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Descriptive Supply Chain Analytics and Performance of Large Manufacturing Firms in Kenya

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Abstract

Purpose: This study examined the influence of descriptive analytics on the performance of large manufacturing firms in Kenya, focusing on inventory situation reporting, demand context visualization, and purchase pattern analysis.

Methodology: Anchored on resource dependence theory, the study adopted a mixed-methods research design. Mixed-methods research design integrates both qualitative and quantitative research approaches in the processes of data collection, analysis, and presentation. The target population for this study was 461 large manufacturing firms. Data was collected from a sample of 210 respondents out of a sample of 222, representing a (94.5%) response rate. Reliability and validity were confirmed through Cronbach's alpha ($\alpha > 0.70$), KMO, and Bartlett's tests.

Findings: Descriptive analytics constructs were widely practiced, with inventory situation reporting and purchase pattern analysis being the most embraced. Approximately 59% of respondents rated descriptive analytics as effective in improving performance of large manufacturing firms. Regression analysis confirmed a positive and significant relationship ($R = 0.660$, $R^2 = 0.436$, Beta = 0.734, $p < 0.001$), indicating that 43.6% of performance variation can be explained by descriptive analytics.

Unique Contribution to Theory, Policy and Practice: This study serves as a foundational reference point for practitioners and policymakers alike. By delineating the pathways through which analytics enhance transparency and competitiveness. Policy makers and regulatory agencies must mandate that firms establish rigorous guidelines for the selection and utilization of analytic tools. The study establishes that sustainable performance is contingent upon the synergistic application of the analytical pillars, which should be institutionalized as follows: descriptive analytics: utilizing historical data to establish operational baselines and performance visibility.

Keywords: *Descriptive Analytics, Inventory Situation Reporting, Demand Context Visualization, Purchase Pattern Analysis, Firm Performance*

JEL Codes: *C55, M11, L23*

1.0 Introduction

1.1 Background of the Study

Globally, supply chain analytics (SCA) has become a strategic necessity for manufacturing firms seeking to optimize operations and improve performance. Descriptive analytics, the foundational layer of SCA, focuses on understanding "what happened" in the supply chain by summarizing historical and transactional data (Davenport & O'Dwyer, 2021). For large manufacturing firms, this involves structured analyses of inventory reports, purchase patterns, and operational metrics to gain visibility into past performance and identify inefficiencies.

The global supply chain analytics market was valued at $5.2 billion in 2022 and is projected to surpass $13.5 billion by 2027, reflecting a CAGR of 21% (Markets & Markets, 2023; KPMG, 2024). Leading firms report that over 100 gigabytes of data flow through their supply chains daily (Economist, 2020).

In Kenya, while large manufacturing firms are increasingly adopting digital supply chain systems, the use of advanced descriptive analytics remains limited. Less than 20% of firms fully utilize analytics for purchase pattern analysis or inventory situation reporting (Munyoki, 2025). Consequently, many firms experience frequent stockouts and overstocking, leading to an estimated 8% loss in potential sales and a 5% increase in warehousing costs (Nyaoga, 2014).

1.1.1 Descriptive Analytics in Supply Chain Management

Descriptive analytics focuses on summarizing historical data to provide insights into past and current operational performance. It addresses the fundamental question, "What has happened?" by leveraging structured data from enterprise systems, procurement records, inventory management platforms, and logistics databases (Davenport & O'Dwyer, 2021).

In practice, descriptive analytics encompasses several key constructs: inventory situation reporting, demand context visualization, and purchase pattern analysis. Empirical evidence indicates that descriptive analytics significantly enhances operational efficiency in manufacturing (O'Dwyer & Renner, 2021).

1.1.2 Firm Performance

Firm performance is a multidimensional construct that spans both functional and organizational boundaries. Strategic objectives often create trade-offs in performance measurement. Hence, the implementation of SCA must adopt a holistic approach, incorporating a balanced scorecard framework that aligns operational improvements with overarching strategic objectives (Kaplan & Norton, 1996).

In Kenya, performance measures for large manufacturing firms include supplier reliability, customer satisfaction, inventory costs, market share, reduction in costs, profitability, on-time

delivery rates, product availability, and customer response times (Nyamwange & Nyaguthie, 2022).

1.1.3 Large Manufacturing Firms

Large manufacturing firms are pivotal in integrating supply chain analytics into operations. In Kenya, the manufacturing sector ranks third in industrial importance, following agriculture and transport and communication (KPMG, 2019). Large manufacturing firms, comprising 461 companies or 41% of KAM membership, employ over 89,000 workers (KAM, 2022).

1.2 Statement of the Problem

Despite compelling global evidence that companies using supply chain analytics achieve a 15% reduction in supply chain costs and an 18% increase in forecast accuracy (KPMG, 2024), large manufacturing firms in Kenya are potentially missing out on substantial performance improvements by not fully embracing descriptive analytics. This gap hinders their ability to compete effectively in regional and international markets.

1.3 Research Objective

To establish the influence of descriptive analytics on the performance of large manufacturing firms in Kenya.

1.4 Research Hypothesis

H_{01}: Descriptive analytics do not significantly influence the performance of large manufacturing firms in Kenya.

2.0 Literature Review

2.1 Theoretical Framework

2.1.1 Resource Dependence Theory

Resource Dependence Theory, developed by Pfeffer and Salancik (1978), explains how organizations' behavior is affected by external resources. In the modern business environment, information and data have become critical organizational resources. Descriptive analytics enables organizations to analyze historical supply chain data and identify patterns, inefficiencies, and opportunities for improvement.

2.2 Conceptual Framework

The dependent variable is the performance of large manufacturing firms, measured in terms of operational efficiency, cost reduction, supply chain reliability, and overall competitiveness. The independent variable is descriptive analytics, involving inventory situation reporting, demand context visualization, and purchase pattern analysis.

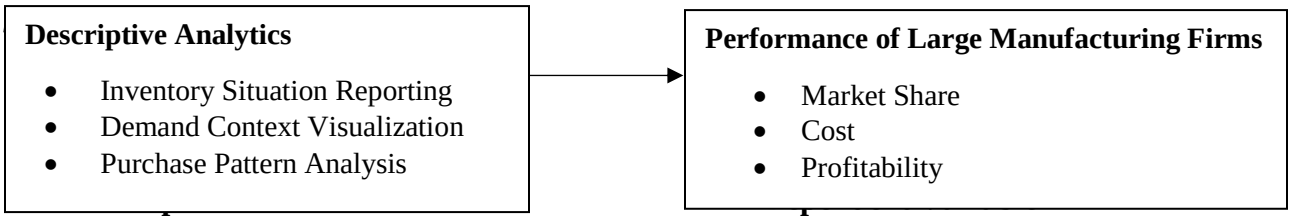


Figure 1: Conceptual Framework

Source: Author (2026)

2.3 Empirical Literature Review

Globally, firms employing descriptive analytics achieve enhanced visibility into inventory levels, demand patterns, and purchase analysis (Forslund & Jonsson, 2017). In Kenya, the adoption of descriptive analytics remains nascent (Munyoki, 2025). Descriptive analytics provides real-time reporting on inventory and purchasing, enabling managers to identify inefficiencies and respond to market fluctuations effectively.

3.0 Methodology

3.1 Research Design

This study adopted a mixed-methods research design, combining quantitative and qualitative approaches (Kinyua, 2015). The study is anchored on positivist philosophy, emphasizing objectivity in data collection and statistical testing of hypotheses.

3.2 Population of the Study

The population comprised 461 large manufacturing firms listed in the KAM directory (2024) across 12 sectors. The unit of observation was the heads of the procurement department in the large manufacturing firms.

3.3 Sample Size and Sampling Technique

The study applied Jill and Roger's (2021) formula for categorical data:

$n_0 = Z^2p(1-p) / e^2$

Where Z = 1.96, p = 0.8, e = 0.05

$n_0 = (1.96^2 \times 0.8 \times 0.2) / 0.05^2 = 246$

Table 1: Sampling Table

Segment	Population	Sample Size	Percentage
Energy, Electrical & Electronics	43	23	9.3%
Chemical & Allied	62	33	13.4%
Food, Beverage & Tobacco	100	54	22.1%
Plastics & Rubber	54	29	11.7%
Building & Construction	8	4	1.7%
Paper & Printing	49	26	10.6%
Textile & Garments	38	20	8.1%
Timber Products	23	13	5.2%
Motor Vehicle Assembly	17	9	3.6%
Metal & Allied	39	21	8.5%
Pharmaceutical & Medical Equipment	20	10	4.1%
Leather Products & Footwear	8	4	1.7%
Total	**461**	**246**	**100%**

Source: KAM Directory (2024)

3.4 Data Collection Instrument

Data was collected using a semi-structured questionnaire divided into six sections.

3.5 Pilot Test

The questionnaire was pilot-tested on 10% of the sample (24 firms) not included in the final study.

3.6 Reliability of the Research Instrument

Table 2: Reliability Test

Variable	Cronbach's Alpha	Number of Items	Decision
Descriptive Analytics	0.816	14	Reliable

Source: Pilot Study (2025)

3.7 Validity of the Research Instrument

Table 3: Construct Validity

Variable	KMO Measure	Bartlett's Test (Sig.)
Descriptive Analytics	.709	0.000

Source: Pilot Study (2025)

3.8 Data Analysis

Data was analyzed using SPSS version 26. Analysis included descriptive statistics, factor analysis, correlation, and multiple linear regression.

4.0 Results and Discussion

4.1 Response Rate

Table 4: Response Rate

Category	Frequency	Percentage
Sampled Population	222	100%
Responses	210	94.5%
Non-Responses	12	5.5%

Source: Survey Data (2025)

4.2 Descriptive Analysis

Table 5: Descriptive Statistics on Descriptive Analytics

Statement	N	SD	D	N	A	SA	Mean	Std. Dev.
Effective inventory situation reporting system	210	2.6%	6.9%	5.9%	47%	37.5%	4.09	0.96
Accurately knows inventory value	210	1%	3%	7.6%	54.6%	33.9%	4.17	0.77
Aware of inventory age and location	210	2.6%	7.9%	20.1%	45.4%	24%	3.99	0.97
Clear demand context visualization techniques	210	4.9%	6.9%	12.2%	45.7%	30.3%	3.98	1.06
Data preparation and cleaning for demand	210	26.9%	28.8%	10.9%	13.1%	10.4%	3.51	1.20
Internal and external contextual demand info	210	32.6%	23.3%	2.6%	6.1%	25.4%	2.08	0.87
Observes purchase pattern analysis	210	3%	9.5%	12.5%	43.4%	31.6%	3.91	1.04
Understands purchase timing	210	5.6%	9.9%	13.8%	47.4%	23.4%	4.03	1.09
Knows product affinity	210	14.8%	24%	25.3%	20.1%	15.8%	2.98	1.29

Key: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree
Source: Survey Data (2025)

Table 6: Ranking of Descriptive Analytics Constructs

Measurement Construct	Least Preferred	Moderately Preferred	Neutral	Preferred	Strongly Preferred	Total
Inventory Situation Reporting	7.3%	16.6%	9.3%	61.7%	5.1%	100%
Demand Context Visualization	12.6%	17.9%	6.4%	56.1%	7.0%	100%
Purchase Pattern Analysis	8.2%	11.4%	3.9%	54.8%	21.7%	100%

Source: Survey Data (2025)

Table 7: Rating the Effectiveness of Descriptive Analytics

Category	Frequency	Percentage
Very Effective	63	30.0%
Effective	61	29.0%
Somehow Effective	46	21.9%
Ineffective	40	19.0%
Total	**210**	**100%**

Source: Survey Data (2025)

4.3 Factor Analysis

Table 8: Factor Analysis for Descriptive Analytics

Factor	Factor Loading
Effective inventory situation reporting system	.685
Accurately knows inventory value	.786
Aware of inventory age and location	.867
Clear demand context visualization techniques	.875
Data preparation and cleaning	.787
Internal and external contextual demand information	.792
Observes purchase pattern analysis	.660
Understands purchase timing	.687
Knows product affinity	.929

Source: Survey Data (2025)

4.4 Hypothesis Testing

Table 9: Model Summary on Descriptive Analytics

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.660[a]	.436	.434	.54926

Predictor: (Constant), Descriptive Analytics; Dependent Variable: Performance

Source: Survey Data (2025)

Table 10: ANOVA Test on Descriptive Analytics

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	70.383	1	70.383	160.691	.000[b]
Residual	91.108	208	0.438		
Total	**161.492**	**209**			

Dependent Variable: Performance; Predictor: (Constant), Descriptive Analytics

Source: Survey Data (2025)

Table 11: Regression Coefficients on Descriptive Analytics

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
(Constant)	.732	.182		4.025	.000
Descriptive Analytics	.734	.048	.660	15.274	.000

Dependent Variable: Performance

Source: Survey Data (2025)

The regression analysis and scatter plot illustrate a statistically significant positive relationship between descriptive analytics and the performance of large manufacturing firms. The unstandardized coefficient ($B = 0.734$, $p < 0.001$) indicates that every unit increase in descriptive analytics yields a 0.734-unit improvement in firm performance. The standardized beta (beta = 0.660) and a high t-value (15.274) confirm its strong predictive power. Furthermore, the upward-sloping scatter plot visually verifies that effective inventory situation reporting, demand context visualization, and purchase pattern analysis strongly drive positive operational outcomes. Thus, descriptive analytics serves as a vital statistical foundation for manufacturing success.

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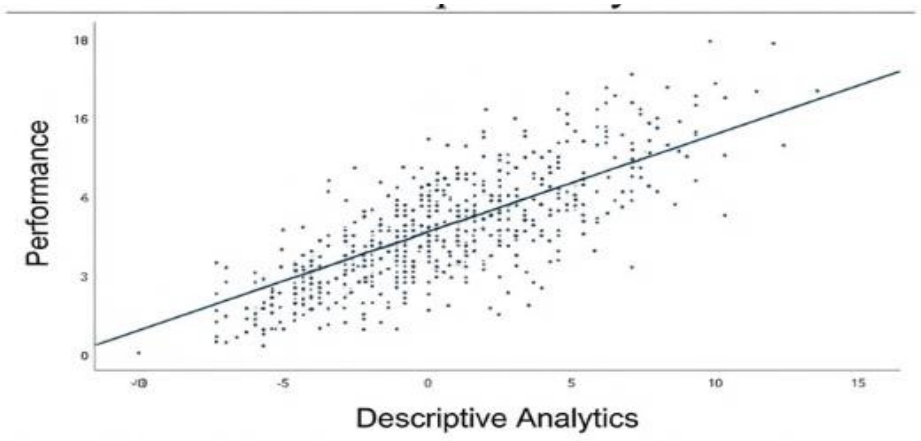


Figure 2: Scatter Plot on Descriptive Analytics

Source: Survey Data (2025)

To ensure the validity of the linear regression model examining the impact of descriptive analytics on the performance of large manufacturing firms, the assumption of normality for error terms was evaluated using a histogram of standardized residuals.

As illustrated in Figure 3, the distribution of the standardized residuals closely approximates a normal distribution, characterized by a symmetric, bell-shaped curve centered at a mean of 0 with a standard deviation approaching 1. This visual verification confirms that the residuals are normally distributed, satisfying a fundamental assumption of Ordinary Least Squares (OLS) regression. Consequently, the statistical inferences, high t-value (15.274), and significance level ($p < 0.001$) established in the regression model are robust, unbiased, and statistically sound.

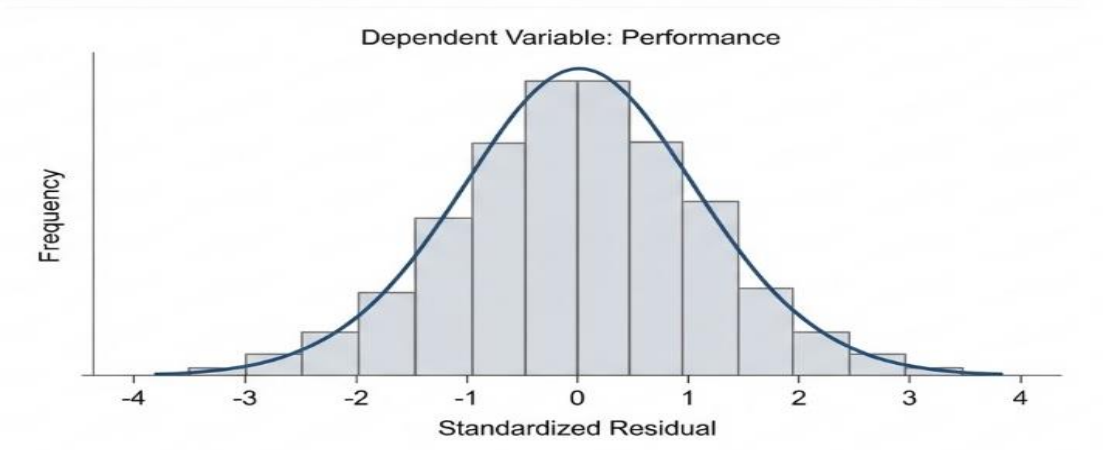


Figure 3: Histogram on Descriptive Analytics

Source: Survey Data (2025)

5.0 Summary, Conclusion and Recommendations

5.1 Summary

This study investigated the influence of descriptive analytics on the performance of large manufacturing firms in Kenya. Descriptive analytics constructs were widely practiced, with inventory situation reporting and purchase pattern analysis being the most embraced. Approximately 59% of respondents rated descriptive analytics as effective.

5.2 Conclusion

Descriptive analytics is a significant driver of operational efficiency, resource optimization, and competitive advantage. The regression analysis confirmed a positive and significant relationship ($R = 0.660$, $R^2 = 0.436$, Beta = 0.734, $p < 0.001$).

5.3 Recommendations

Large manufacturing firms in Kenya should strategically invest in supply chain analytics, institutionalize advanced inventory reporting systems, enhance demand visualization, and develop analytics skills among personnel. Policymakers should create frameworks that promote digital adoption in manufacturing, including incentives for implementing advanced analytics.

5.4 Areas for Further Study

Future research should explore the longitudinal impact of supply chain analytics on firm performance in diverse African manufacturing contexts.

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