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# Artificial Intelligence Demand Forecasting and Supply Chain Performance of Large Supermarkets in Nairobi City County, Kenya

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## Abstract

Artificial Intelligence (AI) has been a transformative power in contemporary supply chain management, with its offerings that optimize operational effectiveness, lower costs, and facilitate data-informed decisions. The general objective of this study is to examine the effect of artificial intelligence applications on supply chain performance among large supermarkets in Nairobi City County, Kenya. The study will be anchored on three theories, namely, the Hybrid Intelligence Model and the Technology Acceptance Theory. This study will adopt the descriptive research design. The population of this study is the employees working in the supply chain department in 10 large supermarkets in Nairobi County, Kenya, while the target population is 10 large supermarkets operating in Nairobi County. The sample size of the study will consist of 70 employees working in the supply chain departments of 10 large supermarkets based in Nairobi City County. The questionnaire will be pretested using 7 respondents who will be selected from two Naivas supermarkets in Kiambu County, Kenya. The primary data will be collected through administration of structured questionnaires. The data collected will be summarized using percentages, means, and standard deviations. Inferential statistics such as correlation and regression analysis will be utilized to identify the relationships between variables. Data obtained for this study will be analyzed using SPSS version 30. Values drawn from the sample will inform the findings, conclusion, and recommendations of this study. The regression findings revealed that AI-demand forecasting had a coefficient of estimate that was significant based on $\beta 1 = 0.714$ (p-value = 0.000, which is less than $\alpha = 0.01$). This study concluded that AI-demand forecasting has a statistically significant effect on supply chain performance among large supermarkets in Nairobi City County, Kenya.

**Keywords:** AI-Demand Forecasting, Artificial intelligence, Supply chain, Supply chain performance

## 1. Introduction

In today's competitive world, organizations are continually under pressure to improve supply chain performance and product delivery efficiency (Kalaitzi et al, 2019). Throughout history, supply chain performance has grown from simple production and distribution systems to very complex global networks (Alomar 2022). The introduction of AI technology has accelerated this transition, allowing businesses to use data-driven insights, predictive analytics, and advanced supply chain performance algorithms to optimize operations, cut costs, and reduce risk (Zong & Guan 2024). The use of artificial intelligence (AI) into supply chain management marks a paradigm change, providing unprecedented prospects to improve efficiency and resilience in current company operations (Muthuswamy & Ali, 2023). As global marketplaces become more integrated and dynamic, organizations seeking to preserve a competitive advantage must prioritize improving supply chain procedures (Zong & Guan 2024).

According to Khadem and Khadem (2023), artificial intelligence (AI) is a rapidly expanding technology used to automate jobs, improve decision-making, and optimize processes, all of which have a significant impact on numerous industries, including supply chain management. Artificial intelligence (AI) has transformed supply chain processes across most industries, particularly large supermarkets (Dash et al., 2019). AI technologies are rapidly being used in the retail industry to automate supply chain processes, improve productivity, and make data-driven decisions (Oosthuizen et al., 2021). With new demand for increasingly complicated supply chain networks and rising customer expectations, AI technologies have become necessary to improve efficiency and save operational costs (Helo et al., 2022). Retailers, particularly major supermarkets, face enormous pressure to meet customer demands for product availability, rapid delivery, and value for money (Hove-Sibanda et al., 2021). Inefficiencies in traditional supply chain models include faulty demand forecasts, inventory overstocking or under stocking, and delivery delays (Kazim, 2018). AI-powered solutions have emerged as a game changer in solving these difficulties, including data-driven insights, predictive analytics, and automation capabilities that streamline supply chain processes (Odumbo et al., 2025).

According to Kumar et al. (2022), the supply chain covers all operations associated with the movement of commodities, from raw material purchase to final product delivery to the end client. Given the rapid evolution of AI technologies, more research into how they affect supply chain performance in large supermarkets is needed (Charles et al., 2021). This study will look at how AI-demand forecasting, AI-inventory management, and AI-route optimization are helping to improve supply chain performance in large supermarkets in Nairobi City County. This study seeks to give relevant findings for enterprises, politicians, and technological service providers wanting to harness AI to stimulate efficiency and competitiveness in the retail sector.

## 1.2 Statement of the Problem

Supply chain management is a crucial business function that guarantees the effective flow of goods and services from suppliers to final consumers (Odumbo & Nimma 2025). Existing literature has shown that supermarkets are however plagued by high inefficiencies in supply chain operations, ranging from poor demand forecasting to inadequate management of inventories, high operating costs, and congestion during transit. Legacy supply chain processes fall behind changing patterns of consumer consumption, unstable market conditions, and more complex distribution patterns. These inefficiencies result in stock outs, overstocking, increased operating expenses, and lower customer satisfaction, which affect the competitiveness of these supermarkets (Sharma et al., 2022). AI-driven solutions have been successfully implemented in global retail supply chains to address these challenges Kithandi & Ondabu (2024).

The studies have shown mixed results on how AI contributes to success of supply chain optimization. For instance, Hangl et al., (2023), discovered that the effective adoption and application of AI-driven supply chain management systems was hampered by complicated integrations. Some studies have shown positive effect while other studies showed negative or insignificant effect. Example, Marcus (2025), found that AI automated check-ins in hospitality firms improved efficiency while Banerjee (2021), found that AI led to increase on cost of cars in UK due to costs of the tech and employee training on the same. This created the need to examine the AI impact the supply chain performances.

Dumitrascu et al., (2020) found that AI led to short term performance of inventory management in automotive industry creating contextual gap. Hassouna et al., (2022) used experimental research design in their study and found that AI led to excellence in transporting goods in the shortest possible time and with the least cost, however this study created both geographical and methodological gap. Liu and Lin (2021), studied application of artificial intelligence to sustainable supply chain management in the construction material industry and found that the new technology infrastructure enabled adoption of AI that lead to flexibility in supply chain. This study created contextual gap, geographical gap and methodology gap.

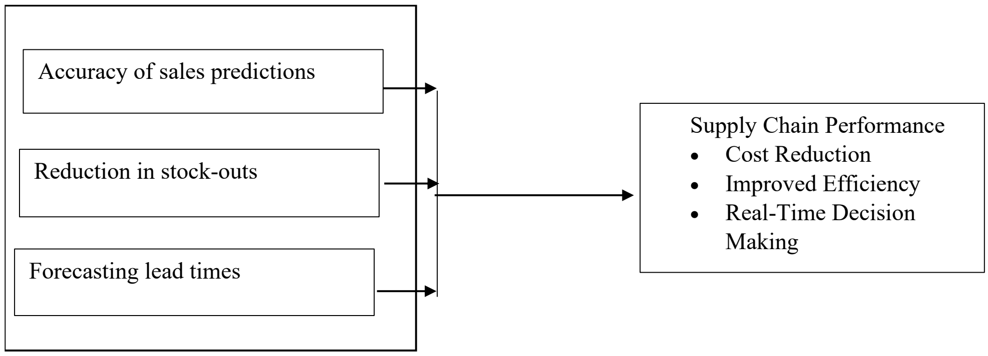
Most of the existing literature had focused on technology growth and adoption of AI robots in working environment. However, little had been investigated on Artificial Intelligence and supply chain performances in the Kenyan context, including the AI tools used in supermarkets, their contribution in the efficiency and effectiveness of the decision making. Therefore, this study filled in this lacuna by determining the impact that AI has on enhancing supply chain optimization among large Supermarkets.

## 1.3 Purpose of the Study

To evaluate the effect of AI-Demand forecasting on supply chain performance among large supermarkets in Nairobi city county, Kenya.

## 1.4 Conceptual Framework

AI-Demand Forecasting:




Independent Variable Dependent Variable

Source: (Author, 2026)

Figure 1: Conceptual framework

## 2. Literature Review

### 2.1 Theoretical Literature

#### Technology Acceptance Theory

Fred Davis established the Technology Acceptance Theory (TAT) in 1989. According to this hypothesis, potential users embrace technology based on two major factors: perceived usefulness and perceived ease of use. This model's main feature is that it emphasizes the views of the potential user. This model postulates that a client's decision-making process regarding the time and methods of implementing an alternative innovation is influenced by a number of elements that come into play when the client is presented with it. This feature clearly proves to be helpful and convenient. According to Ammenwerth (2019), the two most important factors are perceived helpfulness and convenience.

Use of AI is being embraced in today's world and has made significant contributions to the most industries and in the field of forecasting using data (Unal & Uzun, 2021). The intention to adopt AI as well as the sense of utility is influenced by the perceived simplicity of usage. Though theory is a valuable theoretical framework for analyzing how technology is adopted and used, it has limitations that must be recognized. One such restriction is the model's original design goal, which placed an emphasis on simplicity and wide applicability (Kim & Wang, 2021). According to Dutot et al. (2019), the analysis ignores the important elements that restrain the adoption of information communication technology and fails to take into consideration the non-organizational context of the company. Critics argue this oversimplifies the complex, multidimensional nature of technology acceptance and ignores other key factors like: social influence, organizational culture and cost or access barriers

Technology Acceptance Theory was important because it explained and predicted how users come to accept and use a new technology. Increases adoption rates by addressing concerns related to usefulness and ease of use, businesses and institutions can foster faster and broader acceptance of new technologies, reducing training and support costs, improves ROI on technology investments. When technologies are accepted and used effectively, organizations can achieve better outcomes from their investments in software, hardware, or digital platforms.

The successful implementation of AI in supply chain by supermarkets is contingent upon the acceptance and adoption of technology by individuals and institutions (Liu, et al., 2022). This theory will therefore be pertinent to this study since it will assist supermarket managers in integrating AI technology infrastructure to various supply chain department hence leading to cost reduction, improvement in efficiency and aid in real time decision making. In the context of this study, the theory offers valuable insights by linking independent variable to dependent variable.

#### Hybrid Intelligence Model

Hybrid Intelligence Model was first developed by Holger Hoos in 2016 (Hoos 2016). Hybrid Intelligence is an emerging and influential concept in the field of AI that emphasizes the combination of human and machine intelligence to achieve outcomes that neither could have been accomplishes alone (Ali & Fatima 2025). Several researchers and organizations have contributed significantly to the development and advocacy of Hybrid Intelligence model, each from different disciplinary perspectives such as AI, cognitive science, human-computer interaction, and ethics. Example, Jan Marco Leimeister is a researcher that focusses on Hybrid Intelligence, specifically AI-driven decision-making (Leimeister 2020), while Cornelia (2019), has studied Hybrid Intelligence and its impact on coaching and ethics in a tech-driven world. Hoos (2016) has advocated human-in-the-loop AI and hybrid intelligence for trustworthy systems pushing for responsible AI and cooperative systems by incorporating not only from data, but also from humans (Bosman et al., 2023). The model combines symbolic reasoning with connectionist models for better performance and interpretability (Schmidt et al., 2020). It uses neuro-symbolic systems that can learn from data and reason logically (Ali & Fatima 2025). The hybrid intelligence AI systems are designed to interact dynamically with humans through interfaces, language, or gestures. The AI excels at pattern recognition, speed, and scale while humans bring context, ethics, creativity, and common sense and together, they compensate for each other's weaknesses.

Large supermarkets in Nairobi are incorporating AI alongside humans, using sensors to understand context and use them mainly in inventory management, demand forecasting and making logistics decision. AI and other digital decisions are seen as transparent and explainable to customers to build trust hence enabling business to reach a wider population (Nzisa & Kithandi, 2023). Hybrid Intelligence model offers a promising framework, but like any emerging concept, it comes with important critiques and limitations. According to Blalock et al., (2020), he stated that without a clear, shared definition, it's hard to build standardized systems, compare research outcomes, or scale implementations. According to Kumar et al., (2024) they highlight that many hybrid systems depend heavily on human oversight, which can limit scalability and introduce human error or bias. In human-in-the-loop systems, fatigue, inconsistency, or lack of expertise can compromise effectiveness brought by hybrid intelligence.

The importance of AI incorporation in the large supermarket systems lies in its potential to fundamentally reshape how humans and machines interact not by replacing human intelligence, but by enhancing and extending it through collaboration (Nouzri & Ejjami 2024). Additionally, while most AI often aims to replace human labor or decision-making. Hybrid intelligence model shifts the goal to augmentation, helping people make better, faster, and more informed decisions (Nouzri & Ejjami 2024).

This model was therefore being pertinent to the current investigation since it will assist supermarket managers in integrating AI technology infrastructure to improve supply chain optimization. This model explores and deduces the human interactions with AI working from various supply chain departments within the supermarkets to leverage on optimization without laying off the workers. In the context of this study, the model offered valuable insights into how supermarkets should leverage hybrid AI to enhance supply chain optimization, cost reduction, improve process efficiency and real time decision making in large supermarkets.

### 2.2 Empirical Literature

AI in demand forecasting improves accuracy, optimizes inventory, and increases operational efficiency by analyzing data to estimate future demand, find patterns, and respond to changing market conditions (Delen & Hardgrave, 2020). This leads to better inventory management, less waste, and higher customer satisfaction (Dash et al., 2019). AI forecasting automates much of the data gathering, preprocessing, and modeling operations, considerably increasing efficiency, speed, and strategic decision-making (Muchandeepi et al., 2019). AI demand forecasting systems can evaluate massive datasets and provide projections in real time, giving decision-makers up-to-date information. With accurate demand forecast, retailers can minimize overstocks and shortages. This reduces costs and ensures that shelves are always well stocked, which increases customer satisfaction (Chopra & Meindl 2019).

Generative AI in demand planning tailors estimates to particular client preferences based on historical data and real-time interactions. It improves customer segmentation tactics and product recommendations to better suit unique consumer needs (Chopra & Meindl 2019). AI algorithms can analyze massive volumes of data, including historical sales, market trends, and external factors, to uncover complicated patterns and predict future demand more accurately than traditional approaches (Fujimoto 2020). AI systems can constantly update their forecasts with fresh data, allowing firms to respond swiftly to market shifts and consumer requests (Chopra & Meindl 2019).

AI improves lead time forecasting by using machine learning algorithms to analyze large datasets, detect trends, and create more accurate forecasts. This enables organizations to optimize inventory management, proactively resolve supply chain interruptions, and improve market response, resulting in shorter lead times and lower costs (Dash et al., 2019). The use of AI in forecasting can significantly reduce lead times. Businesses with the ability to foresee market changes in real time can nearly instantly adapt production schedules and inventory levels (Delen & Hardgrave 2020). AI-powered demand helps to improve the accuracy of sales estimates, reduce stock-outs, and forecast lead times (Chopra & Meindl 2019).

## 3 Research Methodology

This study adopted research paradigms, positivism: The positivism paradigm emphasized objective reality, deductive reasoning, and quantitative methods. It sought to establish generalizable laws and causal relationships (Park et al., 2020). This study used descriptive research design. This design is appropriate for the study as it accurately described the situation at the time of the study. The population of this study was the employees who worked in supply chain department comprising of Managers, Supervisors and Supply chain officers of 10 largest supermarkets in Nairobi City County. The target population of the study consisted of 70 employees working in the supply chain departments of 10 largest supermarkets based in Nairobi City County, Kenya. The approach guaranteed that the study's focus was on the full target population, which consisted of 70 employees working in the supply chain departments of 10 largest supermarkets based in Nairobi City County, Kenya. In this study, a standardized questionnaire with closed-ended questions was used. According to Copper and Schindler (2019), structured enquiries encourage users to fill out forms with as much information as possible. This study utilized primary dater gathered using questionnaire.

## 4 Results and Discussion

### 4.1 Descriptive Analysis

This section present Descriptive Analysis findings on artificial intelligence applications and supply chain performance.

Results are provided in tables 1, 2, 3, 4, 5, and 6.

## AI-Demand forecasting

The first objective of the study was to evaluate the effect of AI-Demand forecasting on supply chain performance among large supermarkets. This was looked at through broad variables of accuracy of sales predictions, reduction in stock-outs and forecasting lead times. Respondents were provided with several statements and based on their understanding on how AI-Demand forecasting was being practiced in their supermarket, they were to indicate their understanding on a five-point Likert scale (SD = strongly disagree, D =Disagree, N = Neutral, A = Agree, and SA = strongly agree) which was provided for every statement. Findings are as presented in table 1.

Table 1: Accuracy of sales predictions

| | SD | D | N | A | SA | M | STD | STDE |
|---|---|---|---|---|---|---|---|---|
| AI-demand forecasting tool is able to use historical sales data to accurately predictions predict the sales. | 0 | 0 | 0 | 14 (23) | 4 7(77) | 4.77 | 0.42 | 0.05 |
| The sales predictions made by AI-Demand Forecasting are quite reliable. | 0 | 0 | 0 | 28 (45.9) | 33(54.1) | 4.54 | 0.5 | 0.06 |
| AI-Demand Forecasting uses the market trends to accurately predict sales | 0 | 0 | 14 (23) | 14 (23) | 33(54.1) | 4.31 | 0.82 | 0.10 |
| AI-Demand Forecasting uses present data to predict future demand with a higher degree of precision | 0 | 0 | 28 (45.9) | 16 (26.2) | 17(27.9) | 3.82 | 0.84 | 0.11 |
| AI-Demand Forecasting analyze real-time data, such as point-of-sale (POS) data, allowing for immediate adjustments that improves sales prediction accuracy | 0 | 0 | 28 (45.9) | 33 (54.1) | 0 | 3.54 | 0.5 | 0.06 |
| **Average** | | | | | | **4.19** | **0.62** | **0.08** |

Source: (Primary Data, 2025)

The findings indicated that 14(23%) agreed, while 47(77%) strongly agreed that AI-demand forecasting tool was able to use historical sales data to accurately predictions predict the sales. Further, 28(45.9%) and 33(54.1%) agreed and strongly agreed that the sales predictions made by AI-Demand Forecasting were quite reliable. According to Ramya et al., (2024), with AI sales predictions are consistently reliable. Another, 14(23%) remained neutral while 14(23%) and 33(54.1%) agreed and strongly agreed respectively that AI-Demand Forecasting uses the market trends to accurately predict sales. On AI-Demand Forecasting using present data to predict future demand with a higher degree of precision, had a total of 28(45.9%) who remained neutral while 16(26.2%) and 17(27.9%) agreed and strongly agreed respectively. Moreover, the findings indicated that 28(45.9%) remained neutral while 33(54.1%) agreed that AI-Demand Forecasting analyze real-time data, such as point-of-sale (POS) data, allowing for immediate adjustments that improves sales prediction accuracy. The findings revealed that average mean was 4.19 and SD was 0.62, confirming that respondents agreed that there was use of AI-Demand Forecasting among the large supermarkets in Nairobi. These findings agreed with the findings of Venkataramanan et al., (2024), who found that AI-Demand Forecasting enhanced sales prediction accuracy by using machine learning algorithms to analyze vast amounts of historical data, customer behavior, and market trends.

Table 2: Reduction in stock-outs

| | SD | D | N | A | SA | M | STD | STDE |
|---|---|---|---|---|---|---|---|---|
| AI-Demand Forecasting tool has significantly reduce stockouts by optimizing inventory levels | 0 | 14 (23) | 14 (23) | 0 | 33 (54.1) | 3.85 | 1.3 | 0.16 |
| AI-Demand Forecasting usually predict future demand hence reducing stock-outs | 0 | 14( 23) | 14 (23) | 33 (54.1) | 0 | 3.31 | 0.82 | 0.10 |
| The improvement in accuracy of demand predictions has significantly reduces stockouts | 0 | 14 (23) | 14 (23) | 16 (26.2) | 17 (27.9) | 3.59 | 1.13 | 0.14 |
| The prediction of future demand patterns has minimized the risk of stockouts | 0 | 14 (23) | 14 (23) | 16 (26.2) | 17 (27.9) | 3.59 | 1.13 | 0.14 |
| The accuracy prediction has leads to better inventory management and reduces the likelihood of stockouts. | 0 | 0 | 28 (45.9) | 16 (26.2) | 17 (27.9) | 3.82 | 0.84 | 0.11 |
| **Average** | | | | | | **3.63** | **1.04** | **0.13** |

Source: (Primary Data, 2026)

The findings revealed that those who remained neutral and those who disagreed were equal at 14(23%) while 33(54.1%) strongly agreed that AI-Demand Forecasting tool has significantly reduce stock outs by optimizing inventory levels. Another, similar number of the respondents 14(23%) disagreed that AI-Demand Forecasting usually predict future demand hence reducing stock-outs, while 33(54.1%) agreed that AI-Demand Forecasting usually predict future demand hence reducing stock-outs. 14(23%) disagreed that the improvement in accuracy of demand predictions has significantly reduces stock outs, while 16(26.2%) and 17(27.9%) agreed and strongly agreed respectively to the same. Further, 14(23%) disagreed while a similar number remained neutral that the prediction of future demand patterns has minimized the risk of stock outs. 16(26.2%) and 17(27.9%) agreed and strongly agreed respectively. Finally, 28(45.9%) remained neutral while 16(26.2%) and 17(27.9%) agreed and strongly agreed respectively that the accuracy prediction has leads to better inventory management and reduces the likelihood of stock outs. The findings revealed that average mean was 3.63 and SD was1.04, confirming that respondents slightly agreed that there was Reduction in stock-outs due to use of AI-Demand Forecasting among the large supermarkets in Nairobi. These findings echoed the findings of Venkataramanan et al., (2024), who found that I significantly reduce stock-outs by using predictive demand forecasting, analysing historical sales and seasonal trends.

Table 3: Forecasting lead times

| | SD | D | N | A | SA | M | STD | STDE |
|---|---|---|---|---|---|---|---|---|
| The AI-Demand Forecasting is providing more precise estimates of future demand hence forecasting lead times | 0 | 0 | 28 (45.9) | 16 (26.2) | 17 (27.9) | 3.82 | 0.84 | 0.11 |
| AI-Demand Forecasting has led the business to act swiftly to unexpected events, such as product spikes or supply chain disruptions | 0 | 0 | 44 (72.1) | 0 | 17 (27.9) | 3.56 | 0.9 | 0.11 |
| AI-Demand Forecasting has enables businesses to make informed decisions quickly, | 0 | 14 (23) | 14 (23) | 16 (26.2) | 17 (27.9) | 3.59 | 1.13 | 0.14 |
| AI-Demand Forecasting has streamlines supply chain operations hence improved the led time | 0 | 14 (23) | 14 (23) | 16 (26.2) | 17 (27.9) | 3.59 | 1.13 | 0.14 |
| AI-Demand Forecasting has improved resource allocation leading into improve in led time | 0 | 0 | 14 (23) | 30 (49.2) | 17 (27.9) | 4.05 | 0.71 | 0.09 |
| **Average** | | | | | | **3.72** | **0.94** | **0.12** |

Source: (Primary data, 2026)

The findings indicated that 28(45.9%) remained neutral while 16(26.2%) and 17(27.9%) agreed and strongly agreed that the AI-Demand Forecasting was providing more precise estimates of future demand hence forecasting lead times. Another 44(72.1%) remained neutral while 17(27.9%) strongly agreed that AI-Demand Forecasting has led the business to act swiftly to unexpected events, such as product spikes or supply chain disruptions. The findings also indicated that 14(23%) and another 14(23%) disagreed and remained neutral that AI-Demand Forecasting has enables businesses to make informed decisions quickly, while 16(26.2%) and 17(27.9) agreed and strongly agreed to the same statement respectively. Further, 14(23%) and 14(23%) disagreed and remained neutral that AI-Demand Forecasting has streamlines supply chain operations hence improved the led time, while 16(26.2%) and 17(27.9%) agreed and strongly agreed to the same statement respectively. Another 14(23%) remained neutral while 30(49.2%) and 17(27.9%) agreed and strongly agreed respectively that AI-Demand Forecasting has improved resource allocation leading into improve in led time. The findings revealed that average mean was 3.72 and SD was 0.94, confirming that respondents agreed that there was use of AI-Demand Forecasting that led to focus lead time among the large supermarkets in Nairobi. According to Nweje and Taiwo (2025), AI improves lead time forecasting by analyzing complex datasets and real-time factors to create more accurate predictions, enabling businesses to optimize inventory, improve supplier selection, reduce costs, and enhance supply chain efficiency.

## 4.2 Regression Analysis

This section presents the results of regression analysis, prediction and the interpretation of relationships among the various variables under study.

### AI-Demand Forecasting and Supply Chain Performance

Objective one was to evaluate the effect of AI-Demand forecasting on supply chain performance among large supermarkets in Nairobi city county, Kenya.

The regression models adopted to test hypothesis was;

$Y = \beta 0 + \beta 1X1 + έ$ ----------------Objective (i)

Where Y = supply chain performance

B0 –the regression intercept

X1 = AI-Demand forecasting.

Table 4: Model summary

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .991a | 0.983 | 0.982 | 0.07856 |

a Predictors: (Constant), AI-Demand Forecasting

Source: (Primary data, 2025)

The independent variables that were studied accounted for 98.6% of the effects of the controlled variables on supply chain performance as represented by the adjusted R squared. The value of adjusted R is 0.982. This implies that unexplained discrepancies account for 1.4% of the effects of the AI-Demand Forecasting on supply chain performance.

Table 5: ANOVA

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 20.245 | 1 | 20.245 | 3280.725 | .000b |
| | Residual | 0.364 | 59 | 0.006 | | |
| | Total | 20.609 | 60 | | | |

a Dependent Variable: Supply Chain Performance

b Predictors: (Constant), AI-Demand Forecasting

Source: (Primary data, 2025)

The ANOVA model show the coefficient of determination (R2) was significant as evidenced by ($F = 3280.725$, $\rho<0.01$). Thus, the model was fit to predict supply chain performance using AI-demand forecasting.

Table 6: Coefficients

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 0.979 | 0.049 | | 19.973 | 0 |
| | AI-Demand Forecasting | 0.714 | 0.012 | 0.991 | 57.278 | 0 |

a Dependent Variable: Supply Chain Performance

Source: (Primary data, 2025)

Hypothesis1 ($Ho_1$) stated that AI-demand forecasting has no statistically significant effect on supply chain performance among large supermarkets in Nairobi City County, Kenya. Findings showed that AI-demand forecasting had coefficient of estimate which was significant basing on $\beta1 = 0.714$ (p-value = 0.000 which is less than $\alpha = 0.01$). The null hypothesis was thus rejected and it was concluded that AI-demand forecasting has a statistically significant effect on supply chain performance among large supermarkets in Nairobi City County, Kenya. The identified equation to understand this influence was; $Y = 0.979 + 0.714 X1 + \varepsilon$. The findings echoed the findings of Kalusivalingam et al., (2022), who found that AI-powered demand forecasting significantly improves supply chain efficiency by reducing errors, optimizing inventory, cutting costs, and enhancing overall performance.

## 5 Conclusion and Recommendations

The objective of the study was to evaluate the effect of AI-Demand forecasting on supply chain performance among large supermarkets. This was looked at through broad variables of accuracy of sales predictions, reduction in stock-outs and forecasting lead times. On accuracy of sales predictions, the findings indicated that 14(23%) agreed, while 47(77%) strongly agreed that AI-demand forecasting tool was able to use historical sales data to accurately predictions predict the sales. Therefore, this study concluded that AI-demand forecasting tool predicted the sales. Further, on reduction in stock-outs, the study found that the respondents 33(54.1%) overwhelm strongly agreed that AI-Demand Forecasting tool has significantly reduce stock outs by optimizing inventory levels. Therefore, this study concludes that stock outs have significantly reduced due to the use of AI-Demand Forecasting tool. The regression findings revealed that AI-demand forecasting had coefficient of estimate which was significant basing on $\beta1 = 0.714$ (p-value = 0.000 which is less than $\alpha = 0.01$). This study concluded that AI-demand forecasting has a statistically significant effect on supply chain performance among large supermarkets in Nairobi City County, Kenya.

### Declaration of Competing Interests

The authors declare that they are not aware of any competing financial interests or personal relationships that may have influenced the work described in this document.

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### Ethical considerations

The article followed all ethical standards appropriate for this kind of research.

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