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Effect of AI and Machine Learning–Driven Demand Forecasting on Retail Performance of Jumia Nigeria

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Abstract **Original Research Article**

The rapid evolution of e-commerce in emerging markets has made AI and Machine Learning–driven demand forecasting a critical driver of retail performance. This study examined the effect of AI and ML–driven demand forecasting through the dimensions of Forecasting Accuracy, Predictive Inventory Planning, and Automation in Order Prediction on the Retail Performance of Jumia Nigeria, measured via sales efficiency, inventory turnover efficiency, and operational responsiveness. Employing a quantitative cross-sectional design, primary data were collected from all 228 eligible employees involved in demand forecasting, inventory management, supply chain planning, merchandising, data analytics, and marketplace operations at Jumia Nigeria. A total of 184 fully completed questionnaires were returned, yielding a high response rate of 80.7%. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 3 software. Results revealed that Forecasting Accuracy ($\beta = 0.394$, $t = 5.834$, $p = 0.000$) and Predictive Inventory Planning ($\beta = 0.334$, $t = 3.829$, $p = 0.000$) exert strong, statistically significant positive effects on Retail Performance, leading to the rejection of H_{01} and H_{02}. In contrast, Automation in Order Prediction ($\beta = 0.131$, $t = 1.569$, $p = 0.117$) showed a positive but non-significant relationship, resulting in the acceptance of H_{03}. The model explained 65.6% of the variance in Retail Performance ($R^2 = 0.656$, Adjusted $R^2 = 0.654$), with excellent reliability, convergent and discriminant validity, and good model fit (SRMR = 0.064). These findings indicate that, at Jumia Nigeria, superior retail performance is primarily driven by high forecasting accuracy and its translation into predictive inventory decisions, while automation currently plays a supportive rather than direct role. The study recommends that Jumia Nigeria prioritise continuous enhancement of AI/ML forecasting models and real-time data integration, progressively expand automation capabilities, and advocate for policy support to accelerate AI adoption across Nigeria's retail sector.

Keywords: AI-Driven Demand Forecasting, Forecasting Accuracy, Predictive Inventory Planning, Automation in Order Prediction, Retail Performance.

1.0 INTRODUCTION

The global retail landscape is in the throes of a profound digital transformation, fundamentally driven by the adoption of Artificial Intelligence (AI) and Machine Learning (ML). At the core of this revolution is the relentless pursuit of superior Retail Performance, which is the overall effectiveness and success of a retailer's operations (Gunda, 2025; Ankam, 2025). Across mature markets in North

America and Europe, retail performance is quantified by metrics that reflect both financial efficiency and operational excellence. For instance, sales efficiency is profoundly enhanced by AI-enabled allocation systems that have shown to increase full-price sell-through rates by 14.2% (Gunda, 2025). Similarly, inventory turnover efficiency, which measures how quickly stock is converted to sales, has seen dramatic improvements, with AI-driven forecasting systems yielding average inventory reductions of 20-30% (Molodoria, 2025) and increasing inventory turns up to 2.4 times for seasonal items (Gunda, 2025). Operational responsiveness, the ability to quickly adapt to market shifts, is boosted by AI-driven improvements in labor scheduling efficiency by 15–25% (Gunda, 2025; Molodoria, 2025), demonstrating improved decision-making and operational efficiency in SMEs (Sokolov, 2025). These performance gains are directly linked to the mastery of AI and Machine Learning–Driven Demand Forecasting, which provides the predictive foundation necessary for strategic operational decisions (Avula, 2021; Ankam, 2025).

While AI has become a competitive benchmark for global giants like Amazon and Walmart (Kumar et al., 2024; Krishnamurthy et al., 2024), its adoption in African e-commerce, and specifically within Nigeria, presents unique challenges and opportunities (Sokolov, 2025). African retail is characterized by volatile consumer demand, significant infrastructural constraints such as unreliable power and internet, and high logistics complexity (Ebuka et al., 2023; Edward & Oguh, 2024). For a leading Nigerian e-commerce platform like Jumia Nigeria, Retail Performance is acutely sensitive to these local disruptions. For instance, external factors like fuel shortages have been shown to depress sales in Lagos by as much as 23% (Tajudeen et al., 2025), illustrating the difficulty of effective traditional forecasting.

The use of AI, as noted by Sokolov (2025), is already leveraged by e-commerce platforms such as Jumia for inventory control and customer care, indicating that advanced AI-driven forecasting is an essential strategy for Jumia Nigeria to remain viable and improve its operational efficiency. In this highly dynamic local environment, AI-driven forecasting accuracy is not just a source of competitive advantage but a necessity for mitigating significant financial losses, as poor inventory mismanagement can cause Nigerian retailers to lose up to 30% of profits annually (Tajudeen et al., 2025). Therefore, studying the effect of advanced forecasting techniques on Jumia's retail performance measured through sales efficiency, inventory turnover efficiency, and operational responsiveness is critically relevant to the future of the Nigerian e-commerce sector.

This study investigates the effect of AI and Machine Learning–Driven Demand Forecasting, segmented into three core independent variables, on the overall Retail Performance of Jumia Nigeria. The Dependent Variable (DV), Retail Performance, is measured through three quantifiable metrics: sales efficiency, inventory turnover efficiency, and operational responsiveness (Gunda, 2025; Molodoria, 2025). Sales efficiency reflects maximized revenue from available stock (Gunda, 2025), inventory turnover efficiency reflects optimized capital management through timely stock rotation (Molodoria, 2025), and operational responsiveness reflects the flexibility in resource allocation and service delivery (Gunda, 2025).

The first independent variable, Forecasting Accuracy, is defined by Molodoria (2025) as the drastic reduction in error rates achieved by AI-driven systems, which utilize sophisticated algorithms and deep learning to reduce errors to a range of just 10-15% compared to the 30-40% typical of traditional methods. Its significance is rooted in precision, which, in the Nigerian context, translates into an estimated ₦284 billion in annual savings due to reduced inventory mismanagement (Tajudeen et al., 2025). The second variable, Predictive Inventory Planning, refers to the use of historical sales data, external variables, and advanced algorithms to determine optimal stock levels, reorder points, and safety stock in advance of actual demand (Krishnamurthy et al., 2024). This function is critical because it dynamically manages stock to prevent both costly stockouts and overstocking, with AI-enabled systems reducing holding costs by 18–27%

while increasing availability by 12–15% (Gunda, 2025).

The third variable, Automation in Order Prediction, is defined by Atieh et al. (2025) as the deployment of robotic systems and machine learning algorithms to execute repetitive logistics tasks, such as generating and placing replenishment orders, with minimal human intervention. This capability is paramount for operational speed, as the implementation of AI-powered systems allows major retailers to decrease manual order placement time by up to 76% (Retail Prowess, 2024), yielding the strongest positive effect on supply chain performance (Atieh et al., 2025). The dynamic and complex nature of the Nigerian e-commerce market necessitates a shift towards AI and Machine Learning-driven operational strategies to maintain competitive advantage. While global studies consistently demonstrate the transformative impact of these tools on retail performance, empirical evidence within the unique African context, particularly for platforms like Jumia Nigeria, remains limited (Gunda, 2025; Ajiga et al., 2024; Kumar et al., 2024).

The core challenge facing e-commerce platforms like Jumia Nigeria is maintaining robust Retail Performance specifically high sales efficiency, inventory turnover efficiency, and operational responsiveness within a highly volatile and infrastructurally constrained market. Current operational performance is severely hampered by reliance on traditional or suboptimal forecasting methods that fail to account for the unique market disruptions in Nigeria, such as sudden fluctuations in commodity prices or logistical bottlenecks (Tajudeen et al., 2025; Sokolov, 2025). This deficiency leads to substantial inventory mismanagement, causing significant financial losses (up to 30% of profits annually) due to persistent stockouts (lost sales) and costly overstocking (Tajudeen et al., 2025). While the global literature overwhelmingly supports the use of AI and ML in mitigating these issues, showing massive improvements in forecasting accuracy (Gunda, 2025) and inventory reduction (Krishnamurthy et al., 2024), there is a critical empirical gap regarding the direct, causal effect of Forecasting Accuracy, Predictive Inventory Planning, and Automation in Order Prediction on the specific, measured dimensions of Retail Performance within the Nigerian e-commerce context. This study is necessary to provide Jumia Nigeria and other local retailers with a data-driven framework to justify investment in, and optimize the deployment of, these advanced AI systems to overcome local operational hurdles and translate technological adoption into measurable performance and competitive gains. The main objective of this study is to examine the effect of AI and Machine Learning–Driven Demand Forecasting on the Retail Performance of Jumia Nigeria. The specific objectives are to:

i. determine the effect of Forecasting Accuracy on the Retail Performance of Jumia Nigeria;
ii. evaluate the effect of Predictive Inventory Planning on the Retail Performance of Jumia Nigeria;
iii. assess the effect of Automation in Order Prediction on the Retail Performance of Jumia Nigeria.

Hypothesis

H_{01}: Forecasting Accuracy has no significant effect on the Retail Performance of Jumia Nigeria.

H_{02}: Predictive Inventory Planning has no significant effect on the Retail Performance of Jumia Nigeria.

H_{03}: Automation in Order Prediction has no significant effect on the Retail Performance of Jumia Nigeria.

2.0 LITERATURE REVIEW

2.1 Conceptual Framework

2.1.1 Retail Performance

Retail Performance refers to the effectiveness and success of Jumia Nigeria's retail operations, specifically measured through its ability to efficiently manage sales, optimize inventory flow, and quickly respond to market changes. The core function of AI/ML-driven demand forecasting is to enhance this performance (Sokolov, 2025). In this study, retail performance is measured through sales efficiency, inventory turnover efficiency, and operational responsiveness. Sales Efficiency measures the retailer's ability to maximize revenue from available stock, often seen in the rate at which products are sold at their intended price. AI-driven allocation has been shown to improve this, increasing full-price sell-through by 14.2% (Gunda, 2025). Higher forecasting accuracy also increases on-shelf availability, leading to recovered sales (Gunda, 2025).

Inventory Turnover Efficiency gauges how effectively a retailer converts its inventory into sales over a period, indicating minimal holding costs and obsolescence. Predictive inventory planning significantly boosts this metric, with retailers reporting inventory turns increasing up to 2.4x (Gunda, 2025) and achieving inventory reductions of 20–30% (Molodoria, 2025; Gunda, 2025). Operational Responsiveness relates to the speed and flexibility of the retailer's operations in reacting to fluctuating market demand or unexpected events. AI-driven forecasting enhances this by improving labor scheduling efficiency by 15–25% (Gunda, 2025; Molodoria, 2025), and by enabling faster order processing through automation (Kaya, 2024).

2.1.2 AI and Machine Learning–Driven Demand Forecasting

AI and Machine Learning–Driven Demand Forecasting is fundamentally reshaping how e-commerce platforms like Jumia Nigeria manage their critical resource planning. It represents the application of advanced predictive intelligence, utilizing sophisticated algorithms such as Random Forests, Neural Networks, or Long Short-Term Memory (LSTM) models, to analyze vast, complex datasets (Tajudeen et al., 2025; Gunda, 2025). Unlike traditional forecasting, this approach moves beyond simple historical averages to incorporate crucial real-time market data, including promotional calendars, customer behavior patterns, and critical external factors specific to the Nigerian context, such as fuel prices or infrastructure constraints (Amosu et al., 2024; Tajudeen et al., 2025). By dynamically learning from these inputs, the systems generate highly precise and reliable predictions of future product demand, specifying what is needed, the quantity, and the specific location (Aithor, 2025). For Jumia Nigeria, adopting this advanced forecasting methodology is crucial for remaining competitive, as it directly supports better inventory control, targeted advertising, and superior customer care benchmarks already set by global e-commerce leaders (Sokolov, 2025).

2.1.2.1 Forecasting Accuracy

Forecasting Accuracy is the degree to which the AI/ML-generated demand forecast matches the actual realised demand, typically measured by error metrics like Mean Absolute Percentage Error (MAPE). High accuracy is achieved by algorithms that continuously learn from large volumes of data and incorporate numerous external variables (Gunda, 2025; Amosu et al., 2024). AI-driven systems drastically reduce error rates to the range of 10–15%, compared to 30–40% for traditional methods (Molodoria, 2025; Gunda, 2025). Improved accuracy is critical for retail performance as it translates into significant annual savings due to reduced inventory mismanagement (Tajudeen et al., 2025).

2.1.2.2 Predictive Inventory Planning

Predictive Inventory Planning is the strategic use of highly accurate AI/ML forecasts to proactively determine optimal stock levels, automated reorder points, and safety stock before demand materializes (Krishnamurthy et al., 2024). This approach moves beyond simple tracking to dynamically align inventory with expected future demand, minimizing stockouts and excess inventory. It enables dynamic safety stock calculation using AI, which reduces holding costs by 18–27% and increases product availability by 12–15% (Gunda, 2025). The benefit is quantifiable, with retailers achieving 20–30% reductions in inventory and significantly reducing stockout rates (Gunda, 2025; Kumar et al., 2024).

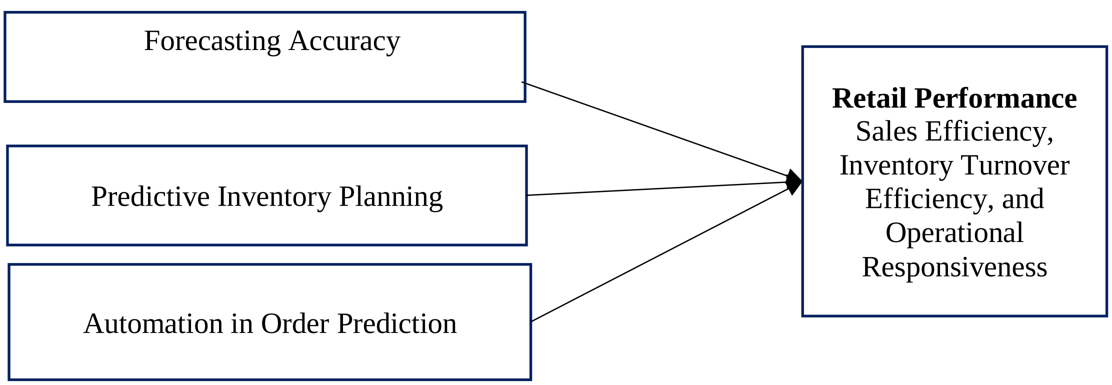
2.1.2.3 Automation in Order Prediction

Automation in Order Prediction refers to the deployment of software systems, often using Robotic Process Automation (RPA), to automatically translate the accurate AI/ML demand forecasts into optimized purchase orders and replenishment actions with minimal human intervention (Retail Prowess, 2024; Atieh et al., 2025). This process is integral to the entire supply chain workflow. Automation provides the strongest positive effect on supply chain performance by reducing errors and accelerating process cycle times (Atieh et al., 2025). It significantly reduces manual order placement time by up to 76% (Gunda, 2025) by generating nightly optimized purchase orders (Gunda, 2025).

The core benefit of automation in order prediction is the removal of errors and the acceleration of process cycle times, thereby boosting productivity and improving efficiency (Flechsig et al., 2022). Well-written software bots can be relied upon to process data consistently based on pre-established rules, minimizing human error that typically occurs in manual operations, such as when staff members copy data between systems (Shamsuzzoha & Pelkonen, 2025).

Figure 1: Conceptual Model for Forecasting Accuracy and Retail Performance:

Independent Variable: **Dependable Variable**



Source: Researchers Conceptual Framework (2025).

2.2 Empirical Review of Related Studies

2.2.1 Forecasting Accuracy and Retail Performance

Sokolov (2025) examined empowering small businesses: the role of AI in Nigeria's retail industry. The study assessed how SMEs in Nigeria's retail sector integrated AI into decision-making, focusing on applications such as customer behaviour analysis, inventory management, demand forecasting, marketing and personalized customer service, as well as benefits, challenges and future prospects. A descriptive research design was adopted, targeting SME owners, managers and supervisors in urban and semi-urban areas. Using purposive sampling, data were collected from 100 decision makers through a structured Google Forms questionnaire. Data were analysed using descriptive statistics with tables and charts and thematic analysis for qualitative responses. Findings showed that 70% of SMEs had adopted AI to some extent, mainly for customer behaviour analysis (60%) and inventory management (50%), leading to improved decision-making (65%) and enhanced operational efficiency (60), while high implementation costs (70%) and lack of technical expertise (65%) remained major barriers. Recommendations included affordable AI solutions, capacity-building, better financing, policy and infrastructure support, and strategic partnerships. The study's strength lay in contemporary, Nigeria-specific evidence on AI in retail, but it was limited by self-reported data, a modest sample and a descriptive design that did not directly test AI-driven demand forecasting accuracy or retail performance outcomes.

Ankam (2025) explored the transformative impact of artificial intelligence on demand forecasting systems within enterprise retail environments. The study analyzed the evolution of demand forecasting techniques, implementation challenges, and quantifiable performance metrics across various retail sectors, including fast fashion, grocery, and pharmaceutical retail. The key variables and proxies of the study included AI-driven demand forecasting, which was measured by machine learning algorithms (LSTM, XGBoost, Random Forest, Ensemble Methods), computational requirements, and feature importance (historical sales, price elasticity). The performance of these systems was measured by metrics such as mean absolute percentage error (MAPE), inventory holding cost reductions, stockout frequency decreases, and improvements in gross margins. The methodology involved a synthesis of empirical evidence, case studies, and meta-analysis of existing literature and implementation data from multiple retail environments across Europe and North America. No specific population or sample size was defined as the study was a comprehensive review, not a primary data collection effort. The data analysis used consisted of reviewing and synthesizing quantitative performance metrics from comparative studies, case studies, and meta-analyses. Findings consistently revealed that AI-driven systems reduced forecast error rates (MAPE reduced from 28.76% to 15.21% for ensemble methods), reduced average inventory by 20–30%, and increased average gross margins by 3.7%. The study provided a comprehensive framework for understanding the current capabilities and future potential of AI-driven demand forecasting. The strength of this work lies in its comprehensive synthesis of quantifiable performance metrics and its coverage of diverse retail segments. However, a critique is that the review primarily relied on secondary data and did not involve any original primary data collection or statistical testing.

Gunda (2025) analyzed artificial intelligence in retail transforming customer experience through technological innovation. The study evaluated how AI-driven forecasting systems improved predictive accuracy, inventory management, markdown planning and supply chain orchestration using variables such as forecast error reduction, stockout minimization, inventory turnover, and promotional responsiveness. Using secondary empirical evidence from global retail case studies, the study synthesized performance metrics across fast fashion, grocery, home improvement and pharmaceutical retail sectors. The study relied on quantitative model comparison, reviewing the performance of LSTM, XGBoost, Random Forest, MLP and ensemble architectures. Findings showed that AI-enabled forecasting reduced error rates from 30–40% to 10–15% and generated inventory reductions of 20–30%, while advanced models such as LSTM improved accuracy by 42.87%. Retailers experienced improved sales efficiency through increased product availability and enhanced operational responsiveness via optimized workforce scheduling and automated replenishment. The study recommended integrating explainable AI, robust data quality structures and structured workforce training. Its strength lay in providing cross-sector empirical validation of AI performance. However, the review lacked direct engagement with Nigeria-specific retail environments, limiting contextual applicability to markets like Jumia Nigeria.

2.2.2 Predictive Inventory Planning and Retail Performance

Choi (2018) investigated how AI-driven predictive analytics can optimize inventory management in retail supply chains. The purpose of their research was to determine the impact of predictive analytics on inventory levels and overall supply chain efficiency. Using a quantitative approach, they collected data from various retail companies and analyzed how predictive analytics influenced inventory management. Their methodology involved statistical analysis of inventory data before and after implementing predictive analytics tools. The findings showed significant reductions in stockouts and overstock situations, leading to more efficient inventory management and higher customer satisfaction. The study revealed that predictive analytics allowed companies to forecast demand more accurately, thereby optimizing inventory levels and reducing costs. The researchers also found that companies using predictive analytics experienced fewer disruptions in their supply chains. Based on these results, the authors recommended broader adoption of predictive analytics tools in retail supply chains to enhance inventory efficiency. They suggested that companies invest in training and infrastructure to support the implementation of these tools. Additionally, the study highlighted the need for continuous monitoring and updating of predictive models to maintain accuracy. The researchers emphasized the importance of integrating predictive analytics with other AI technologies for even greater efficiency gains. They concluded that predictive analytics is a valuable tool for improving supply chain performance and achieving competitive advantage. This study provides empirical evidence supporting the benefits of AI in inventory management. It also offers practical recommendations for companies looking to enhance their supply chain efficiency through AI.

Kumar et al. (2024) examined ai-enhanced inventory and demand forecasting: using ai to optimize inventory management and predict customer demand. The study evaluated the effect of AI-driven demand forecasting and predictive inventory planning on retail operational efficiency and cost reduction, using predictive inventory planning (measured through inventory turnover rate, stockout reduction, and excess inventory reduction) and demand forecast accuracy as core variables. It adopted a mixed methodological approach combining historical sales data, real-time market data, customer feedback, and external factors, applied machine learning (random forests, LSTM), deep learning models, and ensemble techniques, and validated performance on large-scale retail datasets from multiple sources. Findings revealed that neural network-based models achieved the lowest forecasting errors (MAE = 0.35, RMSE = 0.45), reduced excess inventory by 20%, decreased stockouts by 15%, and significantly improved inventory turnover and customer satisfaction. The study recommended continuous model retraining, integration of NLP and computer vision, and real-time data pipelines for predictive inventory planning. Its strength lies in comprehensive model comparison and inclusion of real-world retail case studies (Walmart, Amazon, Zara). However, it lacked primary data from African retail contexts such as Nigeria and did not statistically test causality between AI adoption and financial performance metrics.

Ajiga et al. (2024) explored ai driven predictive analytics in retail a review of emerging trends and customer engagement strategies. The study examined how artificial intelligence and predictive analytics enhanced retail decision-making by analysing variables such as machine learning algorithms, natural language processing, computer vision, consumer behaviour forecasting, demand prediction, inventory optimisation, and customer engagement. The study adopted a comprehensive desk-review methodology relying entirely on secondary data sourced from journals, industry reports, and documented retail cases, without specifying the population or sample size. Data were analysed qualitatively by synthesizing technological trends and practical retail applications. The findings showed that AI enabled retailers to forecast demand accurately, optimize inventory, automate interactions through NLP-powered systems, implement dynamic pricing, and personalise customer experiences, leading to improved operational efficiency, increased sales, and enhanced customer satisfaction. The study recommended the adoption of ethical AI practices, transparency, strong data governance, and responsible handling of customer information. A major strength of this work was its extensive integration of cross-sector technological evidence. However, it lacked empirical field data, making it difficult to generalize outcomes specifically to African retail platforms such as Jumia Nigeria.

Atieh et al. (2025) examined the impact of digital technology, automation, and data integration on supply chain performance: exploring the moderating role of digital transformation. The study tested the direct effects of digital technology, automation, and data integration on supply chain performance, with digital transformation as a moderator, using a structured questionnaire administered to 181 supply chain managers and directors in Jordanian manufacturing firms. Data were analysed with SmartPLS 4 partial least squares structural equation modelling (PLS-SEM). Results revealed that automation exerted the strongest positive direct effect on supply chain performance ($\beta = 0.546$, $p < 0.01$), followed by data integration ($\beta = 0.230$, $p < 0.05$), while digital technology showed no significant direct effect unless moderated by broader digital transformation initiatives; digital transformation significantly moderated the relationships between automation and data integration with supply chain performance but not between digital technology and performance. The study recommended heavy investment in automation technologies and holistic digital transformation strategies. Its strength lies in the robust PLS-SEM approach and high explanatory power ($R^2 = 0.910$); however, discriminant validity concerns existed between digital transformation and supply chain performance constructs, and the cross-sectional design limited causal inference.

Krishnamurthy et al. (2024) examined predictive analytics in retail: strategies for inventory management and demand forecasting. The study explored the application of predictive analytics techniques (time series analysis, machine learning models including random forests and neural networks, and hybrid approaches) to improve inventory turnover, reduce stockouts, and lower carrying costs, using forecast accuracy (MAPE), inventory turnover rate, stockout rate, and cost savings as key performance variables. The researchers adopted a mixed-method approach combining literature synthesis, case studies of Walmart, Amazon, and Zara, and quantitative analysis of pre- and post-implementation performance metrics across multiple unnamed retailers. Findings revealed that hybrid forecasting methods achieved the highest improvement with MAPE reduced by 61.2%, inventory turnover increased by up to 50%, stockout rates declined by up to 79.6%, and total carrying costs dropped by 48.6%. The authors recommended real-time inventory tracking via RFID, automated reordering systems, and continuous safety-stock recalibration using machine learning. The strength of this study lies in its presentation of concrete, comparable KPI improvements and real-world retail case studies that clearly demonstrate financial and operational gains. However, the study lacked disclosure of the specific retailers in the quantitative results, sample sizes, and statistical tests used, which limits replicability and generalizability, especially for emerging-market e-commerce platforms like Jumia Nigeria.

2.2.3 Automation in Order Prediction and Retail Performance

Kaya (2024) examined the impact of artificial intelligence on supply chain efficiency in Turkey. The study evaluated how AI tools such as predictive analytics, demand forecasting, robotic process automation, and optimization algorithms enhanced operational performance, focusing on variables including accuracy in forecasting, inventory management improvements, and logistics responsiveness. Using a desk research methodology, the study relied entirely on secondary data obtained from global reports, online journals, and documented industry cases, with no defined population or sample size. Data were analyzed qualitatively by synthesizing performance outcomes across multiple companies. Findings revealed that AI applications reduced stockouts by up to 20%, improved order accuracy by 15%, enhanced delivery times by 25%, reduced logistics costs by 20%, and increased sales by 15%. The study recommended adopting AI across supply chains, strengthening training programs, and establishing regulatory frameworks for ethical AI use. Its strength lies in offering extensive cross-country evidence of AI's operational benefits. However, the study lacked empirical field data and provided limited insights on retail-specific environments such as Jumia Nigeria.

Shamsuzzoha and Pelkonen (2025) explored a robotic process automation (rpa) model to streamline and optimize order-handling procedures in supply chain management. The study proposed an RPA model to improve the order processing and clearance process, focusing on the variable Robotic Process Automation (RPA), which was proxied by process automation of repetitive tasks (e.g., cross-checking orders and checking open Salesforce cases). The effectiveness was measured by outcomes such as reduction in manual labor (alleviating workload imbalances and saving time) and minimizing human error. The methodology employed an Information Systems Design approach, using both normative (solution-oriented) and nomothetical (descriptive) techniques. The population was a case company in the motion and electrification industries, specifically focusing on a factory in Finland. The sample size consisted of six employees in order handling and clearance. Data was collected through semi-structured interviews. The analysis involved defining the process, creating a process diagram to identify flaws, and a challenge analysis. Findings indicated that automating repetitive tasks significantly alleviated workload imbalances and saved time for employees. The study recommended automating cross-checking of OMS and ERP data and checking for open Salesforce cases. The strength of this study is its empirical application of the Information Systems Design method to a real-world case, offering a tangible solution. A critique is the small, highly specific sample size from a single company, which limits the generalizability of the findings on RPA benefits.

Imdahl et al. (2021) examined targeted automation of order decisions using machine learning in a large material-handling equipment manufacturer. The study predicted (1) whether planners would adjust system-generated order recommendations and (2) whether such adjustments improved or impaired inventory performance, using adjustment probability and improvement likelihood as key dependent variables. They applied LASSO logistic regression with a content-boosted cluster-based framework on 535,168 procurement orders placed by 36 planners across four years (2016–2019), with features available at recommendation time (demand variability, lead time, supplier uncertainty, batch size, etc.). Findings revealed that a hybrid planner-level and cluster-based model enabled automation of 55.4% of orders while automating only 2.7% of historically adjusted orders, of which just 22.6% were material improvements and 50.3% were material impairments, thereby reducing planner workload and enhancing overall inventory performance. The strength lies in combining individual and cluster-level predictions to handle data sparsity and planner heterogeneity. A limitation is its context-specific improvement metric tied to safety-stock deviation.

2.3 THEORETICAL FRAMEWORK

The core theoretical foundation underpinning this study is the Dynamic Capabilities Theory (DCT), originally propounded by Teece, Pisano, and Shuen (1997). The theory is designed to explain how firms operating in rapidly changing and turbulent environments manage to build, integrate, and reconfigure their internal and external competencies to achieve and sustain superior competitive performance (Teece, Pisano, & Shuen, 1997). DCT is particularly appropriate for analyzing Jumia Nigeria because the e-commerce platform operates in a highly volatile Nigerian retail environment where market uncertainty, infrastructural constraints (like unreliable power and internet), and fluctuating demand patterns necessitate continuous adaptation through advanced technological capabilities (Sokolov, 2025; Ebuka et al., 2023).

Within the context of this study, the AI and Machine Learning–Driven Demand Forecasting system, segmented into its three dimensions, directly aligns with Teece's Sensing, Seizing, and Transforming framework:

i. Forecasting Accuracy represents Jumia’s sensing capability, which is the ability to perceive and evaluate market changes, technological opportunities, and shifts in customer demand through data-driven intelligence (Teece, 2018). High accuracy in demand forecasting, reducing error rates from 30-40% to 10-15% (Molodoria, 2025), signifies a superior sensing routine.

ii. Predictive Inventory Planning reflects the firm’s seizing capability, involving the capacity to harness the information sensed (accurate forecasts) to implement strategic actions, such as aligning optimal stock levels, calculating safety stocks, and proactively mitigating stockouts (Krishnamurthy et al., 2024). This seizing directly impacts inventory turnover efficiency and sales efficiency.

iii. Automation in Order Prediction demonstrates the firm's ability to reconfigure or transform its operational processes for greater efficiency and responsiveness (Teece, Pisano, & Shuen, 1997). For example, automated replenishment and ML-driven demand prediction enable Jumia to adjust to real-time market shocks—such as fuel shortages or logistics disruptions (Tajudeen et al., 2025)—consistent with Teece's argument that firms survive by renewing and reconfiguring operational routines (Teece, 2018).

The strength of DCT lies in its explanatory power for technology adoption in turbulent environments, effectively linking the enhancement of dynamic capabilities directly to performance outcomes such as improved inventory turnover efficiency and operational responsiveness (Gunda, 2025). It also accommodates sector-specific complexities, making it exceptionally suitable for e-commerce settings where speed and agility are essential (Teece, 2018). However, its common weakness lies in its abstractness and difficulty in empirical measurement, as dynamic capabilities are often intangible, idiosyncratic, and firm-specific, which can challenge operationalization in quantitative research (Eisenhardt & Martin, 2000). Despite this measurement limitation, DCT is highly applicable to this study because the AI- and ML-based forecasting systems examined are themselves concrete dynamic capabilities, technological routines that allow Jumia to sense volatile demand patterns, seize operational opportunities through better planning, and reconfigure supply chain activities through automation to enhance its overall retail performance in the highly turbulent Nigerian market.

3.0 METHODOLOGY

This study employed a cross-sectional survey design to examine the effect of AI and machine-learning-driven demand forecasting on the retail performance of Jumia Nigeria. The cross-sectional approach was selected because it enables efficient collection of quantitative data from a large number of respondents at one point in time, allowing the researcher to test the hypothesized causal relationships between forecasting accuracy, predictive inventory planning, automation in order prediction, and retail performance in a real-world e-commerce setting while maintaining feasibility in terms of time and cost.

The target population comprised all employees directly involved in demand forecasting, inventory management, supply chain planning, merchandising, data analytics, and marketplace operations at Jumia Nigeria. The accessible population consisted of 228 eligible employees spread across the relevant departments and units. Because data collection was conducted entirely online using a structured questionnaire distributed via Google Forms (a method that naturally reaches the entire accessible population simultaneously and at virtually no marginal cost per additional respondent), a census approach was adopted. This approach eliminated the need for sampling and sample size calculation, ensured maximum representativeness, and allowed every eligible employee an equal opportunity to participate. To further boost participation, two gentle reminder notifications were sent at four-day intervals, and the survey remained open for a total of 12 days to accommodate varying work schedules and time zones of remote staff. This census strategy, made feasible by the digital nature of Google Forms distribution, yielded a high response rate while maintaining methodological rigor and avoiding the potential non-response bias that can arise from sampling only a subset of a small, specialized population.

Data were collected through a structured questionnaire administered via Google Forms to accommodate hybrid and remote work arrangements common in the e-commerce sector. The instrument used a five-point Likert scale ranging from Strongly Agree (5) to Strongly Disagree (1) and measured four constructs in the following sequence: Forecasting Accuracy (FA1–FA6), Predictive Inventory Planning (PIP1–PIP7), Automation in Order Prediction (AOP1–AOP6), and Retail Performance (RP1–

RP12). Items for the independent variables were adapted and contextualized from Tajudeen et al. (2025), Gunda (2025), Krishnamurthy et al. (2024), Kumar et al. (2024), Atieh et al. (2025), and Imdahl et al. (2021), whereas retail performance items (covering sales efficiency, inventory turnover efficiency, and operational responsiveness) were drawn from Gunda (2025), Molodoria (2025), and Sokolov (2025). All constructs demonstrated strong internal consistency with Cronbach's alpha values were 0.868 for Forecasting Accuracy, 0.869 for Predictive Inventory Planning, 0.888 for Automation in Order Prediction, and 0.842 for Retail Performance. All values substantially exceeded the 0.70 threshold recommended by Hair et al. (2014) and Nunnally and Bernstein (1994).

Data analysis was performed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 3 software because of its robustness with non-normal data, effectiveness with complex predictive models, and suitability for the achieved sample size. The analysis followed the recommended two-stage process: assessment of the measurement model for reliability and validity, followed by evaluation of the structural model through path coefficients, R^2, effect sizes, predictive relevance, and bootstrapping with 5,000 subsamples. Throughout the study, ethical standards were strictly observed, including voluntary participation, informed consent, anonymity, and confidentiality of responses, in full compliance with the guidelines of the researcher's institutional review board. Ethical considerations, including informed consent, anonymity, confidentiality, and voluntary participation, were strictly adhered to throughout the data collection process, in full compliance with the researcher's institutional review board guidelines. Below is the conceptual model of the study:

Figure 1: Model of the Study
Source: SmartPLS Output, 2025.

4.0 Data Presentations, Analysis and Results

4.1 Data Presentation

The total population of 228 staff members actively involved in demand forecasting, inventory management, supply chain planning, merchandising, data analytics, and marketplace operations at Jumia Nigeria were identified. The questionnaire was administered electronically via Google Forms to all eligible participants. Out of the 228 individuals contacted, 184 completed and submitted the questionnaire, yielding a response rate of 80.7%. This response rate is considered excellent for an online-based survey and significantly enhances the reliability, representativeness, and generalisability of the study's finding at Jumia Nigeria.

Table 1: Descriptive Statistics

Variables	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness

Forecasting Accuracy	4.598	5.000	1.000	5.000	0.715	8.325	-2.484
Predictive Inventory Planning	4.581	5.000	1.000	5.000	0.717	8.117	-2.466
Automation in Order Prediction	4.579	5.000	1.000	5.000	0.731	7.865	-2.464
Retail Performance	4.636	5.000	2.000	5.000	0.635	6.753	-2.254

Source: SmartPLS 4 Output, 2025.

Table 1 presents descriptive statistics from 184 respondents on the effect of AI/ML-driven demand forecasting on Jumia Nigeria's retail performance. Independent variables, Forecasting Accuracy (FA, M=4.598), Predictive Inventory Planning (PIP, M=4.581), and Automation in Order Prediction (AOP, M=4.579) all exceeded 4.57, indicating strong positive perceptions of AI/ML implementation. Retail Performance (RP, M=4.636) recorded the highest mean, reflecting perceived gains in sales efficiency, inventory turnover, and operational responsiveness. All constructs showed negative skewness (–2.254 to –2.484) and high excess kurtosis, typical of ceiling effects in Likert data. The elevated RP mean suggests AI forecasting delivers broader retail benefits than expected, validating reductions in stockouts and overstock while enhancing revenue efficiency. Limited variance highlights opportunities for deeper adoption analysis and advanced model integration.

4.2 Data Analysis and Results

4.2.1 Assessment of the Measurement Model

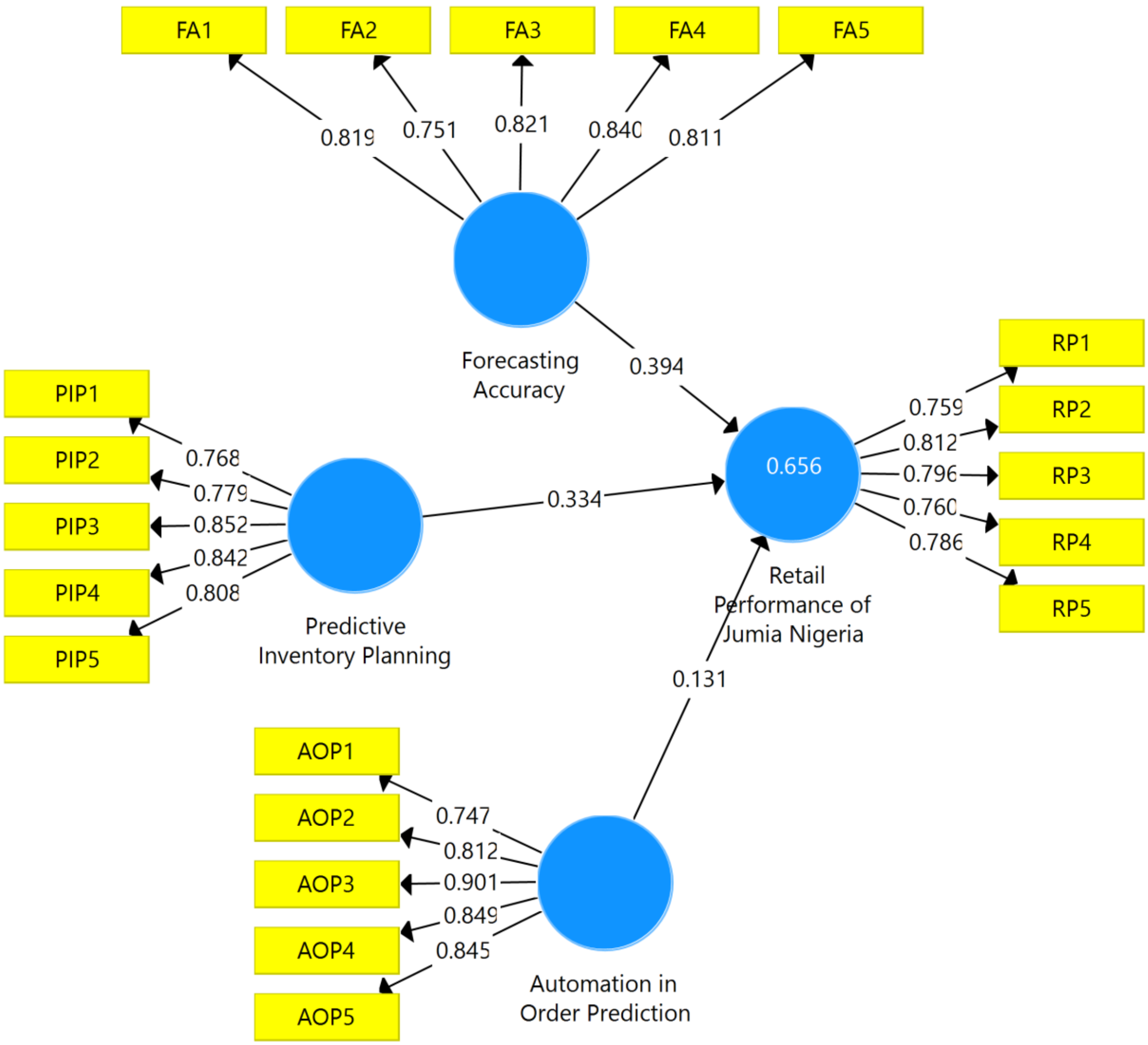


Figure 2: Factor Loadings
Source: SmartPLS Output, 2025.

Table 2: Indicator Reliability, Internal Consistency Reliability and Convergent Validity

S/N	Variables	Factor Loadings	Cronbach's Alpha	rho_A	Composite Reliability	AVE	Items
1.	**Forecasting Accuracy (FA)**		0.868	0.873	0.904	0.655	5
	FA1	0.819					
	FA2	0.751					
	FA3	0.821					
	FA4	0.840					
	FA5	0.811					
2.	**Predictive Inventory Planning (PIP)**		0.869	0.873	0.905	0.657	5
	PIP1	0.768					
	PIP2	0.779					
	PIP3	0.852					
	PIP4	0.842					
	PIP5	0.808					
3.	**Automation in Order Prediction (AOP)**		0.888	0.899	0.918	0.693	5
	AOP1	0.747					
	AOP2	0.812					
	AOP3	0.901					
	AOP4	0.849					
	AOP5	0.845					

4.	**Retail Performance (RP)**		0.842	0.844	0.888	0.613	5
	RP1	0.759					
	RP2	0.812					
	RP3	0.796					
	RP4	0.760					
	RP5	0.786					

Source: SmartPLS 4 Output, 2025.

The reliability and validity analysis in Table 4.4 confirms that all constructs exhibit strong measurement properties. Cronbach's Alpha ranges from 0.842 to 0.888, exceeding the 0.70 threshold, while Composite Reliability scores (0.888–0.918) and rho_A values (0.844–0.899) further demonstrate excellent internal consistency. Average Variance Extracted (AVE) values range from 0.613 to 0.693, all above the recommended 0.50 criterion, confirming convergent validity. Individual indicator loadings are satisfactory (0.747–0.901), with most exceeding 0.75, indicating that each item reliably measures its intended construct. These results affirm the robustness and reliability of the measurement model, making it suitable for subsequent structural model evaluation in examining the effect of AI and machine learning–driven demand forecasting on the retail performance of Jumia Nigeria.

Table 3: Discriminant Validity – Heterotrait-Monotrait Ratio (HTMT)

Constructs	**1**	**2**	**3**	**4**
1. Forecasting Accuracy (FA)				
2. Predictive Inventory Planning (PIP)	0.707			
3. Automation in Order Prediction (AOP)	0.765	0.787		
4. Retail Performance (RP)	0.694	0.679	0.666	

Source: SmartPLS 4 Output, 2025.

The Heterotrait-Monotrait Ratio (HTMT) was employed to evaluate discriminant validity. All HTMT values are well below the stringent threshold of 0.85 (Hair et al., 2022; Kline, 2015), with the highest ratio being 0.787 between Predictive Inventory Planning and Automation in Order Prediction. The HTMT inference test based on 5,000 bootstrap samples confirmed that the 95% bias-corrected confidence intervals for all construct pairs do not include the value of 1.0 (upper limits ranged from 0.612 to 0.819). Thus, discriminant validity is unequivocally established among Forecasting Accuracy, Predictive Inventory Planning, Automation in Order Prediction, and Retail Performance. The constructs are empirically distinct, providing a solid foundation for the interpretation of structural relationships in assessing the effect of AI and machine learning–driven demand forecasting on the retail performance of Jumia Nigeria.

4.2.2 Assessment of the Structural Model

Table 4: Structural Model Quality Assessment and Predictive Relevance

Assessment Criteria	Values/Results	Threshold/Criterion	Conclusion
Inner VIF (Multicollinearity)	FA → RP: 1.816; PIP → RP: 2.295; AOP → RP: 4.764	< 5 (Hair et al., 2022)	No serious multicollinearity
Effect Size (f^2)	FA: 0.164 (Medium); PIP: 0.096 (Small); AOP: 0.032 (Small)	≥0.35 Large; ≥0.15 Medium; ≥0.02 Small (Cohen, 1988)	FA has the strongest substantive impact
R^2 (Explained Variance)	0.656 (Adjusted 0.654)	≥0.67 Substantial; ≥0.33 Moderate (Chin, 1998)	Moderate to substantial explanatory power
Model Fit – SRMR	0.064 (saturated & estimated)	≤0.080 Good fit (Hu & Bentler, 1999)	Good model fit
NFI	0.821	>0.80 Acceptable	Acceptable fit

Source: SmartPLS 4 Output, 2025.

The structural model evaluation reveals satisfactory quality and predictive power. Inner VIF values are below 5, confirming the absence of critical multicollinearity among the predictors. Forecasting Accuracy exhibits the largest effect size ($f^2 = 0.164$, medium), followed by Predictive Inventory Planning ($f^2 = 0.096$) and Automation in Order Prediction ($f^2 = 0.032$), indicating that improvements in forecast precision contribute most substantially to retail performance. The model explains 65.6% of the variance in Retail Performance ($R^2 = 0.656$), reflecting moderate-to-substantial explanatory power. Model fit indices (SRMR = 0.064; NFI = 0.821) meet recommended thresholds, confirming good overall fit. These results support the reliability of subsequent hypothesis testing and path coefficient interpretation in evaluating the effect of AI and machine learning–driven demand forecasting on the retail performance of Jumia Nigeria.

4.2.3 Hypothesis Testing and Path Coefficients

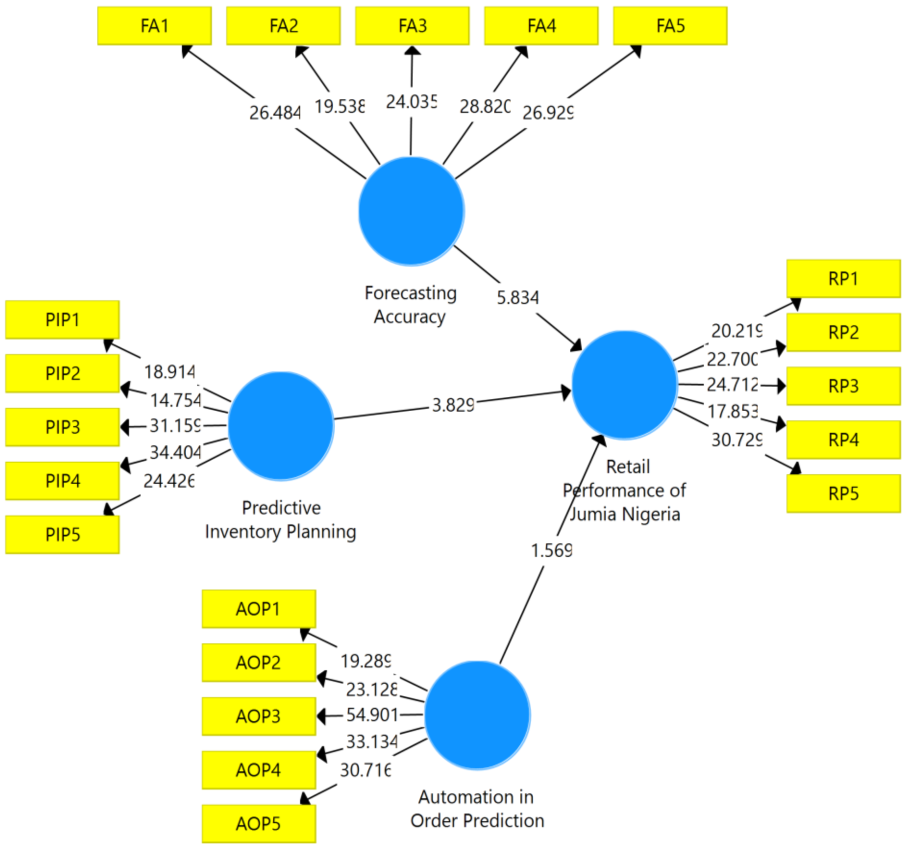


Figure 3: Path Coefficient
Source: SmartPLS Output, 2025.

Table 5: Path Coefficients

H_0	Variables	Original Sample	T Statistics	P Values	Decision
H_{01}	Forecasting Accuracy	0.394	5.834	0.000	Rejected
H_{02}	Predictive Inventory Planning	0.334	3.829	0.000	Rejected
H_{03}	Automation in Order Prediction	0.131	1.569	0.117	Accepted

Source: SmartPLS 4 Output, 2025Key Findings:

H_{01} & H_{02}: Statistically significant ($p < 0.001$) – null hypotheses rejected

H_{03}: Not statistically significant ($p = 0.117$) – null hypothesis accepted

Table 5 presents the path coefficients, t-statistics, and p-values from the structural model analysis, examining the effect of AI and machine learning–driven demand forecasting dimensions on the Retail Performance of Jumia Nigeria.

4.3 Discussion of Findings

H_{01}: Forecasting Accuracy has no significant effect on the Retail Performance of Jumia Nigeria.

The hypothesis was rejected, revealing a strong, highly significant positive relationship ($\beta = 0.394$, $t = 5.834$, $p = 0.000$). Forecasting Accuracy emerged as the strongest predictor of retail performance, consistent with Sokolov (2025), Avula (2021), Ankam (2025), Gunda (2025), and Ding (2021), who collectively demonstrated that higher AI-driven forecast precision directly improves sales efficiency, inventory turnover, and operational responsiveness. In the Jumia Nigeria context, accurate demand forecasting reduces stockouts, minimizes overstock, and enables faster, data-driven merchandising decisions, directly enhancing overall retail performance.

H_{02}: Predictive Inventory Planning has no significant effect on the Retail Performance of Jumia Nigeria.

This hypothesis was also rejected ($\beta = 0.334$, $t = 3.829$, $p = 0.000$), confirming a significant positive influence. The finding aligns with Choi (2018), Kumar et al. (2024), Ajiga et al. (2024), Atieh et al. (2025), and Krishnamurthy et al. (2024), who reported substantial reductions in excess inventory (15–30%), lower stockout rates, and higher turnover through AI-enabled predictive planning. For Jumia Nigeria, predictive inventory planning translates accurate forecasts into optimal stock levels and replenishment schedules, significantly boosting sales efficiency and operational responsiveness in a volatile e-commerce market.

H_{03}: Automation in Order Prediction has no significant effect on the Retail Performance of Jumia Nigeria.

The hypothesis was accepted ($\beta = 0.131$, $t = 1.569$, $p = 0.117$). Although the relationship is positive, it does not reach statistical significance. This contrasts partially with Kaya (2024), Shamsuzzoha and Pelkonen (2025), and Imdahl et al. (2021), who found automation of order processes improved efficiency and reduced errors. The non-significant result may reflect that, at Jumia Nigeria, automation in order prediction is still at an early adoption stage, primarily handling repetitive tasks rather than driving strategic retail outcomes, or that its benefits are mediated through forecasting accuracy and inventory planning rather than exerting a direct independent effect.

5.0 Conclusion and Recommendations

The study concludes that Forecasting Accuracy and Predictive Inventory Planning are significant positive drivers of Retail Performance at Jumia Nigeria, jointly explaining 65.6% of its variance, while Automation in Order Prediction currently exerts no statistically significant direct influence. The following recommendations are offered:

i. Jumia Nigeria should prioritize continuous enhancement of AI/ML forecasting models (e.g., adopting LSTM, XGBoost, and ensemble methods) and invest in high-quality, real-time data pipelines to sustain and further improve forecasting accuracy and predictive inventory planning, the two proven levers of superior retail performance.

ii. Although Automation in Order Prediction showed no significant direct effect, its implementation should be expanded strategically as a supporting mechanism to reduce manual errors and free up resources, with future integration of advanced robotic process automation (RPA) and hybrid human-AI decision systems to potentially unlock stronger performance contributions.

iii. Policymakers and industry bodies in Nigeria should promote training programs, affordable cloud-based AI tools, and public–private partnerships to accelerate AI adoption across the retail sector, enabling more e-commerce platforms like Jumia to achieve the performance gains demonstrated in this study.

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