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

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Abstract

Purpose: This study investigates the influence of diagnostic analytics on the performance of large manufacturing firms in Kenya, focusing on spend root-cause analysis, logistics analytical processing, and capacity planning what-if queries.

Methodology: 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. Instrument reliability and validity were confirmed through Cronbach's alpha (> 0.70), KMO, and Bartlett's tests.

Results: Findings indicate moderate to widespread adoption of diagnostic analytics, with logistics analytical processing most prevalent. Approximately 45.7% of respondents rated diagnostic analytics as effective. Regression results reveal a positive, statistically significant relationship between diagnostic analytics and firm performance ($R = 0.680$, $R^2 = 0.462$, $\beta = 0.718$, $p < 0.001$), explaining 46.2% of performance variation.

Unique Contribution to Theory, Policy and Practice: The study examines the application of diagnostic, prescriptive; this sstudy underscores a critical realization: operational performance is fundamentally contingent upon the sophistication and integration of an organization's analytical framework. Policy makers and regulatory agencies must mandate that firms establish rigorous guidelines for the selection and utilization of analytic tools. Regulatory bodies should mandate that firms implement comprehensive spend root-cause analysis and logistics analytical processing. The study establishes that sustainable performance is contingent upon the synergistic application of the four analytical pillars, which should be institutionalized as follows: Diagnostic analytics: deploying rigorous root-cause analysis to identify and rectify inefficiencies in logistics and procurement workflows.

Keywords: *Diagnostic Analytics, Spend Root-Cause Analysis, Logistics Analytical Processing, Capacity Planning What-If Queries, Firm Performance*

JEL Codes: *C55, M11, L23*

1.0 Introduction

1.1 Background of the Study

Large manufacturers now need operational efficiency, effective decision-making, and risk management to sustain competitive advantage. Intuition is insufficient due to complex supply chains and market volatility (Mutuku, Owango & Wachiuri, 2021). Firms increasingly adopt data-driven strategies, with diagnostic analytics helping explain why inefficiencies, disruptions, and cost overruns occur (Abdullahi, Ibrahim & Bala, 2022). Key techniques include spend root-cause analysis, logistics analytical processing, and capacity planning what-if queries.

Spend analysis examines procurement and expenditure data to identify anomalies, improve supplier performance, and reduce unnecessary costs (Kibogo & Mwangangi, 2014). However, Kenyan adoption remains inconsistent, with many firms relying on intuition or routine reports (Kamoni, 2018). Logistics analytical processing collects and analyzes supply chain data to detect bottlenecks, improve inventory management, reduce lead times, and enhance delivery performance (Rajah, 2018; Sha & Chen, 2022). Capacity planning what-if queries simulate scenarios for resource allocation, production scheduling, and contingency planning, reducing downtime and demand variability risks (Mutuku et al., 2021).

Diagnostic analytics depends on reliable, accurate, and secure data. Globally, diagnostic analytics is central to Industry 4.0, integrated into ERP, supply chain platforms, and IIoT networks, yielding higher productivity and lower costs (Porter & Heppelmann, 2015; Wamba et al., 2020). Developing economies face infrastructure, data fragmentation, and skills constraints (Dubey et al., 2020), yet diagnostic analytics can address procurement, logistics, and planning inefficiencies.

In Africa, initiatives like Agenda 2063 and AfCFTA promote industrial capacity, but advanced analytics adoption remains limited and intuition-based decision-making persists (African Union, 2020; Manyika et al., 2016). Sub-Saharan Africa faces high costs, unreliable infrastructure, and supply chain disruptions (UNIDO, 2020), making diagnostic analytics valuable. In Kenya, manufacturing is pivotal, but firms face procurement inefficiencies, inadequate capacity planning, and logistics bottlenecks (KAM, 2022). Diagnostic analytics can mitigate these challenges. Given Kenya's digital transformation, investigating this interaction is timely to help large manufacturers leverage analytics and information security for competitiveness and resilience.

1.1.1 Diagnostic Analytics in Supply Chain Management

Diagnostic analytics in supply chain management refers to the systematic examination of historical and real-time supply chain data to identify the underlying causes of operational problems, performance variations and supply chain disruptions (Christopher, 2021). It involves the application of analytical techniques such as root cause analysis, correlation analysis, data mining and statistical analysis to establish why particular events occur. For instance, organizations use diagnostic analytics to investigate the causes of procurement delays, inventory shortages, increased

transportation costs, supplier underperformance and order fulfilment inefficiencies. Consequently, diagnostic analytics enables supply chain managers to identify operational weaknesses, address recurring problems and make evidence-based decisions aimed at improving supply chain efficiency and performance (James & Faizul, 2010).

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 (Muthoni & Waiganjo, 2022). 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 (Pietsch et al, 2024).

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

Large manufacturing firms in Kenya continue to face persistent operational inefficiencies, including procurement inefficiencies, supply chain bottlenecks, delayed production schedules, and escalating operational costs (Muthoni & Waiganjo, 2022). While many firms have invested in ERP systems and supply chain management platforms, the utilization of these systems for advanced analytics remains limited. Diagnostic analytics which enable organizations to analyze historical operational data and identify root causes of inefficiencies is not yet fully institutionalized (Davenport & Harris, 2017; Wamba et al., 2020). Consequently, operational decisions are often made based on incomplete information, intuition, or routine reporting.

Specifically, key diagnostic analytics components such as spend root-cause analysis, logistics analytical processing, and capacity planning what-if queries have not been extensively integrated into operational and strategic decision-making (Handfield et al., 2019; Christopher, 2021). The limited adoption is influenced by technological infrastructure gaps, a shortage of skilled personnel, and organizational resistance to change (Dubey et al., 2020). Although international literature highlights the significant role of diagnostic analytics, empirical evidence in the Kenyan context remains scarce. This study addresses this gap by examining how diagnostic analytics practices influence the performance of large manufacturing firms in Kenya.

1.3 Specific Objective

To investigate the influence of diagnostic analytics on the performance of large manufacturing firms in Kenya.

1.4 Research Hypotheses

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

2.0 Literature Review

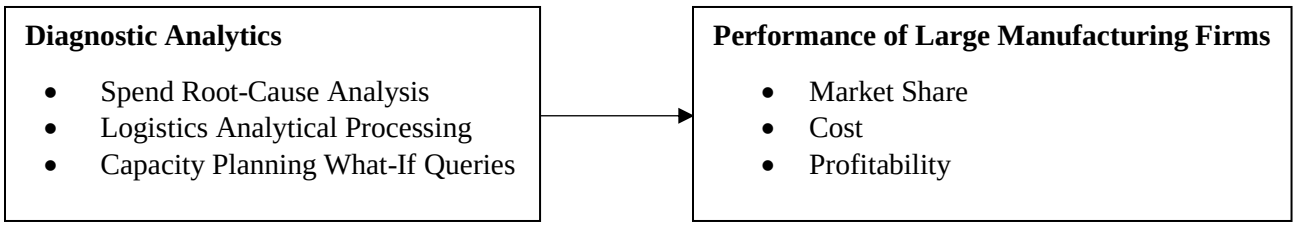
2.1 Theoretical Framework

This study is anchored in Supply Chain Operations Reference (SCOR). The SCOR model provides a framework for understanding supply chain processes and performance metrics (Supply Chain Council, 1996). SCOR defines key processes; Plan, Source, Make, Deliver and guides the application of analytics to improve operational performance (Sha & Chen, 2022). By linking analytics insights to SCOR performance metrics, firms can identify inefficiencies, optimize logistics flows, and improve production planning.

2.2 Conceptual Framework

The conceptual framework examines the relationship between diagnostic analytics and the performance of large manufacturing firms

Figure 1: Conceptual Framework



Source: Author (2026)

2.3 Empirical Literature Review

Diagnostic analytics explains relationships among operational variables, including supplier performance, machine utilization, and demand fluctuations (Sharda et al., 2020; Porter & Heppelmann, 2015). Firms that adopt diagnostic analytics are better positioned to improve operational decision-making and competitiveness (Davenport & Harris, 2017). However, empirical studies on implementation in developing economies are limited. Spend Root-Cause Analysis: Spend root-cause analysis examines procurement data to identify cost drivers, anomalies, and inefficiencies (Kibogo & Mwangangi, 2014). Effective spend analysis allows firms

to detect unnecessary expenditures, optimize supplier contracts, and improve procurement strategies. While benefits are widely acknowledged, many firms in developing economies rely on descriptive reporting rather than systematic root-cause analysis (Handfield et al., 2019).

Logistics Analytical Processing: Logistics analytical processing integrates data across suppliers, warehouses, transportation, and distribution networks to detect inefficiencies (Christopher, 2016). Analytical tools enable firms to optimize transportation routes, warehouse utilization, and inventory flows. Challenges include integrating data from disparate systems and lack of infrastructure in emerging economies (Owago, 2021). Capacity Planning What-If Queries: Capacity planning simulations allow firms to model alternative production scenarios to optimize resource allocation, reduce bottlenecks, and improve production efficiency (Heizer et al., 2020; Mutuku et al., 2021). Despite its importance, adoption in developing economies is limited due to technological constraints and limited analytical expertise (Schmidt, Maier & Härtel, 2020).

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 and Validity

Table 2: Reliability and Validity Tests

Variable	Cronbach's Alpha	KMO Measure	Bartlett's Test (Sig.)
Diagnostic Analytics	0.908	.867	0.000

Source: Pilot Study (2025)

3.7 Data Analysis

Data was edited, coded, and pre-processed for analysis using SPSS version 26 (Kinyua, 2015). Analysis included descriptive statistics, factor analysis, correlation, and multiple linear regression.

4.0 Results and Discussion

4.1 Response Rate

Table 3: 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

The findings in Table 4 reveal that 42.1% of respondents agreed with the statement "The entity does spend root-cause analysis to diagnose the situation appropriately" while 35.8% disagreed. For "The entity does logistics analytical processing to accurately diagnose the situation," 74.3% agreed while 13.5% disagreed. For "The entity has an effective capacity planning what-if queries to accurately diagnose the situation," 59.9% agreed while 25.7% disagreed.

Table 4: Descriptive Statistics on Diagnostic Analytics

Statement	N	SD	D	N	A	SA	Mean	Std. Dev.
The entity does spend root-cause analysis to diagnose the situation appropriately	210	12.8%	23%	22%	21.7%	20.4%	3.13	1.32
The entity gathers relevant data and identifies spending anomalies	210	54.9%	16.1%	3.2%	10.3%	5.5%	3.05	1.08
The entity does brain-storming and peer review validation of expenditure	210	1.6%	8.6%	12.2%	58.2%	19.4%	3.85	0.88
The entity does logistics analytical processing to accurately diagnose the situation	210	3.3%	10.2%	12.2%	47%	27.3%	3.84	1.03
The entity analyses warehouse processes for continuous improvement	210	45.6%	15.1%	12.2%	4.4%	22.7%	3.93	1.15
The entity analyses production schedules to optimise operations	210	8.2%	14.1%	12.8%	44.7%	20.1%	3.97	1.19
The entity has effective capacity planning what-if queries	210	5.3%	20.4%	14.5%	43.1%	16.8%	4.07	1.14
The entity does scenario definition and sensitivity analysis	210	9.2%	19.4%	13.5%	38.5%	19.4%	4.09	1.25
The entity runs simulations and models to identify bottlenecks	210	4.9%	11.5%	14.8%	46.7%	22%	4.01	1.08

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

4.3 Ranking of Diagnostic Analytics Constructs

Table 5: Ranking of Constructs

Measurement Construct	Spend Root-Cause Analysis	Logistics Analytical Processing	Capacity Planning What-If Queries
Least Preferred	2.4%	1.6%	12.4%
Moderately Preferred	33.1%	27.9%	21.6%
Neutral	4.6%	6.0%	2.5%
Preferred	41.7%	53.5%	34.2%
Strongly Preferred	18.1%	11.0%	29.4%
Total	**100%**	**100%**	**100%**

Source: Survey Data (2025)

4.4 Effectiveness Rating

Table 6: Rating the Effectiveness of Diagnostic Analytics

Category	Frequency	Percentage
Very Effective	57	27.1%
Effective	39	18.6%
Somehow Effective	66	31.4%
Ineffective	48	22.8%
Total	**210**	**100%**

Source: Survey Data (2025)

4.5 Factor Analysis

Table 7: Factor Analysis for Diagnostic Analytics

Factors	Factor Loadings
Spend root-cause analysis	.618
Gathers relevant data and identifies spending anomalies	.607
Brain-storming and peer review validation	.788
Logistics analytical processing	.644
Analyses warehouse processes	.976
Analyses production schedules	.998
Effective capacity planning what-if queries	.667
Scenario definition and sensitivity analysis	.892
Runs simulations and models	.837

Source: Survey Data (2025)

4.6 Hypothesis Testing: Diagnostic Analytics

H_0: Diagnostic analytics does not significantly influence performance

Table 8: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.680[a]	.462	.460	.53628

a) Predictor: (Constant), Diagnostic Analytics

Source: Survey Data (2025)

Table 9: ANOVA Test

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	74.636	1	74.636	178.555	.000[b]
	Residual	86.856	208	0.418		
	Total	161.492	209			

Source: Survey Data (2025)

Table 10: Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		Sig.
		B	Std. Error	Beta	t	
1	(Constant)	.918	.161		5.690	.000
	Diagnostic Analytics	.718	.045	.680	16.109	.000

Source: Survey Data (2025)

The model summary shows R = 0.680 and R^2 = 0.462, indicating that 46.2% of the variance in firm performance can be explained by diagnostic analytics. The ANOVA results (F = 178.555, p < 0.001) confirm the model is significant. The regression coefficient (β = 0.718, p < 0.001) indicates a positive and significant relationship. The null hypothesis was rejected.

5.0 Summary, Conclusion, and Recommendations

5.1 Summary

This study examined diagnostic analytics and performance of large manufacturing firms in Kenya, Findings show moderate adoption. Logistics analytical processing and capacity planning were technically strong respectively, but spend root-cause analysis was inconsistently applied due to data integrity and methodological gaps. Regression results confirmed a positive, significant relationship between diagnostic analytics and firm performance (R = 0.680; R^2 = 0.462; β = 0.718; p < 0.001), explaining 46.2% of performance variation.

5.2 Conclusion

Diagnostic analytics is a key determinant of operational performance in Kenya's large manufacturing sector. Spend root-cause analysis, logistics analytical processing, and capacity planning simulations improve efficiency, cost control, and supply chain resilience.

5.3 Recommendations

5.3.1 Managerial: Firms should systematically integrate analytics into procurement, logistics, and production. Prioritize spend root-cause analysis to reduce procurement waste. Embed logistics analytics for real-time supply chain monitoring. Institutionalize capacity planning what-if simulations for proactive scenario testing.

5.3.2 Policy: Policymakers should promote transparency, data security, and accountability. Align analytics practices with standards. Support adoption of Vendor Managed Inventory, MRPII, and Just-in-Time systems.

5.3.3 Contribution to Knowledge: The study validates diagnostic analytics as a determinant of performance, offering a cohesive framework for analytics-driven decision-making.

5.3.4 Theoretical Implications: The findings reinforce the SCOR model, showing that analytics must be embedded within secure data environments.

5.4 Areas for Further Study

Future research should extend to county governments, ministries, and public enterprises. Longitudinal and multi-role studies could assess analytics adoption over time.

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