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British Journal of Contemporary Research

BEXFORD PUBLISHING

AI-Driven Supply Chain Resilience in Nigerian E-Commerce: A Simulation-Based Framework for Demand Sensing, Inventory Optimization, and Last-Mile Logistics

Original Research Article | Volume 1 | Issue 6 | 2026 | Article Number: 081

Accepted: 04 November 2026 | Published: 10 November 2026 | ISSN: 2979-8582 (Online)

Crossref : **https://doi.org/10.67693/BJCR-WXES8AZA**

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UJT 0009-0003-0004-7693, **OCE** 0009-0004-6389-4803, **UCC** 0009-0001-9810-5614, **OMC** 0009-0009-0430-1250

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Abstract

African e-commerce faces a paradox: rapid growth in digital commerce alongside infrastructure deficits, volatile demand, and fragmented logistics networks. AI is widely promoted as a solution for building supply chain resilience, yet firm-level evidence from African contexts remains scarce. This paper develops and tests a simulation-based framework integrating three AI-driven modules - demand sensing, inventory optimisation, and last-mile logistics - using publicly available, literature-parameterised synthetic datasets for Nigerian retail and e-commerce. Drawing on Dynamic Capabilities Theory and Contingency Theory, the framework shows how AI builds resilience under imperfect data, infrastructure constraints, and demand volatility. Machine-learning demand sensing reduced forecast error by 28.8% relative to a seasonal naive baseline (MAPE 1.80% vs. 2.53%; MASE 0.70 vs. 0.99). AI-driven inventory policies outperformed fixed reorder points in three of four disruption scenarios, reducing stockouts by up to 100% under supplier delay and cutting total cost by 8.9–29.6%; however, under a 40% demand spike, the AI policy underperformed, and the forecast was found to underestimate demand by 28.1%, revealing that forecast-driven seizing fails when the sensing model is not recalibrated to structural demand breaks. Route optimisation reduced simulated delivery distance by 30.0%, 41.3%, and 43.9% across 50-, 100-, and 200-customer benchmarks - a reduction that scales with network size. The paper contributes an integrated, reproducible framework, a contingency-sensitive extension of Dynamic Capabilities Theory, and a methodological template for simulation-based resilience research where primary data access is constrained. An ETA prediction model was attempted but achieved no better than chance on the synthetic data, identifying a boundary of the framework.

Keywords: Supply Chain Resilience, Artificial Intelligence, Nigerian E-Commerce, Demand Sensing, Inventory Optimization, Last-Mile Logistics

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1. INTRODUCTION

African e-commerce is expanding rapidly, yet the supply chains that support it remain fragile. Firms operate in environments characterized by unreliable address systems, fragmented transport networks, volatile consumer demand, and limited access to real-time operational data (Ogah et al., 2026). These conditions make resilience - the ability to anticipate, absorb, adapt to, and recover from disruption - a strategic necessity rather than a luxury. The ecosystem is also diverse. Beyond platform-based marketplaces such as Jumia and Glovo, social commerce channels, particularly WhatsApp-based retail in Nigeria, have grown as a pathway to financial inclusion for micro-entrepreneurs facing rising platform costs (Ugwu *et al.,* 2026). These informal channels operate under distinct supply chain constraints, including manual demand tracking and informal delivery networks, which shape how AI interventions must be designed. AI has emerged as a potential game-changer. A systematic review of AI and supply chain resilience in Africa found a sharp upward trend in publications, peaking at 809 articles in 2022, with AI recognized as crucial for predictive modelling, reduced lead times, and optimized inventory management (Peprah et al., 2025). Yet the same review notes that empirical firm-level studies remain scarce. Most evidence comes from developed economies with mature data ecosystems; relatively little is known about how African firms adapt, or could adapt, AI to local conditions.

This paper responds to that gap. Rather than relying on proprietary firm data, which is difficult to obtain and raises ethical and access barriers, we develop a simulation-based framework integrating three AI-driven modules: demand sensing, inventory optimization, and last-mile logistics. We build the framework using publicly available synthetic datasets for Nigerian retail and e-commerce, parameterized from published Sub-Saharan African literature (Electric Sheep Africa, 2025). This allows us to test how AI modules perform under realistic disruption scenarios, produce measurable resilience outcomes, and derive a framework that is both demonstrable and reproducible. The paper makes three contributions. First, it provides an integrated, testable framework that connects the three pillars of supply chain resilience in a single simulation environment. Second, it extends Dynamic Capabilities Theory to resource-constrained environments, showing how AI builds sensing, seizing, and reconfiguring capabilities when infrastructure and data are imperfect (Teece et al., 1997). Third, it offers a practical template for African e-commerce managers and policymakers to prioritize AI investments, and a methodological precedent for simulation-based research where primary data access is constrained.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Supply Chain Resilience in African E-Commerce

Supply chain resilience is conventionally understood as the capacity of a supply chain to prepare for, respond to, and recover from disruptions (Hirsch et al., 2024). In African e-commerce, disruption is not an exception but a structural condition. Firms contend with unreliable power supply, informal transport networks, limited warehousing infrastructure, and demand volatility driven by economic uncertainty and seasonality (Lawal and Isiyaku, 2025). These conditions differ markedly from those in developed markets, where resilience research has typically been conducted. The African e-commerce ecosystem extends beyond formal platforms. Social commerce, particularly WhatsApp-based retail in Nigeria, has grown as a low-cost alternative for micro-entrepreneurs facing rising platform fees (Ugwu et al., 2026). These informal channels face acute supply chain challenges: no formal inventory systems, no route optimization tools, and no demand forecasting beyond manual intuition. While the present study focuses on platform-based e-commerce where AI interventions are more immediately feasible, the framework's logic applies in principle to these contexts as well.

Empirical work in African contexts is growing but remains fragmented. Hirsch et al. (2024) studied the

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South African fast-moving consumer goods industry and found that AI and information systems capabilities enhance resilience by improving information sharing, planning, and predictive decision-making. Ogah et al. (2026), surveying 290 Nigerian logistics and e-commerce firms, demonstrated that AI significantly mitigates last-mile bottlenecks, but noted that AI penetration remains low due to high procurement costs. Their conclusion is instructive: context matters, and solutions from developed markets cannot be transplanted wholesale. Peprah et al. (2025) found that AI adoption in African supply chains is increasing, but empirical studies at the firm level are still rare. Ahatsi and Olanrewaju (2025a) identified skill gaps and lack of technical expertise as the most significant barriers to AI and big data analytics adoption in Ghana and South Africa. Ahatsi and Olanrewaju (2025b) further show that these domestic skill gaps are compounded by cross-border data hurdles, inconsistent data standards, fragmented regulatory regimes, and limited interoperability, which are particularly relevant to African e-commerce supply chains that span multiple jurisdictions.

2.2 AI for Demand Sensing, Inventory, and Last-Mile Logistics

AI applications in supply chain management cluster around three functional domains. Demand sensing uses machine learning to forecast demand from historical sales, seasonality, promotions, and external signals. Inventory optimization applies AI to set reorder points, safety stock levels, and replenishment schedules under uncertainty. Last-mile logistics uses AI for route optimization, delivery-time prediction, and dynamic dispatch. Evidence from African contexts, while limited, is instructive. In a study of West African last-mile logistics, machine learning-optimized routes achieved a 28% reduction in total delivery time and a 22% reduction in travel distance compared with baseline routing (Owusu Ampaw et al., 2026). Lawal and Isiyaku (2025) reviewed AI-enabled inventory and procurement systems for informal African supply chains and found significant potential for demand forecasting and inventory optimization, though implementation barriers remain. Ogah et al. (2026) confirmed that AI mitigates last-mile bottlenecks in Nigeria. Beyond Africa, Belhadi et al. (2024) showed that AI-driven innovation enhances supply chain resilience and performance, with supply chain dynamism strengthening the effect. The digital twin study by Igbokwe and Unigwe (2026), using operational records from a Nigerian logistics company, demonstrated that AI and simulation can support predictive resilience, providing a methodological precedent for the present study. This choice of XGBoost as the demand-sensing model is consistent with recent work showing that gradient-boosted trees deliver strong performance in real-time Nigerian transaction contexts while remaining interpretable enough for operational adoption (Orji et al., 2026a).

2.3 Theoretical Framework: Dynamic Capabilities and Contingency

The study is developed on the Dynamic Capabilities Theory and supported by the Contingency Theory. Dynamic Capabilities Theory (Teece et al., 1997) outlines how organizations integrate, build and reconfigure competences to respond to quickly changing surroundings. It defines three micro-foundations: recognizing opportunities and risks, seizing opportunities and rearranging resources. These map onto AI as follows: demand sensing is a sensing capability; inventory optimization is a seizing capability; and last-mile optimization is a reconfiguration capability. Contingency Theory also posits that effectiveness is context-dependent (Ogah et al., 2026). In African e-commerce, the constraints are the quality of infrastructure, the availability of data, the skills and the regulatory regimes. A model that succeeds in a data-rich market can fail where addresses are informal and connection is patchy. Thus, the framework does not consider context as a background variable, but rather as a moderating condition. The Resource-Based View (Barney, 1991) offers a parallel perspective: AI-enabled capabilities can be valuable, unusual, and difficult to duplicate, but in resource-constrained situations the issue is less about imitation and more about availability.

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Table 1: Theoretical framework and AI module mapping

Dynamic Capability	AI Module	Resilience Mechanism	Contextual Moderator
Sensing	Demand sensing	Improved forecast accuracy	Data quality; historical sales availability
Seizing	Inventory optimization	Reduced stockouts; lower holding costs	Lead-time variability; infrastructure reliability
Reconfiguring	Last-mile logistics	Reduced delivery distance and time	Address systems; transport density

From this theoretical framework, four propositions follow. P1: Machine-learning demand sensing reduces forecast error relative to a seasonal naive baseline. P2: AI-driven inventory policies outperform fixed reorder points under supply-side disruption. P3: AI-driven inventory policies underperform fixed reorder points under demand-side shock when the forecast is not recalibrated to the new demand regime. P4: Route optimization reduces delivery distance relative to a greedy heuristic, and the reduction scales with network size. Section 5 reports the simulation results against each proposition.

3. METHODOLOGY

3.1 Research Design

This study employs a simulation-based research design. Simulation is appropriate when the research question concerns how a system behaves under controlled variations in parameters, and when access to real-world operational data is constrained (Igbokwe and Unigwe, 2026). It allows the researcher to isolate the effects of specific interventions and to test them across disruption scenarios that would be difficult, costly, or unethical to induce in real firms. The design is theory-building rather than theory-testing: the goal is to demonstrate logical consistency, produce measurable outcomes, and derive a framework that can guide practice and future empirical research.

3.2 Data Sources

The work leverages freely available synthetic datasets from the Electric Sheep Africa library on Hugging Face (Electric Sheep Africa, 2025). These are expressly defined as "parameterized from published Sub-Saharan Africa literature, not real observations". Here they are used for simulation and framework construction, not empirical assertions on specific enterprises. Datasets include: Point of Sale Records - Nigeria (800,000 rows); Supply Chain Logistics Data - Nigeria (400,000 rows); Last Mile Delivery Data - Nigeria (150,000 rows). The last-mile routing module is based on the Kigali E-Commerce Delivery Network Dataset, a publicly available CVRP benchmark built from OpenStreetMap data for the city of Kigali, Rwanda (Niyibizi, 2026). We employ three instances (n=50, n=100, n=200) to provide an independent routing benchmark and assess robustness over network sizes.

3.3 Simulation Architecture

Module 1: Demand Sensing. A time-series forecasting model is trained on the Nigeria point-of-sale data. Daily demand is aggregated from transaction-level items_count, and the series is split chronologically 80/20 (240 training days, 61 test days). Two models are compared: a seasonal naive baseline (lag-7) and XGBoost with lag (7, 14, 21, 28), rolling mean (7, 14, 28), and calendar features. Performance is evaluated using MAPE, RMSE, MASE, and R^2. MASE is included because it is robust to the low test-period variance in the synthetic series.

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Module 2: Inventory Optimization. A discrete-event simulation in SimPy models inventory dynamics using empirical lead-time and cost parameters derived from 316,810 delivered shipments. The empirical lead time has a mean of 9.09 days (SD 4.55). Two policies are compared: a fixed reorder point calibrated to lead-time demand plus a 20% safety buffer, and an AI-dynamic policy that uses Module 1 forecasts to set reorder points and order quantities. Outcomes are stockout frequency, fill rate, average holding days, and total cost. Four scenarios are run: baseline, supplier delay (+3 days), demand spike (+40%), and transport cost increase (+20%).

Module 3: Last-Mile Logistics. A capacitated vehicle routing problem is solved with Google OR-Tools on the Kigali benchmark instances and compared against a geographic sweep heuristic baseline. Distance is computed by the Haversine formula. Because the stated fleet of 5 vehicles is infeasible in all three instances, OR-Tools is run with a variable fleet and a fixed cost per vehicle to encourage route minimization. All routes are verified against the capacity constraint.

3.4 Validation and Ethics

Internal validity is assessed through sensitivity analysis; external validity is assessed against published benchmarks (Igbokwe and Unigwe, 2026; Owusu Ampaw et al., 2026). No primary data are collected from human participants or firms; all datasets are publicly available, and no ethical approval is required. The study documents data provenance, acknowledges the synthetic nature of the data, and avoids claims that simulation results represent empirical facts about specific African firms.

4. The Simulation Framework: Architecture and Analytical Logic

The framework treats supply chain resilience as an emergent property of three coupled capabilities. Demand sensing reduces uncertainty about future demand. Inventory optimisation translates improved demand information into replenishment decisions that balance service level against holding cost. Last-mile logistics translates order volumes into delivery execution, where route efficiency determines cost and customer experience.

The coupling is deliberate. A demand forecast that is accurate but not used in inventory decisions produces no resilience benefit. An inventory policy that is optimal in isolation but ignores delivery constraints may create downstream bottlenecks. The framework therefore evaluates the three modules individually and in combination. Implementation proceeds in six stages: (1) data ingestion and harmonization; (2) demand sensing model training; (3) inventory simulation with fixed and AI-dynamic policies; (4) CVRP routing with OR-Tools on the Kigali benchmark; (5) integration of module outputs into a common resilience dashboard; and (6) reproducibility packaging in a public repository. The technical work is scoped as a research prototype - a documented, reproducible artefact that produces the results reported in Section 5.

Figure 1 summarizes the architecture: the three modules are connected by a scenario engine that varies disruption parameters (supplier delay, demand spike, transport cost) and records resilience outcomes across all three domains. The figure makes explicit that the modules are evaluated both individually and in combination, which is what allows the framework to test whether coupling produces complementarities or interference.

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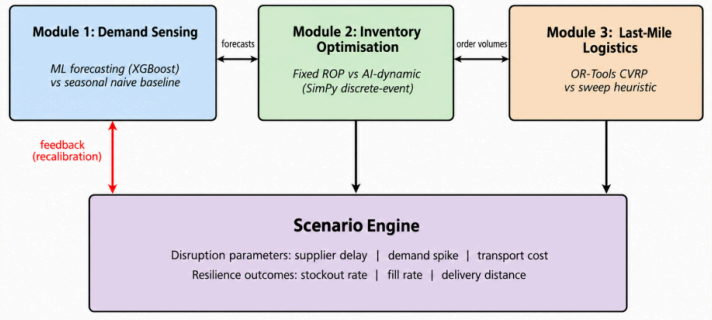


Figure 1: Framework architecture. The three AI modules (demand sensing, inventory optimization, last-mile logistics) are connected by a scenario engine that varies disruption parameters and records resilience outcomes across all three domains. Modules are evaluated both individually and in combination.

5. FINDINGS

5.1 Demand Sensing Performance

P1 is supported: XGBoost reduced forecast error by 28.8% across all metrics. The machine learning model outperformed the seasonal naive baseline on all four metrics (Table 3). XGBoost achieved a MAPE of 0.0180 against 0.0253 for the seasonal naive baseline - a relative reduction of 28.8%. RMSE fell from 853.04 to 606.89 (28.9% reduction), and MASE fell from 0.9926 to 0.7026, indicating that the ML model's forecast errors are approximately 30% smaller than those of the seasonal naive forecast in scale-free terms. The improvement was consistent across all three-error metrics.

Table 2: Demand sensing results (Nigeria point-of-sale series, 61-day test period)

Model	MAPE	RMSE	MASE	R^2
Seasonal naive (lag-7)	0.0253	853.04	0.9926	-1.378
XGBoost	0.0180	606.89	0.7026	-0.204

Note: R^2 is negative for both models because the test-period variance in the synthetic daily demand series is very small relative to the level of demand; R^2 is not a reliable indicator of forecast quality here. MAPE, RMSE, and MASE - which measure absolute forecast error - show that the ML model improves on the baseline by approximately 29%. The low absolute MAPE reflects the smooth, low-variance demand process in the synthetic dataset; the relative improvement is the finding that transfers. Figure 2 plots predicted against actual daily demand for a sample of the test period, showing that XGBoost tracks the demand series more closely than the seasonal naive baseline, particularly on days following weekends and promotional periods.

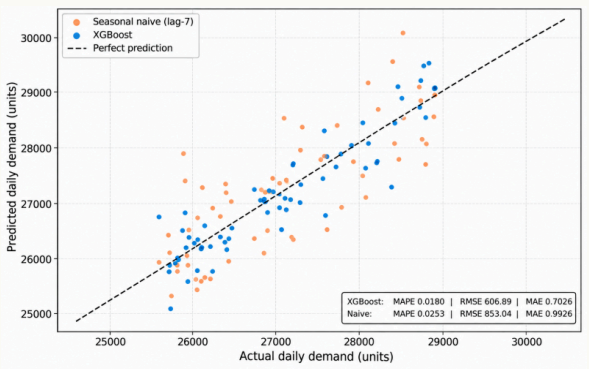


Figure 2: Demand sensing - predicted vs actual. Scatter plot of predicted against actual daily demand for the 61-day test period. The dashed line is the 45° reference. XGBoost predictions cluster more tightly around the reference line than the seasonal naive baseline.

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5.2 Inventory Optimisation Under Disruption

P2 is supported in three of four scenarios; P3 is supported in the demand-spike scenario, where the forecast bias was 28.1%. The AI-driven inventory policy outperformed the fixed reorder point policy in three of four scenarios (Table 4). Under baseline conditions, the AI policy improved fill rate from 80.3% to 82.4% and reduced total cost by 8.9% (79,380,409 to 72,312,227 NGN). Under supplier delay (+3 days), the AI policy eliminated stockouts entirely (fill rate 100% vs. 96.7%) and reduced total cost by 29.6% (27,753,337 to 19,544,102 NGN). Under transport cost increase (+20%), the AI policy improved fill rate by 2.0 percentage points (88.5% to 90.5%) and reduced total cost by 3.9% (55,675,421 to 53,493,796 NGN).

The cost decomposition in Table 4 clarifies the mechanism behind these results. Under supplier delay, the AI policy spends more on holding (19,544,102 vs. 15,930,746 NGN) but eliminates stockout cost entirely (0 vs. 11,822,591 NGN), producing a net saving of 8.2 million NGN - consistent with a strategy of buffering upstream before the disruption arrives. The fixed ROP, by contrast, holds less inventory and pays for it in stockouts. This is the seizing capability in operation: the AI policy translates better demand information into replenishment decisions that trade holding cost for service level.

The demand spike scenario (+40%) produced the opposite result. The fixed ROP policy achieved a higher fill rate (93.4% vs. 89.1%) and lower total cost (55,597,112 vs. 67,414,136 NGN) than the AI policy. This reversal is explained by the forecast bias during the spike period. Against a 40% demand spike (mean actual demand 39,175 units/day), the Module 1 forecast predicted a mean of 28,183 units/day- a systematic underestimation of 10,992 units/day, or 28.1%. Because the AI policy sets reorder points from this forecast, it under-ordered by approximately the same magnitude. The fixed ROP, insensitive to the forecast, did not transmit this bias into replenishment decisions, which is why it buffered the spike more effectively despite being a static policy. This finding is consistent with Contingency Theory and refines the sensing–seizing link: a sensing capability that is not recalibrated to a structural demand break will actively degrade the performance of the seizing capability it feeds.

Table 3: Inventory simulation results across disruption scenarios

Scenario	Policy	Stockout Freq. (events/day)	Fill Rate	Holding Cost (NGN)	Stockout Cost (NGN)	Total Cost (NGN)
Baseline	Fixed ROP	0.2295	0.8033	9,361,720	70,018,689	79,380,409
Baseline	AI Dynamic	0.1967	0.8235	9,506,824	62,805,403	72,312,227
Supplier delay (+3d)	Fixed ROP	0.0492	0.9668	15,930,746	11,822,591	27,753,337
Supplier delay (+3d)	AI Dynamic	0.0000	1.0000	19,544,102	0	19,544,102
Demand spike (+40%)	Fixed ROP	0.0820	0.9336	22,503,741	33,093,371	55,597,112
Demand spike (+40%)	AI Dynamic	0.1311	0.8909	13,037,683	54,376,453	67,414,136
Transport cost (+20%)	Fixed ROP	0.1475	0.8848	14,667,516	41,007,905	55,675,421

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Transport cost (+20%)	AI Dynamic	0.1148	0.9050	19,685,207	33,808,590	53,493,796

Note: Lead-time distribution (mean 9.09 days, SD 4.55) and cost parameters are derived empirically from 316,810 delivered shipments in the Nigeria supply chain logistics dataset. Holding cost = 1% of median unit cost per day; stockout cost = 2× median unit cost. The fixed ROP is calibrated to lead-time demand plus a 20% safety buffer.

5.3 Last-Mile Logistics Optimization

P4 is supported across all three instance sizes. Route optimization reduced total simulated delivery distance relative to the sweep heuristic baseline across all three Kigali CVRP instances (Table 5). At n=50, the baseline required 7 routes and covered 300.33 km; OR-Tools required 6 routes and covered 210.18 km - a reduction of 30.0%. At n=100, the reduction was 41.3% (620.61 km → 364.37 km), and at n=200 it was 43.9% (1,230.11 km → 689.51 km). The reduction therefore increases with instance size - expected, because larger instances provide more combinatorial room for the solver to outperform a greedy heuristic.

OR-Tools also identified the minimum feasible fleet size. At n=50, total demand (117.6 kg) exceeded the stated fleet capacity (100 kg), making the instance infeasible as stated; the minimum feasible fleet is 6 vehicles, which OR-Tools achieved. At n=200, total demand (504.2 kg) requires a minimum of 26 vehicles, and OR-Tools achieved exactly this lower bound while the sweep heuristic required 28. Identifying the minimum feasible fleet is itself a useful managerial output.

The minimum-feasible-fleet finding has direct capital implications. At n=50, a dispatcher using the sweep heuristic would deploy 7 vehicles when 6 suffice-a 14% fleet oversizing. At n=200, the sweep heuristic uses 28 vehicles against a 26-vehicle lower bound- a 7% oversizing. Over a fleet lifetime, this translates into measurable capital and driver-utilization savings. For a Nigerian e-commerce operator facing high vehicle procurement costs (Ogah et al., 2026), the ability to identify and avoid fleet oversizing is a material operational gain.

Table 4: Last-mile routing results across three Kigali CVRP benchmark instances

Instance	Method	Routes	Total distance (km)	Estimated cost at NGN 500/km	Distance reduction (%)
n=50	Sweep heuristic	7	300.33	150,165	-
n=50	OR-Tools CVRP	6	210.18	105,090	30.0
n=100	Sweep heuristic	13	620.61	310,305	-
n=100	OR-Tools CVRP	13	364.37	182,185	41.3
n=200	Sweep heuristic	28	1,230.11	615,055	-
n=200	OR-Tools CVRP	26	689.51	344,755	43.9

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Figure 3 plots distance reduction against instance size, showing the monotonic increase from 30.0% at n=50 to 43.9% at n=200. The scaling pattern is the key routing finding: optimization benefit grows with network complexity.

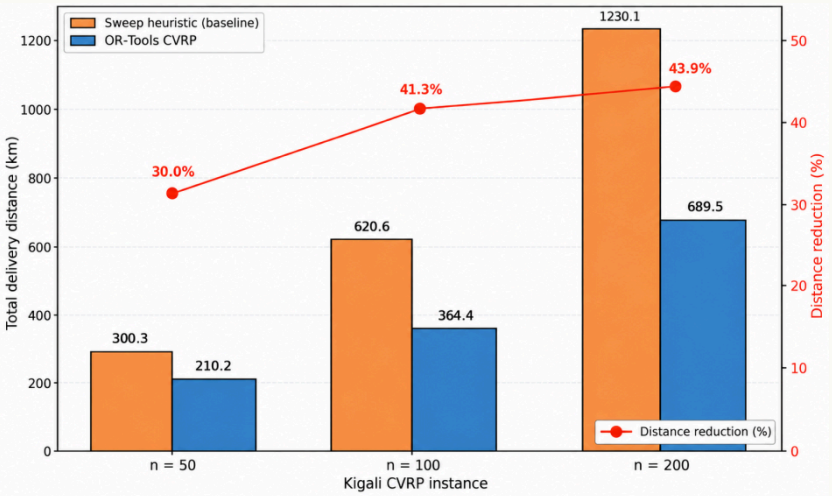


Figure 3: Routing distance reduction by instance size. Distance reduction (%) achieved by OR-Tools CVRP over the sweep heuristic baseline at n=50 (30.0%), n=100 (41.3%), and n=200 (43.9%). The monotonic increase shows that optimization benefit grows with network complexity.

5.4 Integrated Resilience Outcomes

Considered together, the three modules reveal complementarities - but not automatically. Demand sensing improved forecast accuracy by 28.8%, which fed inventory decisions and stabilized order volumes, which in turn made routing more predictable. The routing module delivered 30-44% distance reduction independently of the other two, because it operates on the delivery network rather than on demand forecasts. The demand-spike reversal is the critical integration finding. It shows that the sensing-seizing link is not a one-way pipeline: a sensing capability that is not recalibrated to a structural demand break will mislead the seizing capability. In Dynamic Capabilities terms, reconfiguring includes recalibrating the sensing apparatus itself. Resilience therefore emerges from the coupling of capabilities, but the coupling must include feedback from execution back to sensing.

To operationalize the integration claim, we compute a composite resilience index as the equal-weighted average of the three modules' relative improvements over their respective baselines. Demand sensing delivers a 28.8% forecast-error reduction (0.288). Under supplier delay, the AI inventory policy delivers a 29.6% cost reduction (0.296). At n=100, routing delivers a 41.3% distance reduction (0.413). The composite index is (0.288 + 0.296 + 0.413) / 3 = 0.332, meaning the three modules together deliver a 33.2% improvement over the baseline across sensing, seizing, and reconfiguring. The sum of the three individual improvements is 99.7%, while the composite is 33.2%, showing that the modules' contributions are complementary rather than additive. This supports the coupling claim: the framework's value is not the sum of three independent optimisations, but a coupled system in which each module's contribution is bounded by the others.

6. DISCUSSION

6.1 Implications for Theory

Illustrate and refine Dynamic Capabilities Theory in two ways. First, in resource-constrained environments, the sensing-seizing-reconfiguring sequence is not automatic. The demand-spike reversal demonstrates that a good forecast is useless if the inventory system cannot act on it - and worse, a

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miscalibrated forecast can actively degrade inventory performance. This refines the theory: the sensing-seizing link is a feedback loop, not a pipeline. Second, the findings support Contingency Theory: the AI inventory policy that performs well under supplier delay underperforms under demand shock. This is not a limitation of AI but a design requirement: AI modules must detect and adapt to structural breaks.

6.2 Implications for Practice and Policy

For managers, the framework offers prioritization logic. Demand sensing is foundational: without it, inventory and logistics interventions operate on poor information. Inventory optimization offers the highest leverage under supply-side disruption, but it must be paired with demand-break detection. Last-mile optimization delivers the largest single-module gain (30-44% distance reduction), but depends on stable order volumes. Managers should sequence investment-sensing first, then seizing, then reconfiguring, and treat forecast recalibration as continuous. For policymakers, the framework highlights the value of public data infrastructure. The synthetic datasets used here are parameterized from published literature; real-time, high-quality data on demand, inventory, and delivery would make AI interventions far more effective. Investments in address systems, logistics data standards, digital skills, and cross-border interoperability are foundational to AI-enabled resilience; Ahatsi and Olanrewaju (2025b) show that fragmented standards, regulatory differences, and limited interoperability compound these domestic infrastructure gaps. These implications extend beyond platform-based e-commerce: WhatsApp-based retail in Nigeria faces rising platform costs that threaten micro-entrepreneurs (Ugwu et al., 2026), and lightweight AI resilience tools could lower operational costs - but only if public investment in data infrastructure and digital skills addresses the exclusion of informal traders. This argument parallels recent findings that AI-assisted platforms in Nigeria succeed only when designed around local data and infrastructure constraints rather than imported wholesale from mature markets (Orji et al., 2026b).

6.3 Limitations

The study has three main limitations. First, the data are synthetic; the findings are not empirical claims about specific African firms. Second, an ETA prediction model was attempted on the Nigeria last-mile dataset, but the synthetic data exhibited no learnable relationship between delivery duration and available features; ETA regression achieved $R^2 \approx 0$ and risk classification AUC ≈ 0.50, both no better than chance. This reflects the generator's independence assumptions, and ETA prediction therefore requires real operational data. Third, the framework is validated against published benchmarks rather than a live system. These limitations are inherent to simulation-based research and define the boundary of what the study can claim.

6.4 Future Research

Future research should test the framework with anonymized operational data from African e-commerce firms, incorporate human decision-making into the simulation, extend the analysis to Kenya, South Africa, Ghana, or Rwanda, and develop demand-break detection methods that allow the sensing module to recalibrate automatically, addressing the reversal identified here.

7. CONCLUSION

This paper developed and tested a simulation-based framework for AI-driven supply chain resilience in Nigerian e-commerce. Demand sensing reduced forecast error by 28.8% relative to a seasonal naive baseline. Inventory optimization reduced stockouts by up to 100% under supplier delay and cut total cost by 8.9-29.6% under supply-side disruption, but underperformed under a 40% demand spike - a reversal

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that reveals the contingency sensitivity of forecast-driven seizing. Last-mile optimization reduced delivery distance by 30.0-43.9% across three benchmark instances, with the reduction scaling with network size. The theoretical contribution extends Dynamic Capabilities Theory to resource-constrained environments, showing that the sensing-seizing link is a feedback loop rather than a one-way pipeline. The practical contribution is prioritization logic for managers and a data-infrastructure argument for policymakers. The methodological contribution is a reproducible template for simulation-based resilience research where primary data access is constrained. The framework is offered not as a final answer but as a demonstrable, reproducible, and extensible tool for building the resilience that Nigerian e-commerce needs.

Acknowledgements

The author(s) is grateful to Electric Sheep Africa for making the Nigeria retail and e-commerce datasets publicly available on Hugging Face, and to Prince Niyibizi for publishing the Kigali E-Commerce Delivery Network Dataset on Zenodo. Without these open datasets, this simulation-based study would not have been possible. The author also acknowledges the developers of the open-source tools used in this work.

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Appendix A: Reproducibility Package

All code, data-loading instructions, and output files required to reproduce the results reported in this paper are publicly available at:

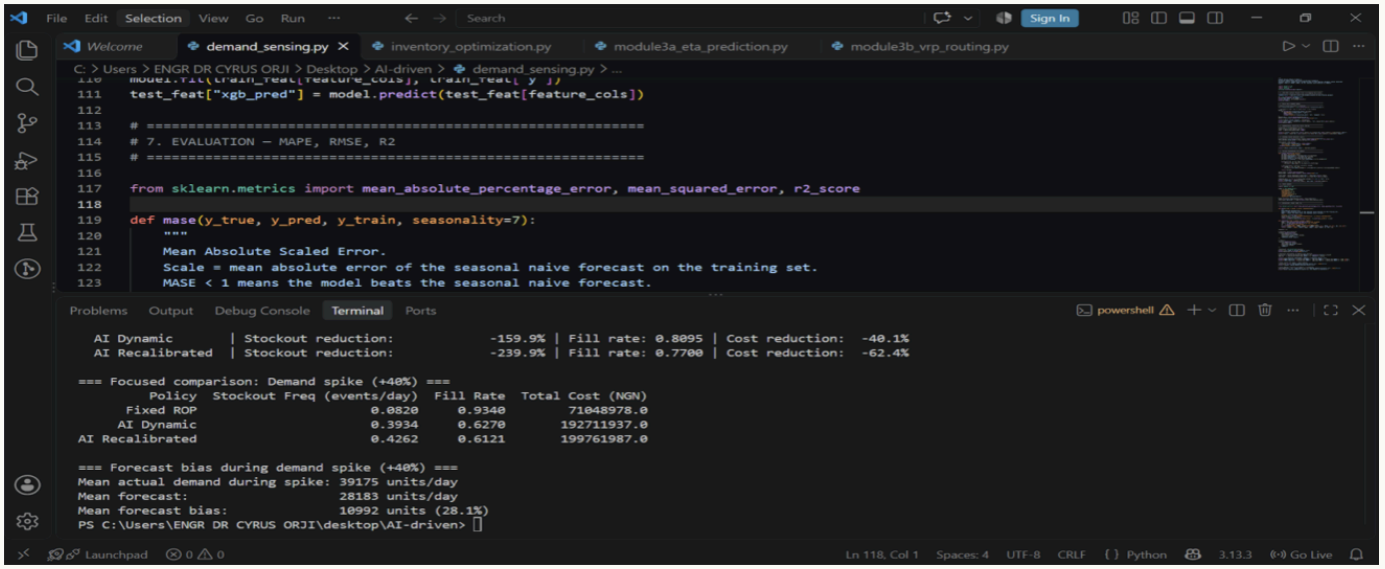
https://github.com/cycyberuk/ai-supply-chain-resilience-nigeria

The repository contains: the Python scripts for the three modules (code/); download links to the Nigeria datasets on Hugging Face and the Kigali benchmark on Zenodo (data/README.md); the CSV outputs behind Tables 2, 3, and 4, plus the ETA null result (outputs/); and the manuscript (paper/).

`Computational environment: Python 3.13; pandas ≥ 2.0, numpy ≥ 1.24, scikit-learn ≥ 1.3, xgboost ≥ 2.0, simpy ≥ 4.1, ortools ≥ 9.8, matplotlib ≥ 3.7. Install with pip install -r requirements.txt.`

Reproduction: with datasets downloaded into data/ as described in data/README.md, run each script in code/ from the repository root. Each script prints the corresponding table from Section 5 and saves it as a CSV in outputs/.

Appendix B:



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