The Role of AI-Driven Analytics in Enhancing Operational Agility among Post-Pandemic Retail SMEs

Authors

Abiodun Okunola, Abi Cit, James Claer

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Abstract

The COVID-19 pandemic fundamentally disrupted retail small and medium enterprises (SMEs), exposing the fragility of intuition-based operational decision-making and accelerating demands for data-driven agility. While digital transformation has been widely studied, the specific contribution of AI-driven analytics to operational agility in post-pandemic retail SMEs remains underexplored, particularly regarding predictive accuracy and implementation pathways. This study addresses this gap by developing and validating a hybrid machine learning framework that integrates point-of-sale transaction data, inventory signals, and demand forecasts to enhance operational responsiveness. Using a quantitative, design-based research approach, the study analyzes a stratified sample of 412 retail SMEs across urban and semi-urban markets over 18 months (January 2023–June 2024). The hybrid Random Forest–XGBoost ensemble model achieved 89.4% predictive accuracy in forecasting stockout events and reduced inventory holding costs by 23.7% compared to static reorder baselines ($p < 0.001$). Feature importance analysis identified demand volatility, supplier lead-time variability, and promotional calendar density as the strongest predictors of agility outcomes. The findings demonstrate that AI-driven analytics can transform operational agility from a reactive posture to a predictive capability, with implications for SME managers, technology providers, and policymakers seeking to strengthen retail resilience in post-crisis economies.

Keywords: artificial intelligence, operational agility, retail SMEs, predictive analytics, post-pandemic recovery

1. Introduction

1.1 Background

The retail sector's recovery from the COVID-19 pandemic has been uneven and profoundly shaped by firms' capacity to adapt operations in real time. Small and medium enterprises—which constitute the overwhelming majority of retail establishments globally—faced disproportionate disruptions, including demand shocks, supply chain breakdowns, and labor shortages. While large retailers leveraged sophisticated analytics infrastructure to navigate these disruptions, SMEs largely relied on heuristic decision-making, leaving them exposed to prolonged instability [1].

Digital transformation has emerged as a critical pathway for enhancing organizational agility in the post-pandemic era, yet the measurement of agility and its technological predictors remains underexplored at scale [2]. Recent scholarship has demonstrated that machine learning techniques can effectively model the complex, non-linear relationships characterizing SME digitalization and agility outcomes, with production technologies such as automation and digital infrastructure proving stronger predictors than customer-facing consumption technologies [2]. This finding challenges prevailing assumptions about which digital investments most directly enhance operational responsiveness.

Within the retail context specifically, AI-driven analytics applications have begun demonstrating measurable impact. Analysis of micro-retail stores using AI-powered recommendation systems revealed a 46% increase in daily gross merchandise value and a 17% rise in total sales, achieved despite operating on 20% fewer active selling days [3]. These results suggest that AI can guide inventory management, product mix optimization, and demand planning in ways that compensate for reduced operating windows—a capability directly relevant to post-pandemic operational constraints.

Yet adoption remains starkly limited. In the Philippines, for instance, only 14.9% of local businesses currently use AI tools, despite widespread computer ownership and internet access [4]. This gap between demonstrated potential and actual uptake underscores the need for research that moves beyond proof-of-concept demonstrations toward validated frameworks that SMEs can realistically implement.

1.2 Problem Statement

Despite growing evidence that AI-driven analytics can improve retail operational outcomes, three critical limitations persist in the existing literature. First, most studies examining AI and organizational agility treat technology adoption as an undifferentiated construct, failing to distinguish between specific analytics capabilities (e.g., demand forecasting, inventory optimization) and their differential effects on agility outcomes [2]. This obscures which AI applications actually matter for SME operations.

Second, the empirical evidence base for AI-driven analytics in retail SMEs relies heavily on small-scale deployments, vendor-reported case studies, or pilot implementations with limited generalizability [3][4]. There is a paucity of research employing rigorous predictive modeling with validated performance metrics across diverse SME populations.

Third, existing frameworks for operational agility tend to emphasize either technological infrastructure or organizational capabilities, without integrating them into a predictive system that can be empirically validated. Dynamic capability theory has been applied to supply chain contexts [5], but its operationalization for SME-level retail analytics remains underdeveloped.

The unsolved issue, therefore, is the absence of a validated predictive framework that integrates AI-driven analytics with operational agility outcomes in post-pandemic retail SMEs, tested against rigorous accuracy benchmarks and capable of identifying which specific analytics features most strongly predict agility improvements.

1.3 Objectives of the Study

General objective: To develop and validate an AI-driven predictive analytics framework that enhances operational agility among post-pandemic retail SMEs.

Specific objectives:

1. To identify the key predictive features of retail operational data (transaction records, inventory signals, demand patterns) that most strongly determine agility outcomes in SME contexts.
2. To design a hybrid machine learning model integrating Random Forest and XGBoost techniques for forecasting operational disruptions and recommending agility-enhancing actions.
3. To validate the framework against traditional static reorder baselines using accuracy, cost reduction, and lead-time metrics across a stratified SME sample.

1.4 Research Questions

1. What combination of operational variables and AI-derived features most accurately predicts stockout events and inventory inefficiencies in post-pandemic retail SMEs?
2. How does the proposed hybrid analytics framework compare to traditional static budgeting and reorder methods in terms of predictive accuracy, cost reduction, and operational lead time?
3. What feature-importance weights distinguish high-agility from low-agility SME operations, and what are the implications for prioritization of AI investments?

1.5 Significance of the Study

For practitioners and administrators: The study provides retail SME managers with an empirically validated roadmap for deploying AI analytics. The identification of demand volatility and supplier lead-time variability as top predictors offers actionable guidance for where to focus data collection and analytics investment first, potentially reducing implementation costs and time-to-value.

For policymakers: Findings inform the design of SME digitalization support programs by specifying which analytics capabilities yield the greatest agility returns. This can help agencies avoid spreading resources across undifferentiated "AI adoption" initiatives and instead target high-impact applications such as demand forecasting and inventory optimization.

For academic literature: The study contributes to dynamic capability theory by operationalizing AI-driven analytics as a specific dynamic capability for retail SMEs, extending prior work that examined big data analytics in larger firm and supply chain contexts [5][6]. It also advances methodological approaches by demonstrating the application of ensemble machine learning to SME-level operational data.

For future researchers: The validated framework and feature-importance results establish baseline benchmarks that subsequent studies can extend across geographic regions, retail subsectors, and firm sizes.

1.6 Scope and Limitations

This study focuses on retail SMEs (defined as firms with 10–250 employees) operating in physical or hybrid store formats across urban and semi-urban markets. The time period spans January 2023 through June 2024, capturing the post-pandemic stabilization phase. Data sources include point-of-sale transaction records, inventory management logs, and supplier delivery data.

Exclusions: Pure e-commerce retailers, micro-enterprises with fewer than 10 employees, and firms in the food service sector are excluded. The study does not examine customer-facing AI applications (e.g., chatbots, recommendation engines) except where they directly influence operational decisions.

Limitations: The use of simulated data for certain supplier lead-time variables (due to data availability constraints) is acknowledged. Generalizability to regions with substantially different digital infrastructure maturity may be limited.

2. Literature Review

2.1 Conceptual Review

AI-Driven Analytics. For the purposes of this study, AI-driven analytics refers to the application of machine learning algorithms to organizational data for the purpose of generating predictive insights and automated recommendations that inform operational decisions. This encompasses demand forecasting, inventory optimization, anomaly detection, and prescriptive analytics [3][4]. It is distinguished from general "digital transformation" by its emphasis on predictive and prescriptive rather than merely descriptive data use.

Operational Agility. Operational agility denotes an organization's capacity to detect and respond to changes in its operating environment with speed and efficiency, specifically in core processes such as procurement, inventory management, and order fulfillment [2][7]. In retail contexts, operational agility manifests in practices such as dynamic reorder points, rapid assortment adjustments, and responsive staffing allocation.

Post-Pandemic Retail SMEs. This term refers to small and medium retail enterprises operating in the period following the acute phase of COVID-19 disruptions (2023 onward), characterized by lingering supply chain volatility, altered consumer behavior patterns, and heightened sensitivity to operational disruptions.

2.2 Theoretical Framework

Dynamic Capability Theory. Dynamic capability theory posits that firms achieve competitive advantage through the capacity to sense, seize, and transform in response to environmental change [5][6]. In this study, AI-driven analytics functions as a sensing capability—enabling SMEs to detect demand shifts and inventory risks earlier—and as a seizing capability, through prescriptive recommendations that translate sensing into operational action. The theory predicts that firms with stronger analytics capabilities should exhibit superior operational agility, a proposition this study tests empirically.

Technology-Organization-Environment (TOE) Framework. The TOE framework explains technology adoption through three contextual categories: technological attributes, organizational readiness, and environmental pressures [2]. This study applies TOE to interpret the conditions under which AI analytics translate into agility gains, particularly examining organizational factors (data quality, managerial support) and environmental factors (supplier volatility) that moderate the technology–agility relationship.

Integration. By combining dynamic capability theory with TOE, this study develops a framework in which AI-driven analytics serves as the technological core, organizational readiness determines its deployment effectiveness, and environmental volatility shapes the urgency of agility outcomes. This integrated perspective addresses the limitation of prior research that examined technology adoption without adequately accounting for organizational and environmental contingencies [2].

2.3 Empirical Review

Sabeena et al. [2] conducted a large-scale analysis of 491,636 SME technology adoption records using Random Forest, XGBoost, and ensemble models. Their Random Forest model achieved a test R^2 of 0.6249, demonstrating that machine learning can effectively capture the non-linear relationships between technology adoption and organizational agility. Critically, they found that production technologies (automation, digital infrastructure) predicted agility more strongly than consumption technologies (customer-facing tools). **What they did not do:** The study did not examine specific analytics applications within retail operations, nor did it validate predictive accuracy for operational outcomes such as stockouts or inventory turnover.

Packworks [3][4] reported that sari-sari stores using AI-driven recommendations achieved a 46% increase in daily gross merchandise value and a 17% rise in total sales, despite operating 20% fewer selling days. **Limitations:** The analysis covered a two-week period with over 300 stores, but did not employ predictive modeling to isolate the contribution of specific AI features, nor did it compare against a rigorous baseline condition.

Research on AI-driven inventory forecasting for SMEs has demonstrated that Random Forest regressors applied to point-of-sale data can generate timely reorder alerts and prevent stockouts [8]. The BillWise system integrated demand forecasts directly into operational POS systems, triggering automated reorder suggestions when predicted demand exceeded available inventory. **What was missing:** The study focused on system architecture and deployment feasibility rather than quantifying agility gains against controlled baselines or identifying which data features drove predictive accuracy.

Ma et al. [9] examined big data analytics capabilities in the Chinese food industry, finding that analytics capability influenced supply chain agility through customer integration, internal integration, and collaborative knowledge creation. Their PLS-SEM analysis established mediating pathways but relied on perceptual survey measures rather than objective operational data. **Limitation for SME application:** The study examined larger firms and did not address the resource constraints and data quality challenges characteristic of SME contexts.

OECD [10] reported that only 23.6% of SMEs using generative AI provide related training to employees, with lack of skills cited as a persistent barrier. This finding contextualizes the implementation challenge: even where AI tools are accessible, organizational readiness gaps constrain effective deployment.

2.4 Research Gap

No validated predictive framework exists that specifically models the contribution of AI-driven analytics features to operational agility outcomes in post-pandemic retail SMEs, using objective operational data and ensemble machine learning methods with reported accuracy benchmarks against rigorous baselines. Existing studies either examine technology adoption at a general level without isolating analytics applications [2], report descriptive outcomes without predictive

validation [3], or focus on system development without controlled performance comparison [8]. This study fills that gap by developing a hybrid ensemble model, validating it against static reorder baselines, and identifying feature-importance weights that specify which analytics capabilities most strongly predict agility.

3. Methodology

3.1 Research Design

This study employs a quantitative, design-based research design combining retrospective data analysis with prospective simulation. Design-based research is appropriate because the study aims to develop and validate a practical artifact (the predictive analytics framework) while generating theoretical insights about its operation in real-world contexts [2][8]. The retrospective component analyzes 18 months of operational data from participating SMEs; the prospective component simulates deployment scenarios to test framework performance against baselines.

3.2 Study Area / Population

The target population consists of retail SMEs (10–250 employees) operating physical or hybrid store formats in urban and semi-urban markets. The sampling frame was constructed from a commercial retail data consortium comprising 1,847 SMEs that had consented to anonymized data sharing for research purposes. The population was stratified by subsector (grocery/convenience, apparel, electronics, household goods) and by digital maturity tier (low, medium, high based on prior technology adoption indicators).

3.3 Sample Size and Sampling Technique

Sample size: 412 SMEs were selected, yielding 18 months of operational records (January 2023–June 2024).

Sampling method: Stratified random sampling with proportional allocation across subsectors and digital maturity tiers. Within each stratum, firms were randomly selected until the target sample size was achieved.

Justification: The sample size provides 80% power to detect a 15% difference in inventory cost outcomes at $\alpha = 0.05$, based on variance estimates from pilot data. Stratification ensures representation across retail subsectors with distinct demand patterns [8].

3.4 Data Collection Methods

Data sources: Point-of-sale transaction logs (daily SKU-level sales), inventory management records (stock levels, reorder events, stockout incidents), and supplier delivery records (lead times, order fulfillment rates).

Types of data extracted: For each SME-day observation: daily unit sales by SKU, inventory position, reorder quantity, supplier lead time (actual and promised), promotional calendar flags, and stockout incidence (binary).

Time period: January 2023–June 2024 (18 months), capturing post-pandemic stabilization and seasonal cycles.

Simulated data: Supplier lead-time variability for 12% of observations was simulated using historical variance parameters due to incomplete supplier record linkage. This is disclosed as a limitation.

3.5 Research Instruments

Software: Python 3.11 with scikit-learn 1.3, XGBoost 2.0, and pandas 2.0 for model development. PostgreSQL 15 for data storage and feature engineering.

Libraries: scikit-learn for Random Forest and preprocessing; XGBoost for gradient boosting implementation; SHAP 0.44 for feature importance interpretation.

Preprocessing steps: (1) Removal of duplicate transaction records; (2) time-series interpolation for missing inventory values; (3) winsorization of extreme sales spikes at the 1st and 99th percentiles; (4) one-hot encoding of categorical features (subsector, region, promotion type); (5) temporal feature engineering (day-of-week, month, holiday proximity, lagged sales at 7, 14, and 28 days) [8][9].

3.6 Validity and Reliability

Content validity: The feature set was reviewed by three retail operations experts and two data scientists to ensure coverage of relevant operational variables and alignment with established inventory management constructs.

Predictive validity: Model performance was assessed on a held-out test set comprising the final 20% of observations (temporally ordered, not randomly split) to simulate real-world forecasting conditions [2].

Inter-rater reliability: For the 10% subsample of stockout events that required manual classification (ambiguous cases), two independent coders achieved Cohen's $\kappa = 0.87$, indicating strong agreement.

3.7 Data Analysis Techniques

Models compared:

1. **Static reorder baseline:** Fixed reorder points calculated as mean demand × lead time + safety stock (traditional method).
2. **Random Forest:** 500 estimators, max depth 15, minimum samples per leaf 5.

3. **XGBoost:** 300 estimators, learning rate 0.05, max depth 6.
4. **Hybrid ensemble:** Weighted average of Random Forest and XGBoost predictions, with weights optimized on validation set.

Performance metrics:

- **Accuracy:** Proportion of correctly predicted stockout/non-stockout events.
- **Precision and recall:** For stockout prediction (positive class = stockout).
- **Mean absolute error (MAE):** For inventory level forecasts.
- **Inventory holding cost reduction:** Percentage reduction relative to baseline.
- **Lead time:** Days between predictive alert and required reorder action.

Cross-validation: Time-series cross-validation with rolling origin (5 folds, expanding window) to respect temporal dependencies [2][9].

Statistical testing: Paired t-tests comparing model performance metrics against baseline across SME strata; significance threshold $\alpha = 0.05$.

3.8 Ethical Considerations

This study used de-identified, anonymized operational data obtained under a data-sharing agreement that prohibited re-identification. No personally identifiable information (PII) or protected health information (PHI) was accessed. The research protocol was reviewed by the institutional ethics committee and granted exemption status under category 4 (secondary use of de-identified data) per institutional guidelines. Data storage and processing complied with applicable data protection regulations.

4. Results

4.1 Data Presentation

Table 1. Key Operational Indicators by Digital Maturity Tier (January 2023–June 2024)

Indicator	Low Maturity (n=138)	Medium Maturity (n=159)	High Maturity (n=115)
Daily sales (mean, SD)	$1,847 (SD 623)	$2,341 (SD 891)	$3,102 (SD 1,245)

Indicator	Low Maturity (n=138)	Medium Maturity (n=159)	High Maturity (n=115)
Stockout incidence (%)	14.2%	10.8%	7.3%
Inventory turnover (annual)	5.1	6.8	8.4
Supplier lead time (days)	8.7 (SD 3.2)	7.9 (SD 2.8)	6.4 (SD 2.1)
Promotional days (%)	12.4%	18.7%	22.1%

Table 1 presents baseline operational differences across digital maturity tiers, confirming that higher-maturity SMEs began the study period with more favorable agility indicators, underscoring the need for models that account for initial conditions.

Table 2. Model Performance Comparison

Model	Accuracy	Precision (Stockout)	Recall (Stockout)	MAE (Inventory)
Static baseline	72.1%	0.61	0.54	18.4 units
Random Forest	87.2%	0.84	0.79	11.2 units
XGBoost	86.5%	0.83	0.81	11.8 units
Hybrid ensemble	**89.4%**	**0.87**	**0.83**	**10.1 units**

Table 2 presents the comparative performance of all models on the held-out test set. The hybrid ensemble achieved the highest accuracy (89.4%) and lowest inventory forecast error (MAE = 10.1 units), outperforming both individual learners and the static baseline.

Table 3. Top Feature Importances (SHAP Values, Hybrid Ensemble)

Feature	Mean |SHAP|	Rank
7-day demand volatility	0.142	1
Supplier lead-time variance	0.118	2
Promotional calendar density	0.097	3
Lagged sales (14-day)	0.089	4
Inventory position at reorder point	0.076	5

Table 3 presents the top five features by mean absolute SHAP value, identifying demand volatility and supplier lead-time variance as the dominant predictors of stockout events and agility outcomes.

4.2 Analysis of Results

The hybrid ensemble model achieved **89.4% accuracy** in predicting stockout events, representing a **17.3 percentage-point improvement** over the static reorder baseline (72.1%). This difference was statistically significant (paired $t = 8.42$, $p < 0.001$, Cohen's $d = 1.24$).

Inventory holding cost reduction: SMEs using hybrid ensemble recommendations reduced inventory holding costs by **23.7%** relative to baseline over the simulated deployment period ($p < 0.001$). This reduction was consistent across digital maturity tiers, though absolute savings were larger for higher-volume firms.

Lead time improvement: The mean lead time between predictive alert and actionable reorder recommendation was **2.3 days**, compared to 4.7 days for manual review processes—a 51% reduction in decision latency.

Feature importance: Demand volatility (7-day rolling standard deviation) emerged as the strongest predictor (mean $|SHAP| = 0.142$), followed by supplier lead-time variance (0.118) and promotional calendar density (0.097). This ordering suggests that agility is primarily driven by the capacity to anticipate demand fluctuations and supplier unreliability rather than by promotional optimization per se.

5. Discussion

5.1 Interpretation

The finding that the hybrid ensemble achieved 89.4% accuracy substantially exceeds prior reported benchmarks for SME inventory prediction. While Sabeena et al. [2] achieved an R^2 of 0.6249 for organizational agility prediction at a general level, the present study demonstrates that operationally specific prediction (stockout events) can achieve higher accuracy when models are trained on granular transactional data. This suggests that agility outcomes are more predictable when operationalized at the process level rather than as firm-level constructs.

The identification of demand volatility and supplier lead-time variance as top predictors aligns with dynamic capability theory's emphasis on sensing external variability [5][6]. SMEs that can detect and respond to these two sources of uncertainty gain disproportionate agility advantages. This finding extends prior work by Ma et al. [9], which established that big data analytics capability influences supply chain agility through integration mechanisms, by specifying which analytics features most directly contribute to that capability in SME retail contexts.

The 23.7% inventory cost reduction compares favorably with the Packworks [3] finding of 17% sales increase, though the metrics differ (cost vs. revenue). Together, these results suggest that AI-driven analytics operates on both sides of the operational equation: increasing revenue through better product mix and reducing costs through more efficient inventory positioning.

The feature-importance finding that promotional calendar density ranks third—below volatility and lead-time variance—challenges the common assumption that promotional optimization should be the primary focus of SME analytics investment. Instead, foundational capabilities in demand sensing and supplier reliability appear more fundamental to agility.

5.2 Implications

Academic implications: This study operationalizes AI-driven analytics as a specific dynamic capability, extending dynamic capability theory from its traditional firm-level application to the operational process level in SMEs. It introduces a validated measurement approach for analytics-driven agility that future research can adapt across contexts. The feature-importance results identify specific capability components (demand sensing, supplier monitoring) that mediate the analytics–agility relationship, refining theoretical understanding of how dynamic capabilities function in resource-constrained firms.

Practical implications: Retail SME managers should prioritize data collection and analytics investment in two areas: (1) demand volatility tracking at the SKU level with at least 7-day rolling windows, and (2) supplier lead-time monitoring with variance logging. Analytics systems should be configured to generate alerts when these indicators exceed threshold levels, with reorder recommendations calculated dynamically rather than through static parameters. Expected lead time from alert to action: 2–3 days with automated recommendations, compared to 5+ days with manual review.

Policymakers designing SME digitalization programs should consider directing resources toward demand forecasting and supplier management analytics rather than undifferentiated "AI adoption" initiatives. The 89.4% accuracy benchmark provides a realistic target for evaluating analytics deployments.

5.3 Limitations

1. **Sample composition:** While stratified, the sample is drawn from a commercial data consortium that may over-represent firms with some prior digital engagement. Generalizability to the least digitally mature SMEs is uncertain.
2. **Simulated supplier data:** Approximately 12% of supplier lead-time observations were simulated, which may affect the precision of feature-importance estimates for that variable.
3. **Temporal stability:** The 18-month observation window captures a specific post-pandemic period. Whether the identified feature relationships remain stable during different economic conditions (e.g., recession, acute supply shock) is unknown.
4. **Single-region focus:** The geographic concentration limits cross-cultural generalizability, particularly regarding supplier relationship norms and digital infrastructure quality.

5.4 Future Research Directions

1. Longitudinal extension examining whether sustained AI analytics use produces cumulative agility gains or reaches a plateau.
2. Comparative validation across regions with different digital infrastructure maturity levels to test framework portability.
3. Examination of organizational factors (managerial analytics literacy, data governance practices) that moderate the analytics–agility relationship.
4. Extension to adjacent SME sectors (food service, services retail) to assess the specificity of the identified feature-importance patterns.

6. Conclusion

This study developed and validated a hybrid AI-driven analytics framework that achieved 89.4% accuracy in predicting stockout events and reduced inventory holding costs by 23.7% among post-pandemic retail SMEs. The primary contribution is a replicable predictive framework that identifies demand volatility and supplier lead-time variance as the strongest operational predictors of agility, providing both theoretical specificity to dynamic capability theory and actionable guidance for SME managers. Retail administrators should prioritize analytics investment in demand sensing and supplier monitoring, where the agility returns are demonstrably highest. As retail SMEs continue to navigate an uncertain post-pandemic landscape, the capacity to transform operational data into predictive insight will increasingly distinguish resilient firms from those that remain vulnerable to disruption.

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