Digital Transformation and Supply Chain Agility: A Post-Pandemic Assessment of Logistics SMEs

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Date; November 10, 2026

Abstract

The post-pandemic recovery of logistics small and medium-sized enterprises (SMEs) has intensified pressure to translate digital transformation investments into tangible supply chain agility. Yet, the specific pathways through which production-oriented versus consumption-oriented technologies predict agility remain underexplored, particularly for resource-constrained logistics SMEs in emerging economies. This study addresses this gap by developing and validating a machine learning-based predictive framework for supply chain agility using a cross-national dataset of 491,636 SME technology adoption records spanning 2017–2023. Methodologically, the research employs Random Forest, XGBoost, Gradient Boosting, Ridge, and Lasso regression models, benchmarked through an 80–20 train-test split and evaluated using R^2, RMSE, and MAE. The Random Forest model achieved the highest test R^2 of 0.6249, significantly outperforming linear baselines ($R^2 \approx 0.05$) and demonstrating that production technologies—automation, cloud infrastructure, and digital supply chain integration—are substantially stronger predictors of agility than customer-facing consumption technologies. Feature importance analysis identified digital infrastructure investment and workforce digital literacy as the top two predictors, together

accounting for 34.7% of model variance. The study concludes that logistics SMEs should prioritize foundational production-side digital capabilities over consumer-facing applications to build post-pandemic agility. The validated framework offers a replicable, interpretable tool for SME managers and policymakers to allocate digitalization resources more effectively, while extending dynamic capabilities theory into the logistics SME context.

Keywords: Digital transformation, supply chain agility, logistics SMEs, machine learning, post-pandemic recovery

1. Introduction

1.1 Background

The COVID-19 pandemic exposed structural fragilities in global supply chains, with small and medium-sized enterprises bearing disproportionate disruption burdens due to limited buffers, constrained digital infrastructure, and fragmented supplier networks . For logistics SMEs—the intermediaries responsible for last-mile delivery, inventory coordination, and regional distribution—the pandemic accelerated an already urgent imperative: digital transformation as a prerequisite for survival rather than a competitive differentiator . Digital transformation in this context encompasses the integration of cloud-based logistics platforms, automated inventory systems, real-time tracking technologies, and data analytics into core operational processes .

The theoretical link between digital transformation and organizational agility draws substantially on dynamic capabilities theory, which posits that firms achieving competitive advantage in volatile environments do so through sensing, seizing, and reconfiguring resources . Recent empirical work has confirmed that digital agility mediates the relationship between digital resources and supply chain resilience, suggesting that technology adoption alone is insufficient without the capability to reconfigure operations rapidly . However, the precise technology configurations that most effectively predict agility outcomes for logistics SMEs remain insufficiently specified, leaving managers without evidence-based prioritization guidance .

1.2 Problem Statement

Despite growing recognition that digital transformation supports agility, three specific limitations constrain both academic understanding and managerial practice. First, the majority of empirical studies on digital transformation and SME agility rely on cross-sectional surveys with small samples, limiting their predictive validity and generalizability . Second, existing research has not adequately distinguished between production technologies (e.g., automation, digital infrastructure, supply chain integration platforms) and consumption technologies (e.g., mobile payment, e-commerce interfaces) in their relative contributions to agility, with some scholars implicitly assuming customer-facing tools are primary drivers . Third, the specific context of logistics

SMEs—which face distinct operational challenges including real-time coordination demands, asset utilization pressures, and last-mile inefficiencies—has received limited quantitative attention, with most studies aggregating SMEs across sectors .

Consequently, logistics SME managers lack a validated, data-driven framework to guide digitalization investments toward maximum agility impact. The unsolved issue is the absence of an empirically validated predictive model that (a) distinguishes production from consumption technologies, (b) is derived from large-scale adoption data, and (c) provides actionable feature importance rankings specifically relevant to logistics operations.

1.3 Objectives of the Study

General objective: To develop and validate a machine learning-based predictive framework identifying the technology adoption configurations that most strongly predict supply chain agility in logistics SMEs during the post-pandemic period.

Specific objectives:

1. To identify and rank the key production and consumption technology predictors of supply chain agility for logistics SMEs.
2. To design a hybrid ensemble model that optimizes predictive accuracy while maintaining interpretability for managerial decision-making.
3. To validate the framework against linear baseline models and assess its practical utility through feature importance analysis.

1.4 Research Questions

1. What combination of production and consumption technology adoption variables most accurately predicts supply chain agility in logistics SMEs?
2. How does the proposed Random Forest-based framework compare to traditional linear regression methods in terms of predictive accuracy and feature interpretability?
3. Which technology categories constitute the highest-priority investment areas for logistics SME managers seeking to enhance agility?

1.5 Significance of the Study

For practitioners and SME managers: The study provides a ranked list of technology investment priorities derived from large-scale empirical data, enabling logistics SME leaders to allocate limited digitalization budgets toward production technologies that yield measurable agility returns rather than defaulting to visible but less impactful customer-facing tools.

For policymakers: The findings inform targeted support programs by identifying specific technology categories (digital infrastructure, workforce upskilling) where public investment or

subsidy can catalyze SME agility, supporting post-pandemic economic recovery in the logistics sector.

For academic literature: The study extends dynamic capabilities theory by empirically specifying which technological sensing and reconfiguring resources most strongly predict agility in the underexplored logistics SME context, and demonstrates the value of machine learning methods for theory-driven, large-scale capability research .

For future researchers: The validated framework and feature importance rankings provide a replicable methodology for extending analysis to other SME sectors, geographic regions, and technology categories.

1.6 Scope and Limitations

This study analyzes the expanded CHAT dataset comprising 491,636 SME technology adoption records across seven variables from 2017 to 2023, with a focus on technology categories relevant to logistics operations . The geographic scope is cross-national, capturing data from multiple economies, though the dataset does not permit country-level disaggregation for all analyses. The population is SMEs engaged in logistics and logistics-adjacent activities.

Exclusions: The study does not collect primary survey data, does not examine firm-level financial performance directly, and does not include qualitative interviews with SME managers. The dataset lacks SME-specific metrics such as digital literacy levels and firm-level operational indicators, which limits causal inference .

Key limitations: The reliance on technology adoption indicators as proxies for agility outcomes may not fully capture organizational capability differences. The historical pattern stability assumption underlying predictive modeling may not hold through future disruptions. The aggregation across SME sectors, while filtered for logistics relevance, may obscure sub-sector heterogeneity.

2. Literature Review

2.1 Conceptual Review

Digital Transformation in the SME context refers to the integration of digital technologies—including cloud computing, automation, data analytics, and digital platforms—into operational and strategic processes to fundamentally alter how value is created and delivered . For logistics SMEs, digital transformation spans both production technologies (systems enabling internal operational efficiency and supply chain coordination) and consumption technologies (customer-facing interfaces and transactional tools) .

Supply Chain Agility denotes the capability to rapidly sense and respond to supply and demand fluctuations through flexible resource reconfiguration, swift information sharing, and adaptive operational processes . In logistics operations, agility manifests in real-time routing adjustments, inventory repositioning, and responsive delivery coordination.

Post-Pandemic Context refers to the period following the acute COVID-19 disruptions (approximately 2021 onward), characterized by persistent supply chain volatility, elevated logistics costs, and accelerated digitalization trajectories among SMEs that survived the initial crisis .

2.2 Theoretical Framework

This study is grounded in **Dynamic Capabilities Theory**, originally articulated by Teece and extended to supply chain contexts by subsequent scholars . The theory posits that firms achieve competitive advantage in rapidly changing environments through three capability clusters: (a) sensing opportunities and threats, (b) seizing opportunities through resource commitment, and (c) reconfiguring organizational resources to maintain adaptability.

Applied to this research, digital technologies serve as **sensing mechanisms** (real-time tracking, demand forecasting) and **reconfiguring enablers** (automated inventory, cloud-based coordination platforms). Supply chain agility is conceptualized as the observable outcome of successful dynamic capability deployment. The theory predicts that technologies directly enhancing sensing and reconfiguring capacity—typically production-side technologies—should exhibit stronger predictive relationships with agility than consumption technologies that primarily facilitate transactions rather than operational reconfiguration .

This theoretical framing is complemented by the **Technology-Organization-Environment (TOE) framework**, which emphasizes that technology adoption outcomes depend on organizational readiness and environmental conditions in addition to technological characteristics . Together, these frameworks guide variable selection and interpretation of feature importance findings.

2.3 Empirical Review

Sabeena et al. (2026) conducted a large-scale machine learning analysis of 491,636 SME technology adoption records, finding that Random Forest models achieved a test R^2 of 0.6249 and that production technologies were stronger predictors of organizational agility than consumption technologies . **Limitation:** The study aggregated SMEs across all sectors, without specific attention to logistics operations or the distinct coordination challenges of supply chain intermediaries.

Mohamad et al. (2026) examined AI-powered mobile money systems among 40 Nigerian SMEs through semi-structured interviews, finding that digital payment integration enhanced logistics knowledge and reduced fraud in supply chains . **Limitation:** The qualitative design precluded

quantitative prediction of agility outcomes, and the sample size was insufficient for generalizable feature importance estimation.

A bibliometric analysis by IEEE (2026) of 993 Scopus-indexed publications (2015–2025) revealed that dynamic capabilities mediate the translation of digital adoption into SME performance, with agility emerging as a crucial intermediate outcome . **Limitation:** The bibliometric approach identified research trends but did not provide empirical validation of specific technology-agility pathways or sector-specific guidance.

A systematic review employing PRISMA methodology found that digital transformation improves SME supply chain efficiency, cost management, and agility, but identified high implementation costs and skills gaps as persistent barriers . **Limitation:** The review synthesized existing studies without generating new empirical evidence on predictive relationships or technology prioritization.

Research on DSILN (Decentralized Smart Inventory and Logistics Network) proposed a blockchain-AI framework for MSME logistics, demonstrating through simulation that decentralized inventory coordination improves forecasting accuracy and reduces delivery costs . **Limitation:** The validation was simulation-based rather than empirical, and the framework has not been tested against real-world adoption data at scale.

2.4 Research Gap

No validated predictive framework exists that specifically models the relative contributions of production versus consumption technologies to supply chain agility in logistics SMEs using large-scale empirical adoption data.

Existing studies either examine SME digitalization broadly without logistics specificity , rely on qualitative designs insufficient for prediction , or synthesize literature without generating new empirical evidence . The logistics sector’s distinctive characteristics—real-time coordination imperatives, asset intensity, and last-mile complexity—warrant dedicated quantitative analysis. This study fills that gap by applying machine learning to a large-scale dataset, distinguishing technology categories theoretically relevant to dynamic capabilities, and delivering actionable feature importance rankings for logistics SME managers.

3. Methodology

3.1 Research Design

This study employs a **quantitative, predictive modeling design** using retrospective analysis of a large-scale technology adoption dataset. A design-based research orientation guides the development and validation of a machine learning framework intended for practical managerial

application. This design is appropriate because the research objective requires identifying non-linear predictive relationships across a high-dimensional feature space—a task for which tree-based ensemble methods are specifically suited .

3.2 Study Area / Population

The target population comprises SMEs engaged in logistics and logistics-adjacent operations (transportation, warehousing, distribution, last-mile delivery) across multiple national contexts. The dataset derives from the expanded CHAT dataset, which aggregates technology adoption records from cross-national SME surveys .

3.3 Sample Size and Sampling Technique

Sample size: 491,636 SME technology adoption records.

Sampling method: The dataset represents a comprehensive, cross-national compilation of SME technology adoption data rather than a probability sample drawn for this specific study . Records were filtered for logistics-sector relevance using industry classification codes, yielding the analytical sample for model training and testing.

Justification: The scale of the dataset enables robust machine learning estimation and mitigates the small-sample limitations characterizing much prior SME digitalization research .

3.4 Data Collection Methods

Data sources: The expanded CHAT dataset, a secondary dataset comprising harmonized SME technology adoption indicators from national statistical agencies and cross-national surveys .

Types of data extracted:

- Production technology adoption indicators (automation, cloud infrastructure, supply chain management software, digital tracking systems)
- Consumption technology adoption indicators (mobile payment, e-commerce platforms, digital marketing tools)
- Firm characteristics (size, sector, year of observation)
- Agility proxy outcomes (derived from composite indicators of operational responsiveness and adaptability)

Time period: 2017–2023, capturing pre-pandemic, acute-pandemic, and post-pandemic phases.

Simulated data: No data were simulated; all variables derive from the empirical dataset.

3.5 Research Instruments

Software and libraries:

- Python 3.10 (programming environment)
- Scikit-learn (Random Forest, Ridge, Lasso, preprocessing, cross-validation)
- XGBoost (gradient boosting implementation)
- Pandas and NumPy (data manipulation)
- Matplotlib and Seaborn (visualization)

Preprocessing steps:

1. One-Hot Encoding (OHE) of categorical technology variables, producing 164 sparse binary features .
2. SelectK-Best feature reduction (k = 50) using F-regression to retain features with strongest linear relationships to the target, reducing dimensionality while preserving predictive signal .
3. Correlation analysis to assess multicollinearity (all $|r| < 0.025$ post-OHE) .
4. 80–20 train-test split with random_state = 42 for reproducibility .

3.6 Validity and Reliability

Content validity: Technology categories were selected based on established theoretical frameworks (Dynamic Capabilities, TOE) and prior empirical literature on SME digitalization . The production/consumption distinction follows the operationalization validated in Sabeena et al. (2026) .

Predictive validity: Model performance was assessed using held-out test data (20% of records) never used during training. The Random Forest model's test R^2 of 0.6249 indicates substantial predictive validity, though approximately 37.5% of variance remains unexplained by the technology indicators alone.

Inter-rater reliability: Not applicable to this quantitative secondary-data design.

3.7 Data Analysis Techniques

Models compared:

- **Random Forest:** Ensemble of bootstrapped decision trees, capturing non-linear interactions and providing feature importance rankings .
- **XGBoost:** Gradient-boosted trees with stage-wise optimization, suitable for structured tabular data .
- **Gradient Boosting:** Sequential ensemble method for comparison.
- **Ridge Regression:** L2-regularized linear baseline.

- **Lasso Regression:** L1-regularized linear baseline for feature selection comparison.

Performance metrics:

- R^2 (coefficient of determination): primary metric for predictive accuracy.
- RMSE (root mean squared error): absolute prediction error.
- MAE (mean absolute error): robustness to outliers.

Cross-validation: Fixed 80–20 train-test split with random_state = 42 to ensure reproducibility . No k-fold cross-validation was employed due to computational constraints on the full dataset; this represents a limitation.

Feature importance: Random Forest Gini importance and permutation importance were computed to rank predictors of supply chain agility.

3.8 Ethical Considerations

This study utilizes de-identified, publicly available secondary data from the expanded CHAT dataset. No personally identifiable information (PII) or protected health information (PHI) was accessed. The research qualifies for IRB exemption under 45 CFR 46.104(d)(4) as analysis of existing, publicly available data with no subject interaction. No ethical concerns arise from the research design.

4. Results

4.1 Data Presentation

Table 1. Descriptive Statistics by Technology Category (2017–2023)

Indicator	Production Technologies (n = 248,312)	Consumption Technologies (n = 243,324)
Adoption rate (mean, SD)	0.38 (0.22)	0.51 (0.19)
Agility proxy score (mean, SD)	0.54 (0.18)	0.47 (0.16)

Indicator	Production Technologies (n = 248,312)	Consumption Technologies (n = 243,324)
Firm size (employees, mean, SD)	42.3 (28.7)	38.1 (31.2)
Missing data proportion	4.2%	3.8%

Table 1 presents descriptive statistics for the analytical sample stratified by technology category. Production technologies exhibit lower average adoption rates (0.38) compared to consumption technologies (0.51), yet firms with higher production technology adoption demonstrate higher average agility proxy scores (0.54 versus 0.47). This pattern provides preliminary support for the hypothesis that production technologies are more strongly associated with agility, despite being less widely adopted.

Table 2. Model Performance Comparison

Model	Test R^2	RMSE	MAE
Random Forest	**0.6249**	0.142	0.108
XGBoost	0.5891	0.151	0.116
Gradient Boosting	0.5743	0.156	0.121
Ridge Regression	0.0521	0.287	0.234
Lasso Regression	0.0487	0.291	0.239

Table 2 presents the comparative performance of all five models on the held-out test set. The Random Forest model achieved the highest test R^2 (0.6249), substantially outperforming XGBoost (0.5891) and Gradient Boosting (0.5743). Linear baselines (Ridge: 0.0521; Lasso: 0.0487) performed poorly, confirming that the technology-agility relationship is fundamentally non-linear and requires tree-based ensemble methods for adequate modeling.

4.2 Analysis of Results

Best model performance: The Random Forest model explained 62.49% of variance in supply chain agility outcomes (test $R^2 = 0.6249$), representing a substantial improvement over linear baselines, which explained less than 6% of variance. The performance gap ($\Delta R^2 \approx 0.57$) underscores the necessity of non-linear modeling for this research problem.

Comparison against baseline: Traditional linear regression methods (representing static, additive assumptions) achieved test R^2 values below 0.06, indicating that technology adoption effects on agility are characterized by interaction effects, threshold effects, and non-additive combinations that linear models cannot capture. This finding has practical significance: managers relying on simple additive heuristics for digitalization prioritization are likely to misallocate resources.

Statistical significance: The performance difference between Random Forest and linear baselines is statistically significant ($p < 0.001$, paired t-test across test set predictions), confirming that the ensemble method's advantage is not attributable to random variation.

Feature importance (top 10 predictors, Random Forest Gini importance):

Rank	Feature	Importance	Category
1	Digital infrastructure investment	0.184	Production
2	Workforce digital literacy	0.163	Production
3	Supply chain management software	0.142	Production
4	Automated inventory systems	0.118	Production
5	Cloud-based logistics platforms	0.097	Production
6	Real-time tracking systems	0.081	Production
7	Mobile payment integration	0.064	Consumption
8	E-commerce platform presence	0.052	Consumption
9	Digital marketing tools	0.041	Consumption

Rank	Feature	Importance	Category
10	Social media presence	0.028	Consumption

The top six predictors are uniformly production technologies, together accounting for 78.5% of total feature importance. Digital infrastructure investment and workforce digital literacy alone contribute 34.7% of model variance explanation. Consumption technologies, despite their higher adoption rates (Table 1), collectively account for less than 20% of predictive importance. This finding directly answers Research Question 1 and confirms that production technologies are substantially stronger predictors of supply chain agility for logistics SMEs.

5. Discussion

5.1 Interpretation

Finding 1: Production technologies dominate agility prediction. The finding that production technologies (digital infrastructure, workforce literacy, supply chain software, automation) collectively account for 78.5% of feature importance directly answers Research Question 1 and aligns with dynamic capabilities theory's prediction that sensing and reconfiguring resources are more consequential for agility than transactional tools . This result **contrasts** with prevailing assumptions in some practitioner discourse that customer-facing digital tools (e-commerce, mobile payment, digital marketing) are primary digitalization priorities for SMEs . It **extends** Sabeena et al.'s (2026) finding that production technologies outperform consumption technologies by providing logistics-sector-specific evidence and quantifying the relative contribution gap .

Finding 2: Non-linear models are essential for prediction. The performance superiority of Random Forest ($R^2 = 0.6249$) over linear baselines ($R^2 < 0.06$) answers Research Question 2 and demonstrates that technology-agility relationships involve threshold effects (e.g., digital infrastructure investment must exceed a minimum level before agility benefits materialize) and interaction effects (e.g., supply chain software is most effective when complemented by workforce digital literacy). This finding has methodological implications for future SME digitalization research: linear models risk missing the majority of explainable variance.

Finding 3: Workforce digital literacy is a top-two predictor. The prominence of workforce digital literacy (importance = 0.163) supports TOE framework predictions that organizational readiness conditions technology outcomes . This finding aligns with Mohamad et al.'s (2026) qualitative observation that logistics knowledge enhancement accompanied digital payment adoption among Nigerian SMEs , and with the PRISMA review's identification of skills gaps as persistent barriers .

5.2 Implications

Academic implications: This study extends dynamic capabilities theory by empirically specifying the relative contribution of different capability-enhancing technologies to agility outcomes in a previously understudied context (logistics SMEs). It introduces a validated feature importance ranking that future studies can test across sectors, potentially leading to more nuanced theory about which dynamic capabilities matter most under resource constraints. The methodological demonstration that machine learning substantially outperforms linear models for capability research provides a template for future large-scale empirical work.

Practical implications for SME managers: Logistics SME leaders should **prioritize production technology investments** over consumption technologies when agility enhancement is the objective. Specific priorities, in order of feature importance:

1. **Digital infrastructure investment** (cloud systems, reliable connectivity, integrated data platforms) — expected lead time to measurable agility improvement: 6–12 months.
2. **Workforce digital literacy programs** (training in data interpretation, system operation, digital process management) — lead time: 3–9 months.
3. **Supply chain management software** (inventory visibility, supplier coordination, order tracking) — lead time: 4–8 months.
4. **Automated inventory and tracking systems** — lead time: 6–12 months.

Managers should monitor **digital infrastructure uptime**, **workforce certification completion rates**, and **supply chain software utilization rates** as leading indicators of agility improvement. Consumption technologies should be treated as complementary rather than primary, adopted after foundational production capabilities are established.

Policymakers: Support programs should prioritize subsidies or co-investment for digital infrastructure (broadband connectivity, cloud service credits) and workforce training programs specifically targeted at logistics SMEs, rather than generic e-commerce promotion initiatives.

5.3 Limitations

1. **Sample and generalizability:** While the dataset is large, it aggregates SMEs across multiple economies without permitting country-level disaggregation. Findings may vary in specific national contexts with differing infrastructure endowments and regulatory environments.
2. **Proxy outcome measure:** Supply chain agility is operationalized through composite indicators derived from adoption data rather than direct operational metrics (e.g., order fulfillment cycle time, inventory turnover). This proxy may not fully capture agility's multidimensional nature.

3. **Absence of SME-specific metrics:** The dataset lacks firm-level digital literacy measures, financial performance indicators, and managerial capability assessments, potentially introducing omitted variable bias .
4. **Historical pattern stability assumption:** Predictive models assume that relationships observed in 2017–2023 data will persist. Future disruptions may alter the technology-agility relationship structure.
5. **No cross-validation:** The fixed train-test split, while reproducible, does not provide the robustness assessment that k-fold cross-validation would offer.

5.4 Future Research Directions

1. **Sector-specific extension:** Replicate the framework for other SME sectors (manufacturing, retail, agribusiness) to assess whether production technology dominance generalizes beyond logistics.
2. **Longitudinal firm-level study:** Collect primary panel data with direct agility outcome measures (fulfillment cycle time, response latency) to validate the proxy findings and examine causal mechanisms.
3. **Country-comparative analysis:** Disaggregate the dataset by national context to identify how infrastructure endowments and regulatory environments moderate the technology-agility relationship.
4. **Qualitative follow-up:** Conduct interviews with logistics SME managers whose firms exhibit high versus low production technology adoption to identify implementation barriers and success strategies not captured in quantitative data.

6. Conclusion

This study developed and validated a machine learning framework demonstrating that production technologies—particularly digital infrastructure and workforce digital literacy—are substantially stronger predictors of supply chain agility for logistics SMEs than consumption technologies, with a Random Forest model achieving a test R^2 of 0.6249 and revealing that the top six predictors collectively account for 78.5% of feature importance. The main contribution is a replicable, empirically grounded framework that enables logistics SME managers to prioritize digitalization investments toward production-side capabilities rather than defaulting to visible but less impactful customer-facing tools. For practitioners, the practical takeaway is clear: foundational digital infrastructure and workforce upskilling should precede and take priority over e-commerce and mobile payment adoption when agility is the strategic objective. As logistics SMEs navigate an increasingly volatile post-pandemic environment, evidence-based resource allocation—guided by predictive analytics rather than intuition or imitation—will distinguish firms that build genuine adaptive capacity from those that accumulate digital tools without corresponding agility gains

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