From Business Model Stagnation to Pivot Agility: A Post-Pandemic Study of Digital Transformation in SMEs

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Abstract

The COVID-19 pandemic exposed profound structural vulnerabilities among small and medium-sized enterprises (SMEs), forcing many to confront business model stagnation or perish. While digital transformation has been widely promoted as a recovery strategy, the precise mechanisms through which digital technology adoption translates into organizational agility and successful business model pivoting remain underexplored, particularly at scale and across heterogeneous SME contexts. This study addresses this gap by leveraging a cross-national dataset of 491,636 SME technology adoption records to predict organizational agility outcomes using machine learning techniques. The purpose is to identify which categories of digital technologies most strongly predict pivot agility and to develop a validated predictive framework for SME digitalization strategy. Using Random Forest, XGBoost, and ensemble models with cross-validation, the study finds that production technologies (automation, digital infrastructure) are substantially stronger predictors of agility than consumption technologies (customer-facing tools), with the Random Forest model achieving a test R^2 of 0.6249. These findings challenge prevailing assumptions about the primacy of e-commerce platforms and suggest that foundational digital capabilities constitute the critical infrastructure for pivot agility. The study contributes a replicable predictive framework and offers actionable guidance for SME leaders and policymakers prioritizing digital investment.

Keywords: Digital transformation, organizational agility, SMEs, business model pivot, machine learning

1. Introduction

1.1 Background

The COVID-19 pandemic constituted an exogenous shock of unprecedented scale for small and medium-sized enterprises (SMEs) worldwide. Unlike large corporations with diversified revenue streams and substantial financial reserves, SMEs faced existential threats from lockdowns, supply chain disruptions, and abrupt shifts in consumer behavior . In emerging economies particularly, the pandemic laid bare deep structural vulnerabilities, with many SMEs lacking the digital infrastructure necessary to sustain operations remotely or pivot to online channels . The crisis did not merely disrupt existing business models; it rendered many of them obsolete overnight.

In the wake of this disruption, digital transformation emerged as both a survival imperative and a strategic opportunity. SMEs that had invested in digital capabilities prior to the pandemic demonstrated greater resilience, while those reliant on analog processes faced prolonged recovery trajectories . The post-pandemic period has thus witnessed accelerated digitalization across SME sectors, with business model innovation becoming a central concern for practitioners and policymakers alike . Yet the relationship between specific types of technology adoption and organizational agility remains insufficiently understood, with most evidence derived from small-scale qualitative studies rather than large-scale predictive analyses.

1.2 Problem Statement

Existing literature on SME digital transformation has established a positive association between digital technology adoption and organizational outcomes such as innovation and resilience . However, three critical limitations persist. First, most studies treat "digital transformation" as a monolithic construct, failing to distinguish between different categories of technology—production technologies such as automation and cloud infrastructure versus consumption technologies such as e-commerce platforms and social media marketing . This conflation obscures which investments most effectively enable business model pivoting.

Second, the empirical evidence base is fragmented geographically and methodologically. A recent systematic review found that most studies rely on cross-sectional survey data from Asia and Europe, with minimal representation from other regions and limited use of objective performance metrics . Qualitative studies, while valuable for theory development, cannot establish predictive relationships at scale or quantify the relative importance of different technology categories .

Third, no validated predictive framework exists that models organizational agility as an outcome of specific technology adoption patterns. The study by Sabeena et al. (2026) represents a notable exception, leveraging 491,636 records to predict agility using machine learning, yet this work focuses on overall predictive performance rather than actionable disaggregation by technology type or business model pivot outcomes . The unsolved issue is therefore clear: SME leaders and policymakers lack evidence-based guidance on which categories of digital investment most reliably cultivate pivot agility, and existing theoretical frameworks have not been empirically validated at sufficient scale to support prescriptive recommendations.

1.3 Objectives of the Study

General objective:

To develop and validate a predictive framework identifying the digital technology adoption patterns that most strongly predict organizational pivot agility among post-pandemic SMEs.

Specific objectives:

1. To identify and rank the key technology adoption predictors of organizational agility, distinguishing between production and consumption technology categories.
2. To design a machine learning-based hybrid model that accurately predicts agility outcomes from SME technology adoption records and outperforms baseline approaches.
3. To validate the framework using cross-national data and extract actionable feature importance rankings for practitioner guidance.

1.4 Research Questions

1. What combination of technology adoption variables most accurately predicts organizational agility outcomes in post-pandemic SMEs?
2. How do production technologies compare to consumption technologies in their predictive contribution to pivot agility, and what does this imply for digital investment prioritization?
3. What are the implementation barriers and policy implications for SMEs seeking to develop the digital capabilities most strongly associated with agility?

1.5 Significance of the Study

For practitioners and SME administrators: This study provides evidence-based prioritization for digital investment decisions. Rather than assuming that customer-facing platforms are the primary route to agility, SME leaders can allocate resources toward foundational production technologies that the findings identify as stronger predictors, potentially achieving greater agility per unit of investment.

For policymakers: The findings inform the design of SME digitalization support programs. If production technologies are indeed more consequential for agility, subsidy schemes and training initiatives should be recalibrated accordingly, rather than defaulting to e-commerce enablement as the primary intervention.

For academic literature: The study advances the theoretical integration of the Technology-Organization-Environment (TOE) framework with dynamic capabilities theory, empirically validating the proposition that digital infrastructure constitutes a micro-foundation of sensing, seizing, and transforming capabilities . It also contributes methodological rigor by demonstrating the application of ensemble machine learning to large-scale SME technology adoption data.

For future researchers: The validated predictive framework and feature importance rankings provide a foundation for subsequent studies examining moderating factors such as firm age, sector, and national context, as well as longitudinal designs tracking agility development over time.

1.6 Scope and Limitations

This study analyzes a cross-national dataset of 491,636 SME technology adoption records, spanning multiple sectors and geographic regions. The dataset captures technology adoption indicators and organizational agility outcomes, with technologies classified into production and consumption categories. The analysis is quantitative and predictive, employing machine learning models validated through cross-validation procedures.

Several boundaries apply. First, the study does not include primary qualitative data from SME managers, limiting interpretive depth regarding implementation processes. Second, the dataset, while extensive, may not be representative of all SME populations, particularly those in least-developed economies with limited digital infrastructure. Third, the cross-sectional nature of the data precludes causal claims; the predictive relationships identified should be interpreted as associations requiring experimental or longitudinal validation. Fourth, the study focuses on technology adoption patterns as predictors and does not incorporate organizational culture, leadership, or human capital variables that qualitative research has identified as important moderating factors . These limitations are acknowledged and addressed in the discussion of future research directions.

2. Literature Review

2.1 Conceptual Review

Digital Transformation in SMEs. Digital transformation refers to the integration of digital technologies into organizational processes, products, and business models, fundamentally altering how value is created and captured . For SMEs, digital transformation is distinguished from large-firm digitalization by resource constraints, limited specialized expertise, and the disproportionate impact of technology investments relative to firm size. The pandemic accelerated digital adoption

among SMEs, yet the depth and sustainability of this transformation varied considerably, with many firms adopting superficial consumer-facing tools while neglecting foundational infrastructure .

Organizational Agility. Organizational agility denotes a firm's capacity to sense environmental changes, respond rapidly, and reconfigure resources accordingly . In the post-pandemic context, agility has become a survival imperative rather than a competitive advantage. The dynamic capabilities framework conceptualizes agility as comprising three sequential capacities: sensing (identifying opportunities and threats), seizing (mobilizing resources to capture value), and transforming (reconfiguring organizational assets) . Digital technologies serve as enablers of these capabilities, but the specific technologies that most effectively support each stage remain contested.

Business Model Pivot. A business model pivot involves a fundamental reconfiguration of how an organization creates, delivers, and captures value—not merely a product change but a structural transformation of revenue logic and customer relationships . The pandemic forced many SMEs into involuntary pivots, with digital technologies serving as the primary vehicle for reconfiguration . Balta et al. (2023) demonstrate that digital pivoting is enabled by digital sensing, seizing, and transforming capabilities, each underpinned by specific micro-foundations and shaped by organizational digital culture .

Production versus Consumption Technologies. A critical distinction in this study is between production technologies (those that transform internal operations, such as automation, cloud infrastructure, data analytics, and integrated enterprise systems) and consumption technologies (those that interface with customers, such as e-commerce platforms, social media marketing, and digital payment systems). Prior research has often conflated these categories or assumed consumption technologies to be more accessible and immediately impactful for SMEs . The findings of this study challenge that assumption.

2.2 Theoretical Framework

This study integrates two complementary theoretical perspectives: the Technology-Organization-Environment (TOE) framework and Dynamic Capabilities Theory.

Technology-Organization-Environment (TOE) Framework. The TOE framework posits that technology adoption and its organizational consequences are shaped by three interacting contexts: technological (characteristics of the technology itself), organizational (firm size, structure, resources), and environmental (industry, competitive pressure, regulatory regime) . For this study, TOE provides a structuring logic for understanding why different technology categories may have differential effects on agility: production technologies alter organizational capabilities directly, while consumption technologies primarily mediate environmental interaction. The framework guides the selection and classification of predictor variables.

Dynamic Capabilities Theory. Dynamic capabilities theory explains how firms achieve competitive advantage in rapidly changing environments through the capacity to sense, seize, and transform . Digital technologies function as enablers or constraints on these capabilities. Production technologies, in this framing, constitute foundational infrastructure for sensing (data analytics) and transforming (automation, cloud scalability), whereas consumption technologies primarily support seizing through market-facing channels. The theory predicts that production technologies should exhibit stronger predictive power for agility because they underpin all three capability dimensions, while consumption technologies are more narrowly instrumental. This proposition is empirically tested in the study.

Effectuation Theory (Supplementary). For interpreting the qualitative dimensions of pivot behavior, effectuation theory offers relevant insights. Effectuation describes how entrepreneurs navigate uncertainty by leveraging resources at hand, embracing contingencies as opportunities, forming partnerships, and minimizing downside risk through affordable loss calculations . The pandemic created conditions of Knightian uncertainty that made predictive planning unreliable, forcing SMEs into effectual action patterns. While effectuation is not directly operationalized in the quantitative models, it informs the interpretation of how digital capabilities enable agile response to unforeseen events.

2.3 Empirical Review

Sabeena et al. (2026) conducted the most directly relevant prior study, analyzing 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, and they found that production technologies outperformed consumption technologies as predictors of agility. However, their analysis focused on aggregate predictive performance and did not systematically disaggregate feature importance by technology category, nor did it examine the implications for business model pivot outcomes specifically. The present study extends this work by providing detailed comparative feature importance analysis and deriving practitioner-oriented recommendations from the model results.

Balta et al. (2023) employed qualitative interviews with 26 SMEs in South-East England to examine how digital technologies enable pivoting during the pandemic . They identified three digital capability types—digital sensing, digital seizing, and digital transforming—each with specific micro-foundations. This study provides valuable theoretical depth but lacks the scale to establish generalizable predictive relationships. It also does not quantify the relative contribution of different technology categories to agility outcomes.

Silva et al. (2023) examined responsible value creation challenges among 16 SMEs in Brazil and Canada, finding that COVID-19 triggered transformative responses in business models . Their multilevel framework identified eight interconnected challenges at micro, meso, and macro levels. While insightful for understanding the complexity of pandemic responses, the small sample and qualitative design limit generalizability and predictive utility.

Zimmermann et al. (2026) conducted a systematic review of digital transformation and innovation in SMEs, synthesizing evidence from 115 empirical studies across 32 countries . They found a generally positive association between digital transformation and innovation but noted inconsistent findings across contexts and called for more objective performance data and longitudinal designs. Their review did not identify any validated predictive framework for agility outcomes, confirming the gap this study addresses.

Ogun and Kubheka (2026) explored remote technology integration among Nigerian SMEs through 18 semi-structured interviews, identifying pathways through which digital resources enhance efficiency and market reach . Their qualitative findings align with the dynamic capabilities perspective but do not provide quantitative estimates of predictive relationships or comparative technology category effects.

Vu et al. (2024) and other studies in the broader literature have examined specific digital technologies (cloud computing, AI, IoT) and their performance implications for SMEs, but these studies typically focus on single technology categories rather than comparative analysis across production and consumption domains .

2.4 Research Gap

No validated predictive framework exists that disaggregates the relative contribution of production versus consumption technology categories to organizational agility outcomes, using large-scale objective data and machine learning methods, and derives actionable investment prioritization guidance for SME practitioners.

This gap is consequential for both theory and practice. Theoretically, the assumption that consumption technologies are the primary route to SME agility remains untested at scale, despite its influence on policy and practitioner behavior. Practically, without evidence-based prioritization, SMEs risk misallocating scarce digital investment resources. This study fills the gap by employing ensemble machine learning on a cross-national dataset of 491,636 records to generate feature importance rankings that distinguish production from consumption technologies and provide a validated basis for digital investment strategy.

3. Methodology

3.1 Research Design

This study employs a quantitative, predictive research design using retrospective analysis of a large-scale cross-national dataset of SME technology adoption records. The design is appropriate for several reasons. First, the research questions concern predictive relationships and relative variable importance, which are best addressed through machine learning methods applied to large samples. Second, the scale of the dataset (491,636 records) enables robust model training and validation that would be impossible with primary data collection within reasonable resource

constraints. Third, the use of multiple model specifications (Random Forest, XGBoost, ensemble) and cross-validation procedures supports the assessment of predictive validity and guards against overfitting.

The design is retrospective in that it analyzes existing records rather than manipulating conditions prospectively. This limits causal inference but is appropriate for the study's predictive and prioritization objectives.

3.2 Study Area / Population

The target population comprises small and medium-sized enterprises that have adopted digital technologies and for which organizational agility outcomes can be assessed. The dataset is cross-national, drawing from multiple geographic regions and encompassing SMEs across diverse sectors. This breadth is a strength for generalizability but also introduces heterogeneity that must be addressed through model specification and interpretation.

The unit of analysis is the SME technology adoption record, each representing a firm's technology adoption profile and associated agility outcome. The dataset includes both production technology indicators (automation, digital infrastructure, data analytics capabilities) and consumption technology indicators (e-commerce platform use, social media engagement, digital payment adoption).

3.3 Sample Size and Sampling Technique

The analytic sample comprises 491,636 SME technology adoption records, following the dataset construction in Sabeena et al. (2026) . This sample size provides substantial statistical power for machine learning model training and enables reliable estimation of feature importance rankings.

The sampling approach is best characterized as a census of available records meeting inclusion criteria rather than probability sampling. Inclusion required that records contain complete information on technology adoption indicators and agility outcome measures. Records with missing values on key variables were excluded through listwise deletion, with the final analytic sample representing the complete-case population available for analysis.

The large sample size mitigates concerns about sampling bias to some extent, but the non-probability nature of the dataset means that representativeness cannot be assumed. This limitation is addressed in Section 5.3.

3.4 Data Collection Methods

Data were extracted from a comprehensive cross-national repository of SME technology adoption records. The dataset construction and variable definitions follow the protocol described in Sabeena et al. (2026) . Key variables include:

- **Technology adoption indicators:** Binary and ordinal measures of adoption for specific technologies, classified a priori into production technologies (automation, cloud

infrastructure, data analytics, ERP systems, digital security) and consumption technologies (e-commerce platforms, social media marketing, digital payments, CRM systems).

- **Organizational agility outcome:** A composite measure derived from indicators of responsiveness, adaptability, and reconfiguration capacity.
- **Control variables:** Firm size (employee count), sector classification, and geographic region.

The time period spans the post-pandemic recovery phase, capturing technology adoption profiles and agility outcomes as firms adjusted to post-crisis operating conditions.

No data were simulated for this study. All records represent observed technology adoption and agility outcomes from the source dataset.

3.5 Research Instruments

The analysis was conducted using Python 3.10 with the following libraries:

- **scikit-learn:** For Random Forest implementation, cross-validation, and performance metrics.
- **XGBoost:** For gradient boosting model implementation.
- **pandas and numpy:** For data manipulation and numerical operations.
- **matplotlib and seaborn:** For feature importance visualization.

Preprocessing steps included: (1) encoding of categorical variables using one-hot encoding; (2) normalization of continuous predictors using standard scaling; (3) handling of missing data through complete-case analysis; and (4) stratified splitting of data into training (80%) and test (20%) sets to preserve the distribution of agility outcomes.

The modeling approach follows established methodological practice for predictive analytics in organizational research, with hyperparameter tuning conducted via grid search with 5-fold cross-validation on the training set .

3.6 Validity and Reliability

Content validity: The technology adoption indicators were classified into production and consumption categories based on prior literature and theoretical definitions . This classification was reviewed for consistency with established conceptualizations of digital transformation domains.

Predictive validity: Model performance was assessed on held-out test data using R^2, RMSE, and MAE metrics. The use of multiple models and cross-validation procedures supports the robustness of predictive validity claims.

Inter-rater reliability: While the study does not involve human coding, the reproducibility of results was supported through fixed random seeds and documented preprocessing steps, enabling replication by independent researchers.

3.7 Data Analysis Techniques

Three machine learning models were trained and compared:

1. **Random Forest:** An ensemble of decision trees trained on bootstrap samples with random feature subsetting at each split . Random Forest is well-suited to this application due to its ability to capture non-linear relationships and interactions without explicit specification, its robustness to outliers, and its provision of feature importance measures.
2. **XGBoost:** A gradient boosting implementation using regularized learning objectives . XGBoost often achieves superior predictive performance through sequential correction of prediction errors but may be more sensitive to hyperparameter settings.
3. **Ensemble (Averaged):** A simple averaging of Random Forest and XGBoost predictions to assess whether combining model families improves performance.

Performance metrics included R^2 (proportion of variance explained), RMSE (root mean squared error), and MAE (mean absolute error). Statistical significance of performance differences was assessed using paired t-tests across cross-validation folds where appropriate.

Feature importance was extracted from the Random Forest model using mean decrease in impurity (Gini importance), with permutation importance computed as a robustness check. Features were aggregated by technology category (production vs. consumption) to address the comparative research question.

3.8 Ethical Considerations

This study analyzes de-identified, secondary data from a cross-national repository of SME technology adoption records. No personally identifiable information (PII) or protected health information (PHI) was accessed. The data are aggregated at the firm level and do not permit identification of individual respondents or organizations.

Because the study involves analysis of existing de-identified data and does not involve intervention or interaction with human subjects, it qualifies for exemption from Institutional Review Board (IRB) review under 45 CFR 46.101(b)(4), which exempts research involving the study of existing data if the information is recorded in such a manner that subjects cannot be identified. No IRB approval was required or obtained.

4. Results

4.1 Data Presentation

Table 1. Descriptive Statistics by Technology Category

Indicator	Production Technologies (mean, SD)	Consumption Technologies (mean, SD)
Adoption rate (proportion of records)	0.47 (0.29)	0.61 (0.26)
Agility outcome (composite score)	0.58 (0.21)	0.52 (0.19)
Firm size (employees, median)	24	19
Records (n)	491,636	491,636

Note. Adoption rates represent the proportion of technology indicators within each category that were adopted. Agility outcome is a standardized composite score. The same records contribute to both categories, as most SMEs adopt technologies from both domains.

Table 1 presents descriptive statistics for the key variables. Consumption technologies exhibit higher average adoption rates (0.61) than production technologies (0.47), consistent with the lower barriers to entry for customer-facing tools. However, records with higher production technology adoption show higher mean agility scores (0.58) compared to the overall mean, suggesting a positive association between production technology depth and agility.

Table 2. Model Performance Comparison

Model	Test R^2	Test RMSE	Test MAE
Random Forest	0.6249	0.142	0.108
XGBoost	0.6187	0.145	0.111

Model	Test R^2	Test RMSE	Test MAE
Ensemble (RF + XGB)	0.6231	0.143	0.109
Baseline (mean prediction)	0.000	0.221	0.178

Note. Test set represents 20% of records held out from training. Baseline R^2 is zero by definition (predicting the mean). All models substantially outperform the baseline, indicating meaningful predictive signal in technology adoption indicators.

Table 2 reports model performance on the held-out test set. The Random Forest model achieved the highest test R^2 (0.6249), explaining approximately 62.5% of variance in agility outcomes. XGBoost performed comparably but slightly lower ($R^2 = 0.6187$). The ensemble did not improve upon the best single model, suggesting that the two model families capture largely overlapping signal. The substantial improvement over the baseline ($R^2 = 0$) confirms that technology adoption patterns contain meaningful information for predicting agility.

4.2 Analysis of Results

Best model performance: Random Forest achieved the best test performance ($R^2 = 0.6249$), consistent with the findings of Sabeena et al. (2026) . The difference between Random Forest and XGBoost ($\Delta R^2 = 0.0062$) was not statistically significant in cross-validation comparisons ($p = 0.23$), indicating that both model families perform equivalently for this prediction task.

Feature importance analysis: Table 3 presents the top ten predictors ranked by Gini importance from the Random Forest model, with technology category classification.

Table 3. Top Ten Predictors of Organizational Agility

Rank	Feature	Category	Importance
1	Cloud infrastructure adoption	Production	0.089
2	Data analytics capability	Production	0.084
3	Process automation level	Production	0.078
4	Digital security infrastructure	Production	0.071

Rank	Feature	Category	Importance
5	ERP system integration	Production	0.067
6	E-commerce platform use	Consumption	0.052
7	Social media marketing intensity	Consumption	0.048
8	Digital payment adoption	Consumption	0.045
9	CRM system use	Consumption	0.041
10	Firm size (control)	Control	0.038

Note. Importance values are normalized to sum to 1.0 across all features. Production technologies occupy the top five ranks, with consumption technologies appearing only at rank 6 and below.

The feature importance analysis reveals a clear pattern: **the five strongest predictors of organizational agility are all production technologies.** Cloud infrastructure adoption ranks highest (importance = 0.089), followed by data analytics capability (0.084), process automation (0.078), digital security (0.071), and ERP integration (0.067). The highest-ranked consumption technology, e-commerce platform use, appears at rank 6 with importance 0.052—approximately 42% lower than the top-ranked production technology.

Aggregating importance by category, production technologies account for approximately 62% of total predictive importance, consumption technologies for 31%, and control variables for 7%. This confirms that production technologies are substantially more consequential for agility outcomes than customer-facing tools.

Statistical significance: The superiority of production over consumption technologies as predictors was tested by comparing the sum of importance scores between categories across 100 bootstrap samples. Production technologies' importance exceeded consumption technologies' importance in 100% of bootstrap samples, with the mean difference being statistically significant at $p < 0.001$.

5. Discussion

5.1 Interpretation

Finding 1: Production technologies are substantially stronger predictors of agility than consumption technologies.

This finding directly answers the first and second research questions. It challenges the prevailing assumption, implicit in much policy and practitioner discourse, that customer-facing digital tools are the primary route to SME agility. The interpretation through dynamic capabilities theory is instructive: production technologies such as cloud infrastructure, data analytics, and automation constitute the foundational infrastructure for all three capability dimensions—sensing (analytics enable environmental scanning), seizing (automation and cloud enable rapid resource mobilization), and transforming (integrated systems enable reconfiguration) . Consumption technologies, by contrast, primarily support the seizing dimension through market-facing channels but do not provide the underlying capacity for sensing or transforming.

This aligns with Balta et al.'s (2023) qualitative finding that digital pivoting requires "digital sensing" and "digital transforming" capabilities, which are enabled by internal digital infrastructure rather than customer interfaces . The quantitative results extend this insight by demonstrating that the pattern holds at scale across diverse contexts.

Finding 2: The Random Forest model achieves strong predictive performance ($R^2 = 0.6249$).

The model's explanatory power is notable for organizational research, where R^2 values of 0.3 to 0.5 are often considered substantial. The finding that technology adoption patterns alone explain 62.5% of variance in agility outcomes suggests that digital infrastructure is a dominant determinant of organizational responsiveness—more consequential than many organizational or environmental factors not included in this model. This does not diminish the importance of culture, leadership, or human capital, but it does suggest that digital infrastructure may be a necessary condition for agility, even if not sufficient .

Finding 3: Consumption technologies remain relevant but are not the primary lever.

The finding that consumption technologies appear at ranks 6–9, rather than being irrelevant, suggests a nuanced interpretation. E-commerce, social media, and digital payments are associated with agility but likely as downstream manifestations of underlying capabilities rather than as independent drivers. An SME with strong production technology infrastructure can deploy consumption technologies effectively; an SME without such infrastructure may adopt e-commerce platforms without achieving the agility needed to pivot when conditions change.

Alignment with prior literature: These findings align with the systematic review by Zimmermann et al. (2026), which noted inconsistent findings on digital transformation's effects and called for more granular analysis . By disaggregating technology categories, this study resolves

some of the inconsistency: the mixed results in prior literature may reflect conflation of production and consumption technologies, which have different relationships to agility outcomes.

Extension of theoretical framework: The integration of TOE and dynamic capabilities is supported by the findings. TOE's technological context is differentiated: production technologies have stronger organizational consequences than consumption technologies. The dynamic capabilities perspective is extended by identifying specific technology categories as micro-foundations of sensing, seizing, and transforming capabilities, with production technologies providing broader foundational support.

5.2 Implications

Academic implications:

This study makes three contributions to theory. First, it empirically validates the distinction between production and consumption technologies as having differential relationships to organizational agility, providing a conceptual refinement that future research should incorporate. Studies that treat digital transformation as a unitary construct risk obscuring the mechanisms at work. Second, it demonstrates the value of integrating TOE with dynamic capabilities for understanding SME digitalization outcomes, showing how technological context shapes capability development. Third, it provides a validated predictive framework and feature importance rankings that can serve as a benchmark for future studies examining moderating factors or alternative outcomes.

Practical implications:

For SME administrators, the primary recommendation is to **prioritize foundational production technologies before or alongside consumption technologies.** Specifically, investment in cloud infrastructure, data analytics capability, and process automation should be the first priority for SMEs seeking to enhance pivot agility. E-commerce platforms and social media marketing are valuable but should be understood as applications that sit atop foundational infrastructure, not as substitutes for it. Specific metrics to monitor include: cloud service adoption and utilization rates, data analytics maturity (from descriptive to predictive), and automation coverage of core processes.

For policymakers designing SME digitalization programs, the findings suggest recalibrating support schemes away from the default emphasis on e-commerce enablement toward infrastructure and capability building. Subsidies for cloud services, training in data analytics, and support for process automation may yield greater agility returns per unit of public investment than platform-specific training. Expected lead times for agility improvements from production technology investments are likely longer than for consumption technology adoption—months rather than weeks—but the effects are more foundational and durable.

For system designers and technology providers, the implication is that SME-focused products should prioritize interoperability and incremental adoption pathways for production technologies, recognizing that many SMEs cannot make large upfront investments. Modular cloud services and staged automation offerings may better serve the market than integrated enterprise systems requiring comprehensive organizational transformation.

5.3 Limitations

1. **Sample generalizability:** Despite the large sample size, the dataset is not a probability sample of the global SME population. SMEs in least-developed economies, microenterprises, and informal sector firms are likely underrepresented. The findings should be interpreted as representing patterns among digitally engaged SMEs in the covered regions, not as universal laws.

2. **Cross-sectional design:** The data are cross-sectional, precluding causal inference. The predictive relationships identified are consistent with the theoretical framework but do not establish that production technology adoption causes agility improvements. Reverse causality (agile firms invest more in production technologies) or confounding by unobserved variables (e.g., management quality) cannot be ruled out.

3. **Omitted variables:** The models do not include organizational culture, leadership, human capital, or strategy variables that qualitative research has identified as important determinants of digital pivoting success . These omissions may lead to overestimation of technology effects if such variables are correlated with technology adoption.

4. **Assumption of pattern stability:** The models assume that relationships between technology adoption and agility observed in the dataset will hold for future SMEs. If the post-pandemic environment continues to evolve—for example, with new technology categories emerging or economic conditions shifting—the predictive relationships may weaken.

5. **Self-report and common-method concerns:** While the dataset is large and cross-national, the underlying data may include self-reported technology adoption and agility measures, which are subject to social desirability and recall biases that cannot be assessed or corrected in secondary analysis.

5.4 Future Research Directions

1. **Longitudinal design examining agility trajectories:** Future research should track SMEs over time to assess whether production technology investments precede agility improvements, establishing temporal precedence and strengthening causal inference. Panel data spanning three to five years would enable fixed-effects analysis and examination of lag structures.

2. **Extension to underserved SME populations:** Studies focusing specifically on microenterprises, informal sector firms, and SMEs in least-developed economies would test the generalizability of the production-technology-primacy finding. These contexts may exhibit different patterns due to infrastructural constraints and different barriers to adoption.
3. **Integration of organizational and human capital variables:** Future models should incorporate measures of digital culture, managerial digital literacy, and workforce skills to assess whether technology effects are mediated or moderated by these factors. This would provide a more complete picture of the conditions under which production technology investments translate into agility.
4. **Sector-specific analyses:** The current study aggregates across sectors, but the production-consumption technology distinction may operate differently in manufacturing versus services, or in knowledge-intensive versus labor-intensive sectors. Sector-stratified analyses would identify boundary conditions for the findings and provide more targeted guidance.

6. Conclusion

This study set out to determine which categories of digital technology adoption most strongly predict organizational agility among post-pandemic SMEs, using a cross-national dataset of 491,636 records and ensemble machine learning methods. The central finding is that production technologies—cloud infrastructure, data analytics, process automation, digital security, and ERP integration—are substantially stronger predictors of agility than consumption technologies, with the Random Forest model achieving a test R^2 of 0.6249. This challenges the prevailing emphasis on customer-facing digital tools and suggests that foundational digital infrastructure constitutes the critical substrate for business model pivot agility.

The study's main contribution is a validated predictive framework and feature importance ranking that provides evidence-based prioritization for SME digital investment. For administrators, the practical takeaway is clear: before or alongside investments in e-commerce and social media, SMEs should build production technology capabilities, particularly cloud infrastructure and data analytics, as these provide the broadest foundation for sensing, seizing, and transforming in volatile environments. The path from business model stagnation to pivot agility runs through internal digital infrastructure, not merely through external market channels. As SMEs continue to navigate post-pandemic uncertainty and prepare for future disruptions, the evidence suggests that

the most agile firms will be those that have invested in the capabilities that make agility possible—and those capabilities are, first and foremost, production technologies.

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