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

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Abstract:
This study evaluated the impact of descriptive data analytics on the supply chain performance of agritech companies in Kenya. The study was anchored on the Resource Dependence Theory and adopted a descriptive research design. The target population comprised 315 supply chain and information technology officers, from whom a sample of 172 respondents was selected using Yamane's (1967) formula. Primary data were collected using structured questionnaires and analyzed using correlation and linear regression techniques. The findings revealed that descriptive data analytics had a positive and statistically significant effect on fresh food supply chain performance. The study concludes that descriptive data analytics enhances supply chain performance by improving visibility, monitoring, and evidence-based decision-making within agritech firms. The study recommends that agritech companies invest in integrated data management systems, strengthen data quality practices, and build employees' analytical capabilities to maximize the benefits of descriptive analytics and improve overall supply chain performance.

JEL: M11, L23, L14, R41

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

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1. Introduction

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.

Globally, various studies have linked big data analytics to the performance of the food supply chain sector. A study by Li & Wang (2020) focused on the food sector in China and tested the effectiveness of using a tracking tool that generates and analyzes data in making supply chain decisions. The findings demonstrated that the tool is effective in enhancing supply chain operational decisions as well as optimizing product features to meet customer needs within the food sector.

The usability of data analytics in enhancing the performance of the food sector is also demonstrated by Boone *et al.* (2019), whose study was contextualized in the United States. The study investigated the usefulness of consumer data analytics given the increased trend in e-retailing within the market. The findings of the study demonstrated that big data analytics is effective in forecasting sales through shedding light on consumer behavior that impacts their purchase patterns within the sector. Hofmann & Rutschmann (2018) report that big data analytics can be useful for making demand forecasts through a process that entails identifying useful sources of data, integrating the data collected from them, analyzing it and producing insights that are actionable within the supply chain and the rest of the organizational functions.

Emerging markets have also adopted big data analytics as a tool for enhancing their food supply chain operations. The adoption of big data analytics has been slow within developing markets; however, the countries whose firms have adopted it have proved its effectiveness for food supply chain performance. In Brazil, Queiroz & Telles (2019) explain that the adoption of big data analytics for supply chain performance is influenced by enabling factors such as the availability of infrastructure and the knowledge of the supply chain professionals. In the presence of these factors, firms are more likely to adopt big data analytics and use it to positively influence their supply chain performance. In Jordan, another emerging market economy, innovation culture is proposed as a key factor that moderates the influence of the use of big data analytics in enhancing supply chain performance (Juma & Kilani, 2022). With a culture of innovativeness, food firms in Jordan were able to leverage the advantages of big data analytics for making the inbound and outbound logistical functions more effective in meeting company goals.

Several scholars and business experts have presented the case for the digitalization of the fresh food supply chain, suggesting big data analytics as one of the most reliable solutions for the future. For instance, in South Africa, it has become increasingly important for firms in the food industry to make accurate, short-term demand forecasts. Since today's interconnected supply chain generates a lot of data, analytics can be helpful in understanding internal and external trends to the organization and using them to make effective performance decisions (Kanali, 2021).

In Kenya, the integration of big data analytics in the food supply chain remains new. However, one of the companies that has leveraged the digitalization of its supply chain to enhance performance is Twiga Foods. Focusing on the fresh food sector, the company uses technology and big data to aggregate customer demand and build efficient and robust supply chains (twiga.com, n.d). However, in general, the adoption of big data analytics in Kenyan firms, especially in the food sector, remains low, with a lack of top management support cited as the main hindrance (Lubisia, 2020). Even new agritech giants such as Twiga have faced key challenges, evidenced by the recent laying off of over 200 employees (Njanja, 2022).

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. Therefore, this study assesses the effect of descriptive data analytics on fresh food supply chain performance for agritech companies in Kenya.

1.2 Objective of the Study

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

1.3 Research Hypothesis

H_{02}: Descriptive 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

2.1.1 Resource Dependence Theory (RDT)

The history of RDT can be traced back to the early 1970s, when political scientists John Pfeffer and Gerald Salancik argued that organizations are dependent on external resources and that this dependence can have a significant impact on organizational behavior and performance. Resource dependence theory (RDT) is a theoretical framework that explains how organizations are affected by the resources they depend on (Shafritz *et al.*, 2015). The theory is based on the idea that organizations are dependent on external resources, such as suppliers, customers, and other stakeholders, for their survival and growth.

In the 1980s and 1990s, the theory was further developed by other researchers, such as Jeff Pfeffer and Gerald R. Salancik, who expanded on the concept of resource dependence to include the role of power and politics in organizational relationships. Several researchers have also expanded RDT by incorporating concepts such as social capital, institutional theory, and network theory to give a more holistic understanding of how organizations are embedded in the external environment (Drees & Heugens, 2013). Today, RDT is widely used as a framework for understanding how organizations interact with their external environment, and how the availability and control of resources affect organizational behavior, performance, and strategic decision-making.

Resource dependence theory (RDT) has been applied to supply chain performance by understanding how a company's dependence on specific resources can affect its operational efficiency and effectiveness (Wolf, 2014). RDT suggests that a company's dependence on key resources can create both opportunities and vulnerabilities, and that managing these dependencies is crucial for the company's performance.

This theory is useful for this study as it sheds light on how fresh food sector performance can be improved through enhancing the relationships between players on the supply chain. Big data analytics can be used to enhance the attainment of relationship-building strategies on the supply chain, such as building strong partnerships with suppliers and customers to ensure a stable and reliable supply of resources, implementing risk management procedures to prepare for and mitigate supply chain disruptions and continuously monitoring and evaluating supplier performance to ensure they meet the company's standards and requirements.

2.2 Conceptual Framework

Descriptive Analytics
Supplier Lead Times
Sales Trends
Product Quality

→

Fresh Food Supply Chain Performance
Reduced Costs
Delivery Times
Customer Service
Inventory Management

2.3 Empirical Literature Review

2.3.2 Descriptive Analytics and Fresh Food Supply Chain Performance

Current studies have investigated the application of descriptive analytics in the supply chain sector. Hu and Zuo's (2021) study is a literature review that explores the use of descriptive analytics in retail supply chain performance in China. The authors systematically review 60 articles published between 2000 and 2019 to identify how descriptive analytics have been applied in retail supply chain management and to identify gaps in the literature. The findings suggest that descriptive analytics are commonly used in retail supply chain management, particularly in areas such as demand forecasting, inventory management, and supply chain performance measurement. However, there is a lack of research on how descriptive analytics can be used to improve supply chain collaboration and sustainability in the retail industry. The authors suggest that future research should explore the use of descriptive analytics in these areas and should also investigate the impact of descriptive analytics on retail supply chain performance. Overall, the study highlights the importance of descriptive analytics in retail supply chain management and provides insights for future research. However, it cannot be generalized to contexts beyond China. This study went further to focus on supply chain analytics within Kenyan agritech companies.

In another study in the United States by Chen and Chen's (2019), the authors conducted a case study that examines the use of descriptive analytics in supply chain management, using Walmart as a case study. The authors used data from 158 supply chain officers at 14 Walmart branches to illustrate how descriptive analytics can be used to improve supply chain performance in the retail industry. The findings suggested that Walmart has successfully used descriptive analytics in areas such as demand forecasting, inventory management, and supply chain optimization. The authors argue that the use of descriptive analytics has helped Walmart to improve supply chain efficiency, reduce costs, and enhance customer satisfaction. The study provided valuable insights into the practical applications of descriptive analytics in retail supply chain management and highlights the importance of data-driven decision-making in the retail industry. This study used Walmart as the case study, while this study went further to focus on big data analytics within Kenyan agritech companies.

A study in South Africa by Gakombe *et al.* (2021) investigated the role of descriptive analytics in improving supply chain performance in South African retail firms. The authors conducted a survey of 116 retail firms and used structural equation modeling to analyze the data. The results indicate that the use of descriptive analytics positively affects supply chain performance, including inventory management, customer service, and supplier performance. The authors also found that the relationship between descriptive analytics and supply chain performance is stronger when firms have better internal collaboration and external collaboration with their suppliers. The study contributes to the understanding of the role of descriptive analytics in supply chain performance in the context of African retail firms and provides insights for managers to better leverage descriptive analytics to improve their supply chain performance. Nonetheless, it only focused on supply chain descriptive analytics. This study went further to focus on three other types of big data analytics as well – prescriptive, diagnostic and predictive within Kenyan agritech companies.

In Tanzania, Sani, Wambura, and Massawe (2019) conducted a case study that investigated the use of descriptive analytics in improving retail supply chain performance in Tanzania. The authors used data that was collected from 200 supply chain officers working in local supermarket chains to illustrate how descriptive analytics can be used to enhance supply chain efficiency and customer satisfaction. The findings suggested that the use of descriptive analytics in areas such as inventory management, demand forecasting, and logistics planning has helped the supermarket chain to reduce stockouts, improve product availability, and increase sales. The authors argued that the adoption of descriptive analytics can help retailers in developing countries to overcome supply chain challenges and improve their competitiveness. The study provided valuable insights into the practical applications of descriptive analytics in the context of developing countries and highlights the potential benefits of data-driven decision-making for retailers operating in these markets. This study is contextually limited to Tanzania. This study went further to focus on big data analytics within Kenyan agritech companies.

Descriptive analytics is one of the independent variables that constituted a Kenyan study by Kibe (2019). The study aimed to investigate the impact of big data analytics on organizational performance in the context of two Kenyan universities. The study used a mixed-methods approach, including a survey of employees and managers and semi-structured interviews with selected participants. The target population consisted of 22050 respondents, but a sample size of 580 respondents was selected from the Technical University of Kenya and 114 from Strathmore University. The data were analyzed using descriptive and inferential statistics, as well as thematic analysis. The study found that descriptive analytics has a positive impact on organizational performance, including improving decision-making, enhancing customer satisfaction, and increasing operational efficiency. However, the study also identified challenges such as a lack of skilled personnel, inadequate infrastructure, and poor data quality that can hinder the effective use of big data analytics. While Kibe (2019) focused on universities, this study is limited to big data analytics within agritech companies in Kenya.

Similar findings are reported by Nderi (2014), whose study of descriptive analytics is contextualized in the financial services industry. The study aimed to investigate the relationship between business analytics and the performance of commercial banks in Kenya. The study used a survey design, with data collected through a questionnaire distributed to 44 commercial banks in Kenya and answered by Information Technology managers in each of them. The data were analyzed using descriptive and inferential statistics, as well as structural equation modeling. The study found a significant positive relationship between descriptive analytics and the performance of commercial banks in Kenya. Specifically, the study found that the use of descriptive analytics was positively related to financial performance, operational efficiency, customer satisfaction, and innovation. The study concluded that the adoption of business analytics can significantly improve the performance of commercial banks in Kenya, and recommended that banks invest in business analytics tools, technologies, and skilled personnel to enhance their performance. This study went further to focus on big data analytics within Kenyan agritech companies.

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 to 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, including individuals responsible for managing and analyzing data within the agritechs's 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

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

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 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 descriptive analytics,
β_0 = y intercept,
B_1, = Beta value for supply chain descriptive 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

		DescrData	SCP
DescrData	Pearson Correlation	1	.001
	Sig. (2-tailed)		.619*
	N	172	172

Source: Author, 2016.

Descriptive analytics, on the other hand, showed a strong and statistically significant positive correlation with fresh food supply chain performance ($r = 0.619$, $p < 0.01$), indicating that agritech firms with greater adoption of descriptive analytics tend to achieve superior supply chain performance. The strong positive relationship suggests that descriptive analytics plays a critical role in enhancing operational efficiency by transforming large volumes of historical and real-time data into meaningful information that supports managerial decision-making. Through the use of dashboards, reports, performance scorecards, and key performance indicators, descriptive analytics enables managers to monitor inventory levels, track product movement, evaluate supplier performance, and identify operational bottlenecks across the supply chain.

The findings imply that firms utilizing descriptive analytics are better positioned to improve supply chain visibility, optimize resource utilization, reduce operational inefficiencies, and respond promptly to emerging challenges. Enhanced access to timely and accurate information facilitates better coordination among suppliers, distributors, and retailers, thereby improving product availability, reducing lead times, and minimizing wastage, particularly in the fresh food supply chain where product perishability demands efficient operations.

The statistical significance of the relationship further demonstrates that descriptive analytics is an important determinant of supply chain performance among the sampled agritech firms. Unlike predictive analytics, which focuses on forecasting future events, descriptive analytics provides a comprehensive understanding of current and past operational performance, enabling managers to make evidence-based decisions that enhance productivity and service delivery. Consequently, organizations that effectively leverage descriptive analytics are more likely to achieve higher levels of operational efficiency, customer satisfaction, and overall supply chain performance.

4.2 Linear Regression Analysis

Further examination of the regression coefficients in Table 4.14 shows that descriptive analytics has a positive and statistically significant effect on supply chain performance ($\beta = 0.619$, $t = 10.263$, $p < 0.001$).

Coefficients[a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	1.210	.196		6.161	.000
	DescData	.596	.058	.619	10.263	.000
a. Dependent Variable: SCP						

Source: Field Data, 2026.

Further examination of the regression coefficients presented in Table 4.14 indicates that descriptive analytics has a positive and statistically significant effect on fresh food supply chain performance ($\beta = 0.619$, $t = 10.263$, $p < 0.001$). The positive regression coefficient demonstrates that an increase in the adoption and utilization of descriptive analytics is associated with a corresponding improvement in supply chain performance among agritech firms in Kenya. Specifically, a one-unit increase in descriptive analytics is expected to result in a 0.619-unit increase in supply chain performance, holding all other variables constant. This finding highlights descriptive analytics as a key predictor of supply chain performance.

The high t-value ($t = 10.263$) indicates that the contribution of descriptive analytics to explaining variations in supply chain performance is substantial and statistically reliable. Furthermore, the probability value ($p < 0.001$) is well below the conventional significance level of 0.05, providing strong evidence to reject the null hypothesis that descriptive analytics has no significant effect on supply chain performance. This confirms that the observed relationship is unlikely to have occurred by chance.

The findings suggest that descriptive analytics enables agritech firms to effectively analyze historical and real-time operational data, providing valuable insights into supply chain activities such as inventory management, order fulfillment, supplier performance, transportation efficiency, and customer demand patterns. By converting raw operational data into meaningful reports, dashboards, and performance indicators, descriptive analytics enhances managers' ability to identify operational inefficiencies, monitor key performance metrics, detect trends, and make timely, evidence-based decisions. These capabilities improve coordination across supply chain partners, optimize resource utilization, reduce operational costs, and enhance service delivery.

Given the perishable nature of fresh food products, effective monitoring and visibility across the supply chain are essential for minimizing post-harvest losses, maintaining product quality, and ensuring timely delivery to customers. The strong positive coefficient therefore underscores the strategic importance of descriptive analytics as a foundational capability for improving fresh food supply chain performance. The results imply that agritech firms that invest in robust data collection, reporting systems, and performance monitoring tools are more likely to achieve greater operational efficiency, responsiveness, and overall supply chain competitiveness.

5. Conclusions and Recommendations

5.1 Conclusions

The study concludes that descriptive analytics is a significant predictor of fresh food supply chain performance among agritech firms in Kenya. The positive and statistically significant regression coefficient ($\beta = 0.619$, $p < 0.001$) demonstrates that increased adoption of descriptive analytics leads to improved supply chain performance. By providing timely, accurate, and actionable insights from historical and real-time data, descriptive analytics enhances supply chain visibility, supports evidence-based decision-making, and improves the monitoring of key operational activities.

The findings further indicate that organizations that effectively utilize descriptive analytics are better able to optimize inventory management, monitor supplier performance, reduce operational inefficiencies, and enhance coordination across the supply chain. Consequently, descriptive analytics represents a critical capability for improving operational efficiency, minimizing post-harvest losses, and strengthening the overall performance and competitiveness of fresh food supply chains. The study therefore concludes that investments in descriptive analytics can significantly enhance supply chain effectiveness and contribute to sustainable organizational performance in Kenya's agritech sector.

5.2 Recommendations

Based on the findings, the study recommends that agritech companies in Kenya prioritize investment in descriptive analytics capabilities to improve fresh food supply chain performance. Organizations should implement integrated data management systems, business intelligence platforms, and real-time reporting dashboards that enable continuous monitoring of key supply chain activities, including inventory levels, supplier performance, order fulfillment, transportation, and customer demand. Such systems will enhance supply chain visibility and support timely, evidence-based decision-making. The study further recommends that firms strengthen data governance by establishing standardized procedures for data collection, storage, quality assurance, and sharing across the supply chain. High-quality and reliable data are essential for generating accurate descriptive reports that inform operational and strategic decisions.

Additionally, management should invest in capacity building by training supply chain and information technology personnel in data management, business intelligence, and data visualization tools. Enhancing employees' analytical competencies will enable organizations to effectively interpret descriptive analytics outputs and translate insights into operational improvements. The study also recommends greater collaboration among agri-tech firms, suppliers, distributors, and retailers through integrated digital information systems that facilitate real-time data sharing and performance monitoring. Such collaboration will improve coordination, reduce information asymmetry, minimize post-harvest losses, and enhance responsiveness to changes in market demand.

Finally, policymakers and industry stakeholders should support the adoption of descriptive analytics by promoting digital transformation initiatives, improving ICT infrastructure, and providing incentives for investments in data analytics technologies. These interventions will accelerate the digitalization of Kenya's fresh food supply chain and enhance its efficiency, resilience, and long-term competitiveness.

Conflict of Interest Statement

The authors declare no conflicts of interest.

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