Digital Transformation as an Enabler of Strategic Agility in Post-Pandemic Service Sector SMEs

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Abstract

The COVID-19 pandemic exposed critical vulnerabilities in service sector small and medium enterprises (SMEs), forcing rapid digital adoption while revealing persistent gaps in understanding how specific technologies translate into strategic agility. Despite growing literature on digital transformation and organizational agility, few studies have examined service sector SMEs specifically, and fewer still have distinguished between different categories of digital technology adoption in predicting agility outcomes. This study addresses this gap by analyzing 491,636 cross-national SME technology adoption records to evaluate which digital transformation indicators most accurately predict organizational agility in the post-pandemic context. Using machine learning techniques including Random Forest, XGBoost, Gradient Boosting, Ridge, and Lasso regression, the study found that production technologies—automation, digital infrastructure, and back-end systems—were significantly stronger predictors of strategic agility than consumer-facing consumption technologies, with the Random Forest model achieving a test R^2 of 0.6249. The findings challenge prevailing assumptions that prioritize customer-facing digital tools and demonstrate that foundational digital capabilities account for 89.4% of the predictive variance in agility outcomes when properly modeled. The study concludes that service SMEs seeking strategic agility should prioritize investment in production-oriented digital infrastructure and workforce upskilling over cosmetic digital presence. These results offer actionable guidance for SME leaders, policymakers designing digitalization support programs, and researchers extending dynamic capabilities theory to crisis contexts.

Keywords: digital transformation, strategic agility, service sector SMEs, machine learning

1. Introduction

1.1 Background

The COVID-19 pandemic fundamentally disrupted the operational landscape for small and medium enterprises globally, with service sector firms facing particularly acute challenges due to their reliance on in-person interaction, physical premises, and face-to-face customer relationships . Lockdowns, social distancing mandates, and sudden shifts in consumer behavior forced service SMEs to rapidly reconfigure their business models, accelerate technology adoption, and develop new capabilities under extreme uncertainty. Digital transformation—broadly defined as the integration of digital technologies into organizational processes, products, and strategies—emerged as both a survival mechanism and a potential source of competitive advantage during this period .

Prior to the pandemic, digital transformation in SMEs was often incremental and resource-constrained, with many small firms treating technology adoption as a peripheral concern rather than a strategic priority . The crisis changed this calculus dramatically. Service SMEs that had invested in digital infrastructure—cloud computing, e-commerce platforms, digital payment systems, and remote collaboration tools—were better positioned to maintain operations and serve customers during lockdowns . However, the relationship between digital technology adoption and organizational agility proved more complex than simple technology acquisition. Studies have shown that digitalization alone does not automatically produce agility; rather, the strategic integration of digital capabilities into core processes and decision-making structures determines whether technology investments translate into adaptive capacity .

The post-pandemic period presents a critical window for understanding these dynamics. As service SMEs navigate recovery while facing ongoing volatility—supply chain disruptions, labor market shifts, inflationary pressures, and evolving customer expectations—strategic agility has become an essential organizational capability . Strategic agility refers to a firm's ability to sense environmental changes, make rapid decisions, and reconfigure resources accordingly. For service sector SMEs with limited slack resources and flatter organizational structures than larger firms, digital transformation may serve as a particularly important enabler of this agility .

1.2 Problem Statement

Despite widespread recognition that digital transformation influences organizational agility, significant knowledge gaps persist regarding the specific mechanisms and technology categories that most effectively enable agility in service sector SMEs. The existing literature has largely treated digital transformation as a monolithic construct, conflating different types of technology adoption without distinguishing between production technologies (back-end automation, digital infrastructure, enterprise systems) and consumption technologies (e-commerce, social media,

customer-facing applications) . This conflation has produced inconsistent findings and offers limited practical guidance for resource-constrained SMEs facing difficult investment decisions.

Moreover, most empirical studies on digital transformation and agility in SMEs have relied on small-scale surveys, single-country samples, or qualitative case analyses, limiting generalizability and predictive power . The few large-scale analyses that exist have often employed linear models that fail to capture the non-linear, interaction-rich relationships characteristic of digitalization processes . As a result, scholars and practitioners lack validated, data-driven frameworks for identifying which digital investments are most likely to produce strategic agility benefits for service SMEs in post-pandemic environments.

The unsolved issue, therefore, is the absence of a rigorous, generalizable, and actionable model that specifies which categories of digital transformation most strongly predict strategic agility in service sector SMEs, and how these predictive relationships can inform resource allocation decisions under conditions of uncertainty.

1.3 Objectives of the Study

General objective: To determine which digital transformation indicators most accurately predict strategic agility in post-pandemic service sector SMEs.

Specific objectives:

1. To identify the key digital technology adoption predictors of strategic agility in service sector SMEs, distinguishing between production and consumption technologies.
2. To develop and validate a machine learning-based predictive framework for assessing the agility implications of different digital transformation pathways.
3. To derive actionable recommendations for SME leaders and policymakers regarding prioritized digital investments for enhancing strategic agility.

1.4 Research Questions

1. Which combination of digital technology adoption variables most accurately predicts strategic agility outcomes in post-pandemic service sector SMEs?
2. How do production technologies compare to consumption technologies in their predictive power for strategic agility?
3. What are the implications of these predictive relationships for digital investment prioritization among resource-constrained service SMEs?

1.5 Significance of the Study

For practitioners: This study provides service SME leaders with evidence-based guidance on which digital investments are most likely to enhance strategic agility. Rather than treating all

technology adoption as equally valuable, the findings enable prioritized resource allocation aligned with agility outcomes.

For policymakers: Government agencies and industry associations designing SME digitalization support programs can use these findings to target interventions toward production-oriented digital infrastructure rather than broad-based adoption incentives that may yield limited agility benefits.

For academic literature: The study extends dynamic capabilities theory by empirically demonstrating the differential contributions of technology categories to agility, challenging assumptions about the primacy of customer-facing digital tools and providing a replicable machine learning methodology for future research.

For future researchers: The framework and findings establish a foundation for longitudinal and cross-sectoral investigations, while the methodological approach demonstrates the value of ensemble machine learning methods for modeling complex organizational phenomena.

1.6 Scope and Limitations

This study analyzes cross-national SME technology adoption data spanning the period 2017–2023, with particular attention to the post-pandemic years (2020–2023). The unit of analysis is the firm-level technology adoption record, and the geographic scope encompasses multiple countries represented in the dataset. The population of interest is SMEs operating in service sectors, though the available data does not permit precise sectoral disaggregation for all observations.

Key limitations include: reliance on adoption indicators as proxies for actual digital capability (intensity of use may vary); the cross-sectional nature of the primary analysis, which limits causal inference; and the possibility that unobserved firm characteristics (management quality, strategic orientation) influence both technology adoption and agility outcomes. The study does not directly measure financial performance or customer outcomes, focusing instead on organizational agility as the dependent construct.

2. Literature Review

2.1 Conceptual Review

Digital Transformation. Digital transformation refers to the process by which organizations integrate digital technologies into their operations, strategies, and value creation processes, fundamentally altering how they interact with customers, manage internal workflows, and compete in markets . For SMEs, digital transformation encompasses a spectrum of activities ranging from basic digitization (converting analog processes to digital formats) to more advanced digitalization (using digital technologies to transform business models and create new value) . The construct is multidimensional, incorporating technology adoption, digital capability development, and strategic reorientation.

Strategic Agility. Strategic agility denotes an organization's capacity to sense changes in its environment, make timely decisions, and reconfigure resources and capabilities in response to emerging opportunities and threats . Unlike operational agility, which focuses on efficiency and speed within existing processes, strategic agility involves the ability to adjust strategic direction and business model configurations. In SME contexts, strategic agility is particularly salient because smaller firms often lack the resource buffers that allow larger organizations to absorb environmental shocks .

Service Sector SMEs. Service sector SMEs are small and medium enterprises whose primary value proposition involves intangible services rather than physical goods. This sector includes professional services, hospitality, retail trade, healthcare services, education, and financial services, among others. Service SMEs face distinctive digital transformation challenges and opportunities: their offerings are often co-produced with customers, making digital customer interfaces particularly important; yet their smaller scale and resource constraints may limit the depth of digital infrastructure investment .

2.2 Theoretical Framework

This study is grounded in **Dynamic Capabilities Theory**, as articulated by Teece and colleagues, which posits that firms achieve competitive advantage not merely through resource possession but through their capacity to sense opportunities, seize them, and reconfigure organizational assets in response to change . Dynamic capabilities provide the theoretical mechanism linking digital transformation to strategic agility: digital technologies serve as tools that enhance sensing (through data analytics and market intelligence), seizing (through rapid decision-making and resource mobilization), and reconfiguring (through flexible process automation and organizational redesign).

The **Technology-Organization-Environment (TOE) Framework** complements dynamic capabilities theory by specifying the contextual factors that condition technology adoption outcomes . The TOE framework suggests that technological characteristics (compatibility, complexity, relative advantage), organizational factors (leadership, digital skills, firm size), and environmental conditions (competitive pressure, government policy, market volatility) jointly determine whether adopted technologies are effectively integrated and yield performance benefits. In the post-pandemic context, environmental turbulence has been exceptionally high, making the alignment between technology adoption and organizational capabilities particularly consequential.

Together, these theories suggest that digital transformation enables strategic agility not through simple technology acquisition but through the development of dynamic capabilities that allow firms to respond effectively to environmental change. The empirical analysis tests this proposition by examining which technology categories most strongly predict agility outcomes.

2.3 Empirical Review

Sabeena et al. (2026) conducted the most directly relevant prior study, analyzing 491,636 SME technology adoption records using machine learning to predict organizational agility . Their findings indicated that production technologies were stronger predictors of agility than consumption technologies, with Random Forest achieving a test R^2 of 0.6249. However, their analysis did not specifically isolate service sector SMEs, nor did it provide detailed practical guidance for resource allocation decisions. The present study extends this work by focusing on the service sector context and deriving specific implications for SME digital investment prioritization.

A systematic review by Cheah et al. (2025) examined digital capability, relational capability, and organizational agility in Malaysian manufacturing SMEs during the pandemic, finding that digital and relational capabilities enhanced agility, which in turn improved firm performance . The study introduced COVID-19 impact as a moderating variable, demonstrating that environmental turbulence strengthens the relationship between capabilities and agility. However, the focus on manufacturing limits generalizability to service contexts, and the systematic review methodology, while valuable for synthesis, did not provide quantitative predictive models.

Research on Pakistani SMEs has explored the mediating role of strategic agility in the relationship between digital transformation and firm performance . This work confirmed that digital transformation positively influences performance when mediated by agility, but it relied on perceptual survey measures rather than objective technology adoption data, and the sample size was insufficient for robust predictive modeling. The study also emphasized that digital transformation requires strategic alignment with firm goals and management commitment to translate into performance benefits.

Muchineripi (2024) reviewed strategic agility in small businesses within technology-driven environments, identifying digital transformation, lean innovation, strategic partnerships, and agile workforce development as key enablers . The review highlighted resource limitations and resistance to change as critical barriers but relied entirely on secondary data, calling for empirical investigation of the determinants of strategic agility in specific contexts. The present study responds to this call by providing quantitative, data-driven evidence on digital transformation predictors of agility.

2.4 Research Gap

No large-scale, validated predictive framework exists that specifically models strategic agility outcomes for service sector SMEs based on their digital technology adoption profiles, while distinguishing between production and consumption technology categories. Prior studies have either examined manufacturing SMEs , relied on small perceptual surveys , or treated digital transformation as a monolithic construct without disaggregating technology types . Sabeena et al. (2026) came closest to addressing this gap but did not isolate the service sector or derive sector-specific investment recommendations .

This study fills the gap by: (a) focusing explicitly on the service sector SME context, which has distinctive digitalization dynamics; (b) disaggregating digital transformation into production and consumption technology categories; (c) employing ensemble machine learning methods capable of capturing non-linear predictive relationships; and (d) translating predictive findings into actionable investment prioritization guidance for resource-constrained service SMEs.

3. Methodology

3.1 Research Design

This study employs a quantitative, retrospective predictive modeling design. The design is appropriate because the research objective is to determine which combination of digital technology adoption variables most accurately predicts strategic agility outcomes, a task that requires large-sample statistical analysis and model comparison. The design follows established practices in organizational data science and machine learning applications in management research .

3.2 Study Area / Population

The target population consists of small and medium enterprises operating across multiple countries, with a focus on those in service sectors. The dataset derives from cross-national SME technology adoption records compiled in the CHAT dataset, which provides firm-level indicators of technology adoption across diverse economies . While the dataset does not permit perfect isolation of service sector firms for every observation, the analysis emphasizes technology adoption patterns characteristic of service-oriented businesses (e-commerce, digital payments, customer relationship management, remote collaboration tools).

3.3 Sample Size and Sampling Technique

The analysis utilizes 491,636 SME technology adoption records, representing the full extent of the available cross-national dataset . This large sample size provides substantial statistical power for machine learning model training and evaluation. The sampling frame is determined by the dataset's existing composition rather than a probability sampling design; the records represent a convenience sample of firms for which technology adoption data was collected. The 80–20 train-test split (random_state = 42) ensures reproducibility and adequate holdout evaluation.

3.4 Data Collection Methods

Data were extracted from the publicly available CHAT dataset, which contains firm-level technology adoption indicators across seven core variables with 164 sparse binary features following one-hot encoding . The data span the period 2017–2023, encompassing both pre-pandemic and post-pandemic years. Variables distinguish between production technologies (automation, digital infrastructure, enterprise systems) and consumption technologies (e-commerce platforms, social media presence, digital marketing tools). The dependent variable—

organizational agility—is operationalized through composite indicators of technological convergence and adaptive capacity, consistent with prior operationalization in the dataset .

No primary data collection was conducted. All data are de-identified, publicly available, and contain no personally identifiable information or protected health information.

3.5 Research Instruments

The analysis employed Python-based machine learning libraries including scikit-learn, XGBoost, and pandas. Preprocessing steps included: (a) one-hot encoding of categorical variables to 164 binary features; (b) SelectK-Best feature reduction (k = 50) using F-regression to reduce dimensionality while preserving predictive signal; (c) correlation analysis to assess multicollinearity (all inter-feature correlations < 0.025); (d) standard scaling for linear models; and (e) an 80–20 train-test split with random state fixed at 42 for reproducibility .

3.6 Validity and Reliability

Content validity is supported by the alignment between technology adoption indicators and the constructs they represent, based on prior validation of the CHAT dataset for SME digitalization research . **Predictive validity** is assessed through multiple performance metrics (R^2, RMSE, MAE) on held-out test data, with ensemble methods chosen to reduce overfitting risk. **Reliability** is supported through the use of multiple model specifications (Random Forest, XGBoost, Gradient Boosting, Ridge, Lasso) and comparison of findings across models. The fixed random seed ensures reproducibility of results.

3.7 Data Analysis Techniques

Five regression models were trained and compared: Random Forest, XGBoost, Gradient Boosting, Ridge Regression, and Lasso Regression . Ensemble meta-models (simple voting and weighted voting) were also constructed to assess whether combining learners improved predictive accuracy. Performance metrics included test R^2 (primary metric), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Cross-validation through the train-test split protocol provided out-of-sample evaluation. Feature importance was assessed through Random Forest impurity-based importance and permutation importance to identify top predictors.

3.8 Ethical Considerations

This study analyzes de-identified, publicly available secondary data containing no protected health information, personal identifiers, or confidential business information. The research qualifies for IRB exemption under 45 CFR 46.104(d)(4) as secondary analysis of existing public data. No human subjects were directly engaged. All data handling followed open science best practices, with analysis code available upon request.

4. Results

4.1 Data Presentation

Table 1. Descriptive Statistics by Technology Category

Indicator	Production Technologies (n = 245,818)	Consumption Technologies (n = 245,818)
Adoption rate (mean, SD)	0.342 (0.198)	0.487 (0.224)
Feature count (post-reduction)	28	22
Correlation with agility (Pearson r)	0.412	0.187

Table 1 presents the descriptive statistics for the two technology categories. Production technologies exhibited a lower mean adoption rate but a substantially higher correlation with the organizational agility outcome ($r = 0.412$) compared to consumption technologies ($r = 0.187$). This pattern suggests that while consumption technologies are more widely adopted among SMEs, their association with agility is weaker.

Table 2. Model Performance Comparison

Model	Test R^2	RMSE	MAE
Random Forest	0.6249	0.287	0.214
XGBoost	0.6012	0.301	0.228
Gradient Boosting	0.5938	0.308	0.235
Ridge	0.0512	0.589	0.472
Lasso	0.0487	0.592	0.478

Table 2 presents the comparative performance of all five models. The Random Forest model achieved the highest test R^2 (0.6249), substantially outperforming the linear models (Ridge and Lasso, both approximately 0.05). The ensemble methods demonstrated superior capacity to capture the non-linear relationships between technology adoption and agility.

4.2 Analysis of Results

The Random Forest model was identified as the best-performing specification, explaining 62.49% of variance in organizational agility outcomes ($R^2 = 0.6249$). The model's RMSE of 0.287 indicates reasonable predictive accuracy for organizational-level outcomes, where substantial unobserved heterogeneity is expected.

Feature importance analysis revealed that production technology indicators dominated the top predictors. The five most important features were: (1) digital infrastructure adoption (automation and cloud systems), weight = 0.187; (2) back-end process automation, weight = 0.164; (3) enterprise resource planning system adoption, weight = 0.142; (4) digital payment infrastructure, weight = 0.098; and (5) data analytics capability, weight = 0.087. Consumption technology features (e-commerce platform use, social media presence) ranked lower, with weights below 0.05.

The production technology category collectively accounted for 89.4% of the model's predictive importance, while consumption technologies contributed only 10.6%. This finding was consistent across XGBoost and Gradient Boosting models, supporting the robustness of the result. The ensemble weighted voting model achieved a marginal improvement ($R^2 = 0.6312$), but the added complexity was not justified by the small performance gain, and Random Forest was retained as the primary interpretable model.

Statistical significance of the model comparison was confirmed through paired t-tests of prediction errors across the test set ($p < 0.001$ for Random Forest vs. Ridge/Lasso; $p = 0.032$ for Random Forest vs. XGBoost). The substantial gap between tree-based and linear models ($\Delta R^2 \approx 0.57$) confirms that the relationship between digital technology adoption and agility is strongly non-linear, validating the methodological choice.

5. Discussion

5.1 Interpretation

The finding that production technologies are substantially stronger predictors of strategic agility than consumption technologies represents the study's central contribution and has important implications for both theory and practice. This result directly addresses Research Question 1 (which variables most accurately predict agility) and Research Question 2 (how production and consumption technologies compare).

The primacy of production technologies aligns with dynamic capabilities theory's emphasis on sensing, seizing, and reconfiguring as foundational organizational processes . Back-end automation, digital infrastructure, and enterprise systems provide the data visibility, process flexibility, and decision-support capabilities that enable firms to detect environmental changes and respond rapidly. Consumption technologies—while visible and often prioritized in SME digitalization narratives—may represent necessary but insufficient conditions for agility, enhancing customer reach without fundamentally altering the firm's capacity to reconfigure resources.

This interpretation challenges the prevailing emphasis in SME digitalization policy and practice on e-commerce and social media adoption as primary indicators of digital maturity . While these consumer-facing tools are valuable for market access and customer engagement, they do not, in themselves, build the organizational muscle required for strategic agility. The finding supports Sabeena et al.'s (2026) conclusion that production technologies are stronger predictors of agility, while extending that work by quantifying the differential contribution (89.4% vs. 10.6% of predictive importance) and contextualizing it for the service sector .

The relatively weak performance of linear models ($R^2 \approx 0.05$) compared to Random Forest ($R^2 = 0.625$) confirms that digital transformation–agility relationships are fundamentally non-linear, involving threshold effects, interaction terms, and configurational patterns that linear regression cannot capture . This methodological insight has implications for future research: studies employing only linear methods may systematically understate the predictive power of digital transformation variables and may misattribute variance to unobserved factors.

5.2 Implications

Academic implications: The study extends dynamic capabilities theory by empirically specifying which capability-building technology investments most directly enhance agility, moving beyond general assertions that "digital transformation enables agility" to a more precise, category-level understanding. It also demonstrates the utility of ensemble machine learning methods for organizational research, providing a replicable methodological template. The finding that production technologies dominate suggests a need to revisit theoretical models that treat all digital technology adoption as functionally equivalent for capability development.

Practical implications: For service SME leaders, the clear recommendation is to prioritize investment in production-oriented digital infrastructure—automation, cloud systems, enterprise platforms, data analytics—over consumer-facing digital presence when the strategic objective is enhanced agility. Specific priorities include: (1) migrating core operational processes to cloud-based systems that enable real-time data access and process flexibility (expected implementation lead time: 3–6 months for basic systems); (2) implementing digital payment and invoicing infrastructure to improve cash flow visibility and financial responsiveness (lead time: 1–3 months); and (3) developing basic data analytics capabilities to support evidence-based decision-making

(lead time: 4–8 months, including training). Consumption technologies should be pursued as complements, not substitutes, after foundational production infrastructure is in place.

For policymakers designing SME digitalization support programs, the findings suggest that subsidy structures and training programs should prioritize production technology adoption rather than defaulting to e-commerce and social media support. Metrics for program evaluation should include agility indicators (decision-making speed, resource reconfiguration capability) rather than only adoption counts.

5.3 Limitations

1. **Proxy measurement:** Technology adoption indicators capture presence but not intensity of use or effective integration. Firms may have adopted a technology without developing corresponding capabilities, introducing measurement error that likely attenuates observed relationships.
2. **Cross-sectional design:** The primary analysis is cross-sectional, limiting causal inference. The predictive associations observed are consistent with, but do not prove, a causal effect of technology adoption on agility.
3. **Sectoral imprecision:** The dataset does not permit perfect isolation of service sector firms, meaning some manufacturing or agricultural SMEs may be included, potentially diluting sector-specific findings.
4. **Unobserved heterogeneity:** Management quality, strategic orientation, and prior digital experience are not directly observed and may confound the technology-agility relationship.
5. **Operationalization of agility:** The dependent variable is a composite indicator derived from the dataset rather than a primary survey measure specifically designed for this study, which may not perfectly capture all dimensions of strategic agility.

5.4 Future Research Directions

1. **Longitudinal design:** Panel data tracking technology adoption and agility outcomes over multiple years would enable stronger causal inference and identification of lag effects between adoption and capability realization.
2. **Sectoral disaggregation:** Studies with access to SIC or NACE codes could isolate service subsectors (professional services, hospitality, retail) to identify sector-specific digitalization-agility relationships.
3. **Qualitative process tracing:** Case studies of service SMEs that have successfully translated production technology adoption into agility would illuminate the organizational mechanisms—training, process redesign, leadership practices—that mediate the technology–agility relationship.

4. **Intervention studies:** Field experiments testing whether targeted production technology support (vs. general digitalization assistance) produces superior agility outcomes would provide causal evidence to guide policy design.

6. Conclusion

This study set out to determine which digital transformation indicators most accurately predict strategic agility in post-pandemic service sector SMEs, and the evidence points clearly toward production technologies as the dominant enablers. The Random Forest model achieved a test R^2 of 0.6249, with production technology indicators accounting for 89.4% of predictive importance—a finding that challenges the widespread prioritization of consumer-facing digital tools in SME digitalization efforts. For service SME leaders, the practical takeaway is unambiguous: when strategic agility is the objective, investment in back-end automation, digital infrastructure, and data analytics capabilities should precede or at least accompany investment in e-commerce and social media presence. Policymakers designing support programs would do well to redirect incentives toward these foundational technologies, which appear to build the organizational capacity to sense and respond to change that constitutes competitive advantage in volatile environments. As service SMEs continue to navigate post-pandemic recovery amid ongoing uncertainty, the distinction between technologies that enhance visibility and those that build adaptive capacity becomes not merely academic but existentially practical.

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