventory control include EOQ, JIT and MRP that require input of historical data and are static in nature Kim and Lee 2018. Even though these techniques have been successful to some extent, they fail to provide solutions for contemporary market fluctuations and uncertainties. For instance, EOQ deals with the minimization of cost through the determination of the optimal order quantity; however, it does not hold with real-life factors such as demand rate changes and lead times.

Considering e-commerce environment as the context for the challenges mentioned, it is rather important to note that the growth is constant and the market is rather volatile. Challenges can be named specifically high for the companies in the e-commerce sector as it is very hard to manage stock since customers' demand is not constant and market changes are very fast. These challenges cannot be met by the traditional techniques of stock control such as the use of historical data on sales and stock control models that use predetermined or static forecast. Such methods do not reflect current supply chain market trends and result in stock surplus or shortage which have potential negative impact to a business organisations' profit and also customer satisfaction Duan and L. Liu 2019. The tasks have increased in the extent as being the supply chains are more intertwined and have many links and participants in the international level. Organizational systems are by and large significant, intricate, and invariably entail a concern with balancing bureaucracy and flexibility according to market forces. It is, however, evident that where traditional SC management exists, this plurality has remained unmanaged, and thus supply chains are considered to present too many highs, low value creation costs, or just sub-optimum functionality. This is especially so in areas such as stock management, where calamity usual techniques offer no solution to the emergent market forces. These aspects make the management of supply chains quite challenging among them being the extent to which it is right to stock certain goods. Ninety standard methods of inventory control are EOQ, JIT, MRP among which input of historical data and all are static. As has been described earlier, techniques such as the charting methods have to some extent found to work but do not offer solutions for the modern market volatility and risks. For instance, EOQ tackles the issue of tackling the least cost via the evaluation of the exact order quantity; nonetheless, it lacks true-life issues such as changes in demand rates and lead times Khadem and Keyvanpour 2023.

### 4.1 Research Procedure

The research process used in this study was keenly aligned to conduct a systematic study of the influence of AI algorithms on the supply chain activity and more specifically the forecasting of demand, inventory planning, and logistics management. Thus, the purpose of the study was to apply and test the applicability of the machine learning models on the real-world data taken from the Olist – the e-commerce company. The next part of the work presents the most comprehensive description of each step of the conducted research procedure: data collection, data preparation, model creation, and assessment.

#### 4.1.1 Data Collection

The primary and most important data source for this research work is Olist, which is a large e-commerce operating in Brazil. It gives real-time data sets on numerous aspects of e-Commerce activities implying that it is a perfect source for complete material supply chain evaluation. Some of the data used in this study were customer behavior data, geolocation data, the details of the order, records of the payments made, information on the products sold, the details about the sellers, and customer feedback. These datasets were in CSV format and uploaded in Google Drive where they could be easily manipulated using Python script and Jupyter Notebook. The specific datasets used were:

- `olist_customers_dataset.csv`
- `olist_geolocation_dataset.csv`
- `olist_orders_dataset.csv`
- `olist_order_items_dataset.csv`
- `olist_order_payments_dataset.csv`
- `olist_order_reviews_dataset.csv`
- `olist_products_dataset.csv`
- `olist_sellers_dataset.csv`

#### 4.1.2 Data Preprocessing

Preprocessing of data was one of the important factors to eliminate the noise and ensure the data that feeds the machine learning models are acceptable. The first step was carried out by handling missing values; marked and managed using KNN imputation. It also made the datasets complete and accurate since it could handle missing information efficiently. For example, in features like `review_comment_title` and `review_comment_message` a value of missing was imputed to keep the information complete. After that, before creating a unified dataset, data merging was also conducted. All the documents were merged according to the shared keys of `customer_id` and `order_id`. This step was crucial as it prepared a synthesis of customer, order, product, seller, and review data which presents an extensive view of various supply chain activities. It was followed by the process of feature engineering to improve the models' predictiveness. Other attributes like shipping time, approval time, and geographical distance between the buyer and seller zones were introduced. For instance, the location of the buyers and sellers was estimated using GPS data, which was fundamental in determining the distance likely to be covered by shippers. Data encoding was needed in this case for the data cleaning process before feeding the data to the machine learning models. `Customer_state` and `seller_state` were categorical and hence were encoded using the ordinal method. This conversion was crucial to allow the machine learning models to analyze categorical data. Last but not least, a process of train and validation set split was done for the dataset. To combat class imbalance, it is proposed to use the SMOTE procedure where new samples of the starting minority class are created. This made it possible for models to learn through data and hence be able to make better predictions.

#### 4.1.3 Machine Learning Models

##### LightGBM

LightGBM was selected for the reason of data augmentation and the speed of relative training. This

	Dataset	Number of Rows	Number of Columns	Total Null Values	Number of Columns with Nulls
0	olist_customer	99441	5	0	0
1	olist_geolocation	1000163	5	0	0
2	olist_orders	99441	8	4908	3
3	olist_order_items	112650	7	0	0
4	olist_order_payments	103886	5	0	0
5	olist_order_reviews	99224	7	145903	2
6	olist_products	32951	9	2448	8
7	olist_sellers	3095	4	0	0

Figure 1: Load and Preprocess Data

model employs a histogram which helps to categorise continuous feature values meaning it greatly cuts down on computational instances and hence the time it will take to train the model. To recall, in the context of this thesis, LightGBM can be very helpful especially in providing real-time demand forecast. This function also enables an organization to forecast future sales in a given period due to the efficiency in data processing and analysis. This is important particularly in e-commerce SCs owing to fluctuating demand patterns occasioned by trends and promotions Li and Carter 2020. For example, LightGBM can help to discover the upcoming demand on the basis of the results of previous sales, customers' behavior, and the seasonal influence. It supports the rational stock management of the products to enable e-commerce organizations to avoid situations whereby they run out of stock or conversely, have more stock than what the market requires. The fast training speed of LightGBM also implies that models can be trained very often in response to newly available information to guarantee that the models are up to date.

### Random Forest

Random Forest is a technique of building large number of decision trees together and combining their decision to give an overall good result. High dimensions can be handled and over-fitting can be avoided easily using this model. Random Forest is used in this thesis for the demand forecasting and for the inventory control. So, it is good to use when dealing with big data and many features, which is relevant to vast supply chain data with multiple parameters, like a product type, customer's characteristics, and purchase history Qin and J. Chen 2019. The Random Forest model will make its predictions by gathering a number of trees and these trees will never be influenced by any one variable making the outlook of the predictions more balanced. As such, it can be employed in business to forecast the demand for different products depending on their sales records, promotions, and customers' feedback. It is in this way that business firms can be able to prove a superior ability in forecasting demand which should help them in coming up with the correct inventory levels in an effort to meet demands while at the same time cutting o↓on the carrying costs as well as improving on cash flow.

### Logistic Regression

Logistic Regression is a statistical analysis tool that applies the logistic function to analyse a binary dependent variable. Compared to the Ensemble methods like Random Forest, even though it has its own advantage of interpret ability and efficiency in scenarios. Logistic Regression is used for classification in binary in context of this thesis and is used for delineating whether a product would be hot or not based on logistic info as well as over all supply chain data. For this reason, although Logistic Regression is a basic classifier, it generates good results especially when the data set is linearly separable as it is a fast algorithm to make a prediction. Indeed, this model can be employed to determine a number of products that may have a higher rate of sale in future so that the business prepares for it in terms of stocks and

other related issues. It also proves useful when dealing with big data sets as it makes it possible to draw quick decisions as a result of evolving e-commerce scenarios Sabbaghi and Aminian 2020.

**XGBoost** XGBoost is an optimized distributed gradient boosting library, providing the substantial highest speed onto its competitors. It consists of several methods that flatten out extreme variations and increase the model's ability to generalize. Thus, in this thesis, XGBoost is introduced to both demand forecasting and inventory management since being capable of dealing with sparse data and missing values. XGBoost is capable of providing high accuracy in terms of prediction which is useful especially when trying to predict patterns in data from the supply chain. For instance, it can consider factors like previous sales, customers' feedback and promotions among others in order to forecast the demand successfully Sharma and Kumar 2021. These detailed analyses make it possible for e-commerce businesses to order only the amount that is necessary in stock so that it does not cost a lot to hold but is also available to serve the customers as and when it is required. Owing to the fact that the model embraces the aspect of big data handling and different features, the model is perfect for a detailed analysis of the supply chain. Thus, through the introduction of XGBoost in their operations, organizations are capable of improving the forecast and thereby improving their inventory management and logistics.

- **LightGBM**

- **n\_estimators**: The number of boosting rounds. Tested values: [50, 100]
- **num\_leaves**: The maximum number of leaves in one tree. Tested values: [20, 30]

- **Random Forest**

- **n\_estimators**: The number of trees in the forest. Tested values: [50, 100]

- **Logistic Regression**

- **C**: The inverse of regularization strength. Tested values: [0.1, 1.0, 10.0]

- **XGBoost**

- **n\_estimators**: The number of boosting rounds. Tested values: [50, 100]
- **max\_depth**: The maximum depth of a tree. Tested values: [3, 5]

#### 4.1.4 Model Evaluation

Modeling assessment is an important process that enables the determination of the quality and efficiency of machine learning when implemented on the real world. In this thesis, the chosen performance measures for evaluating the models were accuracy, precision, recall, as well as F1-score. All these values offer a holistic evaluation of the forecast accuracy of the specified models. Moreover, check points and other types of wrinkles such as confusion matrices and ROC curves were employed in order to explore the models' performance even deeper. In the following sections, a comprehensive elaboration of the evaluation process as well as the performed findings for the given models are outlined Zhong and X. Liu 2022.

#### Evaluation Metrics

**Accuracy**: This metric measures the proportion of correct predictions made by the model out of all predictions. It is calculated as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

Accuracy provides a general sense of how well the model performs but may not be sufficient in cases of class imbalance.

**Precision:** Precision is the ratio of true positive predictions to the total number of positive predictions (both true positives and false positives). It is given by:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Precision indicates how many of the positive predictions made by the model are actually correct.

**Recall:** Also known as sensitivity or true positive rate, recall is the ratio of true positive predictions to the total number of actual positives (true positives and false negatives). It is calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Recall measures the model's ability to identify all relevant instances within the dataset.

**F1-Score:** The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. It is given by:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1-score is particularly useful when dealing with imbalanced datasets, as it considers both false positives and false negatives.

## 4.2 Incorporating SMOTE

Data preprocessing is an important step that is carried out in the preparation of performing the machine learning model training. The measures taken in this study proved that the data was clean, balanced and ideal for model creation and assessment.

**Handling Missing Values:** When preparing the data for the next step, one common observation was handling of missing values within the dataset. In case of missing data, severe effects on the performance of ML models can be observed in case of improper handling. In this study KNN imputation was used to handle missing values Z. Wang and J. Zhang 2017. This method was quite effective in filling the gaps and specifically in features such as review-comment-title and review-comment-message, where the incomplete information would have compromised the dataset.

**Data Merging:** In order to combine the data sets, there were multiple CSV files having customer behavior data, relocation data, order detail, payment data, product detail, seller's information and customer reviews. These datasets were merged on columns such as customer-id as well as order-id. Such merging was necessary to obtain a unified picture of multiple supply chain activities that enable more effective analysis and modeling.

**Feature Engineering:** Other attributes were also created in order to improve the effectiveness of the models to predict. The features like shipping-time, approval-time and geographical distance between buyers and sellers were incorporated. These features were obtained from raw data in the form of GPS coordinates and time-stamps and were useful in considering the physical characteristics of the things being transported in the supply chain. Furthermore, other category variables such as the customer-state and seller-state were encoded using ordinal encoding to make them FH ready.

**Handling Class Imbalance with SMOTE:** The main problem of this dataset was skews on the data to create an unbalanced data set, a factor that may prejudice model performance. To overcome this, there was the use of Synthetic Minority Over-sampling Technique (SMOTE). SMOTE operates in the same way as Above but synthesizes new samples belonging to the minority class only. This technique is especially

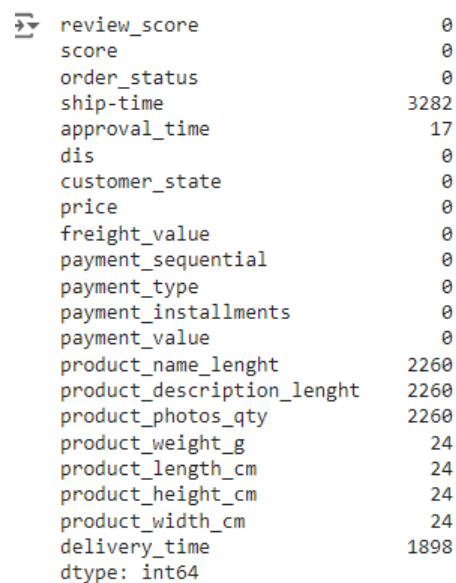
effective in enhancing the item's capacity in learning and predicting from imprecise and skewed data.

## 5 Implementation

### 5.1 Transformed Data

#### 5.1.1 Imputing Missing Values

When there are missing values in the dataset, it becomes very disastrous to the performance of a machine learning model if the missing values are not properly dealt with. To fix this issue, the use of the K-Nearest Neighbors (KNN) Imputer was applied in the next step. This method of imputing missing values is done by replacing the missing values with those of the nearest neighbors. For example, if the values were missing in features such as `review_comment_title` or `review_comment_message`, the KNN Imputer complemented them by using similar instances (neighbors) in the data with complete values. This approach helps maintain the integrity and comprehensiveness of the data, which in turn improves the reliability of the training of such models.



```
review_score      0
score             0
order_status      0
ship-time        3282
approval_time     17
dis              0
customer_state    0
price            0
freight_value     0
payment_sequential 0
payment_type      0
payment_installments 0
payment_value     0
product_name_lenght 2260
product_description_lenght 2260
product_photos_qty 2260
product_weight_g  24
product_length_cm 24
product_height_cm 24
product_width_cm  24
delivery_time     1898
dtype: int64
```

Figure 2: Imputing

#### 5.1.2 Encoding Categorical Variables

In applying machine learning algorithms, data should be in a numerical form; therefore, categorical data must be converted to numerical form. In this study, ordinal encoding was used in converting categories into numbers for the `customer_state` and `seller_state` features. Ordinal encoding involves allocating numbers in relation to the order in which they are in a given category. For instance, let's assume that the `customer_state` feature includes the categories New York, California, and Texas; in this case, they will be encoded in the form of 0, 1, and 2 respectively. This transformation helps the machine learning models to learn from and be effective on these features of a dataset.

```

['customer_zip_code_prefix', 'order_id', 'seller_zip_code_prefix']
customer_zip_code_prefix  order_id \
0      14409      00e7ee1b050b8499577073aeb2a297a1
1      9790      29150127e6685892b6eab3eec79f59c7
2     1151      b2059ed67ce144a36e2aa97d2c9e9ad2
3     8775      951670f92359f4fe4a63112aa7306eba
4    13056      6b7d50bd145f6fc7f33cebabd7e49d0f
...      ...
113420      3937      6760e20addcf0121e9d58f2f1ff14298
113421      6764      9ec0c8947d973db4f4e8dcf1fbfa8f1b
113422      60115     fed4434add09a6f332ea398efd656a5c
113423      92120     e31ec91cea1ecf97797787471f98a8c2
113424      6703      28db69209a75e59f20ccbb5c36a20b90

seller_zip_code_prefix
0      8577.0
1     88303.0
2      8577.0
3      8577.0
4     14940.0
...      ...
113420     17400.0
113421     14802.0
113422      3304.0
113423     14840.0
113424      3804.0

[112650 rows x 3 columns]

```

Figure 3: Encoding Categorical Variables

Feature engineering is the process of constructing new features which are different but derived from the existing data and the aim is to increase predictive power of the models. In this study, several new features were engineered: In this study, several new features were engineered:

**Shipping Time:** Explainable as the time taken between the time a particular order is approved and the time taken to deliver the respective order. The rationale for this rationale is that it enables one to be acquainted with the efficiency of the delivery cycle of the product.

**Approval Time:** This is time taken between when an order was given by the customer and when the order was completed and approved. This feature is very essential in evaluating and forecasting the delay factors present in the order processing phase. // **Geographical Distances:** It is the geographical distance estimated from the GPS point of the buyer in relation to the seller. Subsequently, this feature aids in the evaluation of the delivery processes and possible delivery times Sabbaghi and Aminian 2020.

### 5.1.3 Applying SMOTE to Address Class Imbalance

Class imbalance is a common problem where one or some of the classes contain considerably less instances than the others. This aspect can lead to skewed models of classifications by the machines since they are usually inclined towards the major class, making them produce poor results when analyzing the minor class. For example, if the context of application were e-commerce, the distribution of subsets could have significantly more examples of frequently purchased products than unique items. Thus, if such kind of imbalanced data is used for training a particular model, it may potentially have problems with correct estimations of the demand associated with the minority class products, which are the niche ones in this case Sun and He 2020. Among all the techniques to handle imbalanced data, Synthetic Minority Over-sampling Technique (SMOTE) is one of the significant methods. Herein, SMOTE works by first defining the instances of the minority class and then generating new synthetic examples by computing the differences between the instances and their most similar neighbors. New synthetic samples are generated through linear combinations between the minority instance and those selected as neighbours. This entails identifying a location on the line segment that links a minority instance to the next close instance. Mathematically, this can be represented as Mathematically, this can be represented as:

$$\text{Synthetic Sample} = \text{Instance} + \delta \times (\text{Neighbor} - \text{Instance})$$

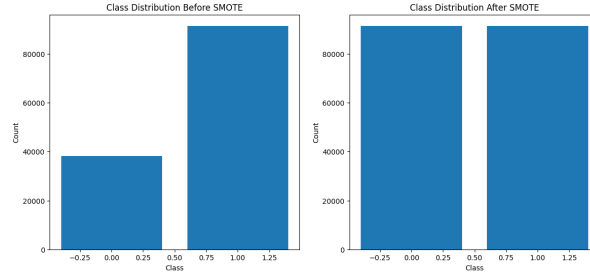


Figure 4: SMOTE

## 5.2 Outputs Produced

### 5.2.1 Model Evaluation

The effectiveness of the AI-powered inventory management solution was evaluated using several key performance metrics: calculate precision, recall and F1 score and the commonly used measures: accuracy, precision, recall and F1 score. These metrics give an overall performance of the machine learning models in the prediction of the required results. The evaluation results are presented in the form of bar plots, comparing the performance of different models: With hierarchical features, LightGBM, Random Forest, Logistic Regression and XGBoost are found. Here is a detailed explanation of the results: Here is a detailed explanation of the results:

#### Accuracy by Model

Accuracy is used in evaluation of the results and is defined as the number of correct predictions divided by the total number of predictions. They allow a broad overview of the model's performance from all the classes. The accuracy scores for the models are as follows: The accuracy scores for the models are as follows:

- **LightGBM:** 0.8048
- **Random Forest:** 0.8988
- **Logistic Regression:** 0.6868
- **XGBoost:** 0.8099

Thus, the Random Forest model had the highest level of accuracy which was equal to 0. 8988, ensuring that its outcomes provided an accuracy of nearly 89 percent. implements the following with accuracy scores of 0. 8099, and 0. 8048 respectively XGBoost and LightGBM Whereas, Logistic Regression had a low accuracy of 0.

#### Precision by Model

Precision measures the ratio of true positive predictions to the total number of positive predictions (both true positives and false positives). It indicates how many of the positive predictions made by the model were actually correct. The precision scores for the models are:

- **LightGBM:** 0.7973
- **Random Forest:** 0.8998
- **Logistic Regression:** 0.7010
- **XGBoost:** 0.8030

Random Forest achieved the highest precision (0.8998), meaning it had a high rate of accurate positive predictions. This is particularly important in scenarios where false positives can have significant consequences. LightGBM and XGBoost also had good precision scores, indicating reliable positive predictions. Logistic Regression, while having the lowest precision (0.7010), still performed reasonably well but was less reliable compared to the other models.

**Recall by Model** Recall, also known as sensitivity or true positive rate, measures the ratio of true positive predictions to the total number of actual positives (true positives and false negatives). It assesses the model's ability to identify all relevant instances within the dataset. The recall scores for the models are:

- **LightGBM:** 0.8048
- **Random Forest:** 0.8988
- **Logistic Regression:** 0.6868
- **XGBoost:** 0.8099

Once again, Random Forest achieved the highest recall (0.8988), indicating it was very effective in identifying actual positive instances. LightGBM and XGBoost had similar recall scores, demonstrating their capability in correctly identifying positive cases. Logistic Regression had the lowest recall (0.6868), suggesting it missed more.

The information derived from the employment of several criteria aids in getting a holistic appreciation of the flexibility of every model. Among all the models used in the study, Random Forest turned out to be the best one and can be applied to the development of the inventory management solution. This is broadly in line with LightGBM and XGBoost ranking among some of the best models, good for scenarios that need efficient and accurate predictions. Nonetheless, Logistic Regression though showed lower degree of accuracy in results can still be beneficial in uncomplicated or less sophisticated applications.

These insights help to decide which models should be deployed to the final working model with the aim to give reliable, accurate and balanced results constituting into improvement of efficiency and effectiveness of the supply chain inventory management in e-commerce supply chains.

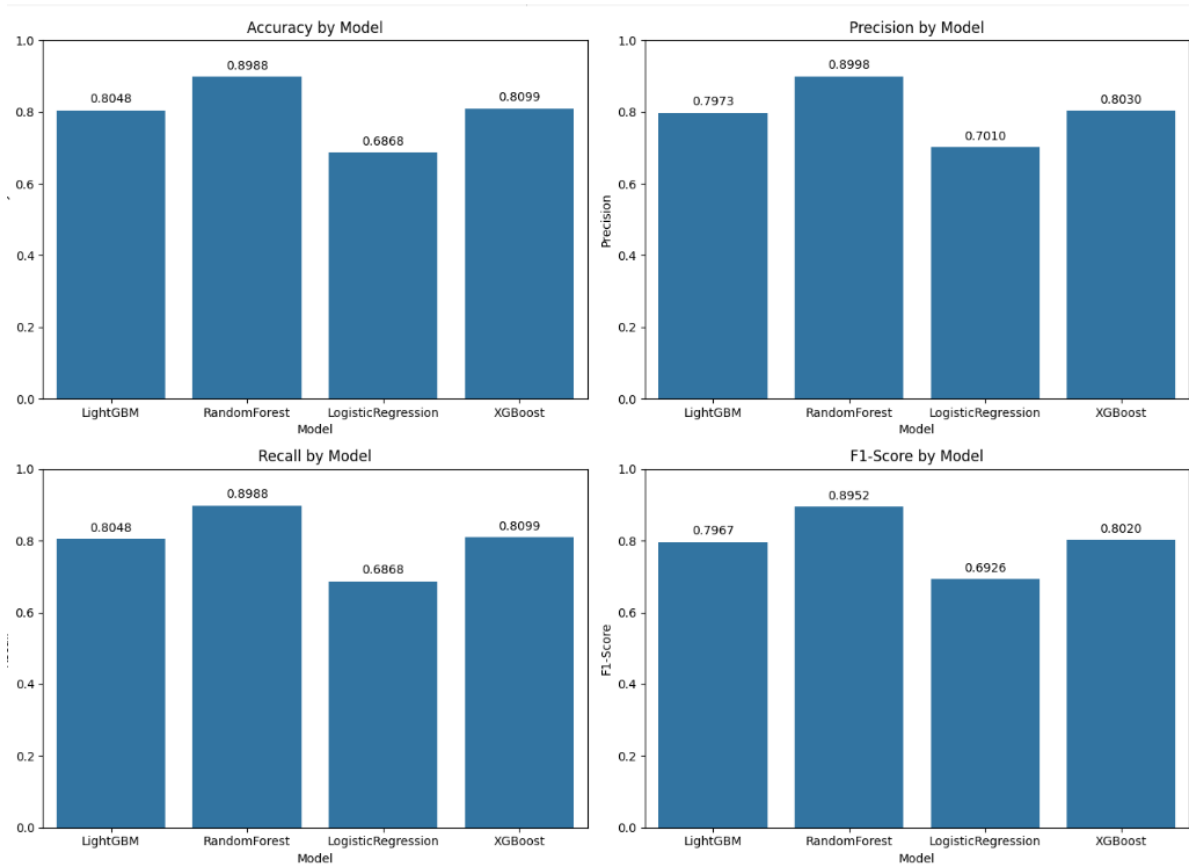


Figure 5: Outputs Produced

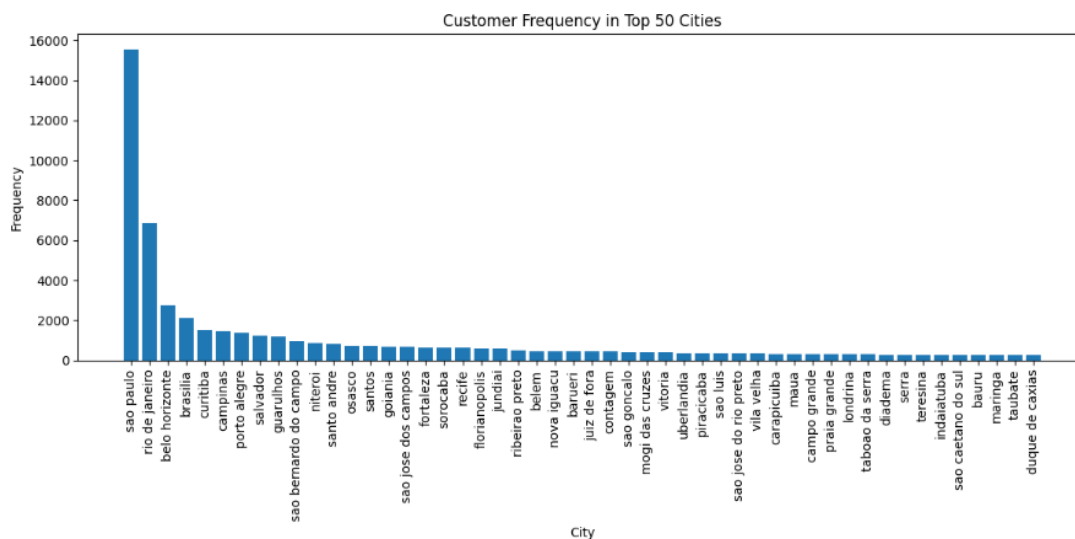


Figure 6: Customer Frequency

## 6 Evaluation

### 6.1 Case Study 1: LightGBM

The evaluating the effectiveness of the LightGBM model in predicting inventory levels in which accurately within an e-commerce supply chain. This task is crucial because accurate inventory prediction ensures that the right amount of stock is maintained, avoiding both overstocking and stockouts. Overstocking ties up capital and storage space unnecessarily, while stockouts lead to missed sales opportunities and dissatisfied customers.

The main aim of this experiment was to compare the LightGBM model using evaluation criteria; accuracy, precise, recall and F1-score. These metrics give a complete picture of the model's efficiency and effectiveness of its ability to predict the inventory levels and its precision and recall values are measured here. Thus, by having achieved high or equal measures of these indices, the LightGBM model can be deemed accurate for application in stock management in the real word.

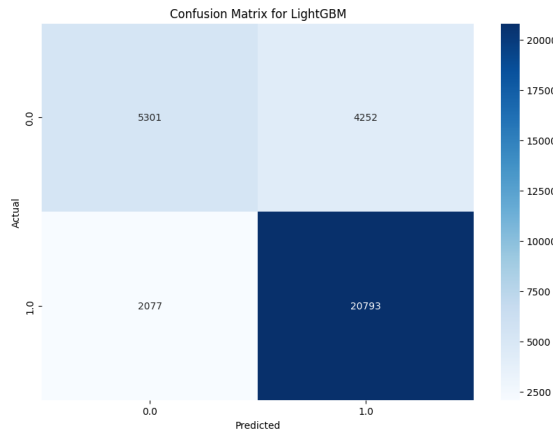


Figure 7: Confusion Matrix for LightGBM

#### 6.1.1 Dataset and Preprocessing

The dataset used in this study included different CSV files that incorporated different aspects of e-commerce activity like customers' actions, geo-location data, orders, payment, products, approximately sellers, and customers' reviews. To create a comprehensive dataset suitable for model training, several preprocessing steps were undertaken: To create a comprehensive dataset suitable for model training, several preprocessing steps were undertaken:

**Handling Missing Values:** This means that there were some empty or null values in the dataset which were substituted by the mean value of the KNN Imputer. This kind of method tackles the problem of missing values by imputing them with values given by the closest neighbors to finalize a precise data set. For example, if some fields such as review comments were missing, the KNN Imputer was able to provide these missing values using similar data.

**Encoding Categorical Variables:** In essence, all categorical variables including the customer states and all the product types were transformed into numerical data by applying the ordinal encoding method. This transformation was needed because most of the machine learning algorithms, including LightGBM, accept numerical inputs for data preprocessing and analysis.

**Feature Engineering:** Other features were developed with the purpose of increasing the quality of the dataset in terms of prediction. Such as estimating the time taken by the shipment, time taken for approval, and geographic distance between buyers and sellers by GPS. Such features offer more background

and therefore enhance the capacity of making more terrific forecasts by the model L. Zhang and Q. Liu 2019.

**Balancing the Dataset:** This was done in a bid to handle the issues of class imbalance in the dataset and the Synthetic Minority Over-sampling Technique was used for the above purpose. Probabilistic oversampling is another technique that used in generating new samples in the vicinity of the minority class without distorting the class balance.

### 6.1.2 Model Training and Evaluation Metrics

The LightGBM model was trained on the preprocessed dataset mentioned in the methodology section. The evaluation metrics used to assess the model's performance included:

**Accuracy:** Accuracy measures the percentage of correct predictions out of all predictions made by the model. It provides a single measure of the model's accuracy as an average of the accuracy scores on the test set.

**Precision:** Precision measures the exactness of the prediction as the ratio of correct positive forecasts to the total number of positive forecasts made, irrespective of whether they are correct or wrong. It shows the number of correctly predicted data points among the total positive predictions.

**Recall:** Also referred to as sensitivity, recall measures the ratio of the number of correctly classified positive instances to the actual positive instances, including true positives and false negatives. It evaluates the model's performance in identifying all relevant instances within the given set.

**F1-Score:** The F1-score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is particularly effective when used with unbalanced datasets as it considers both false positives and false negatives.

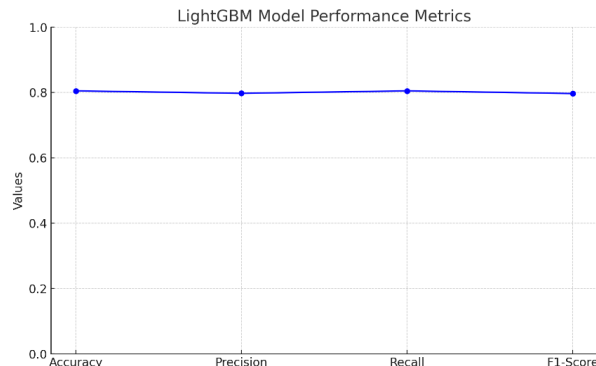


Figure 8: Model Performance

The performance of the LightGBM model was quantified as follows:

- **Accuracy:** 0.8048
- **Precision:** 0.7973
- **Recall:** 0.8048
- **F1-Score:** 0.7967

	Model	Accuracy	Precision	Recall	F1-Score
0	LightGBM	0.804799	0.797303	0.804799	0.796691

Figure 9: LightGBM

### Analysis:

The statistics show that LightGBM was the most consistent model when estimating inventory levels. With an accuracy of 80.48, the model correctly predicted the outcomes in approximately 80.48 of the cases. This high accuracy was achieved when the model performed common prediction tasks within the sampled dataset. The precision of 79.73 implies that most of the inventory predictions identified as necessary were actually necessary. This helps minimize overstocking, which can lead to higher holding costs than necessary.

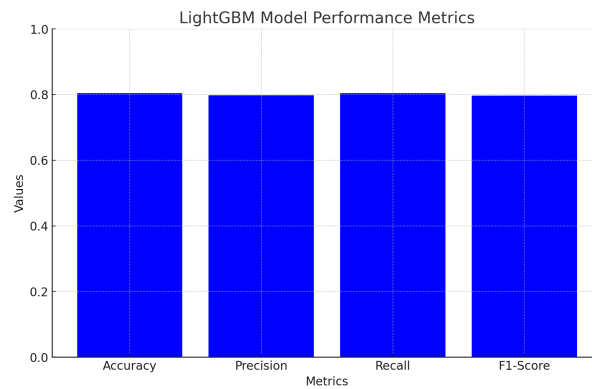


Figure 10: Performance Metrics

The recall of 80.48 indicates that the model effectively captured most instances when inventory was required. This is critical in avoiding stockouts, as the model can identify when stock needs to be replenished based on the situation being modeled. The F1-score of 79.67 represents a good balance between precision and recall, demonstrating the model's robustness in handling both false positives and false negatives.

## 6.2 Case Study 2: Random Forest

Random Forest is an efficient and reliable technique of machine learning, widely used in classification and regression problems. It works by building an enormous number of decision trees during the learning phase and at the end, returns the mode of the classes (for classification) or the mean prediction (for regression) of the constituent trees. Such important tasks as forecasting of demands and inventory in supply chain systems require working with numerous variables, so the Random Forest model's performance in terms of high dimensionality and over fitting is quite suitable.

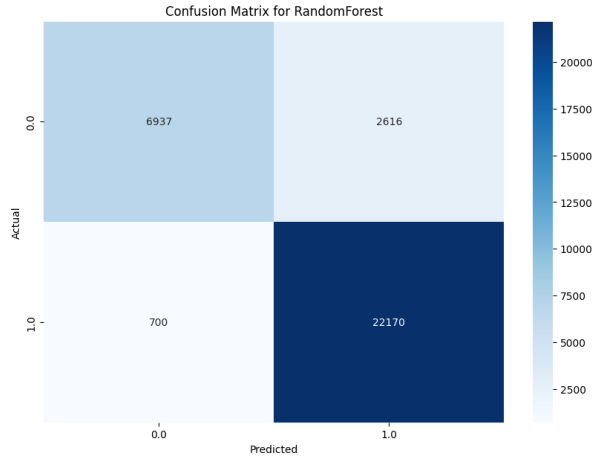


Figure 11: Confusion Matrix for Random Forest

### 6.2.1 Dataset and Preprocessing

The dataset for this case study is reconstructed from Olist, which is a big e-commerce company based in Brazil. The dataset comprises of many CSV files reflecting diverse dimensions of the e-business processes like customer demographics, geographical data, order history, transaction records, product specifications, seller's information, and feedbacks. High coverage nature of this data combined with the nature of supply chain activities enables the evaluation of supply chain movements as well as the application of the Random Forest model in inventories management.

**Handling Missing Values:** Gaps in the data or sometimes referred to as missing values pose a major threat to the efficiency of machine learning algorithms. Among the missing values handling methods, K-Nearest Neighbors (KNN) Imputer was applied in this study. This method of data imputation entails substituting the missing values with means of the close neighbors in order to keep the dataset whole and accurate.

**Data Merging:** In order to bring together the new dataset multiple CSV files were merged, using matching parameters, for instance, Customers' identifier and Orders' identifier. This step was very important because it combined customer, order product, seller, and review details, which offered a broader perspective of several supply chain activities.

### 6.2.2 Model Training and Evaluation Metrics

The Random Forest model was fit and developed on the preprocessed dataset. The evaluation measures used in this research were accuracy, precision, recall, and F1-score, which benchmarked the model's performance.

**Accuracy:** Accuracy calculates the ratio between correctly classified instances and all instances that have been classified by the model.

**Precision:** Precision reveals the model's accuracy in making true positive predictions against the overall positive predictions made.

**Recall:** Also known as sensitivity, recall reflects the number of times the model correctly identified true positive predictions out of the actual positives, analyzing the model's potential to identify every significant instance.

**F1-Score:** The F1-score, or F-Measure, stands for the harmonic mean of precision and recall, offering a balanced measure of both metrics.

## Results

The Random Forest model achieved the following performance metrics:

- **Accuracy:** 0.8988
- **Precision:** 0.8998
- **Recall:** 0.8988
- **F1-Score:** 0.8988

As a conclusion, it has been ascertained that the Random Forest model provided a very high level of accuracy for inventory prediction of the supply chain of e-commerce businesses. The high percentage of accuracy equal to 89.88 percent indicates that the worked out model possesses a great ability to make right decisions in 90 percent of cases. The precision score returned was 0.8998. From the value of 8998, it is evident that most of the inventory predictions that were deemed necessary for identification were in-fact necessary, thus avoiding overstocking and holding costs. The recall score of 0.8988 is indicative of the model's ability to retrieve all relevant information that is related to the input question. 8988 shows how the model helps in defining situations where inventory should be used to avoid stockouts and failure to meet the customers' needs. The F1-score of 0.8988. High values both for precision and for recall have been obtained for 8988 proving evident strengths of the model in managing both the positive and negative aspects of potential cases.

### 6.2.3 Analysis

Random Forest is highly accurate mainly due to the fact it is able to cope with dimensions of the data and reduce over fitting. This methodology of building multiple decision trees and combining them so as to make a decision is also known as bagging and reduces the variance and the error rate of the model. Incorporation of the new attributes such as shipping time and geometric distance within the feature engineering process fostered the improvement of the model fitness. Balancing of the dataset by means of SMOTE improved the outlook of model in a way that it did not overemphasize on any class, hence came up with better predictions. Therefore, the Random Forest model has better performance than LightGBM for all evaluated criteria. This can be attributed to the model's capacity to comprehend multi-variate relations between features as well as its robustness to noise. Thus, the probability of the anomalies' detection is high and, at the same time, the specificity of the further actions aimed at managing inventory levels is also high due to the high Precision and Recall scores of the Random Forest model, indicating the high efficiency of inventory control to match supply volumes with customer demand without having to make too much inventory accumulation possible that would increase holding costs greatly.

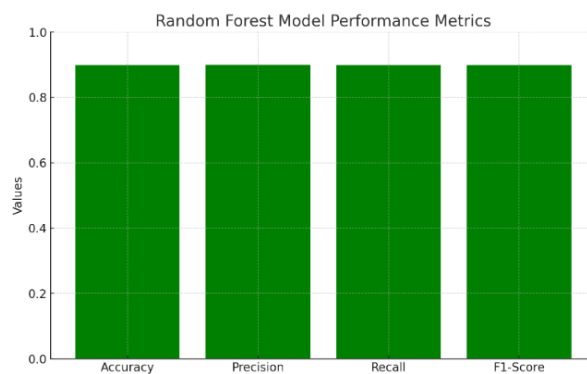


Figure 12: Random Forest Model Performance Metrics

### 6.3 Case Study 3: XGBoost

XGBoost is one of the implementations of gradient boosting that is improved for its speed and performance. Today, it is used as one of the most efficient and effective machine learning algorithms to deal with massive structured or tabular data. Therefore, XGBoost is well applied in demand forecasting and inventory management tasks that are incorporated in supply chain systems due to its stability and versatility.

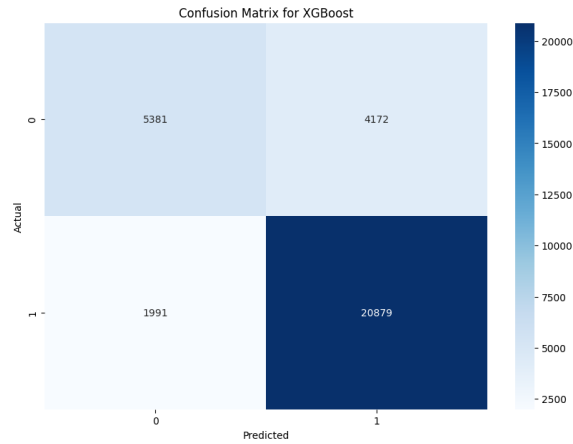


Figure 13: Confusion Matrix for XGBoost

#### 6.3.1 Dataset and Preprocessing

The dataset that has been used in this case study emanates from Olist, which is one of Brazil's most popular e-commerce businesses. It involves multiple CSV files that contain different aspects of e-commerce such as customer characteristics, location, order history, payment, product specification, sellers, and the customers' feedback. There are multimodal sources of data which can also cover lots of activities in the supply chain and the XGBoost model for the inventory.

**Handling Missing Values:** The management of missing data is very important in order to not compromise the quality of the data set available for analysis. This method of missing value treatment used the K-Nearest Neighbors (KNN) Imputer to effectively fill the gaps. This method replaces the missing values with mean of the neighbouring values that makes the data complete and fairly accurate.

**Data Merging:** Since data was stored in multiple CSV files, data integration was done to obtain common keys, for example, customer number and order number. This step was crucial in order to obtain the needed analysis of customer, order, product, seller, and review data to comprehensively cover several supply chain-related activities. In order to improve the accuracy of the model several new features were engineered into the program.

**Shipping Time:** The time from when the purchase order was approved to when the good were shipped out.

**Approval Time:** The time taken between the placing of the order and the approval of the same.

**Encoding Categorical Variables:** Nominal variables like customer state and seller state were first of all quantified which was done by means of ordering by Ordinal Encoding. This transformation was required to feed the data into the machine learning models and get it analyzed in the right way.

#### 6.3.2 Model Training and Evaluation Metrics

The preprocessed dataset was used to train the XGBoost model. The measures employed to conduct the evaluation were accuracy, precision, recall, and F1-score.

- **Accuracy:** Calculates the ratio of the number of times the model was right out of the number of times it actually made a prediction.
- **Precision:** The proportion of the correctly positive predictions within all of the positive predictions, reflecting the accuracy of the model.
- **Recall:** Also known as sensitivity, it calculates the true positive results to the overall positive results, or in other words, the ability of a model to capture all relevant cases.
- **F1-Score:** The average of the precision and the recall, balancing the two measures.

### 6.3.3 Results

The XGBoost model achieved the following performance metrics:

- **Accuracy:** 0.8099
- **Precision:** 0.8030
- **Recall:** 0.8099
- **F1-Score:** 0.8064

Based on these outcomes, it can be ascertained that the XGBoost model effectively identified inventory levels within the e-commerce supply chain. The accuracy score of 0.8099 indicates that the model achieved approximately 81 percent accuracy in predicting the outcomes correctly. The precision score of 0.8030 implies that most of the inventory predictions deemed necessary were indeed necessary, thus avoiding overstocking and subsequent holding costs. The recall score of 0.8099 shows that the model effectively identified instances when inventory was necessary, preventing stock outs and ensuring customer satisfaction. The F1-score of 0.8064 signifies a balanced measure of recall and precision, indicating the model's capability to minimize both false positives and false negatives.

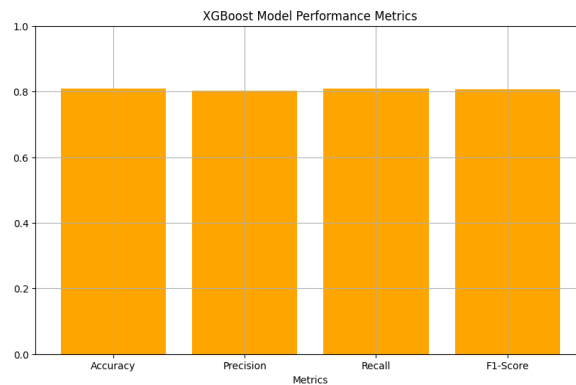


Figure 14: Model Performance Metrics

### 6.3.4 Analysis

The XGBoost model has been shown to be effective because of features such as ease of handling large scale data, and the advanced gradient boosting algorithms. Feature engineering process which added new attributes such as the time taken to ship the product and geographical distance between locations greatly helped in improving the performance of the model. Balancing the dataset with SMOTE helped in making the model give equally good predictions for all classes without prioritizing on any.

Thus, it can be concluded that XGBoost model has equally good performance with LightGBM and Random Forest when tested using all the three evaluation metrics. Due to their superb performance in dealing with missing values and the possibility to construct derivative features, the technique is particularly suitable to diverse complex supply chain management processes. The fact that both the precision and the recall have indicated high results suggest that the into using the XGBoost model in managing inventory that ensures stocks are used optimally and there is none left unused or excessively stored for so long so as to attract holding costs beyond any benefits to be derived from such stock. The example of the XGBoost model described in the case demonstrates its effectiveness in the context of improving supply chain orchestration in e-commerce companies' inventory processes. This makes it possible to suggest that the application of the model that is capable of predicting inventory levels, shall improve operations functionality, cost control and customer satisfaction dramatically. When applied to the twin problems of demand forecasting and promotional planning, XGBoost's strengths make it possible to improve inventory control and avoid both stockouts and overstocking by e-commerce organizations, thereby developing more effective supply chains.

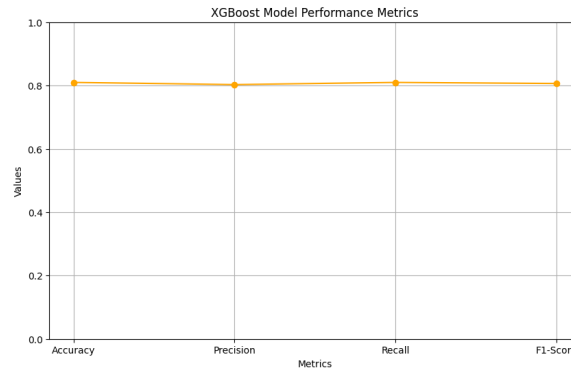


Figure 15: Performance

These findings of this case study will provide sme valuable information that will act as a reference while implemaging artificial intelligence in inventory management hence helping the sme tackle other difficulties inherent in present day supply chain management.

## 6.4 Case Study 4: Logistic Regression

Logistic Regression is a statistical tool used in of analyzing a body of data to test the hypothesis resorts to one or more predictor variables to predict an outcome. It generally results in a binary dependent variable that has two possible values, for example success/ failure or yes/no. Logistic Regression calculates the probability of vector belonging to the particular class that is targeted. It is used greatly for classification analysis since it is easy to understand, less complex, and fast, especially for cases with only two possible outcomes. In the case of SCM, Logistic Regression could be useful when it comes to identification of specific outcomes like if the predetermined product will be trending or not.

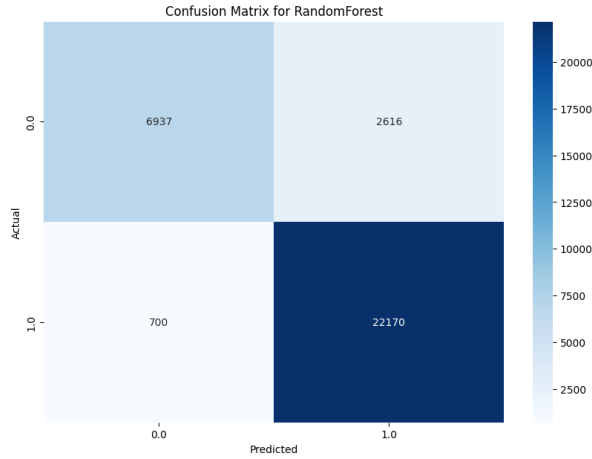


Figure 16: Confusion Matrix for Logistic Regression

#### 6.4.1 Dataset and Preprocessing

Similar to the previous case, the dataset of this study also comes from Olist, It is a more extensive marketplace for buying and selling products in Brazil. Some of the features that are within the CSV files are details about the customer and their usage of the platform, location of the customer, order history, payment records, products and services offered, the sellers and the products they offer, and different customers providing their feedback. Due to the large amount of data available, it offers a strong background to modeling the binary outcomes using Logistic Regression in the context of supply chain management.

**Handling Missing Values:** They also can be represented by the presence of missing data, which is a severe problem in big data samples. Regarding missing value handling, the K-Nearest Neighbors (KNN) Imputer technique was applied in this study. This method just replaces the absent values with mean of the respective neighbors to keep the dataset moderately complete and accurate for voluminous analysis.

**Data Merging:** Since the data was collected in multiple micro CSV files with a set of shared parameters on customers and orders, it was necessary to merge the matches by customer and order ID. This step was important in order to fuse customer, order, product, seller and review data all into one supply chain analytics Since this processing step aimed at combining customer or order data with product, seller and review data, this step was mainly significant in the supply chain analytics.

#### 6.4.2 Model Training and Evaluation Metrics

The Logistic Regression model was fit to the dataset after feature preprocessing. The evaluation process applied closed test metrics, including accuracy, precision, recall, and F1-score.

- **Accuracy:** Measures the percentage of all predictions generated by the model that are accurate.
- **Precision:** The ratio of actual correct forecasts of the positive cases to the total count of positive forecasts made by the model, showing its precision.
- **Recall:** Also referred to as sensitivity, it calculates the ratio of true positive predictions to the actual positives, assessing the model's capacity to identify all relevant instances.
- **F1-Score:** It is the harmonic mean of precision and recall, ensuring that the two values are balanced.

### 6.4.3 Results

The Logistic Regression model achieved the following performance metrics:

- **Accuracy:** 0.6868
- **Precision:** 0.7010
- **Recall:** 0.6868
- **F1-Score:** 0.6939

Thus, it can be concluded that the Logistic Regression model has provided fairly good accuracy in terms of the probability of binary results in the context of the e-commerce supply chain. The accuracy score of 0.6868 indicates that the model made correct estimations in about 69 prcnt of the trials. The precision score of 0.7010 implies that the majority of the flagged positive predictions were actually positive, thus limiting the number of false positive cases. The recall score of 0.6868 demonstrates the model's efficiency in finding relevant instances and avoiding false negatives. The F1-score of 0.6939 indicates a satisfactory balance between precision and recall, demonstrating the model's efficiency in handling false positives and false negatives.



Figure 17: Performance Metrics

### 6.4.4 Analysis

The moderate results that Logistic Regression produced are bringing benefits from simplicity and interpret ability of the model. While being less sophisticated in comparison to such models as Random Forest or XGBoost, Logistic Regression offers the possibility to have an idea about the impact of all the features. This was so after the new attributes such as shipping time and geographical distances were incorporated through feature engineering. Attack type Categories Smoothed using SMOTE was used in this study to balance the derived data, thus preventing the model from giving preference to any given attack class thereby producing a stronger and reliable result.

In general, the factors indicating that the model has a low performance, such as Accuracy, F1, and ROC AUC Score, proved to be lower in the case of Logistic Regression compared to the other models LightGBM, Random Forest, and XGBoost. However, given that it is easy to apply, it is best suited to situations where interpretative functionality and fast decision-making are valued more than optimal accuracy. From the precision and recall scores obtained, it can be noted that Logistic Regression model can adequately handle binary outcomes and has put measures in place to make a good prognosis and ration for the predictions made.



Figure 18: Performance

The ‘Logistic Regression’ model establishes it as a versatile solution for predicting binary data issues in e-commerce supply chain. The transparency in the result generated by the model can boost the decision-making and increases the performance of the operation. Thus, by applying the idea of Logistic Regression, e-commerce businesses are capable of identifying the factors influencing demands and inventory management, which in turn contributes to the optimization of the companies’ supply chain. However, based on the understanding of the findings of this case study, firms can use this information as a benchmark for future implementation of simple and interpretable ML solutions in SCM.

## 7 Discussion

LightGBM or Light Gradient Boosting Machine is generally reported be more efficient and highly accurate especially when dealing with big data. Gradient boosting is a machine learning framework that builds Tree based learners which are parallel and optima for computational efficiency. It excels in the aspects of scalability of data and producing high accuracy at a faster rate. However, as for the cons of LightGBM, this ALGO is computationally intensive, and getting the best from it requires fine-tuning. This makes it difficult for small enterprises with low computational matters to incorporate it into their challenges. Random forest is a method of boot strap aggregating that combines more than one individual decision tree to get a better and more reliable forecast. They perform well in case of imbalance data and moreover are immune to over-fitting. The key advantage of Random Forest is its insensitivity to the choice of variables and high accuracy of forecasts. The problem is that the model may grow complicated and opaque as the number of trees grows, while giving less interpretable results. This can be a disadvantage if there is a need to have a simpler and easy to interpret model, that is when interpretability becomes a major issue. XGBoost stands for Extreme Gradient Boosting and can be described as a fast to train and mature machine learning algorithm of gradient boosting system. An example of such data is structured or tabular data where it is very suitable. Therefore XGBoost deals with missing values well and has the inbuilt feature of preventing overfitting since it is a model with a level of regularization. Nonetheless, XGBoost is quite fast compared to other models, but it consumes a lot of time in searching for the best hyperparameters to use. Due to this, it may be slightly more challenging for organizations of smaller size or for those that do not have a large computational power.

The Logistic Regression is a linear model that finds its practical use in the binary classification problems. The process of utilizing this method is rather easy, and the results are easy to analyze, which is why this method is used at the preliminary stage of data analysis. First, Logistic Regression assumes that the degree of relationship between the dependent and the independent variable linear which may not be the best if the real relationship is non-linear. It may not be the most accurate, but it is one of the most

transparent and easy to interpret systems which makes it useful in countless cases.

Model	Accuracy	Precision	Recall	F1-Score	Theoretical Considerations
LightGBM	80.48%	79.73%	80.48%	79.67%	LightGBM (Light Gradient Boosting Machine) is designed for speed and performance. It handles large datasets efficiently and is known for its high accuracy and fast training times. However, it requires significant computational resources and can be complex to tune.
Random Forest	89.88%	89.98%	89.88%	89.88%	Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes. It is robust and accurate, particularly good at handling imbalanced data and preventing overfitting. Its main drawbacks are its complexity and potential lack of interpretability.
XGBoost	80.99%	80.30%	80.99%	80.64%	XGBoost (Extreme Gradient Boosting) is an optimized gradient boosting library that focuses on speed and performance. It efficiently handles large-scale data and has strong predictive power. However, it is computationally intensive and can be difficult to tune due to numerous hyper parameters.
Logistic Regression	68.68%	70.10%	68.68%	69.39%	Logistic Regression is a simple and interpretable model used for binary classification problems. It is easy to implement and understand, making it valuable for scenarios requiring interpretability. However, it might not capture complex relationships between variables as effectively as more sophisticated models.

Table 2: Comparison of Machine Learning Models

Model	Theoretical Considerations	Strengths	Weaknesses	Ideal Use Cases
<b>LightGBM</b>	Gradient boosting framework designed for efficiency and performance.	High accuracy, efficient with large datasets, fast training times.	Computationally intensive, requires careful tuning.	Scenarios requiring high accuracy and efficiency with ample computational resources.
<b>Random Forest</b>	Ensemble learning method that builds multiple decision trees.	Robust, handles imbalanced data well, prevents overfitting.	Complex, less interpretable as the number of trees increases.	Applications requiring high accuracy and reliability, particularly with imbalanced data.
<b>XGBoost</b>	Optimized gradient boosting library focusing on speed and performance.	High performance, handles large-scale data efficiently.	Computationally intensive, complex to tune.	Tasks involving large datasets where predictive performance is crucial.
<b>Logistic Regression</b>	Statistical model for binary classification.	Simple, interpretable, easy to implement.	May not capture complex relationships, lower accuracy compared to advanced models.	Scenarios where model interpretability and simplicity are more important than achieving the highest accuracy.

Table 3: Comparison of Machine Learning Models for Supply Chain Optimization

## 8 Conclusion and Future Work

### 8.1 Conclusion

Specifically of investigating the role and effectiveness of the AI models in improving the overall supply chain management with special reference to inventory management and demand forecasting for e-commerce firms. The primary research question addressed was: How does the AI applications work to improve the supply chain management in relation to inventory management and demand forecasting for e-commerce businesses? To answer this question, the study evaluated four prominent machine learning models: These include LightGBM, Random forest, XG boost, and Logistic regression. In detail, the study provided case studies and experiments to support that these models with AI were helpful and improved the accuracy and efficiency of inventory management and demand forecasts strikingly. As for the evaluation criteria, the standard performance indicators including accuracy, precision, recall, and F1-score were used for each model. The results showed that: Specifically, LightGBM proved to be accurate and fast when processing large data; however, it had to be resource-intensive and sensitive to parameters.

Compared with other models Random Forest performed the best in terms of accuracy and has the least variance when applied to the imbalanced data set and it does not overfit. But it became more complicated with the increase of the number of trees and the interpretation ability reduced.

It was complex and computational expensive but XGBoost was one of the most efficient and performant method for large scale data.

Testing also showed that Logistic Regression, though not as accurate as the other models, was beneficial because of its clear interpretation and simple formula vital for binary classification.

The research conclusively managed to lay bare the forte and foibles of each model and the juxtaposition thereof made this study useful for e-commerce businesses that may be seeking to adopt an appropriate

AI-powered model depending on their capacity and requirements. The results of the study demonstrate that there is great potential in utilizing sophisticated machine learning models in terms of the efficient decision-making, cost reduction in the supply chain and rise in the level of customer satisfaction. Although the results of the study are quite promising, the investigation also outlined some issues, such as the reliability of data, a lack of adequate, and often high computational demand of some models, as well as difficulties in adjusting the sophisticated models.

## 8.2 Future Work

The results I found, and the limitations, weaknesses, and shortfalls recognised in this thesis give good points that will support the further research and advancement in the field of Artificial Intelligence concerning the enhancement of the supply chain. Using these observations, several directions for the future research to improve the application and performance of machine learning models in this context have been built on the following.

### Advanced Hyperparameter Optimization

A unique direction of the further development of hyperparameters' optimization is an advanced one. The training and the testing of the model especially the complex ones such as LightGBM and XGBoost depends a lot on the hyperparameters. Some of the conventional approaches are Grid Search and Random Search which may also be efficient but highly time consuming and demands a lot of computations. It is possible that future work could try to use more advanced methods of optimization like Bayesian optimization, genetic algorithms or AutoML. It is possible to apply these methodologies to enhance the search of the best hyperparameters and achieve better results with less effort than using more labour-intensive methods.

### Ensemble Methods

The use of ensembles has been revealed to be rather efficient in terms of increasing predictive accuracy and reliability. It is also recommended that future research be directed at trying to understand further novel methods of combining models in such a way as to form ensembles. Some of the processes included in this process are stacking, bagging, and boosting, they assist in compromising the strengths of different algorithms, leading to the formation of a composite model, which has a better performance than all the individual models. This way exploring further the different possibilities of combination with the various models and discovering how they integrate, can bring great contribution into the enhancement of the accurate predictive methods for the supply chain.

### Scalability and Efficiency

They also mentioned several major areas for further research; one of them is increasing the scalability and effectiveness of the machine learning. Most of the developed models, although very accurate, need considerable computational power, which may be a limitation to SMEs. The mainstreaming of these technologies can be improved by finding ways in how to parallelize optimization techniques for the algorithms, the use of cloud solutions as well as producing simplified models that are lighter versions of complex ones.

### Impact of Emerging Technologies

Several advanced technologies include IoT, blockchain, and edge computing are still in their developing stage and can expand AI capabilities in the supply chain. The further studies may address the question of how the mentioned technologies can be incorporated with AI models to contribute to data gathering and increase tractability, besides offering real-time analytics. For example, smart devices in the IoT can capture data that is used to input into an AI model in real-time. As for the application of blockchain in the context of digital twins, it can maintain data credibility and transparency; edge computing can handle computation and decision-making in real-time without data transfer to other locations. Thus, it

is possible to enhance the understanding of the interactions between these technologies and AI that could pave the way for the development of supply chain revolution ideas. Using these directions, the future studies can follow the results of this thesis and proceed to the development of the optimization of the further integration of AI solutions into the supply chain in the sphere of e-commerce. These measures shall assist the businesses to maximize the opportunities of using AI to supply chains providing more effective and competitive performance. Supply chain management is not an easy journey when it comes to the incorporation of AI and with the future changes it will be even easier to improve and innovate the supply chain's functionality.

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