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THE EFFECT OF PREDICTIVE DATA ANALYTICS ON FRESH FOOD SUPPLY CHAIN PERFORMANCE FOR AGRITECH COMPANIES IN KENYA

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Abstract:
This study assessed the effect of predictive data analytics on the supply chain performance of Agritech Companies in Kenya. The study was grounded in Organizational Information Processing Theory. A descriptive research design was adopted. The target population consisted of 315 supply chain and information technology officers, from which a sample of 172 respondents was selected using Yamane's formula (1967). Data were collected using structured questionnaires and interviews. Analysis was conducted using correlation analysis, and multiple regression analysis. The findings revealed that predictive data analytics had a positive and significant effect on food supply chain performance. The study findings indicated that predictive analytics improved demand forecasting and planning accuracy. The study concluded that predictive data analytics significantly enhances food supply chain performance, particularly when supported by strong organizational capabilities. It recommended that agritech firms invest in predictive data analytics systems to improve effective utilization of analytics tools in supply chain operations.

JEL: M11, L23, L14, R41

Keywords: predictive data analytics, fresh food supply chain performance, Agritech companies in Kenya

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1. Introduction

The fresh food supply chain sector has significantly evolved over the years, transitioning from a largely informal and centralized system into a fragmented, technology-enabled, and increasingly competitive network of producers, aggregators, logistics providers, and distributors. In 2025, the global fresh food supply chain market is valued at approximately USD 9 trillion, and this value is projected to grow to USD 18 trillion by 2028 (Fortune Business Insights, 2024). Increasingly, fresh food supply chains are becoming information-intensive systems in which timely data collection and analytics play a critical role in procurement planning, distribution, loss reduction, and overall supply chain coordination (Rahman, 2017).

In Kenya, the fresh food supply chain sector is closely linked to national development priorities, including food security, value addition, and employment creation under Vision 2030. Agritech companies have emerged as key actors within this ecosystem by digitizing agricultural production, market linkages, logistics, and distribution systems. Recent industry reports highlight increasing digital adoption, regulatory shifts, and the expansion of technology-driven supply chain models as defining features of the sector's future (Cytonn Investments, 2024). In this context, big data analytics is increasingly viewed as a strategic capability that can improve fresh food supply chain performance by enhancing efficiency, resilience, coordination, and market responsiveness among agritech firms.

Fresh food supply chain performance is an important area of study because it affects food security, economic growth, and public well-being. Research in both developed and developing countries shows that effective supply chain practices improve performance by enhancing efficiency, responsiveness, and reliability. For example, Anand and Grover (2015) found that in the United States, supply chain performance is influenced by practices such as resource optimization, transport planning, inventory management, and the use of information technology. Similarly, Banerjee and Mishra (2017) emphasize that performance depends on multiple factors, including speed, flexibility, information sharing, technology adoption, customer focus, partnerships, integration, postponement, and inventory control.

In Africa, fresh food supply chains were traditionally dominated by informal wholesalers and small retailers. However, modern systems are expanding due to economic growth, population increase, and wider use of technology. Consumer spending on fresh food is significantly high, creating both opportunities and pressure for firms to develop reliable supply chains. Despite this, the supply chains remain costly, accounting for about 75% of total product costs (The Economist, 2024), and inefficiencies persist due to multiple intermediaries and mismatches between supply and demand (Twiga Foods, 2022). Only large multinational firms that handle mostly processed foods, such as Coca-Cola, Unilever, and Nestlé, have successfully built fully integrated chains that deliver products efficiently from production to end users (Chakravarthy & Coughlan, 2011). Fresh foods, by contrast, are more perishable, require faster distribution, and face greater risks of spoilage, making supply chain performance particularly critical for agritech companies.

The increasing complexity of fresh food supply chains has made technology and data more important. The adoption of digital tools generates large volumes of diverse, real-time data (Nandi *et al.*, 2020; Kitchin & McArdle, 2016). Supply chain analytics uses this data to improve performance through four main approaches: descriptive analytics, which analyzes past events; diagnostic analytics, which identifies causes of problems; predictive analytics, which forecasts future outcomes; and prescriptive analytics, which recommends optimal actions (Barga *et al.*, 2015). For Kenyan agritech companies handling fresh foods, big data analytics provides a strategic tool to improve coordination, reduce inefficiencies, optimize resources, and enhance overall fresh food supply chain performance.

In recent years, Kenya has emerged as a hub for agritech innovation, with a growing number of startups transforming the way fresh foods are produced, distributed, and accessed. According to Kissinger (2022), Kenya ranks as the leading African destination for agritech ventures, attracting substantial investment in the sector. Notably, Apollo Agriculture and Twiga Foods have raised $40 million and $80 million, respectively, over the past three years, reflecting investor confidence in the country's potential to modernize agricultural supply chains.

While there is currently no comprehensive registry of agritech companies in Kenya, the sector continues to grow rapidly, driven by innovations in fresh food supply chains. Generally, agritech companies in Kenya can be grouped based on the focus of their business models and services. Some are market linkages platforms connecting smallholder farmers directly to vendors or consumers; others focus on input and advisory services, offering seeds, fertilizers, financing, and farm management guidance through digital platforms. Others are logistics solutions specializing in storage and transport, while others are data firms that provide insights for forecasting demand, monitoring crop health, and optimizing resource allocation. This study focused on agritech companies that facilitate the movement and distribution of fresh foods along the supply chain, examining how their adoption of big data analytics and firm characteristics influences overall supply performance.

The fresh food supply chain is a critical contributor to sustainable development and economic growth, with the global fresh food retail market projected to expand significantly by 2030 (FAO, 2021; Pérez-Escamilla, 2024). In Kenya, the sector contributes approximately 13.5% of the country's Gross Domestic Product (KNBS, 2020), yet it continues to face persistent supply chain inefficiencies characterized by fragmented distribution networks, high post-harvest losses, inconsistent product quality, and costly multi-layered intermediaries (Berger & van Helvoirt, 2018; Rischke *et al.*, 2022). Supply chain analytics and predictive data analytics have been identified as transformative technologies capable of improving demand forecasting, inventory management, logistics, and overall supply chain performance (Wang *et al.*, 2016; Hofmann & Rutschmann, 2018). Despite the emergence of agritech firms leveraging data-driven solutions, adoption remains low, with only a small proportion of Kenyan firms realizing value from big data investments (Grant Thornton, 2019). Furthermore, previous studies on predictive data analytics in Kenya have largely focused on sectors such as telecommunications, banking, insurance, education, and manufacturing, with limited attention to the fresh food supply chain. This study therefore seeks to bridge this gap by examining the influence of big data analytics on fresh food supply chain performance among agritech companies in Kenya.

1.2 Objective of the Study

To establish the effect of predictive data analytics on fresh food supply chain performance for agritech companies in Kenya.

1.3 Research Hypothesis

H_{01}: Predictive data analytics has no significant effect on fresh food supply chain performance for agritech companies in Kenya.

2. Literature Review

2.1 Theoretical Literature Review

This study was guided by Organizational Information Processing Theory.

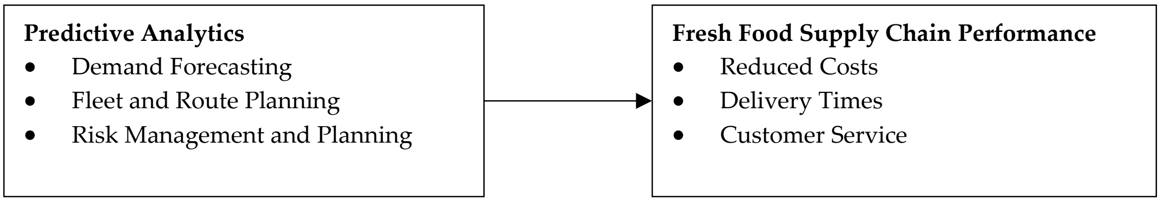
2.1.1 Organizational Information Processing Theory

Jay Galbraith postulated the OIPT theory in 1973, which argued that organizations face the challenge of uncertainity and their structures should be built around being able to reduce this uncertainty (Haußmann *et al.*, 2012). To solve these issues with organizational design, firms should invest in information systems that help in reducing uncertainties. The theory is based on the assumption that organizations are systems of information processing dealing with information from internal and external sources. This information is uncertain depending on the gap that exists between the organization's requirements for information processing and its actual capacity to process information (Galbraith, 2021). The goal of organizations is to reduce or eliminate this gap through the use of various mechanisms for control and coordination. One of these mechanisms is investing in proper information systems.

Even though the OIPT theory was originally rooted in the information technology function, over the years, scholars have developed it to make it relevant for other organizational functions as well. Srinivasan & Swink (2018) sought to apply the OIPT to the supply chain function by explaining that supply chain organizations could use their analytical capability to enhance their performance. Their ability to analyze information and data requires the firms to enhance visibility on both the demand and supply sides of the chain. Essentially, supply chain organizations could initiate visibility strategies to reduce uncertainty in supply chain operations and thus enhance their performance.

This theory is useful in explaining the relationship between the independent variable (big data analytics) and the dependent variable (fresh food supply chain performance). Players along the food supply chain could use big data analytics to reduce uncertainty by using it to improve their information processing capacity, thereby positively influencing their performance by enhancing their transparency, level of integration on the demand and supply side and operational efficiency.

2.3 Conceptual Framework



2.4 Empirical Literature Review

2.4.1 Predictive Analytics and Fresh Food Supply Chain Performance

A study by Gunasekaran *et al.* (2017) investigated the link between predictive supply chain analytical capabilities and organizational performance. The study was contextualized in India and used a survey instrument on a 5-point Likert scale to supply chain management functional heads in e-commerce, consulting and manufacturing companies in Pune, Bangalore and Hyderabad. The findings of the study demonstrated that predictive analytics had a positive effect on the supply chain and subsequently, on the performance of the organizations. However, the relationship is mediated by the commitment of management towards enhancing the firm's ability to collect and analyze data. This study went further to investigate how big data analytics, inclusive of predictive analytics, impacts fresh food supply chain performance within a different context-agritech companies in Kenya.

The article "Impact of big data and predictive analytics capability on supply chain sustainability" by Jeble *et al.* (2018) examines the impact of big data and predictive analytics capabilities on supply chain sustainability. The quantitative study was conducted by administering questionnaires to 205 respondents within the supply chain sector in the United Kingdom. The findings of the study demonstrated that the integration of predictive analytical capabilities can enable organizations to improve their environmental and social performance, while also enhancing their operational and financial efficiency. The article presents a conceptual framework that integrates the concepts of big data analytics, predictive analytics, and sustainability to explain the mechanisms through which these capabilities can improve supply chain sustainability. The authors discuss the importance of data quality, analytics talent, and organizational culture in enabling the successful implementation of these capabilities. While useful, Jeble *et al.* (2018) is limited in that it only focuses on predictive analytics in the United

Kingdom. This study went further by exploring big data analytics within the Kenyan region.

The article "The Role of Big Data and Predictive Analytics in Humanitarian Supply Chains: Enabling Visibility and Coordination in the Presence of Swift Trust" by Ademoye *et al.* (2021) reviews the literature on the use of big data and predictive analytics in humanitarian supply chains. The study relied on surveys that were administered to 205 respondents from non-governmental organizations. The findings of the study demonstrated that the adoption of these technologies can improve the efficiency and effectiveness of humanitarian supply chains by enabling greater visibility, coordination, and information sharing. The article specifically focused on the concept of "swift trust," which refers to the ability of humanitarian actors to quickly establish trust in uncertain and rapidly changing environments. The authors argued that big data and predictive analytics can facilitate the development of swift trust by providing real-time information on supply chain operations, enabling better coordination and collaboration among stakeholders, and allowing for more efficient allocation of resources. Ademoye *et al.* (2021) is limited since it relies on a literature review to show the impact of analytics on performance. This study relied on primary data to provide first-hand information about big data analytics within the Kenyan fresh food supply chain context.

In Africa, literature documents a mixed picture about the use of predictive analytics and supply chain performance. Evidence from Ghana" by Owusu *et al.* (2020) investigates the impact of predictive analytics on supply chain performance in a Ghanaian context. The study uses a case study approach to examine the implementation of predictive analytics in a Ghanaian company and the resulting impact on supply chain performance. 111 questionnaires were administered to employees in the supply chain and information technology functions. The authors found that the implementation of predictive analytics can improve supply chain performance in a number of ways. First, predictive analytics can enhance demand forecasting accuracy, which can reduce stockouts and overstocking, leading to improved inventory management. Second, predictive analytics can help to identify and reduce bottlenecks in the supply chain, improving operational efficiency. Third, predictive analytics can support better decision-making by providing insights into customer behavior and trends, enabling companies to respond more effectively to changing market conditions. The study also identifies some of the challenges associated with the implementation of predictive analytics in a developing country context, such as the need for adequate data infrastructure, skilled personnel, and appropriate IT systems. However, the authors suggest that these challenges can be addressed through appropriate investments and training. This study went beyond predictive analytics as analyzed by Owusu *et al.* (2020) to shed light on big data analytics in general within the context of agritech companies in Kenya.

A study that was conducted in South Africa reported similar findings. The article "Assessing the impact of predictive analytics on supply chain performance in a South African context" by Kotzé *et al.* (2019) examines the impact of predictive analytics on supply chain performance in a South African context. The authors conducted a survey of

70 supply chain professionals from various industries in South Africa to explore the use of predictive analytics in their supply chains and assess its impact on performance. The study finds that the adoption of predictive analytics can improve supply chain performance by enhancing demand forecasting accuracy, reducing lead times, improving inventory management, and supporting better decision-making. The study also identifies some of the challenges associated with the adoption of predictive analytics, such as data quality and accessibility, as well as the need for specialized skills and expertise. The authors suggest that these challenges can be addressed through appropriate investments in technology and training programs for employees. Nonetheless, these findings cannot be generalized to this study due to contextual differences between South Africa and Kenya. This study focused on agritech companies in Kenya.

In Nigeria, a study was conducted to investigate the implementation of predictive analytics in the supply chain function. The study by Alao *et al.* (2019) explored the impact of predictive analytics on supply chain management in Nigeria. The authors conducted a survey of 105 supply chain professionals from various industries in Nigeria to investigate the use of predictive analytics in their supply chains and assess its impact on performance. The study finds that the adoption of predictive analytics can improve supply chain performance by enhancing demand forecasting accuracy, reducing lead times, improving inventory management, and supporting better decision-making. The authors also challenge associated with the adoption of predictive analytics, such as data quality, accessibility, and the need for specialized skills and expertise. The authors suggest that these challenges can be addressed through appropriate investments in technology and training programs for employees. This study focused on the Kenyan context and studied big data analytics within agritech companies.

Recent Kenyan studies have also documented the relationship between predictive analytics and supply chain performance. In the article "Predictive analytics and its role in supply chain management in Africa: A case study of a Kenyan company" by Mwaura *et al.* (2021) investigates the use of predictive analytics in supply chain management in an African context, using a case study approach to examine a Kenyan company. The authors issued surveys to a sample population of 114 employees within the Kenyan company. The study found that the implementation of predictive analytics can improve supply chain performance by enhancing demand forecasting accuracy, improving inventory management, and supporting better decision-making. The authors highlighted that the adoption of these technologies is particularly relevant in the African context, where supply chain disruptions are common, and companies face a number of challenges related to poor infrastructure, limited resources, and a lack of data. The study also identified some of the challenges associated with the implementation of predictive analytics in an African context, such as data privacy and security concerns, as well as issues related to data quality and accessibility. The authors suggested that these challenges can be addressed through appropriate investments in IT infrastructure and training programs to develop the necessary skills among employees. Mwaura *et al.* (2021)

focused on predictive analytics in a single company, while this study expanded the scope to include other types of big data analytics in several agritech companies in Kenya.

3. Research Methodology

3.1 Research Design

This study relied on a descriptive research design. A descriptive research design is a type of research design that aims to describe or document a particular phenomenon or situation. It involves collecting data that describe the characteristics, behavior, or attitudes of a group of people, objects, or events (Nassaji, 2015). The main goal of descriptive research is to answer the questions of "what," "where," "when," and "how" about a particular phenomenon or situation, without attempting to establish cause-and-effect relationships.

This research relied on the descriptive research design because of its ability to provide a detailed and accurate description of a particular phenomenon or situation, which can inform further research or policy decisions. It can also help to identify patterns or trends that can be used to develop hypotheses or generate new ideas for research. For this study, a descriptive research design was used to describe the use of big data analytics for fresh food supply chain performance and use the findings to inform further policies or research on the subject.

3.2 Population of Study

The population of study refers to the group of individuals or elements that researchers aim to investigate and draw conclusions from in their research (Asiamah *et al.*, 2019). It is crucial to define and understand the population of study as it forms the basis for generalizing research findings. The population of study also guides the sampling process, research objectives, and data analysis methods.

The target population of this study will consist of supply chain officers and Information Technology (IT) officers within the selected agritech companies in Kenya. Supply chain officers are selected because they are responsible for overseeing the overall supply chain operations within the companies, including inventory management, logistics, procurement, and distribution. They play a crucial role in decision-making related to supply chain performance. IT officers are selected because, given the focus on supply chain analytics, individuals responsible for managing and analyzing data within the agritechs' IT department can provide valuable insights into the implementation and utilization of supply chain analytics. These officers are well-versed in the subject matter of this study, which is big data analytics and fresh food supply chain performance within their organizations. The unit of observation was supply chain managers and information technology managers. Table 1 below demonstrates the target population from each of the agritech companies, totaling 311.

Table 1: Target Population

	Company	Supply Chain Officers	IT Officers	Total
1	Twiga	64	16	80
2	Farmdrop Foods	10	7	17
3	Mfarm	12	8	20
4	Sendy	44	13	57
5	KOKO Networks	18	9	27
6	FarmDrive	12	10	22
7	Taimba	7	4	11
8	MarketForce	11	7	18
9	Soko Watch	47	12	59
	Total	**225**	**86**	**311**

Source: Human Resource Departments, Twiga Foods, Farmdrop Foods, MFarm, Sendy, KOKO Networks, FarmDrive, Taimba, MarketForce, Soko Watch, 2026.

3.3 Sample Size and Sampling Procedure

Sampling in research involves selecting a subset of individuals or elements from a larger population of interest (Banerjee & Chaudhury, 2010). It serves the purpose of making inferences and drawing conclusions about the population while studying a more manageable and practical subset. Sampling enhances the efficiency, generalizability, and precision of research by allowing researchers to collect representative data, save resources, and respect ethical considerations. The study will rely on stratified proportionate sampling, which entails dividing the population into distinct subgroups or strata based on specific characteristics. Each stratum is then represented in the sample in proportion to its size in the population (Iliyasu & Etikan, 2021). Kothari (2004) explains that the sampling procedure ensures that each subgroup is adequately represented, allowing for more accurate and precise estimates for each stratum.

The study grouped the respondents into two strata: supply chain officers and IT officers. From each group, the study used simple random sampling to select 175 respondents from the total target population of 311.

3.3.1 Sample Size

A sample refers to a subset of individuals, elements, or units selected from a larger population for the purpose of research or study (Kothari, 2004). It is a representative group that is chosen to provide insights, data, or observations that can be generalized or applied to the entire population. The sample is typically smaller and more manageable than the population, allowing researchers to collect data efficiently and draw conclusions about the broader population based on the characteristics and behaviors observed within the sample.

The study will rely on Yamane's (1967) formula to calculate the sample size as highlighted below:

$$n = \frac{N}{1 + N(e)^2}$$

Whereby:
n represents the sample size that will be used for the study,
N is the target population,
e is the limit of error.

For this study, the target population (N) is 299. When substituted in the formula above, the sample size is

$$\frac{311}{1 + 311(0.05)^2}$$

Therefore, the sample size is 175.

The sample size of 175 respondents is calculated using proportional sampling with the target population and demonstrated in Table 2 below:

Table 2: Sample Size

	Company	Supply Chain Officers	IT Officers	Total
1	Twiga	36	10	46
2	Farmdrop Foods	5	4	7
3	Mfarm	6	5	11
4	Sendy	25	8	32
5	KOKO Networks	10	6	16
6	FarmDrive	8	3	11
7	Taimba	4	2	6
8	MarketForce	7	2	9
9	Soko Watch	27	7	34
	Total	**128**	**47**	**175**

Source: Author, 2023.

3.3.2 Sampling Frame

A sampling frame is a list, database, or other representation of the target population from which a sample is drawn and serves as a reference or source from which the researcher can select the individuals or elements to be included in the sample (Kothari, 2004). This study has a sampling frame that consists of all supply chain officers and IT officers in the agritech companies in Kenya.

3.3.3 Sampling Procedure

This study will use stratified proportionate sampling to select its respondents. The study categorized officers in the companies depending on their functional areas (Strata). From each strata, the study used simple random sampling to select officers from each of the agritech companies as shown in Table 3.2.

3.4 Regression Analysis

Regression analysis is a statistical technique used to examine the relationship between a dependent variable and one or more independent variables (Sahu *et al.*, 2015). In the context of this study, regression analysis will be applied to investigate how the independent variable of supply chain analytics influences the dependent variable of food retail performance. The study used summated scores of the responses on the questionnaire. The researcher assigned scores to individual items within a questionnaire that assess different aspects of the variables of interest. These scores were then summed up to create a composite score for each respondent, representing their overall level of the variable being measured.

The regression analysis involved using the summated scores as the dependent variable and the independent variable(s) of the study. The goal was to determine how the independent variable(s) predict or explain the variation in the dependent variable (Asadoorian & Kantarelis, 2005). The regression analysis estimates the coefficients for the independent variables, which indicate the strength and direction of their relationship with the dependent variable.

First, the study will use linear regression to investigate the strength and direction of the relationship between each of the independent variables (supply chain predictive data analytics) and the dependent variable (food retail performance). The following model was used for linear regression:

$$Y = \beta_0 + \beta_1 X_1 + \mathcal{E}$$

Where:
Y = Food Retail performance,
X1= Supply Chain Predictive Analytics,
β_0 = y intercept,
B_1, = Beta value for supply chain predictive data analytics,
$\mathcal{E}$= error term.

4. Data Analysis, Presentation and Discussion

4.1 Correlational Analysis

Correlation analysis examines the strength and direction of relationships between variables (McCormick & Salcedo, 2017). In this study, it was used to determine how prescriptive data analytics relate to fresh food supply-chain performance. Given that the variables were measured on continuous scales and the study sought to identify linear associations, the Pearson Product-Moment Correlation Coefficient (r) was adopted. Pearson correlation values range from −1 to +1: positive values indicate a direct relationship, negative values an inverse relationship, and values near 0 suggest a weak or no relationship (Hair *et al.*, 2019). Correlations significant at the 0.01 level (2-tailed) were considered statistically strong and meaningful for interpretation.

Table 3: Correlation Analysis

		PredData	SCP
PredData	Pearson Correlation	1	.132
	Sig. (2-tailed)		.005
	N	172	172

Source: Author, 2016.

As presented in Table 3, the relationships among the dimensions of big data analytics and fresh food supply chain performance were generally positive, indicating that increased adoption of data-driven analytical capabilities is associated with improved supply chain outcomes. The correlation analysis provides preliminary evidence that the dimensions of big data analytics contribute to enhancing operational efficiency, although the magnitude of these relationships varies across the different analytical capabilities.

Predictive analytics recorded a weak but statistically significant positive correlation with fresh food supply chain performance ($r = 0.132$, $p < 0.05$). This finding indicates that greater utilization of predictive analytics is associated with modest improvements in supply chain performance among the sampled agritech firms. The statistically significant relationship suggests that predictive analytics plays a role in supporting supply chain activities by enabling organizations to forecast demand, anticipate market trends, estimate inventory requirements, and proactively respond to potential disruptions. Through the use of historical and real-time data, predictive analytics assists managers in making informed operational decisions that contribute to improved planning and resource allocation.

However, the weak magnitude of the correlation implies that predictive analytics alone is insufficient to produce substantial improvements in supply chain performance. This may be attributed to the complexity of the fresh food supply chain, which is influenced by multiple factors such as perishability of products, weather variability, transportation infrastructure, supplier reliability, and market price fluctuations. Consequently, while predictive analytics enhances forecasting accuracy and decision-making, its effectiveness is likely to depend on complementary organizational capabilities, including adequate technological infrastructure, data quality, skilled personnel, and integration with other analytical tools and supply chain processes. Therefore, the findings suggest that predictive analytics should be viewed as one component of a broader big data analytics capability that collectively contributes to enhancing fresh food supply chain performance.

4.2 Linear Regression Analysis

The regression coefficients in Table 4 show that predictive analytics has a positive and statistically significant effect on supply chain performance ($\beta = 0.132$, $t = 1.733$, $p = 0.005$). This means that an increase in predictive analytics practices is associated with a slight improvement in performance.

Table 4: Regression Coefficients for Predictive Analytics

Coefficients[a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	2.767	.233		11.891	.000
	PredData	.121	.070	.132	1.733	.085
a. Dependent Variable: SCP						

Source: Field Data, 2026.

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5. Conclusions and Recommendations

5.1 Conclusions

The study concludes that predictive analytics has a positive and statistically significant relationship with fresh food supply chain performance among agritech firms in Kenya.

Although the relationship is weak, the findings indicate that the use of predictive analytics contributes to improved demand forecasting, inventory planning, and operational decision-making, which are essential for enhancing supply chain efficiency. The weak correlation, however, suggests that predictive analytics alone is not sufficient to generate substantial improvements in supply chain performance.

The findings further imply that maximizing the benefits of predictive analytics requires complementary capabilities, including high-quality data, appropriate technological infrastructure, skilled personnel, and integration with other big data analytics tools and supply chain management practices. Therefore, organizations should adopt predictive analytics as part of a comprehensive data-driven supply chain strategy rather than as a standalone solution. Such an integrated approach is more likely to improve responsiveness, reduce operational inefficiencies, minimize post-harvest losses, and enhance the overall performance of the fresh food supply chain.

5.2 Recommendations

Based on the findings, the study recommends that agritech firms in Kenya strengthen their investment in predictive analytics capabilities to improve demand forecasting, production planning, inventory management, and distribution scheduling. Although the relationship between predictive analytics and fresh food supply chain performance was weak, the positive and statistically significant association demonstrates that predictive analytics can contribute to enhanced operational efficiency when effectively implemented.

The study further recommends that organizations integrate predictive analytics with other big data analytics capabilities, including descriptive, diagnostic, and prescriptive analytics, to support end-to-end supply chain decision-making. Firms should also invest in robust data management systems, improve data quality, and establish integrated information platforms that facilitate real-time data sharing across suppliers, distributors, and retailers.

Additionally, management should build the technical competencies of employees through continuous training in data analytics, forecasting techniques, and data-driven decision-making to maximize the value derived from predictive analytics. Investments in modern ICT infrastructure, cloud computing, and Internet of Things (IoT) technologies should also be prioritized to support the collection, processing, and analysis of real-time supply chain data.

Finally, policymakers and industry stakeholders should create an enabling environment that encourages the adoption of predictive analytics by supporting digital transformation initiatives, improving digital infrastructure, and promoting collaboration between agritech firms, research institutions, and technology providers. Such initiatives will enhance the effective utilization of predictive analytics and contribute to more efficient, resilient, and sustainable fresh food supply chains in Kenya.

Conflict of Interest Statement
The authors declare no conflicts of interest.

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