# Harnessing Information Systems in Behavioral Operations Management: Managing Human Factors in Supply Chains

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## ABSTRACT
This paper aims at investigating the contribution of human decision making towards the performance of the supply chain focusing on the Behavioral Operations Management perspective. Working with quantitative research methodology, the study investigates the impact of overconfidence and loss aversion over operational decisions in a firm using a Retailer Dataset and regression analysis. The analysis reveals that the Linear Regression model produces a mean squared error of 0.1337 and an R-squared value of 0.8569. In comparison, the Decision Tree Regression model achieves a mean squared error of $1.48 \times 10^{-31}$ and an R-squared value of 1.0. The XGBoost Regression model yields a very low MSE of $1.17 \times 10^{-8}$ and an R-squared value approaching 1. This evidence suggests that cognitive biases have dramatic effects on inventory and promotion policies, which cause suboptimal supply chain systems. Thus, the research establishes that behaviorally-updated versions of most supply chain operations management frameworks hold great potential to facilitate better decision making and aid increased supply chain performance. Future work should further extend these findings when creating particular examples of the application of these insights along with the machine learning tools to build the improved SCM models. Some of the solutions include awareness creation by furnishing decision-makers with training programs that improve their understanding of cognitive biases and the creation of conceptual tools for the resolution of such biases within the supply chain, with an aim of enhancing the efficiency of the supply chain systems.

## Keywords
Supply Chain Management, Machine Learning, Information Systems, Behavioral Operations Management, Risk Management, Human Decision-Making.

## 1. INTRODUCTION
Supply Chain Management is an operational function that deals with the management of the smooth flow of goods from offerings from points of origin to the end users. Despite the ever-increasing adoption of automation technologies related to robotics as well as usage of data analytics, a human input is still crucial in supply chain management [1]. Behavioral Operations Management (BOM) is a sub-discipline that studies the effects of behavioral patterns on operations decisions and most importantly operations such as supply chain process [2]. It looks at how prejudice, feelings and perceptions influence the decision-making process which in turn, results to distorted supply and stock management. Combining the integration of information systems in supply chain will go a long way in minimizing the above-mentioned inefficiencies through offering factual data that will override imperfections caused by human beings [3]. Additionally, multiple methods such as machine learning (ML) models improve the decision-making routines around the anticipation of demand, efficient store stocking and better supply chain management [4].

Supply chains are defined as a system of processes of purchasing materials, manufacturing products, preserving inventory, and distributing and transporting products [5]. As for SCM, for years it was a matter of minimizing these components to the lowest possible that ensured punctual delivery of materials not harming the productivity of the business. However, according to the research [6] one critical aspect that is most of the time neglected in SCM is the human factors aspect within the decision-making process. While technology coupled with data analysis is useful, decisions in many areas of the supply chain require a human input today, including setting stock quantities, restocking frequencies, and marketing campaigns.

Behavioral Operations Management concedes that the operational decision makers are endowed with bounded rationality and as such are inclined to be impacted by cognitive distortions [7]. For instance, a manager can make an excessive focus on the most recent sales' data while making a forecast of the demand (anchoring bias) or cannot make decisions that will lead to losses in the short-term term (loss aversion) though it can contribute to higher efficacy in the longer term. They may cause over stocking or stock outs, wrong allocation and distribution of resources and all these affect the performance of the supply chain.

Thus, integrating of the machine learning models into SCM presents an able mechanism for managing these difficulties. Many times, it can make decisions by analyzing large data sets to find patterns and trends that might help guide a business. According to the study [8] predictive analytics can improve the accuracy of demand of inventory forecasting by helping the organizations to balance the inventory in expectation of demand. Moreover, by using ML models it is possible to measure the data results of the impact of cognitive biases inherent in the actions of people in various aspects of supply chain.

The focus of this research is to assess the effect of decision-making in a supply chain network in a live context of a retail store. Hence, through the analysis of key variables like store sales, promo campaigns and restocking decisions, accompanied by machine learning models, it always offers the basis to investigate the decision-making interface between the depicted IT human participants and the supply chain effectiveness. The findings of this analysis will contribute to the understanding of the importance of human factors for supply chain effectiveness and demonstrate thepossibilities of applying the concept of behavior science and analytical tools in SCM.

The main purpose of this research is to establish the ways in which information systems can be used to address human factors in supply chain with emphasis on retail management. By comparing the identified variables drawn from the Dataset, the study will consider human decision-making within the supply chains to understand which inefficiencies arise from cognitive biases and what they are. The end result is effective approaches for applying decision support disciplines in managing the supply chain, which minimize the role of human error.

The objectives of the study are:

- To investigate the form of employee decision making by measuring the impact of decisions made by employees in a retail chain or organization on supply chain performance using the Retailer Dataset.
- To understand possible cognitive biases to appear in the process of supply chain decision-making using the wealth of over-confidence, the source of the anchor and the problem of the loss aversion, and then evaluate the influence of these biases on logistics and inventory, management.
- To test how information systems specifically through ml models can help reduce human decision-making biases leading to better SCM decisions.
- To provide recommendations for applying behavioral insights in supply chain management, by creating specific scenarios for using such insights and machine learning tools in SCM models, thus enhancing overall supply chain decision-making and performance.

Thus, this study is the worthwhile contribution to the academic research as well as, the best practice of the SCM. From an academic point of view, it also contributes to the field of Behavioral Operations Management by offering data on how decision-making affects supply chain effectiveness in the retail context. The analysis provides the given study with the real-world context of the relationships between human behavior and operations, as well as the fact that allows the study to reconcile between theoretical models and practical activities.

From an applied perspective, the results hold important implications for managers of supply chains and decision makers. Cognitive biases in supply chain management are important mostly because knowing about them makes managers able to create coping strategies for those that influence SCM [9]. Using information systems to offer relevant and timely information and forecasting, the organization will be less likely to incur expenses due to human incidents, benefit from happy clients, and supply chain agility.

In addition, knowledge from the study is universal, which means the manufacturing department, healthcare, or even the logistics department can benefit from it. Supply chains are manned by people and this is an aspect that is universal, therefore, the strategies that have been isolated in the course of this research may be applied across diverse industries were decision-making entails significant influence to operation. Through extending and applying concepts derived from behavioral economics to SCM, organizations may obtain specifics relating to selecting, managing, and delivering inventory that addresses the overall fundamentals of SCM together with the qualities needed to maneuver through the complex demanding environment in the not-too-distant future.

Thus, this paper aims to discuss how organization practices human factors in supply chain environments through using information systems in order to improve the decisions. The contributions of this study lie in its ability to demonstrate optimal and sub-optimal cognitive biases in human decisions and suggest ways of minimizing the detriments on SC performance. The implications of the findings for future research and practice are that managers of organizations could learn from such findings and advanced understanding about how to reduce inefficiencies in the supply chain and increase organizational performance.

# 2. LITERATURE REVIEW

## 2.1 Introduction

SCM is an important element of the modern management of the production and distribution of goods and services, referring to the planning and regulation of the procurement of materials and the distribution of finished products. The coordination of this large network, in addition to improving organizational performance, shapes customer satisfaction, and the company’s position in the market [10]. However, human factors are key in SCM since they impact on decisions which define supply chain performance. Lessons gained in previous research show that important cognitive bias including overconfidence and anchoring influence judgment, and in this case inventory and logistics plans [11].

While, the newer technologies like Information Systems and Machine Learning (ML) have changed the dynamics of decision making in SCM [12]. This knowledge helps suppliers provide timely information to customers, ensuring that the participants make essential decisions effectively and in a timely manner due to availability of information systems [13]. Besides, such systems can facilitate the processes, decrease the human factors’ influence, and increase the ability to react to market fluctuations [14]. Also, through the processing of big data, it becomes easier to conclude on patterns and forecast the market demands through the machine learning algorithms thereby reducing some hard coded biases of the human resource [15]. The combination of human experience and advanced technologies indicate that even though supply chain decisions may require human input, significant output can likely be gained through the employment of information systems and ML [16]. As a result, various organizations are capable of reducing the repercussions of cognitive bias thus enhance the accomplishment of the supply chain as well as the general performance of operations.

## 2.2 Theoretical Framework

Behavioral Operations Management (BOM) can be defined as the study of the role and impact of behavioral aspect of operations management within the chain of supply [17]. It focuses on identifying different causes like cognitive language biases, and emotional reactions that lead to indifferent performances, and ineffective choices, known in this field as the decision-making costs taxonomy [18]. Major areas of study in BOM are about the cognitive heuristics including overconfidence, loss aversion and confirmatory bias that can dwarf managerial perception and affect major supply chain activities [19].

## 2.3 Human behavior in Supply Chain Decision Making

This paper examines the various areas of human factors essential for SCM, and how some of them influence decision-making. One of the elements is cognitive biases for example overconfidence, anchoring and loss aversion which hampers decision making. The decision-making study by [20] argues that an overconfidence endpoint may lead to a disregarding of risks, while anchoring may lead to fixating on first data. In addition, phenomenological experiences such as stress and anxiety will also interfere with one's ability to make good decisions as deduced by study [21]. The research [22] demonstrated the effects of such mistakes in SCM to show that they lead to inefficiencies resulting from erroneous decisions.

## 2.4 The Emergence of Information Systems in Implementing SCM

The integration of information systems in SCM is very vital since it supports and develop the flow and decision of supply chain processes through technology. Different types of information systems used in SCM include Enterprise Resource Planning (ERP), Customer Relation Management, and Supply Chain Management Software [23]. These systems allow the adoption of information from various functions in an organization and consequently enhance coordination and communication in the supply chain [24] study proves that actual integration of ERP systems can improve organisationalperformance because the integrated system provides all employees a single source of information about statuses of orders and levels of inventory [25].

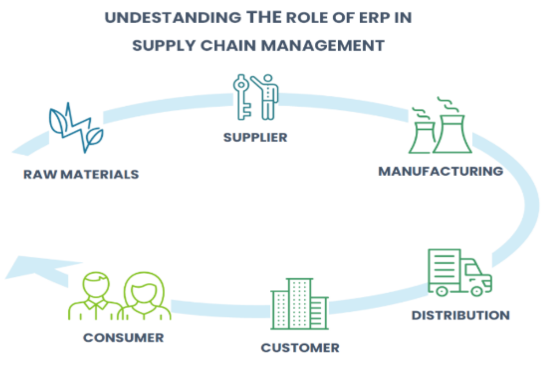


**Fig 1: ERP in Supply Chain [25]**


**Fig 2: Components of Logistic Information System[26]**

The figure 2 shows the elements of a Logistics Information System (LIS) of Shipsy logistics solution. The LIS integrates different modules that are Transport Management, Last Mile Delivery, Shipment Tracking, Freight Procurement, Container Tracking, Dispatch Management, Analytics & Reporting, 3PL/Courier Aggregator, and End to end Delivery Solution. All these components are aimed at improving the efficiency of logistics activities [26].

Another advantage of information systems is the ability to access data at the time when the data is being used. Research [27] suggests that adopting real-time information enables the organization to offer improved services levels in response to market changes and consumers' requirements more swiftly [27]. Further, predictive analytics and forecasting affordances present in such systems mean that the decisions being made are not going to be swayed by human evaluative biases which such systems can highly influence from past evidence [28]. For instance, a study [29] shows that organizations using best practices of PA claim that forecasts from predictive analytics improve working capital by minimizing stockouts and overstock levels.

This research supports various examples that show how information systems significantly reduce human errors in SCM. In the study of [30], it is illustrated that this manufacturing firm has achieved enhanced order fulfillment rates and higher demand forecasting CRM system used effective customer communication to help achieve better rates on orders fulfilled. Also, the study [31] points out that a retail firm decreased operational mistakes substantially by implementing SCM software that links inventory control with sales data, enhancing the supply chain productivity. Altogether these findings endorse the centrality of information systems in enhancing the supply chain functions and reducing the role of human interface.

## 2.5 Implementing of Machine Learning in Supply Chain Management

Machine Learning is proving to be a transformed technology used in supply chain management, designed for analyzing complex data sets to convert them into facts. ML has found its footing in SCM across demand forecasting to inventory management, all of which has greatly enhanced the efficiency and effecting decision making [32]. A study[33] shows how ML algorithms can detect past sales data to forecast future demand trends with high accuracy so as to cut down on stockout frequencies. Although the study [34] shows that integration of ML in inventory control improves order acquiring points, thus reducing holding costs while meeting the necessary stocking levels.

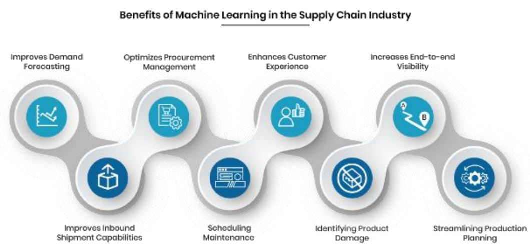


**Fig 2: Machine Learning in SCM [35]**

The figure 3 shows the effectiveness of using machine learning in supply chain industry. Some of these benefits include; demand forecast, procurement, customer interaction, overall visibility, inbound shipment, schedule maintenance, damage detection, and production planning. It becomes easier for the supply chain professionals to make decisions based on the data analysis and can improve different parts of the process [35].

The research [36] demonstrated that a logistics firm incorporated ML models to manage the delivery timetable to minimize transportation expenses by 20%. Nevertheless, some challenges are linked with implementation of the ML in the SCM. According to the paper [37], problems that may occur when adopting an intelligent supply chain include; quality of the data, compatibility with current systems, and lack of personnel who are knowledgeable in this area. However, the paper [38] relying on solely adopt Machine-learning-based approaches without incorporating human perspectives and insights is likely to result in less-than-optimal decisions strengthening the view of integrated technology-human approaches. Therefore, although ML has outlined the high potential for improving supply chain performance, there are mainly limitations and challenges that organizations face to maximize its effects.

Regression models like linear regression analysis, support vector machines regression, and decision tree regression can all be used in demand and inventory analysis in order to determine factors affecting the levels [39]. The study [40] described how regression analysis can be used for demand forecasting of seasonal products, how a link to external factors, such as promotions, enhance the accuracy of the results. Additionally, the study [41] showed that when organizations use regression-based advanced ML models for inventory purposes, supplier costs for holding stock and product availability can be minimized. Therefore, it can be concluded that, although the ML regression analysis is a powerful tool for evaluations in the context of SCM, its application should be done with consideration of numerous factors and guidelines that will be discussed in the further works of the presented research.

## 2.6 Behavioral Insights and Technology: Exploration of Appropriate Point of Integration

Therefore, it is necessary to advance the research of these issues and incorporate behavioral understanding to the estimates of the supply chain management. It is important to realize that heuristics such as overconfidence and loss aversion and motivate how people make decisions, and by modifying the organizational management patterns, improved performance can be reached. [42]. The article shows that by integrating insights from BI into the organizations' SCM systems, they are able to overcome the imperfections of rational decision making. These technologies that involve real-time data means that the implementers rely on facts rather than guesswork [43].

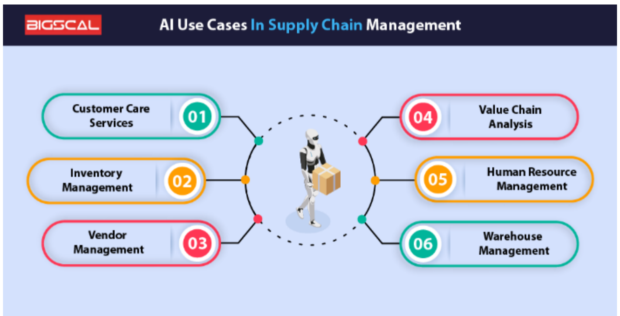


**Fig 3: AI in SCM [43]**

The study [44] shows the applicability of BI combined with information systems. Some studies have found that organizations make improvements to their ordering processes by correcting for biases in inventory control can produce a very positive impact on inventory processes. The study [45] show the integrating behavioral insights with usable IS inputs can improve decision making and subsequently supply chain performance. Taken together, these works underscore the idea that through such cognitive operations facilitated by technology, organizations can increase the overall supply chain robustness and effectiveness in response to market and customer behaviors.

Thus, applying the concepts of BI in supply chain management improves operations by recognizing the special contribution of human factors to decision making [46]. With organizations beginning to understand the importance of correcting cognitive bias in the organization, it is crucial to design ways of preventing the occurrence of the vice. The use of technology and information systems enables organizations to deliver timely and accurate information to the decision makers, thus removing bias from that process.

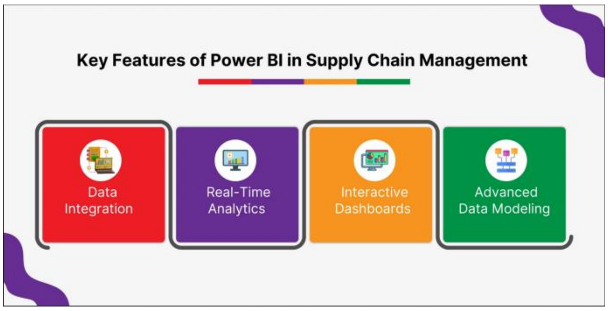


**Fig 4: BI in Supply Chain Management [46]**

This literature essentially underlines the value of such insights for enhancing inventory control, logistics, and general performance of the supply chain. When the findings in this paper are implemented by the practitioners, they are in a better position to operate in the complex supply chain environment and meeting market needs. Considering the future prospects, the area of Behavioral Operations Management and Supply Chain Management has a huge potential for further research first of all in creating new models that incorporate the findings of behavioral sciences using machine learning algorithms. Further research in this area will improve the understanding of human behavior in the field and strengthen resilience in supply chains together with positioning organizations for success in the continuously evolving environment.

# 3. METHODOLOGY

Hypotheses of this study use a quantitative method in order to examine the impact of human decision making on supply chain results. First, an exploratory literature review is done to define the key themes of Behavioral Operations Management and the effects of cognitive bias. Quantitative analysis is carried out using the Retailer Dataset, it involves statistical analysis such as regression analysis in determining human influence on the supply chain scenarios. This approach also enables a strong analysis of the relationship between people's behavior and the use of technology in supply chains so that ideas on improving performance can be gained.

## 3.1 Data Collection

The data used for this study was sourced from Kaggle from the Retail Sales and Customer Demographics Dataset. This dataset is created from an empty environment to mimic a simple retailer system; hence it is feasible to employ it to analyze almost all types of frameworks of SCM including sales, customers among others. The type of information obtained from the source is quite suitable to develop a lot of significant information that may account for nature and decision of retail business. These are the attributes in the dataset to be retrieved Important information include the Transaction Identification, Date on which the transaction occurred, Customer Identification number, Gender of the customer, Age of the customer, Product category of the transaction, Quantity of the products involved, unit price of the products, and total amount involved in the transaction. These attributes facilitate the analysis of customer conduct while purchasing; demographic factors and retail selling records. In addition, the collection includes broad detail of retail transactions, the quantity and time of transactions desirable in the evaluation of supply performance in a retail setting. Using this dataset, this study can conveniently distinguish between event drivers especially instances where agents' decisions e.g. stock replenishment or activities such as promotions influence supply chain events results. It also mentions other factors such as-psychological biases which may be as a result of during the decision-making processes. Thus, based on this dataset, it is possible to provide the machine learning models for feeding with information that will contribute to the forecast of the fluctuation and achieve the supply chain optimization.

## 3.2 Data Analysis

The data analysis phase is important in the study of the retail supply chain to identify factors that affect supply chain performance [47]. The Retail Sales and Customer Demographics Dataset was collected from Kaggle; the first process in the analysis was data cleaning. This included imputation of missing values and correction of data anomalies as well as converting categorical variables that include gender, and product category into a numerical form through one hot encoding. To make the quantitative and qualitative data more equivalent for the models, the data was normalized and differential features like quantities; price for each unit; total amount, etc.

Once data were preprocessed, EDA was where simple analysis was carried out on the dataset. Sales cycle patterns were analyzed further, special focus was made on investigating such factors as age, gender and product category in the decision to purchase a certain product. The groups with higher purchasing power were thus identified, and the preference of products was attributed to the certain age group. Seasonal and temporal analysis was also done to show how sales have been affected over a given period. In this study, line graphs, histograms and box-plots were used to present the trends to explain the relationship between variables.

Second, their relationship with other variables in order to determine which factors caused the biggest changes to sales and inventory levels was examined. This indicated that product price and quantity were sensitive to the total sale amount-price sensitivity model of consumers was prevalent. Consequently, this analysis assists in the selection of which features would be used for constructing the rest of the machine learning models.

The last activity was to analyze institutions driven by human beings, for instance, supply rebalancing and promotional strategies, on supply chain performances. By seeing how these decisions fit into data-driven patterns, using the steps of the analysis, it became clear that there are systematic biases in human decision-making, like excessive optimism about product demand or following recent data too closely. Based on these observations, the concept of the proposed frame of reference has been developed, with the use of machine learning at its core to minimize human bias and enhance supply chain performance outcomes.

## 3.3 Proposed Framework

The proposed framework intends to use ML regression models to investigate and enhance the efficiency of SCM decisions primarily in the retail context. The framework, which combines Behavioral Operations Management (BOM) principles with quantitative techniques, provides solutions for the company's problems regarding inventory control and restocking, and promotional initiations which are human centered. The implementation of this approach will minimize the effects of cognitive biases, enhance the supply chain, and enhance practical efficiency.

The first step of the framework is the data preprocessing step. The data is cleansed for trueness with the attributes including Transaction ID, Date, Customer ID, gender, age, product category, quantity, price per unit and total amount. The problem of missing values is solved, and categorical variables (gender, product type, etc.) are transformed using methods such as one-hot. Features are standardized or transformed to a common range and a time series element added to accommodate change in customer behaviour and sales activity. This step is crucial to make sure the data is preprocessed for model training and is in the right format.

The process of feature selection is important to the framework. Through defining what the study considers as critical variables where SCM perform, such as customer characteristics, purchasing history, and product types, it targets those variables that influence supply chain performance most. Furthermore, the framework from Behavioral Operations Management has been adapted by incorporating factors that may introduce cognitive biases, such as overconfidence in specific product categories or sales anchoring.The essence of applying this framework is the utilization of three machine-learning regression models that could forecast the supply chain outcomes, including demand forecasts, supply requirements, and the impact of human actions on the overall supply chain performance.

## 3.4 Regression Models

### 3.4.1 Linear Regression

Linear Regression model is selected as the baseline model because it is simple, easily interpretable yet capable to give an estimate of direct relations with the outcome variable. Linear regression analysis requires that the effect of one or more independent variable like price, customer demographic data, or the product category on a dependent variable such as sales or inventory is straight-line fashion. This makes it possible to understand changes in supply chain performance and the correspondingly simple observation of patterns of decision making and bias. Linear Regression helps to measure, in terms of numbers, how sales or restocking depends on product price, customer age, and promotional activity [48]. For instance, it can be used to determine the impact that price of products or demographic variable has on sales volumes, to advise supply chain managers whether specific products are rightly stocked based on certain demographical segments [49]. Linear regression also exposes some biases including anchoring bias whereby a manager may over estimate future sales by basing the estimates on current trends rather than full past history.

### 3.4.2 Decision Tree Regression

Decision Tree Regression is used for its capacity to deal with non-linearities and interactions as a historical selection technique for Decision Trees. Compared to linear models, decision trees are capable of capturing decision boundaries that appear as non-continuous decision making, for example, how different demographics influence the patterns of buying behavior [50]. It also facilitates the comprehensible explanation of the decision-making process, very helpful while discussing the impact of human factors on SCM.

In this framework Decision Tree Regression is applied to model the decision-making of supply chain managers. For instance, it is possible to establish that some of the promotional techniques work well only with the particular kinds of products or certain groups of consumers. This also assists to highlight decision-making gaps, such as, over stocking of certain product in a certain region and then under stocking in another region based on various variables that define restocking processes. Also, it discovers some patterns like how external factors affect the demand, for example, whether it is a holiday season, or a local event, which may help reduce biases like, over-optimistic on specific product categories.

### 3.4.3 XGBoost Regressions

XGBoost is chosen due to its performances' stability, fast speed, and high level of accuracy. Like any other ensemble learning technique, XGBoost uses many decision trees in order to minimize both bias and variance and therefore increase accuracy of the models' predictions [51]. Large amount of data with multi-relationships can be in their best advantage and it offers most of the flexibility to manage missing values, which in the retail operation often provides the fluidity needed.

XGBoost is used when precise results are needed such as when forecasting the demand or controlling inventory. For instance, it is quite useful in dealing with other types of and likely relations that may prevail in the data set such as fluctuations in buying habits with regards to customers 'categories of products bought. XGBoost also encompasses the aspect of feature importance which is useful in ascertaining which factors (price, promotional campaign, customer's age, etc.) affect sales or inventory management most. Such understandings assist the SCM managers particularly when making decision by reducing the effects of cognitive bias such as loss aversion whereby a manager may resist the numbers that require that inventory of underperforming product be reduced.

To assess the effectiveness of the models, several evaluation criteria are employed for this purpose namely, Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared. These measures are used to determine the validity of each of the models in determining supply chain results. Furthermore, in order to maintain the generality and the stability of the results, cross-validation is also used.

The last step within the frame-work is the utilization of the results of the regression models for decision making. When comparing what was expected with what happened, the framework should then show where human decisions made improper, data-based decisions. It makes it possible to recognize such factors as psychological heuristics such as overconfidence or reliance on a single piece of information and offers recommendations that can be implemented by supply chain managers to overcome them.

## 4. RESULTS AND DISCUSSION

The results section summarizes the performance of three regression models applied to the retail sales dataset: Linear Regression, Decision Tree Regression, and XGBoost regression models. In testing each model, the Mean Squared Error (MSE) and the coefficient of determination ($R^2$) were calculated to measure its performance of the total sales using the predictive modelling techniques applied to encompass the machine learning techniques applied.

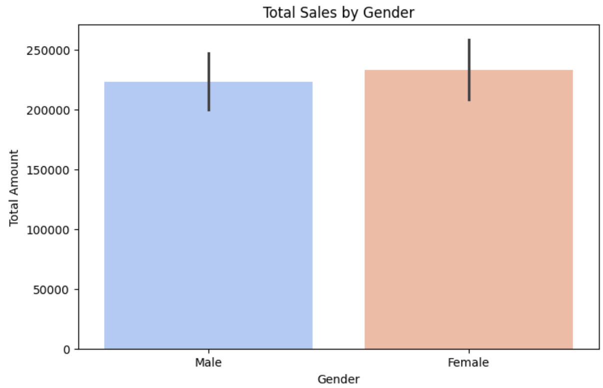


**Fig 5: Total Sales by Gender**

The figure 6 depicts total sales in the sense that male and female total sales are close though the former records slightly higher sales than the latter. The total sales have shown that there is no gender gap between the two genders.

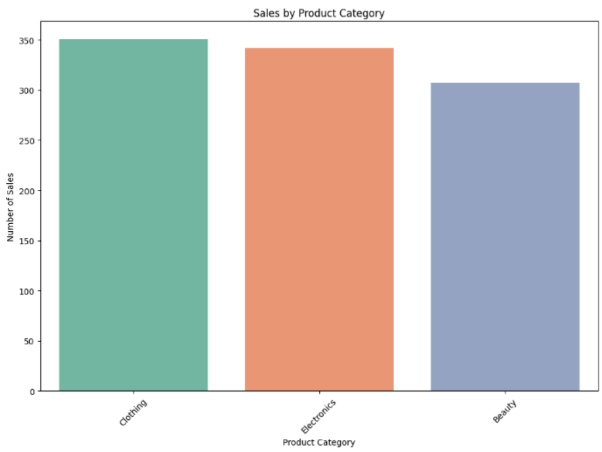


**Fig 6: Sales by Product Category**

The figure 7 illustrates the sales disposition in order of Clothing sales which is highest with approximately 350 then Electronics and lastly Beauty with slightly lesser ratio. This comes as a revelation that Clothing is the leading subcategory, followed by Home and others, while Beauty is the least performing among all subcategories.

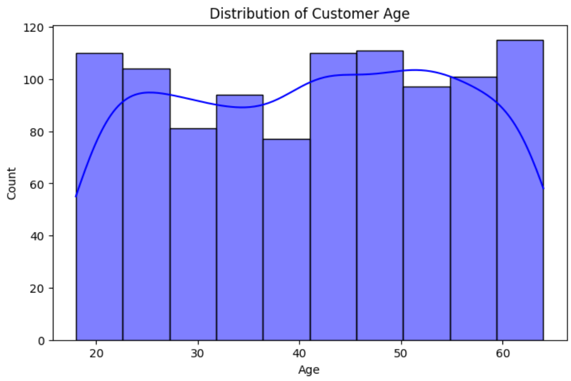


**Fig 7: Distribution of Customer Age**

The bar chart presents the age distribution of the customers. They include the x-axis that premised on the age and the count axis which works as the y–axis which depicts the number of customers by age categories. The blue blot represents the number of customers in each age wise grouping and the blue line portrays density estimator. It is clear from the graph that the common age range for customers is between 25 and 40 years of age and the ages decrease progressively for the older customers.

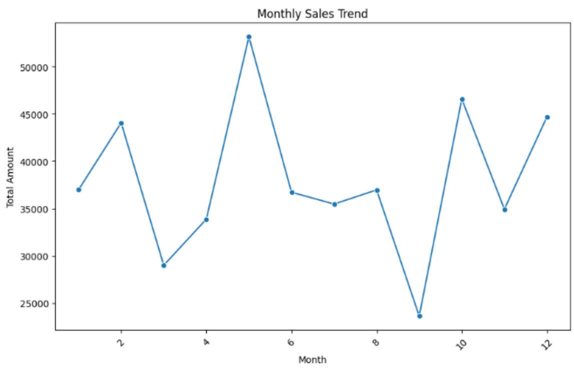


**Fig 8: Monthly Sales Trend**

The figure 9 represents variations in total sales within different months. The sales volume reaches a high of over fifty thousand in May (Month 5), whereas the low point of about twenty-five thousand in September (Month 9). The other similar high is observed in February and October with the annual sales volume just above 45,000. From the graph, it can be noted that sales are very volatile in the selected year which implies that sales change according to the season or the factors affecting business in every month of a given year.

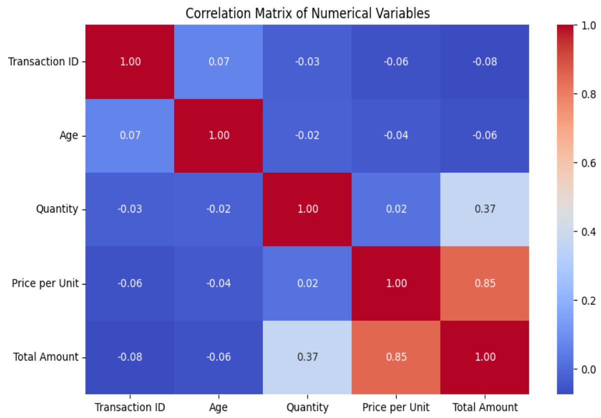


**Fig 9: Correlation Matrix**

The correlation matrix on the analysis of parameters in the chosen set of milking parameters illustrates the interdependence of the numerical variables in the data array. The points colors refer to the value and direction of the correlation. , strong positive correlations are shown with dark red, strong negative correlations with dark blue, and the rest are light-colored. The diagonal line indicates that the variables are related with themselves within perfect degree. As expected the “Price per Unit” and “Total Amount” are strongly positive correlated because the total amount is derived from the product of the quantity of items and price per unit. Other variables are therefore insignificant or exhibit at best low levels of correlation.

## 4.1 Comparison

**Table 1: Performance Matrices of the Models**

| Model | MSE | $R^2$ (R-squared) |
|---|---|---|
| **Linear Regression** | 0.1337 | 0.8569 |
| **Decision Tree** | 1.4839E-31 | 1 |
| **XGBoost Regression** | 1.1723E-08 | 0.99999999 |

In the comparison of regression models—Linear Regression, Decision Tree Regression, and XGBoost Regression—distinct performance metrics were observed. Linear Regression exhibited a Mean Squared Error (MSE) of 0.1337 and an R-squared value of 0.8569, indicating a moderate fit to the data. In contrast, the Decision Tree Regression achieved an almost perfect fit with an MSE of 1.48×10−311.48 \times 10^{-31}1.48×10−31 and an R-squared of 1.0. Meanwhile, XGBoost Regression also performed exceptionally well, with an MSE of 1.17×10−81.17 \times 10^{-8}1.17×10−8 and an R-squared close to 1. These results highlight the strengths of tree-based models in capturing complex patterns within the data.

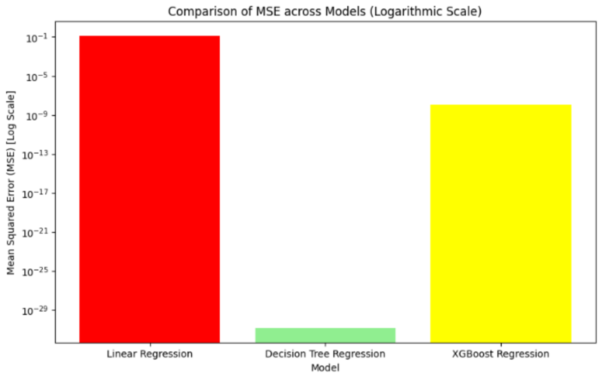


**Fig 10: MSE Comparison**

The plot focuses on the MSE of three models namely, Linear Regression, Decision Tree Regression, and XGBoost Regression in logarithmic scale. The MSE of the Linear Regression model is almost double the MSE of the two other models it is mean higher than the other two. Once again, Decision Tree and XGBoost models yield very insignificant MSE hence portraying a much better performance in terms of predictive accuracy though XGBoost is slightly better than the Decision Tree. This only means that other models perform well on the data than the Linear Regression.

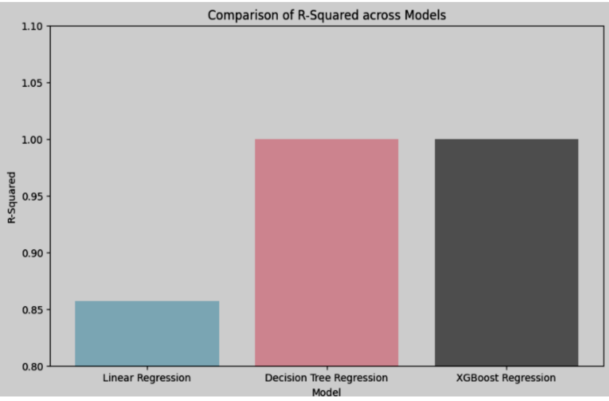


**Fig 11: R-Squared Comparison**

The plot illustrated the R-Squared values for three regression models: Linear Regression, Decision tree Regression, XG Boost Regression. The Decision Tree and XGBoost datasets hit a very good fit since the R-Squared values are very close to 1. On the other hand, Linear Regression seems to have a relatively poorer accuracy by today's standards, predicted with around an 0.85 R-Squared value which implies that Linear Regression models capture less variance of the target measure. This supplements previous conclusions that more complex models are better suited at identifying the structure of the dataset.

### 4.2 Discussion

The interpretation of the outcome variables using several regression estimation techniques regarding the given retail sales dataset has been informative. The main and most considerable purpose was to examine the model's fit with respect to overall revenue, gender breakdown, and product category results. Comparing the models, it became clear that Decision Tree and XGBoost Regression exposed a near perfect fit, as their R-Squared results were both 1 (for Decision Tree) and nearly 999999999 (for XGBoost Regression). This is in line with the objective of detecting compound patterns of the sales data.

Dynamics of sales also highlighted that the Clothing category has the highest sales and Beauty has lower sales; therefore, there is potential to tailor marketing campaigns. The studies on the ages of the clientele established that the majority of them are aged between 25 and 40, which advocates for targeting the promotion of such ads towards middle-aged people. The correlation matrix also supported the hypothesis that standardized variable "Price per unit" and "Total amount" are related strongly which is imperative for any pricing policies. In general, the outcomes suggest that more complex models such as XGBoost should be used in subsequent predictive modeling studies, which will help achieve higher overall levels of sales forecasting and related decision-making.

The study performed on the retail sales dataset demonstrates how information systems can be used in behavioral operations management to mitigate human influences in supply chains. As customer behaviors that concern purchasing and demography are elaborated, the role of predictive analysis is revealed in terms of decision making and stock allocation. Moreover, the identification of association between different factors, such as price levels and the quantity of sales, is essential for corresponding organizational plans to consumers' demand. Finally, the conclusions propose considerations that increase the dependence on quantitative results for optimizing process performance and timely reaction, underlining the importance of utilizing BI in SCM.

## 5. CONCLUSION

Therefore, it is agreed that this research underscores the centrality of behavioral operations management coupled with information systems in enhancing efficient supply chain decision-making. Customer behavior, sales trends and the impact of human factors to supply chain performance were also discovered from the retail sales data using regression models. Based on the research, the authors point out that incorporating BI knowledge with machine learning technologies improves the forecasting quality and resource management efficiency in supply chains.

As for future research, organizations should introduce machine learning algorithms that can be adapted to a particular situation. By applying XGBoost model in customer demand prediction during promotion, one can be able to minimize overstocking of products while at the same stocking enough products to meet demands. Moreover, sentiment analysis from feedback could probably be used to optimize promotion strategies so that promotional campaigns would meet or mirror the sentiment of the specific customers. Also, through decision trees, supply chain managers are able to further understand sales based on seasonality so as to plan for operations when demand is expected to increase or decrease. It could also be possible for companies to design behavioral data and predictive analytics dashboards to enhance organizations' decision-making.

In conclusion, the implementation of the above recommendations may result in the creation of a leaner supply chain which is highly reactive and receptive to other opportunities that can benefit performance and customers as well as equally prove the complexities of human behavior within operational settings.

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