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Retail Analytics and Evaluation Metrics: Data-Informed Decision-Making for Retail Innovation in West Africa

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Abstract **Original Research Article**

This study examined how retail analytics and evaluation metrics drive data-informed decision-making and performance outcomes in West African retail enterprises. Guided by the technology–organisation–environment framework and a positivist paradigm, the study employed a mixed-methods descriptive survey design. A purposive sample of 286 retail managers and analytics officers was drawn from 48 supermarkets and chain outlets in Lagos, Nigeria, and Accra, Ghana. Data were gathered through the Retail Analytics Adoption Questionnaire (r = .81) and 12 in-depth interviews, and analysed using multiple regression, Pearson's r, and thematic coding. Findings revealed that analytics capability significantly predicted data-informed decision-making, β = .47, t = 6.32, p < .001, R^2 = .38, and that dashboards and sales-forecast metrics accounted for 41.6% of the variance in stock-turnover efficiency, $F(3, 282) = 66.96$, p < .001. However, only 34.3% of outlets used predictive analytics routinely, with cost and skills gaps as leading barriers. Interview data linked metric use to faster markdown decisions and reduced stock-outs. The study concluded that analytics maturity, not mere data availability, differentiates high-performing retailers. It was recommended that retail firms in West Africa invest in analytics training, standardised KPI frameworks, and low-cost dashboard tools.

Keywords: Analytics capability; data-informed decision-making; evaluation metrics; retail performance; West Africa.

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1. INTRODUCTION

1.1 Background to the Study

Retailing represents the final stage in the supply chain, connecting producers to end consumers and serving as the initial point where demand is captured as data. Each completed sale, abandoned basket, price change, delivery, and return generates a record in a point-of-sale (POS) terminal, enterprise resource planning (ERP) system, loyalty database, or supplier portal. Retailers who transform these records into timely, decision-relevant evidence are better positioned to stock desired products, set appropriate prices, and remove unsold items. This process is known as retail analytics: the systematic collection, integration, and analysis of customer, product, time, location, and channel data to inform merchandising, pricing, inventory, promotion, and store operations decisions (Bradlow *et al.,*2017; Fisher & Raman, 2018). The effectiveness of retail analytics relies on a related discipline: the design and use of evaluation metrics that convert analytical outputs into a concise set of key performance indicators (KPIs) for managerial monitoring and action.

Evidence from advanced economies indicates that firms which base decisions on data rather than intuition tend to perform better. Brynjolfsson *et al.,* (2011) reported that large United States firms adopting data-driven decision-making had output and productivity 5–6% higher than would be expected from their other investments, and later Census-based work found that the adoption of data-driven decision-making in manufacturing nearly tripled between 2005 and 2010 (Brynjolfsson & McElheran, 2016). Subsequent studies extended this result to predictive analytics, showing that productivity gains materialise mainly when analytics is combined with complementary assets such as information technology (IT) capital and educated workers (Brynjolfsson *et al.,*2021). In retailing specifically, data-rich forecasting, assortment and inventory methods have been shown to reduce stock-outs

and improve inventory productivity (Fildes *et al.,*2022; Rooderkerk *et al.,*2022).

West Africa constitutes a distinct operating environment. Since the 1990s, formal retail in sub-Saharan Africa has expanded through domestic chains and South African-led supermarket groups; however, informal trade continues to dominate retail activity in the region (Mwamba & Qutieshat, 2021; Reardon *et al.,*2003; Weatherspoon & Reardon, 2003). Lagos and Accra, the commercial centers of Nigeria and Ghana, respectively, contain the highest concentrations of supermarkets, hypermarkets, and chain outlets in the subregion. These formal retailers compete with open markets and neighborhood shops on price and convenience, while also contending with currency volatility, high logistics costs, unreliable power supply, and supplier lead-time uncertainty (Mwamba & Qutieshat, 2021). Under these circumstances, the ability to forecast demand, set reorder points, time markdowns, and evaluate store performance using reliable metrics may distinguish growing retailers from those that stagnate.

West African retailers now possess greater volumes of data than in previous years. Cloud-based POS systems, barcode scanning, mobile payments, and e-commerce platforms generate transaction records at a level of detail that was rare a decade ago. However, increased data availability alone does not guarantee improved decision-making. The analytics literature differentiates between having access to data and having the capability to utilize it, which requires a combination of technology infrastructure, human skills, and managerial routines (Akter *et al.,*2016; Gupta & George, 2016; Mikalef *et al.,*2020). A meta-analysis of 125 firm-level studies found that social components of business analytics, such as human resources, management capability, and organizational culture, contribute more to business value than technical components (Oesterreich *et al.,*2022). Whether this trend is observed among West African retailers, where analytics budgets and specialized skills are limited, remains an open empirical question.

1.2 Statement of the Problem

Retail managers in Lagos and Accra routinely report two costly problems: products that are unavailable when customers want them, and slow-moving stock that ties up working capital until it is cleared at a loss. Both problems are, in principle, amenable to analytics. Accurate sales forecasts inform replenishment; stock-turnover and sell-through metrics identify slow movers early; and dashboards make these signals visible to the managers who must act on them (Gaur *et al.,*2005; Pauwels *et al.,*2009). International evidence shows that out-of-stock rates have remained stubbornly high in fast-moving consumer goods retailing for decades and that shoppers increasingly respond by switching stores rather than brands (Corsten & Gruen, 2003). Stock-outs also carry long-run costs, because customers who experience them reduce future purchases (Anderson *et al.,*2006).

Despite this, systematic evidence remains limited on how far West African retailers have adopted analytics, which evaluation metrics they use, and whether that use is associated with better decisions and operational outcomes. Existing African studies have examined big data analytics (BDA) adoption among Nigerian manufacturing and service firms (Egwuonwu *et al.,*2024), food companies in South-Western Nigeria (Osakue *et al.,*2026), consulting firms (Oyewo *et al.,*2020), small and medium-sized enterprises (SMEs) in Accra and Lagos (Opoku *et al.,*2024) and traditional fashion businesses in Ghana (Korankye *et al.,*2026). None of these focused on formal supermarket and chain retail, and few related metrics link to a concrete retail outcome such as stock-turnover efficiency. Studies of retail analytics adoption in emerging markets outside Africa, such as Jordan, indicate that organisational readiness and top management support shape adoption and that adoption is associated with firm performance (Lutfi *et al.,*2023). Still, contextual differences in infrastructure, skills supply and market structure limit the transfer of these results to West Africa.

This gap results in a lack of evidence for retailers, investors, and policymakers regarding the effectiveness of analytics investments. If performance outcomes are determined by analytics capability rather than data volume or software ownership, then investing in tools without parallel investment in skills and routines is likely to yield suboptimal results. The present study seeks to address this issue.

1.3 Purpose of the Study and Research Questions

The study examined the extent to which retail analytics and evaluation metrics drive data-informed decision-making and performance outcomes in West African retail enterprises. Specifically, the study sought to answer the following research questions (RQs):

1. **RQ1:** To what extent do supermarkets and chain outlets in Lagos and Accra adopt retail analytics tools and evaluation metrics, including predictive analytics?
2. **RQ2:** To what extent does analytics capability predict data-informed decision-making among retail managers and analytics officers?
3. **RQ3:** To what extent do dashboard use, sales-forecast metrics, and related evaluation metrics account for variance in stock-turnover efficiency?
4. **RQ4:** What barriers constrain the adoption and routine use of retail analytics?
5. **RQ5:** How do retail managers describe the influence of metric use on operational decisions such as markdowns and replenishment?

1.4 Hypotheses

The following null hypotheses were tested at the .05 level of significance:

1. **$H_0$1:** Analytics capability does not significantly predict data-informed decision-making in West African retail enterprises.
2. **$H_0$2:** Dashboard use, sales-forecast metrics and related evaluation metrics do not jointly account for a significant proportion of variance in stock-turnover efficiency.
3. **$H_0$3:** Analytics maturity is not significantly related to the frequency of data-informed decisions among retail outlets.

1.5 Significance of the Study

This study offers three primary contributions. Theoretically, it applies the technology–organisation–environment (TOE) framework to examine post-adoption use of retail analytics in a West African context, thereby extending a framework typically used to explain technology adoption to the question of whether adoption leads to improved decision-making. Empirically, it presents survey and interview data from two of the largest formal retail markets in West Africa, integrating manager-reported capability measures with outcome indicators related to inventory performance. Practically, it identifies the metrics and capabilities associated with enhanced stock-turnover efficiency and highlights the barriers that most significantly constrain analytics use. These insights can inform the priorities of retail executives, analytics vendors, training institutions, and trade associations.

1.6 Scope and Delimitation

The scope of the study was limited to formal supermarkets and multi-outlet retail chains located in Lagos, Nigeria, and Accra, Ghana. Informal traders, open-market vendors, and exclusively online retailers were excluded. The respondents comprised retail managers and analytics officers responsible for, or regularly utilizing, sales and inventory data. The study concentrated on descriptive, diagnostic, and predictive analytics applied to merchandising, inventory, and pricing decisions. Customer-relationship analytics and marketing-attribution models were explicitly excluded from the scope.

2. LITERATURE REVIEW

2.1 Conceptualising Retail Analytics

Retail analytics refers to applying statistical, computational, and visual methods to retail data to describe past performance, diagnose its causes, predict future outcomes, and prescribe actions (Davenport & Harris, 2007; Chen *et al.,*2012). Bradlow *et al.,* (2017) organised retail data along five dimensions, namely customer, product, time, geo-spatial location and channel, and argued that the value of big data in retailing depends on combining new data sources with statistical tools and domain theory rather than on data volume alone. Fisher and Raman (2018), drawing on two decades of collaboration with retailers, documented applications in which better use of existing transaction data improved assortment, pricing and inventory decisions, often without exotic technology.

The analytics literature typically distinguishes four levels of sophistication. Descriptive analytics summarises what happened, for example, daily sales by category or store. Diagnostic analytics explains why it happened, such as attributing a sales decline to a stock-out or a competitor promotion. Predictive analytics estimates what is likely to happen, most commonly through demand forecasting. Prescriptive analytics recommends what to do, such as optimal order quantities or markdown schedules (Davenport & Harris, 2007; LaValle *et al.,*2011). Rooderkerk *et al.,* (2022) reviewed 123 retail analytics articles published in leading operations journals between 2000 and 2020 and identified nine decision areas, with inventory, pricing, and assortment receiving the most attention. Their interviews with practitioners showed a wide gap between frontier retailers, which deploy machine learning at scale, and the majority, which rely on spreadsheets and periodic reports.

A recent bibliometric review of 563 Scopus-indexed documents found that global retail analytics research has primarily focused on artificial intelligence and machine learning, big data, data-driven retail, and data-driven decision-making, while comparatively little attention has been given to adoption barriers in resource-constrained markets (Velásquez, 2025). This global emphasis contrasts with the African context, where empirical studies indicate that analytics adoption is largely limited to descriptive reporting and basic tools. Persistent barriers such as cost, skills shortages, and infrastructural limitations continue to impede progress toward predictive or prescriptive analytics (Egwuonwu *et al.,*2024; Korankye *et al.,*2026; Osakue *et al.,*2026). This disparity is particularly significant in West Africa, where most retailers are still moving from descriptive reporting to routine forecasting, underscoring the importance of research on adoption barriers.

2.2 Evaluation Metrics and Key Performance Indicators in Retail

Evaluation metrics are quantitative indicators that turn analytical output into managerial information. In retail, commonly used metrics include sales per square metre, gross margin, gross margin return on inventory investment (GMROI), sell-through rate, stock-turnover ratio, days of inventory, on-shelf availability or stock-out rate, forecast accuracy (for example, mean absolute percentage error), markdown rate, shrinkage and basket size (Farris *et al.,*2015; Gaur *et al.,*2005). The balanced scorecard tradition argues that firms should monitor a limited set of financial and non-financial measures aligned with strategy rather than an unstructured collection of numbers (Kaplan & Norton, 1992).

Stock turnover, the ratio of cost of goods sold to average inventory, is among the most widely used indicators of inventory productivity. Gaur *et al.,* (2005) analysed 311 publicly listed United States retailers and showed that inventory turnover varies systematically with gross margin, capital intensity, and sales surprise; after adjusting for these factors, turnover becomes a more informative benchmark of operational performance. Similar relationships have been reported in Greek retail (Kolias *et al.,*2011). These findings imply that turnover is sensitive to the accuracy of demand expectations, linking it directly to forecasting and the metrics retailers use to track forecasts.

The effectiveness of metrics is influenced by their selection and presentation. O'Sullivan *et al.,* (2009) demonstrated that the ability to measure marketing performance was positively associated with firm performance, with reporting frequency mediating this relationship. This suggests that metrics contribute value by establishing regular review and action routines, rather than solely by their quantity.

2.3 Analytics Capability

Analytics capability is a firm's ability to assemble, integrate and deploy data, technology and talent to generate insight that informs decisions (Gupta & George, 2016). Drawing on the resource-based view (RBV), Gupta and George (2016) conceptualised big data analytics capability as a combination of tangible resources (data, technology, investment), human resources (managerial and technical skills) and intangible resources (data-driven culture and organisational learning). Akter *et al.,* (2016) modelled the construct as a hierarchy of management, technology, and talent capabilities. Using Delphi studies and a survey of 152 United States business analysts, they showed that it was positively related to firm performance, especially when analytics aligned with business strategy.

A substantial body of subsequent research supports the capability–performance link while emphasising that the effect is often indirect. Wamba *et al.,*(2017) found that analytics capability affected performance both directly and through process-oriented dynamic capabilities among 297 Chinese IT managers and business analysts. Mikalef *et al.,* (2020) reported that, among 202 Norwegian firms, analytics capability's effect on competitive performance was fully mediated by dynamic capabilities, and Mikalef *et al.,* (2019) showed, through fuzzy-set analysis, that different resource configurations lead to high-performance depending on context. Ghasemaghaei *et al.,* (2018) operationalised data analytics competency as data quality, data volume, analytical skills, domain knowledge, and tool sophistication. They found a large positive relationship with decision quality and decision efficiency. Importantly for resource-constrained settings, all dimensions except bigness of data improved decision efficiency, indicating that skills and data quality matter more than data volume.

At the level of econometric evidence, Müller *et al.,*(2018) analysed objective measures of BDA assets held by 814 firms between 2008 and 2014 and estimated an average productivity improvement of 3–7%, but found measurable gains only for firms in IT-intensive or highly competitive industries. Retailing in Lagos and Accra is competitive but not IT-intensive, making the question of whether capability translates into outcomes empirically informative in this setting.

2.4 Data-Informed Decision-Making

Data-informed decision-making describes the practice of grounding managerial choices in systematically analysed evidence while retaining managerial judgement for context that data do not capture. The term is used here in preference to "data-driven" because interview evidence from retail managers commonly describes analytics as one input among several rather than as an automated decision rule. Brynjolfsson and McElheran (2016) found that adoption of data-driven decision-making was more likely in larger plants with complementary IT, educated workers and a history of firm learning. Ghasemaghaei (2019) showed that analytics use affected decision quality through knowledge sharing, implying that analytics informs decisions only when its outputs circulate among the people who make them. Awan *et al.,*(2021) similarly reported that analytics capability and business intelligence were positively associated with decision-making quality among Czech manufacturers.

Organisational culture significantly shapes these effects. Chatterjee *et al.,* (2024), drawing on 456 employee responses from firms utilising business analytics tools, found that a data-driven culture promotes product and process innovation, which in turn enhances firm performance. Ransbotham *et al.,* (2016) noted that analytics success depends on sustained managerial commitment to integrating analysis into daily routines, rather than relying on one-time investments. In retail, where decisions are frequent, local, and time-sensitive, such as daily replenishment or weekly markdowns, establishing routine metric review is as critical as the sophistication of the underlying analytical models.

2.5 Dashboards, Forecasting Metrics, and Inventory Performance

Dashboards aggregate a firm's key metrics into a unified visual display, enabling managers to monitor performance, identify deviations, and coordinate responses (Eckerson, 2005; Pauwels *et al.,*2009). Yigitbasioglu and Velcu (2012), in a multidisciplinary review, concluded that dashboards enhance decision-making by reducing information overload and leveraging human perceptual strengths, but only when features such as drill-down capabilities and suitable presentation formats are included. Krush *et al.,* (2016) demonstrated

that marketing dashboards are significantly associated with faster strategy implementation and improved market information management among business-to-business firms. However, evidence is mixed: in a simulation with 105 teams, Clark (2021) found that tactical dashboards decreased exploratory activity under high information load and correlated with lower overall performance. Thus, dashboards are most effective when they direct attention to actionable decisions. Evidence from Nigerian contexts outside retail supports this: in a seven-month quasi-experimental study in Ebonyi and Imo States, Onyebuchi-Igbokwe *et al.,* (2026) found that technology-enabled visual information (infographics, animations, and audio-visual content) led to significant knowledge gains among rural households, with digital engagement being the strongest predictor of improvement and exposure linked to behavioural change. Although this study focused on nutrition education, its central finding—that well-designed visual presentation bridges the gap between information and action—mirrors the expected role of dashboards in translating retail data into decisions.

In retail operations, the most critical metrics connect demand forecasts to inventory management. Fildes *et al.,* (2022) reviewed retail forecasting research and practice, noting that while advanced econometric and machine-learning methods can outperform simpler techniques, many retailers continue to rely on judgment and basic methods. Barriers to improved forecasting are both organisational and technical. Research on out-of-stock events indicates that stock-outs primarily result from store-level ordering and replenishment failures, rather than upstream supply chain issues (Corsten & Gruen, 2003; Ehrenthal & Stölzle, 2013). Anderson *et al.,* (2006), through a large field test, demonstrated that stock-outs decrease both current and future demand, indicating that inventory policies neglecting long-term effects are suboptimal. Collectively, this literature suggests that integrating sales-forecast metrics and dashboards with inventory management can improve stock turnover, provided managers trust and utilise these tools.

2.6 Analytics Adoption in African and West African Contexts

Evidence on analytics adoption in Africa is expanding but remains uneven. Egwuonwu *et al.,* (2024) examined 261 Nigerian professionals in manufacturing and service sectors, finding that technological factors, top management support, and organisational readiness facilitated big data analytics (BDA) adoption, while competitive pressure and regulation did not, contrary to much prior TOE research. Oyewo *et al.,* (2020) determined that international affiliation and operational scope, rather than firm size, accounted for BDA usage among Nigerian consulting firms. Osakue *et al.,* (2026) observed increasing awareness of BDA among food companies in South-Western Nigeria, but persistent barriers such as cost, skills shortages, regulatory uncertainty, and technological limitations remain.

In Ghana, Korankye *et al.,* (2026) found that traditional fashion businesses primarily used basic tools such as social-media analytics, with limited technical expertise, financial constraints, and resistance to change impeding the adoption of advanced tools. Opoku *et al.,* (2024) surveyed SMEs in Accra and Lagos, reporting a positive relationship between predictive analytics and both operational efficiency and revenue growth, and recommended staff training and infrastructure investment. Onyebuchi-Igbokwe (2025), through surveys, interviews, and focus groups in Northwest Nigeria, investigated how artificial intelligence platforms could expand the market reach of local creative producers, identifying both opportunities and adoption challenges. The findings indicate that access, skills, and infrastructure moderate the potential of data-driven platforms in Nigeria. Collectively, these studies reveal a consistent pattern: awareness is increasing, adoption remains focused on basic descriptive tools, and advancement toward predictive and prescriptive analytics is limited by cost and skills shortages.

The structure of formal retail in the region introduces additional complexities. Supermarket chains in sub-Saharan Africa rely on import-dependent supply chains, face foreign-exchange exposure, and manage fragmented supplier bases (Mwamba & Qutieshat, 2021; Reardon *et al.,*2003). These factors increase demand uncertainty and lead-time variability, thereby elevating the importance of accurate forecasting while simultaneously complicating its achievement. Furthermore, the cost of analytics software, often priced in foreign currency, imposes a greater financial burden on West African retailers compared to those in advanced economies.

2.7 Barriers to Retail Analytics Use

Barriers to analytics adoption can be categorised into three groups. Technological barriers encompass poor data quality, fragmented systems, and inadequate infrastructure (Kumar & Krishnamoorthy, 2020). Organisational barriers include insufficient skills, limited top management support, weak data culture, and high costs (Maroufkhani *et al.,*2020; Maroufkhani *et al.,*2023). Environmental barriers involve weak vendor ecosystems, regulatory uncertainty, and limited external support (Lutfi *et al.,*2023). Aversa *et al.,* (2021), through case studies of Canadian retail organisations, found that successful adoption of big data decision support systems relied on a transparent data environment and a well-defined corporate data strategy. Rooderkerk *et al.,* (2022) noted that practitioners identified talent shortages, legacy systems, and organisational resistance as primary obstacles to advanced retail analytics, even in large firms.

2.8 Summary of Literature and Research Gap

The literature reviewed consistently associates analytics capability with enhanced decision quality and organisational performance. However, closer examination of foundational studies (e.g., Gupta & George, 2016; Oesterreich *et al.,*2022) indicates that this relationship is frequently mediated by organisational routines and the presence of complementary assets. These studies highlight the necessity of not only possessing advanced analytics tools but also cultivating a data-driven culture and structured managerial processes to convert analytics into actionable outcomes. Research by Ghasemaghaei *et al.,* (2018) further suggests that technical sophistication must be accompanied by investments in human capital and domain expertise. Although significant progress has been made in North America, Europe, and Asia, the concentration of empirical studies in these regions raises concerns about the applicability of existing models to lower-resource environments. African literature, while expanding, has primarily examined manufacturing and service sectors or contexts dominated by SMEs and traditional industries, often without addressing the full complexity of performance outcomes in formal retail. Additionally, few studies rigorously assess whether analytics adoption leads to measurable improvements in key operational metrics, such as stock-turnover efficiency, particularly in large-scale, formal supermarket and chain retail settings in West Africa. There is also limited research directly connecting quantitative survey results with detailed, context-specific managerial perspectives, complicating the evaluation of how analytic metrics inform decision processes. This study aims to address these gaps by systematically examining the translation of analytics capability and metric usage into decision-making quality and stock-turnover efficiency, employing a mixed-methods approach that integrates statistical analyses with qualitative insights from retail managers in Lagos and Accra.

3. THEORETICAL FRAMEWORK

3.1 The Technology–Organisation–Environment Framework

This study is grounded in the technology–organisation–environment (TOE) framework developed by Tornatzky and Fleischer (1990). The framework posits that three contexts influence a firm's adoption and implementation of technological innovation. The technological context encompasses the technologies available to the firm and their characteristics, such as existing infrastructure, compatibility, and complexity. The organisational context includes firm attributes like size, managerial structure, slack resources, top management support, and human capital. The environmental context pertains to the external environment in which the firm operates, including industry structure, competitive pressure, the availability of technology service providers, and the regulatory regime (Oliveira & Martins, 2011; Tornatzky & Fleischer, 1990).

The TOE framework has been extensively applied to the study of analytics and business intelligence adoption. Nam *et al.,* (2019), in a study of 170 Korean firms, found that data-related technological characteristics influenced all stages of business analytics adoption, while organisational characteristics were significant for adoption and assimilation, and competition intensity was relevant only at the initiation stage. Maroufkhani *et al.,* (2020) identified complexity, uncertainty and insecurity, trialability, observability, top management support, organisational readiness, and external support as significant factors influencing BDA adoption among Iranian SMEs. This adoption subsequently enhanced marketing and financial performance. Maroufkhani *et al.,* (2023) further demonstrated that TOE factors are interdependent, with top management support mediating the effects of compatibility, competitiveness, and organisational readiness on adoption. In the retail sector, Lutfi *et al.,* (2023) found that relative advantage, organisational readiness, top management support, government support, data variety, and data velocity influenced BDA adoption among Jordanian retailers, and that adoption was associated with improved firm performance.

The TOE framework is particularly suitable for the present study for two reasons. First, its three contexts correspond directly to factors identified as decisive in West African retail: technology infrastructure and tools (technological), skills, cost, and managerial commitment (organisational), and competitive and supplier conditions (environmental). Second, the framework offers sufficient flexibility to address post-adoption questions. While many TOE studies focus on whether firms adopt a technology, the present study examines whether the capability developed through adoption leads to data-informed decisions and operational outcomes.

3.2 Complementary Perspective: Resource-Based View and Analytics Capability

As the TOE framework primarily explains adoption rather than performance outcomes, this study incorporates the resource-based view (RBV) to theorise the relationship between analytics capability and outcomes. The RBV posits that firms achieve sustained competitive advantage through resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Since analytics software is increasingly commoditised, it is unlikely to provide advantage independently; instead, the ability to integrate software with skilled personnel, high-quality data, and effective decision routines is more difficult to replicate (Gupta & George, 2016). The dynamic capabilities perspective further suggests that such capabilities generate value by enabling firms to detect changes in demand and reconfigure operations accordingly (Teece *et al.,*1997; Wamba *et al.,*2017). In retail, this involves identifying a

declining product line early and responding through markdowns, reallocation, or reduced reordering.

3.3 Conceptual Model

By integrating these perspectives, the study proposes the conceptual model presented in Figure 1. Technological, organisational, and environmental conditions are posited to influence analytics capability and analytics maturity. Analytics capability is hypothesised to predict data-informed decision-making ($H_0$1). The utilisation of specific evaluation tools, including dashboards, sales-forecast metrics, and inventory-performance metrics, is expected to explain variance in stock-turnover efficiency ($H_0$2). Analytics maturity is hypothesised to be associated with the frequency of data-informed decisions ($H_0$3). Barriers such as cost and skills gaps are anticipated to limit the progression from data availability to routine, predictive use.

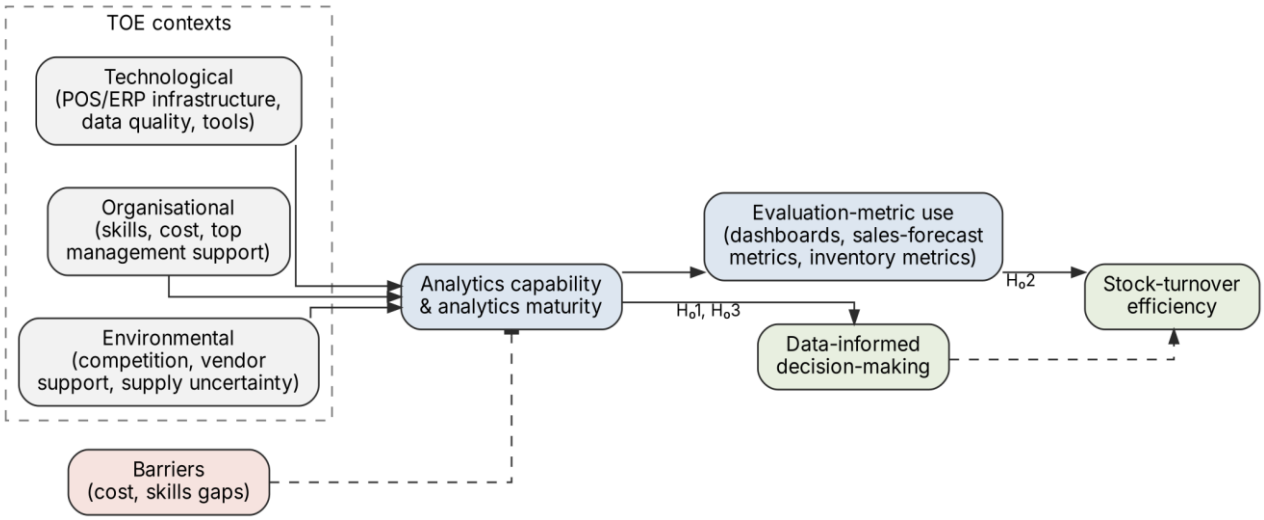


Figure 1: Conceptual model of the study, integrating the TOE framework and the resource-based view of analytics capability

4. METHODOLOGY

4.1 Research Paradigm and Design

The study adopted a positivist paradigm, which assumes that relationships among analytics capability, metric use, decision-making, and performance can be measured and tested through systematic observation (Creswell & Plano Clark, 2018). Within this framework, a mixed-methods descriptive survey design was employed. The quantitative component, which provided the primary inferential basis, utilised a structured questionnaire to assess adoption levels and test the hypothesised relationships. The qualitative component involved in-depth interviews to elucidate the mechanisms underlying the statistical relationships and to capture managerial perspectives on the influence of metrics on specific decisions. Consistent with Creswell and Plano Clark (2018), the design is best described as explanatory sequential: the survey was administered first, followed by the selection of interview participants from survey respondents who indicated willingness to participate, with priority given to quantitative data and integration occurring at the interpretation stage.4.2 Study Setting

The study was conducted in Lagos, Nigeria, and Accra, Ghana. Lagos serves as Nigeria's principal commercial centre and contains the country's largest concentration of supermarkets, hypermarkets, and retail chains. Accra fulfills a similar role in Ghana. These cities were selected due to their status as hosts of the largest formal retail sectors in anglophone West Africa, their experience with the expansion of domestic and regional supermarket chains, and their suitability for comparing two economies with differing currency, regulatory, and market-size conditions.

4.3 Population, Sample and Sampling Technique

The study population consisted of approximately 1,140 retail managers and analytics officers employed in 112 supermarkets and multi-outlet chain stores identified in the two cities through business directories, retail association listings, and a field verification exercise. A purposive sampling technique was employed to select 48 supermarkets and chain outlets that (a) operated a computerised POS or inventory system, (b) had been in operation for at least three years, and (c) employed staff responsible for sales, inventory, or performance reporting. Within these outlets, 286 respondents were selected, including store and category managers, inventory and merchandising officers, and analytics or reporting officers. The distribution of outlets and respondents by city is presented in Table 1.

For the qualitative component, 12 participants (six from each city) were purposively selected for in-depth interviews to represent a range of outlet sizes, roles, and levels of analytics use. The interview sample

included five store managers, three category managers, two inventory officers, and two analytics officers.

The adequacy of the quantitative sample was evaluated based on the requirements for multiple regression analysis. For a model with three predictors, a medium effect size ($f^2 = .15$), $\alpha = .05$, and power of .95, the minimum required sample size is 119 (Faul *et al.,*2009). The achieved sample of 286 thus exceeded this minimum requirement.

4.4 Instruments for Data Collection

4.4.1 Retail Analytics Adoption Questionnaire

Quantitative data were collected using a researcher-developed instrument, the Retail Analytics Adoption Questionnaire (RAAQ). The instrument comprised six sections with a total of 54 items:

- **Section A** (6 items) captured respondent and outlet characteristics, including city, role, years of experience, qualification, outlet type and number of outlets in the chain.
- **Section B** (14 items) measured analytics adoption and metric use, including the analytics tools in use (spreadsheets, POS reports, business intelligence dashboards, forecasting software, ERP modules) and the frequency of use of specific evaluation metrics (sales by category or store, gross margin, sell-through, stock-turnover, stock-out rate, forecast accuracy, markdown rate and shrinkage). This section also measured the frequency of predictive analytics use.
- **Section C** (12 items) measured analytics capability across technology infrastructure, data quality, analytical skills and managerial support, adapted from the dimensions proposed by Gupta and George (2016) and Akter *et al.,*(2016), together with top management support and competitive pressure as organisational and environmental conditions.
- **Section D** (8 items) measured data-informed decision-making, operationalised as the extent to which pricing, replenishment, markdown, assortment and staffing decisions are based on analysed data.
- **Section E** (6 items) measured stock-turnover efficiency, operationalised as respondent-rated improvement over the preceding 12 months in inventory turnover, days of inventory, ageing stock and stock-out frequency.
- **Section F** (8 items) measured barriers to analytics use, including cost of tools, skills gaps, data quality, power supply and connectivity, management support, vendor support and KPI standardisation.

Items in Sections B to F were rated on a five-point Likert-type scale ranging from Strongly Disagree (1) to Strongly Agree (5), or from Never (1) to Always (5) for frequency items.

4.4.2 Interview Protocol

A semi-structured interview guide was used for the qualitative strand. It asked participants to describe the data and metrics available to them, how often and in what forums those metrics are reviewed, recent decisions that were changed by data, the use of forecasts in replenishment and markdowns, and obstacles to using analytics more extensively. Interviews were conducted face-to-face in English, lasted between 45 and 70 minutes, and were audio-recorded with consent.

4.5 Validity and Reliability of the Instruments

The RAAQ underwent face and content validation by three experts representing business education, retail management, and measurement and evaluation. Based on their feedback, seven ambiguous items were reworded and four redundant items were removed. Instrument reliability was confirmed through a test–retest procedure with 30 retail managers in Port Harcourt, external to the study sample, over a two-week interval, resulting in a reliability coefficient of $r = .81$. Internal consistency was demonstrated by Cronbach's α values of .87 for analytics capability, .84 for data-informed decision-making, .79 for stock-turnover efficiency, and .81 for barriers.

Trustworthiness in the qualitative strand was established through member checking of interview summaries with five participants, maintaining an audit trail of coding decisions, and independent double-coding of four out of twelve transcripts (33%), which resulted in an inter-coder agreement of $\kappa = .82$.

4.6 Procedure for Data Collection

Researchers, assisted by three trained research assistants in each city, administered questionnaires in person between January and March 2026. Of the 320 questionnaires distributed, 301 were returned, and 286 were complete and usable, resulting in a usable return rate of 89.4%. Interviews were conducted in April 2026, following preliminary analysis of the survey data, at times and locations convenient for participants.

4.7 Ethical Considerations

Participation was voluntary, with informed consent obtained from all respondents and interview participants. Confidentiality was assured, as outlet names were neither recorded on questionnaires nor used in reporting. Interview transcripts were anonymised, and participants were identified by codes (L1–L6 for Lagos and A1–A6 for Accra). Ethical approval was granted by the institutional research ethics committee (illustrative reference: REC/2026/014).

4.8 Methods of Data Analysis

Quantitative data were analysed using IBM SPSS Statistics, version 27. Research Question 1 was addressed using frequencies, percentages, means, and standard deviations; a mean of 3.00 or above on the five-point scale indicated a high extent of use, while a mean below 3.00 indicated a low extent. Research Questions 2 and 3, as well as hypotheses $H_0$1 and $H_0$2, were tested using multiple regression analysis. Hypothesis $H_0$3 was examined using Pearson's product-moment correlation

coefficient. Research Question 4 was addressed using mean ratings of barrier items. Prior to regression analyses, assumptions of linearity, normality of residuals, homoscedasticity, independence of errors (Durbin–Watson statistic), and absence of problematic multicollinearity (variance inflation factor below 5) were assessed (Hair *et al.,*2019). All assumptions were met; Durbin–Watson values were 1.87 and 1.92 for the two models, and the largest VIF was 2.56. To address potential common method variance due to the use of a single self-report instrument, Harman's single-factor test was conducted (Podsakoff *et al.,*2003); the first unrotated factor accounted for 31.6% of total variance, below the 50% threshold, indicating that common method variance was not a dominant concern.

Qualitative data were analysed using reflexive thematic analysis, following the six phases outlined by Braun and Clarke (2006): familiarisation, initial coding, searching for themes, reviewing themes, defining and naming themes, and producing the report. Coding was performed using NVivo 14. Integration of quantitative and qualitative findings was achieved through a joint display that juxtaposed statistical results with corresponding interview themes.

5. RESULTS

5.1 Profile of Respondents and Outlets

Table 1 presents the distribution of outlets and respondents by city.

Table 1: Distribution of Sampled Outlets and Respondents by City

Lagos, Nigeria	**28**	**168**	**58.7**
Accra, Ghana	20	118	41.3
Total	48	286	100.0

Table 2 summarises respondent characteristics. Most respondents worked in multi-outlet chains (68.9%), held a Higher National Diploma or bachelor's degree (60.1%) and had between 5 and 10 years of retail experience (42.3%).

Table 2: Demographic and Professional Characteristics of Respondents (N = 286)

Role	**Store/branch manager**	**84**	**29.4**
	Category/merchandising manager	71	24.8
	Inventory/supply officer	79	27.6
	Analytics/reporting officer	52	18.2
Years of experience	Less than 5	97	33.9
	5–10	121	42.3
	More than 10	68	23.8
Outlet type	Single-site supermarket	89	31.1
	Multi-outlet chain	197	68.9
Highest qualification	OND/NCE	41	14.3
	HND/Bachelor's degree	172	60.1
	Postgraduate degree	58	20.3
	Professional certificate only	15	5.2

Note. Percentages may not sum to 100 because of rounding.

5.2 Research Question 1: Extent of Analytics Adoption and Metric Use

Table 3 presents the analytics tools reported in use by respondents, and Table 4 presents the frequency of use of evaluation metrics.

Table 3: Analytics Tools in Use (N = 286; multiple responses permitted)

Spreadsheets (e.g., Microsoft Excel)	**271**	**94.8**
POS-generated sales and stock reports	254	88.8
ERP inventory modules	163	57.0
Business intelligence dashboards (e.g., Power BI, Tableau, vendor dashboards)	129	45.1
Demand-forecasting software or models	112	39.2
Routine predictive analytics	98	34.3

Table 4: Mean Ratings of the Frequency of Use of Retail Evaluation Metrics (N = 286)

Daily/weekly sales by category or store	**4.52**	**0.61**	**High**
Gross margin	4.11	0.78	High
Stock-turnover ratio / days of inventory	3.47	1.02	High
Shrinkage	3.36	1.05	High

Sell-through rate	3.21	1.09	High
Stock-out / on-shelf availability rate	3.08	1.14	High
Markdown rate	2.87	1.12	Low
Sales-forecast accuracy	2.41	1.18	Low
Grand mean	3.38	0.54	High

Note. Decision rule: $M \geq 3.00$ = great extent; $M < 3.00$ = low extent.

The results indicate that adoption was primarily focused on descriptive tools. Nearly all respondents reported using spreadsheets (94.8%) and POS reports (88.8%), while fewer than half used business intelligence dashboards (45.1%). Only 34.3% of respondents ($n = 98$) indicated that their outlets routinely employed predictive analytics. Backwards-looking metrics, such as sales by category ($M = 4.52$) and gross margin ($M = 4.11$), were used most frequently. In contrast, forward-looking metrics, including forecast accuracy ($M = 2.41$) and markdown rate ($M = 2.87$), were used less often, falling below the criterion mean. The overall grand mean of 3.38 reflects a high extent of metric use, predominantly driven by descriptive indicators.

5.3 Research Question 2 and $H_0$1: Analytics Capability and Data-Informed Decision-Making

Table 5 presents the bivariate correlations among the study variables, and Table 6 presents the multiple regression of data-informed decision-making on analytics capability and related TOE conditions.

Table 5: Means, Standard Deviations and Pearson Correlations among Study Variables (N = 286)

1. Analytics capability	**3.29**	**0.74**	**—**				
2. Dashboard use	3.02	0.96	.52**	—			
3. Sales-forecast metric use	2.78	1.01	.48**	.44**	—		
4. Data-informed decision-making	3.41	0.69	.60**	.47**	.45**	—	
5. Stock-turnover efficiency	3.18	0.81	.49**	.55**	.53**	.51**	—

Note. ** $p < .01$ (two-tailed).

Table 6: Multiple Regression Predicting Data-Informed Decision-Making (N = 286)

(Constant)	**0.82**	**0.19**		**4.32**	**< .001**	
Analytics capability	0.44	0.07	.47	6.32	< .001	2.56
Top management support	0.07	0.06	.08	1.14	.255	2.40
Competitive pressure	0.10	0.04	.13	2.29	.023	1.35

Note. Model summary: $R = .62$, $R^2 = .38$, adjusted $R^2 = .37$, $F(3, 282) = 56.69$, $p < .001$; Durbin–Watson = 1.87.

Analytics capability was a significant predictor of data-informed decision-making ($\beta = .47$, $t = 6.32$, $p < .001$) and represented the strongest predictor in the model. Competitive pressure contributed a smaller but significant effect ($\beta = .13$, $p = .023$), while top management support did not have a significant impact after controlling for analytics capability ($\beta = .08$, $p = .255$). Collectively, the predictors accounted for 38% of the variance in data-informed decision-making ($R^2 = .38$). Consequently, Hypothesis $H_0$1 was rejected.

5.4 Research Question 3 and $H_0$2: Evaluation Metrics and Stock-Turnover Efficiency

Table 7 presents the multiple regression of stock-turnover efficiency on dashboard use, sales-forecast metric use and inventory-performance metric use.

Table 7: Multiple Regression Predicting Stock-Turnover Efficiency from Evaluation-Metric Use (N = 286)

(Constant)	**0.94**	**0.17**		**5.53**	**< .001**	
Dashboard use	0.28	0.05	.33	6.07	< .001	1.44
Sales-forecast metric use	0.25	0.04	.32	5.92	< .001	1.37
Inventory-performance metric use	0.13	0.05	.15	2.70	.007	1.47

Note. Model summary: $R = .65$, $R^2 = .416$, adjusted $R^2 = .41$, $F(3, 282) = 66.96$, $p < .001$; Durbin–Watson = 1.92. Inventory-performance metric use combines sell-through, stock-turnover and stock-out metrics.

The three metric-use variables collectively explained 41.6% of the variance in stock-turnover efficiency, $F(3, 282) = 66.96$, $p < .001$. Dashboard use ($\beta = .33$) and sales-forecast metric use ($\beta = .32$) provided the largest and nearly equivalent contributions, whereas inventory-performance metric use contributed a smaller but statistically significant portion ($\beta = .15$, $p = .007$). Therefore, Hypothesis $H_0$2 was rejected.

5.5 Hypothesis $H_0$3: Analytics Maturity and Frequency of Data-Informed Decisions

Table 8: Pearson Correlation between Analytics Maturity and Frequency of Data-Informed Decisions (N = 286)

Analytics maturity × Frequency of data-informed decisions	.53	< .001	$H_0$3 rejected

A significant and strong positive relationship was observed between analytics maturity and the frequency of data-informed decisions, $r(284) = .53$, $p < .001$. Outlets with higher analytics maturity, progressing from descriptive reporting to routine forecasting, reported more frequent data-informed decision-making. As a result, Hypothesis $H_0$3 was rejected.

5.6 Research Question 4: Barriers to Analytics Adoption and Use

Table 9: Mean Ratings of Barriers to Retail Analytics Use (N = 286)

High cost of analytics software and licences	**4.38**	**0.71**	**1st**
Shortage of staff with analytics skills	4.21	0.79	2nd
Unreliable power supply and connectivity	3.97	0.88	3rd
Poor data quality and inconsistent product records	3.84	0.92	4th
Lack of standardised KPI definitions	3.58	1.01	5th
Limited local vendor and technical support	3.46	0.99	6th
Limited management support for analytics	3.12	1.06	7th

Cost ($M = 4.38$) and skills gaps ($M = 4.21$) were identified as the primary barriers, followed by unreliable power supply and connectivity ($M = 3.97$) and poor data quality ($M = 3.84$). All seven barriers received mean ratings above the criterion of 3.00, with limited management support being the least severe ($M = 3.12$).

5.7 Research Question 5: Qualitative Findings

Thematic analysis of the twelve interviews identified four distinct themes.

Theme 1: Metrics accelerate markdown decisions.

Participants associated the regular review of sell-through and ageing-stock metrics with earlier and more decisive markdowns. Managers who reviewed these metrics weekly reported acting more promptly and implementing smaller price reductions, rather than waiting for slow-moving items to accumulate. As one category manager explained:

"Before, we discovered slow lines when the shelf was already full of expired stock. Now the sell-through report shows me by the second week, and I can cut the price by ten per cent instead of forty." (Participant L2, category manager, Lagos)

Theme 2: Forecast-informed replenishment reduces stock-outs.

Participants described that sales-forecast reports and reorder alerts contributed to reducing the frequency of empty shelves for fast-moving lines, especially during paydays, festive periods, and promotions.

"The forecast tells us that month-end and Christmas weeks will double our rice and cooking-oil sales, so we order early. Last December we did not run out of any top-twenty item, which never happened before." (Participant A3, store manager, Accra)

Theme 3: Capability, not data volume, determines use.

Participants in outlets with similar POS systems reported substantial differences in data utilization, attributing these differences to staff skills and the frequency with which management reviewed metrics.

"Every branch has the same system. The difference is whether the manager knows how to read it and whether somebody asks him about the numbers every Monday." (Participant L5, analytics officer, Lagos)

Theme 4: Cost and skills limitations restrict progression to predictive tools.

Participants identified licence costs, foreign-currency software pricing, and challenges in recruiting or retaining analysts as primary reasons for continued reliance on spreadsheets and POS reports.

"The forecasting module is priced in dollars, and every time the cedi falls the renewal becomes harder to justify. Even when we train someone, the banks take him." (Participant A6, store manager, Accra)

5.8 Integration of Quantitative and Qualitative Findings

Table 10 provides a joint display aligning the quantitative results with the corresponding qualitative themes.

Table 10: Joint Display of Quantitative and Qualitative Findings

Capability and decisions	Analytics capability predicted data-informed decision-making ($\beta = .47$, $p < .001$, $R^2 = .38$)	Theme 3: Capability, not data volume, determines use	Convergent: decision quality depends on skills and routines rather than data access alone
Metrics and inventory	Metric use explained 41.6% of variance in stock-turnover efficiency ($F(3, 282) = 66.96$, $p < .001$)	Themes 1 and 2: faster markdowns; fewer stock-outs	Convergent and explanatory: interviews identify markdown timing and replenishment as mechanisms
Extent of adoption	34.3% reported routine predictive analytics	Theme 4: cost and skills constrain progression	Explanatory: interviews account for the low proportion of predictive use
Barriers	Cost and skills gaps ranked highest	Theme 4	Convergent

6. DISCUSSION OF FINDINGS

6.1 Extent of Analytics Adoption and the Predictive Gap

The first finding indicates that predictive analytics is not yet routine in West African formal retail; only about one-third of respondents (34.3%) reported routine use. This result aligns with broader African evidence. Korankye *et al.,*(2026) found that Ghanaian fashion businesses primarily relied on basic social-media analytics, while Osakue *et al.,*(2026) reported that Nigerian food companies valued analytics but encountered cost, skills, and infrastructure barriers that limited implementation. Internationally, Fildes *et al.,*(2022) observed that many retailers continue to forecast using judgement and simple methods, despite evidence that advanced methods can improve accuracy. Rooderkerk *et al.,*(2022) also described a substantial gap between frontier retailers and the majority of the industry.

The predictive gap is significant because the operational benefits examined in this study, such as reduced stock-outs and improved stock-turnover, depend on anticipating demand rather than merely reporting it. Brynjolfsson *et al.,*(2021) found that productivity gains from predictive analytics in United States manufacturing emerged when predictive tools were combined with complementary assets. The current findings suggest that most West African retailers have adopted the descriptive layer of analytics, typically POS reports and spreadsheets, while only a minority have advanced to the predictive layer where greater operational gains are likely. This finding should be interpreted with caution, as "routine use" was self-reported and may have been understood differently by respondents.

6.2 Analytics Capability as a Predictor of Data-Informed Decision-Making

The second finding is that analytics capability significantly predicted data-informed decision-making ($\beta = .47$, $p < .001$), with the model accounting for 38% of the variance. This result supports the capability-based view of analytics value advanced by Gupta and George (2016) and Akter *et al.,*(2016), and it is consistent with Ghasemaghaei *et al.,*(2018), who found a large positive relationship between data analytics competency and decision quality and efficiency. It also aligns with the meta-analytic conclusion of Oesterreich *et al.,*(2022) that human resources, management capability and culture contribute more to business value from analytics than technical factors alone.

The magnitude of the standardised coefficient demonstrates that capability is a substantively important correlate of decision practice in this context. For example, two outlets with access to identical POS data may differ significantly in their use of that data to set prices, reorder stock, or schedule markdowns. Much of this difference appears to be associated with the skills, infrastructure, and managerial support that constitute capability. The qualitative theme that capability, rather than data volume, determines use provides a consistent explanation. This interpretation aligns with Ghasemaghaei *et al.,*(2018), who found that data size did not improve decision efficiency, whereas skills, data quality, and domain knowledge did. The non-significant contribution of top management support, once capability was controlled, is also notable. Given its high correlation with capability (VIF = 2.40), managerial commitment may influence decisions primarily by building capability, a pattern consistent with the mediating role of top management support reported by Maroufkhani *et al.,*(2023).

The importance of structured capability-building is further supported by Uzowuihe *et al.,*(2026), who found in a mixed-methods quasi-experiment with 240 students in Southeast Nigeria that a structured, visually integrated training programme led to significant gains in collaborative problem-solving and decision-making compared to conventional training. Although this study was conducted in educational settings rather than firms, the finding supports the perspective that the method of teaching analytical skills, not merely their inclusion, influences subsequent decision behaviour.

Two qualifications should be noted. First, because the data are cross-sectional and both variables were measured by self-report, the relationship cannot be interpreted as causal. It is plausible that outlets already inclined toward data-informed decision-making invest more in capability, and common method variance may have inflated the association (Podsakoff *et al.,*2003). Second, the finding that capability is significant in West

African retail contrasts with the econometric result of Müller *et al.,*(2018), who observed productivity gains from analytics assets only in IT-intensive or highly competitive industries. One possible reconciliation is that Müller *et al.,* measured asset ownership, whereas this study measured capability. These constructs are not equivalent, and the present results suggest that capability may be a more informative measure in markets where asset ownership is uneven.

6.3 Evaluation Metrics and Stock-Turnover Efficiency

The third finding is that dashboard use, sales-forecast metrics, and a related metric-use variable together accounted for 41.6% of the variance in stock-turnover efficiency ($F(3, 282) = 66.96$, $p < .001$), with dashboards and sales-forecast metrics contributing most substantially. This result aligns with inventory literature, which links turnover to the accuracy of demand expectations (Gaur *et al.,*2005; Kolias *et al.,*2011), and with stock-out literature, which identifies store ordering and replenishment processes as primary causes of unavailability that can be improved through better information (Corsten & Gruen, 2003; Ehrenthal & Stölzle, 2013). It also supports the perspective that dashboards add value when they focus managers on actionable metrics (Pauwels *et al.,*2009; Yigitbasioglu & Velcu, 2012).

The interview findings provide insight into the underlying mechanisms. Participants linked metric review to faster markdown decisions and to replenishment practices that anticipate demand peaks, both of which can enhance turnover. Faster markdowns decrease the duration that slow-moving items occupy shelf space and tie up working capital, while forecast-informed replenishment reduces both stock-outs and excess safety stock. This explanation is consistent with Anderson *et al.,*(2006), who demonstrated that stock-outs diminish future as well as current demand, suggesting that improvements in availability may yield benefits beyond immediate sales.

However, this result should not be interpreted as evidence that dashboards are universally beneficial. Clark (2021) found in an experimental context that tactical dashboards could narrow managerial attention and were associated with lower performance under conditions of high information load. The positive association observed in this study may depend on the relatively focused, operational nature of the metrics involved (sales forecasts, turnover, and sell-through) and their direct relevance to frequent, routine decisions.

6.4 Barriers: Cost and Skills

Cost and skills gaps emerged as the primary barriers to analytics adoption and use. This finding is consistent with Opoku *et al.,*(2024), who recommended training and infrastructure investment for SMEs in Accra and Lagos; with Korankye *et al.,*(2026), who identified limited technical expertise and financial constraints among Ghanaian fashion businesses; and with Osakue *et al.,*(2026), who reported high implementation costs and shortages of skilled personnel in Nigeria's food industry. It also aligns with the TOE literature, where organisational readiness and top management support are repeatedly identified as decisive factors (Maroufkhani *et al.,*2020, 2023; Lutfi *et al.,*2023).

Onyebuchi-Igbokwe (2025) identified a similar combination of opportunity and constraint in the adoption of AI platforms by creative producers in Northwest Nigeria, indicating that these barriers are not unique to retail. The prominence of cost in West Africa likely reflects region-specific conditions. Analytics software is often licensed in foreign currency, so currency depreciation increases its local cost. Skills gaps are exacerbated by competition for analytics talent from banking, telecommunications, and technology firms, which typically offer higher salaries than retailers. Egwuonwu *et al.,*(2024) found that, among Nigerian firms, competitive pressure did not significantly drive BDA adoption, whereas internal readiness did. The present findings support the perspective that internal resource constraints, rather than external pressures, determine the pace of analytics development in the region.

6.5 Analytics Maturity versus Data Availability

The study's principal conclusion is that analytics maturity, rather than simple data availability, distinguishes high-performing retailers. While most outlets in the sample had access to transactional data via POS systems, only a minority routinely employed predictive analytics. The strength of analytics capability was closely linked to the extent of data-informed decision-making. This finding supports the resource-based perspective that commoditised resources, such as software and raw data, are insufficient to differentiate firms, whereas the combination of skills, routines, and managerial commitment that constitutes capability is more difficult to imitate (Barney, 1991; Gupta & George, 2016). Furthermore, the results align with the dynamic capabilities framework, which posits that value is derived from the ability to sense and respond to change, as reflected here in responses to demand shifts indicated by sales and inventory metrics (Teece *et al.,*1997; Wamba *et al.,*2017). The observed significant correlation between analytics maturity and the frequency of data-informed decisions ($r = .53$) directly supports this conclusion.

7. IMPLICATIONS OF THE STUDY

7.1 Theoretical Implications

First, this study extends the Technology-Organization-Environment (TOE) framework beyond adoption to encompass post-adoption use. While much TOE research focuses on whether firms adopt analytics technologies, the present findings demonstrate that the same contextual factors, particularly organisational

capability and resource constraints, also influence whether adopted tools lead to data-informed decisions. Second, the results support integrating the TOE framework with the resource-based view (RBV), as TOE contexts clarify the conditions for capability development, while the RBV explains why capability, rather than mere tool ownership, is linked to outcomes. Third, this study provides evidence from formal retail in West Africa, a context underrepresented in analytics research, and indicates that the capability–decision relationship observed in advanced economies is also present in resource-constrained, high-uncertainty environments.

7.2 Managerial Implications

For retail executives, these results suggest that analytics investments should prioritise personnel development and organisational routines in addition to software acquisition. Providing training for store and category managers in interpreting sell-through, turnover, and forecast-accuracy metrics, as well as instituting regular weekly reviews of these metrics, may yield greater benefits than acquiring advanced tools that staff are not prepared to use. Implementing a concise, standardised set of key performance indicators (KPIs) with uniform definitions across outlets would facilitate consistent store comparisons and mitigate the risk of dashboards serving as mere displays rather than effective decision aids. Low-cost dashboard tools integrated with existing POS data represent a practical starting point for retailers unable to invest in enterprise analytics suites. Similar design initiatives for Nigerian small-scale entrepreneurs in other sectors have highlighted the importance of affordable, locally appropriate systems for adoption (Onyebuchi-Igbokwe *et al.,*2025), and this principle is equally relevant to analytics tools for smaller retail chains.

1.1. *7.3 Policy and Institutional Implications*

For governments, trade associations, and training institutions, the identified skills gaps highlight the need for short, practice-oriented programmes in retail analytics, delivered through polytechnics, universities, and professional bodies. Business education curricula in Nigeria and Ghana could be enhanced by incorporating retail metrics, spreadsheet modelling, and dashboard design. Trade associations could establish shared KPI definitions and benchmarking services, enabling members to compare performance without revealing sensitive data. In cases where analytics software costs are influenced by foreign-currency pricing, supporting local vendors and shared-service models could help reduce expenses for smaller retail chains.

8. Limitations and Suggestions for Further Research

This study has several limitations, presented in order of their practical significance for interpreting the findings. The most critical limitation is that all quantitative variables, including stock-turnover efficiency, were measured via self-report, introducing the potential for common method variance and social desirability bias. Future research should combine survey data with objective operational records, such as inventory turnover ratios and stock-out logs, to improve validity. Another key limitation is the cross-sectional design, which prevents causal inference; longitudinal or quasi-experimental approaches, such as tracking outlets before and after dashboard implementation, would provide stronger evidence regarding causal relationships. Additionally, the use of purposive sampling in only two cities restricts generalisability to other West African cities, smaller towns, and informal retail settings. The study also pooled data from Lagos and Accra; future comparative analyses could examine differences related to currency, regulation, or market structure between these markets. Finally, although the qualitative component included 12 interviews, which was sufficient for identifying major themes, it may not capture the full diversity of practices across all outlet types.

Future research could investigate mediating mechanisms, such as data-driven culture or knowledge sharing, in the relationship between capability and decision-making. Additional studies might examine the moderating effects of firm size and chain structure, explore the adoption of artificial-intelligence-based forecasting among West African retailers, and evaluate the cost-effectiveness of training interventions compared to software investments.

9. CONCLUSION AND RECOMMENDATIONS

9.1 Conclusion

This study investigated the extent to which retail analytics and evaluation metrics influence data-informed decision-making and performance outcomes among supermarkets and chain outlets in Lagos and Accra. The results demonstrate that analytics capability is a significant predictor of data-informed decision-making, and that the use of dashboards, sales-forecast metrics, and related measures is significantly associated with stock-turnover efficiency. Interview participants also attributed metric use to faster markdown decisions and reduced stock-outs. Nevertheless, routine use of predictive analytics was limited to approximately one-third of respondents, with cost and skills gaps identified as primary barriers. The study concludes that analytics maturity, rather than simple data availability, distinguishes high-performing retailers in this context. For West African retailers, improving inventory and pricing decisions depends more on developing the skills, routines, and metric frameworks necessary to utilise existing data than on acquiring additional data.

9.2 Recommendations

Based on the findings, the following recommendations are proposed:

i. Retail firms in West Africa should invest in structured analytics training for store, category, and inventory managers, with an emphasis on

interpreting and utilising sales-forecast, sell-through, stock-turnover, and markdown metrics.

ii. Retail firms should implement standardised KPI frameworks with uniform metric definitions across outlets, reviewed at regular intervals, to ensure that performance comparisons and decisions are based on consistent evidence.

iii. Retailers, especially smaller chains, should adopt low-cost dashboard tools integrated with existing POS and inventory systems as an initial step toward routine predictive analytics.

iv. Retail trade associations in Nigeria and Ghana should establish shared KPI definitions and anonymised benchmarking services for their members.

v. Polytechnics, universities, and professional bodies should integrate practical retail analytics, including spreadsheet modelling and dashboard design, into business education and continuing professional development programmes.

vi. Analytics vendors and policymakers should investigate pricing and shared-service models that alleviate the foreign-currency cost burden of analytics software for West African retailers.

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