The Impact of Legacy System Digitization on Organizational Agility in Post-Pandemic SMEs

Authors

Abiodun Okunola, Abi Cit, James Claer

Date; November 3, 2026

Abstract

The post-pandemic business environment has compelled small and medium enterprises (SMEs) to accelerate digital transformation, yet many continue to operate with legacy systems that constrain their capacity to respond to market volatility. While prior research has examined digital transformation and organizational agility broadly, the specific mechanism through which legacy system digitization contributes to agility outcomes in resource-constrained SMEs remains underexplored. This study addresses this gap by developing and validating a predictive framework that models the relationship between legacy system modernization and organizational agility, drawing on a cross-national dataset of 491,636 SME technology adoption records and integrating Technology-Organization-Environment (TOE) and dynamic capabilities perspectives. Using machine learning techniques including Random Forest, XGBoost, and ensemble models, the study identifies production technologies (automation, digital infrastructure) as stronger predictors of agility than consumption-oriented tools. The Random Forest model achieved the highest predictive accuracy (Test $R^2 = 0.6249$), demonstrating that legacy system digitization accounts for substantial variance in agility outcomes. Key findings indicate that foundational digital infrastructure investments yield disproportionately higher agility returns than customer-facing applications, challenging conventional digitalization priorities. The study contributes a replicable, theory-driven predictive framework for SME digitization strategy and offers actionable guidance for administrators and policymakers seeking to optimize agility through targeted legacy system modernization.

Keywords: legacy system digitization, organizational agility, SMEs, post-pandemic recovery, machine learning

1. Introduction

1.1 Background

The COVID-19 pandemic exposed the structural fragility of small and medium enterprises (SMEs) worldwide, with lockdowns, supply chain disruptions, and shifting consumer behaviors forcing rapid operational adaptation . In the pandemic's aftermath, organizational agility—defined as a firm's capacity to sense and respond to environmental changes—has emerged as a critical determinant of SME survival and competitiveness . Digital transformation has been widely promoted as the primary pathway to achieving such agility, yet SMEs face distinctive constraints: limited financial resources, inadequate technical expertise, and entrenched legacy systems that resist integration with modern digital architectures .

Legacy systems, often comprising aging on-premises infrastructure, isolated software applications, and paper-based or semi-digital workflows, represent a particularly acute barrier for SMEs attempting to enhance agility . Unlike large enterprises with resources to undertake comprehensive system overhauls, SMEs must navigate digitization incrementally, often prioritizing low-cost, customer-facing technologies over foundational infrastructure investments . This prioritization may be counterproductive: recent evidence suggests that production technologies, including automation and backend digital infrastructure, are stronger predictors of organizational agility than widely adopted consumption technologies such as e-commerce platforms .

The post-pandemic period has therefore created a critical juncture for SMEs: those that effectively digitize legacy systems may achieve durable agility advantages, while those that defer or misdirect investments risk persistent rigidity in increasingly volatile markets .

1.2 Problem Statement

Existing literature has established a positive association between digital transformation and organizational agility in SMEs . However, three critical gaps persist. First, most studies treat "digital transformation" as a monolithic construct, failing to distinguish between the digitization of legacy systems—the foundational back-end infrastructure—and the adoption of front-end consumption technologies . This conflation obscures the specific contribution of legacy system modernization to agility outcomes.

Second, methodological limitations constrain the generalizability of prior findings. Studies have relied predominantly on cross-sectional surveys with modest sample sizes, typically fewer than 500 respondents , and have employed linear modeling approaches that cannot capture the non-

linear, threshold-dependent relationships characterizing digitalization's effects on agility . Third, the post-pandemic context—characterized by heightened uncertainty and accelerated technology adoption—remains underexplored in SME-specific research, with most empirical work predating or ignoring the pandemic's structural effects .

The consequence is a practical void: SME leaders and policymakers lack evidence-based guidance on where to direct limited digitization budgets to maximize agility returns. As Sharma et al. note, "organizational agility and IT readiness had the most substantial effects on transformation success," yet the specific technologies through which IT readiness translates into agility remain unspecified. This study addresses this gap by developing a predictive framework that isolates the contribution of legacy system digitization to organizational agility in post-pandemic SMEs, using large-scale data and machine learning methods capable of modeling complex, non-linear relationships.

1.3 Objectives of the Study

General objective: To develop and validate a predictive framework for assessing how legacy system digitization influences organizational agility in post-pandemic SMEs.

Specific objectives:

1. To identify which categories of legacy system digitization (production technologies versus consumption technologies) most strongly predict organizational agility outcomes in SMEs.
2. To design and evaluate a machine learning-based model that predicts agility from digitization indicators, benchmarked against linear regression approaches.
3. To derive evidence-based recommendations for SME administrators and policymakers regarding prioritization of legacy system modernization investments.

1.4 Research Questions

1. Which legacy system digitization indicators—distinguishing production and consumption technologies—most accurately predict organizational agility in post-pandemic SMEs?
2. How does a machine learning-based predictive framework compare to conventional linear methods in modeling the digitization-agility relationship?
3. What are the primary barriers to effective legacy system digitization among SMEs, and how do these barriers affect agility outcomes?

1.5 Significance of the Study

For practitioners/administrators: The study provides SME leaders with empirical evidence on which digitization investments yield the highest agility returns. By demonstrating that production technologies outperform consumption technologies as agility predictors, it offers a corrective to prevailing assumptions that customer-facing digitalization should take priority.

For policymakers: The findings inform the design of SME support programs. If foundational digital infrastructure is indeed the primary enabler of agility, policies should prioritize subsidies or incentives for backend system modernization rather than solely promoting e-commerce adoption.

For academic literature: The study advances theory by integrating TOE and dynamic capabilities frameworks in the context of legacy system modernization, and by demonstrating the value of machine learning methods for modeling nonlinear digitalization effects. It also contributes a replicable predictive framework for future SME agility research.

For future researchers: The methodology and findings provide a foundation for longitudinal studies examining how digitization-agility relationships evolve over time, and for comparative research across different SME sectors and national contexts.

1.6 Scope and Limitations

This study focuses on SMEs in the post-pandemic period (2017–2023 data range), drawing on a cross-national dataset of technology adoption records. The geographic scope is global, though the dataset's composition reflects the distribution of SME technology adoption patterns across participating regions. The population comprises SMEs that have undertaken or are undertaking legacy system digitization initiatives. The study does not include large enterprises, nor does it examine specific sectoral differences (manufacturing versus services) in detail, though such heterogeneity is acknowledged as a limitation.

Key limitations include: the use of secondary data, which constrains the depth of contextual information available for each SME; the absence of longitudinal firm-level tracking, which limits causal inference; and the reliance on technology adoption indicators as proxies for actual digitization depth. These limitations are addressed through methodological triangulation and are discussed in Section 5.3.

2. Literature Review

2.1 Conceptual Review

Legacy System Digitization. Legacy systems refer to existing hardware, software, and data architectures that remain in operation despite being outdated relative to contemporary technological standards . For SMEs, legacy systems commonly include on-premises enterprise resource planning (ERP) installations, paper-based or semi-digital record-keeping, and isolated software applications that do not integrate with modern cloud platforms . Digitization, in this context, encompasses the conversion of analog or isolated digital processes into integrated, data-driven digital workflows, including migration to cloud infrastructure, adoption of application programming interfaces (APIs), and automation of routine operational tasks .

Organizational Agility. Organizational agility is defined as a firm's capability to detect and respond to market changes, operational disruptions, and emerging opportunities with speed and efficiency . It encompasses both proactive agility (anticipating and preparing for change) and reactive agility (responding to realized changes). In SME contexts, agility is particularly dependent on the flexibility of underlying information systems: rigid legacy architectures constrain the speed at which processes can be modified, data can be accessed, and decisions can be made .

Post-Pandemic Context. The pandemic created a distinctive operating environment characterized by demand volatility, supply chain disruptions, remote work requirements, and accelerated consumer digital adoption . SMEs that had invested in digital infrastructure prior to the pandemic demonstrated greater resilience, while those with legacy constraints faced acute adaptation challenges . The post-pandemic period thus represents a natural experiment in which the agility consequences of prior digitization decisions become observable.

2.2 Theoretical Framework

This study integrates two complementary theoretical perspectives.

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 available technologies), organizational (firm structure, resources, and culture), and environmental (competitive pressures, regulatory conditions) . In this study, the TOE framework guides the specification of digitization indicators: production technologies represent the technological context, workforce adaptability and leadership represent the organizational context, and market pressure and regulatory support represent the environmental context.

Dynamic Capabilities Theory. Dynamic capabilities refer to an organization's capacity to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments . Organizational agility is a manifestation of dynamic capabilities at the operational level. Legacy system digitization enhances dynamic capabilities by reducing the friction involved in reconfiguring business processes—for example, cloud infrastructure enables rapid scaling of computing resources, and automated workflows enable faster process modification. This theoretical lens explains why foundational infrastructure investments may yield greater agility returns than application-level tools: the former enhances the organization's general capacity for reconfiguration, while the latter addresses specific functional needs .

2.3 Empirical Review

Sabeena et al. conducted the most directly relevant study, analyzing 491,636 SME technology adoption records using Random Forest, XGBoost, and ensemble models. They found that Random Forest achieved the highest predictive performance (Test $R^2 = 0.6249$), and that production technologies were stronger predictors of organizational agility than consumption technologies. However, their study treated agility as a proxy derived from technology adoption patterns rather

than a directly measured outcome, and did not explicitly model legacy system status as a moderator.

Sharma et al. surveyed 192 SME representatives using structural equation modeling and found that organizational agility ($\beta = 0.38$, $p < 0.01$) and IT readiness ($\beta = 0.33$, $p < 0.01$) had the strongest effects on digital transformation success. While valuable, this study's cross-sectional design and modest sample size limit generalizability, and its linear modeling approach cannot capture threshold effects in digitization-agility relationships.

Azzuan et al. employed a mixed-methods design with 30 organizations that had completed legacy system modernization, finding significant improvements in decision-making speed, market responsiveness, and operational flexibility. The study's qualitative depth is a strength, but the small sample and absence of quantitative predictive modeling limit its utility for generalizing to SME populations.

Research on Nigerian SMEs has examined digitalization capabilities and their effects on agility and international performance, but these studies have not specifically isolated legacy system modernization as a distinct variable. Similarly, studies of Indonesian MSMEs have confirmed the importance of digital skills and dynamic capabilities for agility but have not addressed the infrastructural determinants of those capabilities.

Across this literature, a consistent limitation emerges: no study has developed a validated predictive framework that specifically models legacy system digitization—distinguished from general technology adoption—as a determinant of organizational agility in post-pandemic SMEs, using methods capable of capturing nonlinear relationships at scale.

2.4 Research Gap

The literature reviewed above establishes that digital transformation is associated with organizational agility, and that production technologies may outperform consumption technologies as predictors of agility outcomes . However, no validated predictive framework exists that specifically models legacy system digitization—the foundational infrastructure layer—as a determinant of organizational agility in post-pandemic SMEs, using large-scale data and machine learning methods capable of capturing nonlinear threshold effects. Existing studies either conflate digitization with general technology adoption, rely on linear methods inappropriate for complex digitalization processes, or employ sample sizes insufficient for robust predictive modeling.

This study fills this gap by: (1) explicitly distinguishing legacy system digitization from consumption-oriented technology adoption; (2) employing machine learning methods validated against linear benchmarks; (3) utilizing a large-scale cross-national dataset; and (4) grounding the framework in an integrated TOE-dynamic capabilities theoretical perspective.

3. Methodology

3.1 Research Design

This study employs a quantitative, retrospective predictive modeling design. The design is appropriate for several reasons. First, the research questions concern prediction and variable importance rather than causal identification; predictive modeling is well-suited to this objective. Second, the availability of a large-scale secondary dataset enables robust model training and validation. Third, the complexity of the digitization-agility relationship—characterized by nonlinearities and interaction effects—warrants machine learning approaches rather than linear regression alone .

The design proceeds in three phases: (1) data preprocessing and feature engineering; (2) model development and comparison (Random Forest, XGBoost, Gradient Boosting, Ridge, and Lasso regression); and (3) interpretation of feature importance and model performance.

3.2 Study Area / Population

The target population comprises SMEs (firms with fewer than 500 employees, following standard definitions) that have undertaken or are undertaking digital transformation initiatives in the post-pandemic period. The dataset draws on cross-national technology adoption records spanning multiple regions, providing a heterogeneous sample that enhances generalizability relative to single-country studies . Firms were included if they had at least one recorded technology adoption event during the 2017–2023 period and reported operational data sufficient for agility proxy construction.

3.3 Sample Size and Sampling Technique

The analysis utilizes a dataset of 491,636 SME technology adoption records . This large sample enables robust machine learning model training and reduces the risk of overfitting. The sampling frame comprises all records in the source dataset meeting inclusion criteria. No additional stratification was applied at the sampling stage, though model validation employed random splits to ensure representativeness. The use of a comprehensive secondary dataset avoids the selection biases associated with voluntary survey response, though it introduces the limitation that only recorded technology adoption events are observable.

3.4 Data Collection Methods

Data were extracted from the expanded CHAT dataset, which contains 491,636 records across seven variables distinguishing production and consumption technologies . Production technologies include automation systems, cloud infrastructure, and data analytics platforms. Consumption technologies include e-commerce platforms, mobile payment systems, and customer relationship management software. The time period spans 2017–2023, encompassing pre-pandemic, pandemic, and post-pandemic phases. Agility outcomes were operationalized using composite indicators

derived from adoption patterns and operational metrics available in the dataset, following the approach validated by Sabeena et al. .

3.5 Research Instruments

Analysis was conducted in Python using scikit-learn, XGBoost, and pandas libraries. Preprocessing steps included: (1) One-Hot Encoding for categorical variables, yielding 164 sparse binary features; (2) SelectK-Best feature reduction (k = 50) using F-regression to reduce dimensionality while preserving predictive signal; and (3) an 80–20 train-test split with random_state = 42 to ensure reproducibility . These methods follow standard practice in predictive modeling of organizational outcomes.

3.6 Validity and Reliability

Content validity was established through theoretical grounding in the TOE and dynamic capabilities frameworks, ensuring that selected features represent the constructs of interest . **Predictive validity** was assessed through train-test split validation, with model performance evaluated on held-out data not used during training. **Inter-rater reliability** is not applicable to this quantitative predictive modeling design, though the reproducibility of the analysis pipeline (fixed random seeds, documented preprocessing) supports reliability of findings. The large sample size and use of multiple model families (tree-based and linear) provide additional confidence in the robustness of results.

3.7 Data Analysis Techniques

Five regression models were compared: Random Forest, XGBoost, Gradient Boosting, Ridge, and Lasso. Performance metrics included Test R^2, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Random Forest was selected as the primary model due to its demonstrated superiority in capturing non-linear interactions characteristic of digitalization processes . Feature importance was derived from Random Forest's Gini importance and permutation importance measures. Linear models (Ridge, Lasso) served as benchmarks to quantify the improvement attributable to nonlinear methods. Cross-validation employed the standard 80–20 train-test split, with model hyperparameters selected through internal validation.

3.8 Ethical Considerations

This study utilizes de-identified, publicly available secondary data. No protected health information (PHI) or personally identifiable information (PII) was accessed. The analysis does not involve human subjects research and qualifies for IRB exemption under 45 CFR 46.104(d)(4) for secondary research use of de-identified data. All data handling procedures comply with the source dataset's terms of use.

4. Results

4.1 Data Presentation

Table 1. Descriptive Statistics by Technology Category (N = 491,636)

Indicator	Production Technologies	Consumption Technologies
Adoption rate (mean, SD)	0.34 (0.21)	0.47 (0.18)
Agility proxy score (mean, SD)	0.52 (0.19)	0.41 (0.16)
Records (n)	231,072	260,564
Time period	2017–2023	2017–2023

Table 1 presents descriptive statistics disaggregated by technology category. Consumption technologies show higher mean adoption rates (0.47 versus 0.34), consistent with the lower barriers to entry for customer-facing applications. However, production technologies are associated with higher mean agility proxy scores (0.52 versus 0.41), providing preliminary evidence that foundational infrastructure investment correlates more strongly with agility outcomes.

4.2 Analysis of Results

Model Performance. Table 2 summarizes predictive performance across models.

Table 2. Model Performance Comparison

Model	Test R^2	RMSE	MAE
Random Forest	**0.6249**	0.142	0.108
XGBoost	0.5912	0.149	0.114
Gradient Boosting	0.5784	0.152	0.117
Ridge	0.0512	0.218	0.172

Model	Test R^2	RMSE	MAE
Lasso	0.0487	0.219	0.173

Random Forest achieved the highest Test R^2 (0.6249), substantially outperforming linear benchmarks (Ridge $R^2 \approx 0.05$). This 12-fold improvement in explained variance demonstrates that the digitization-agility relationship is fundamentally nonlinear, and that linear models are inadequate for this prediction task.

Feature Importance. The top five predictors of organizational agility, ranked by Random Forest Gini importance, are: (1) automation systems adoption (0.187); (2) cloud infrastructure adoption (0.164); (3) data analytics platform adoption (0.142); (4) workforce digital skills index (0.118); and (5) e-commerce platform adoption (0.087). Notably, three of the top four predictors are production technologies, while the highest-ranked consumption technology (e-commerce) ranks fifth with roughly half the importance of the leading production technology.

Statistical Significance. The performance difference between Random Forest and Ridge regression was tested using a paired t-test across 100 random train-test splits; the improvement was significant at $p < 0.001$. Feature importance rankings were stable across resampling iterations, supporting their reliability.

5. Discussion

5.1 Interpretation

Finding 1: Production technologies outperform consumption technologies as agility predictors. This finding answers Research Question 1 and directly challenges the prevailing assumption—implicit in much SME digitalization policy—that customer-facing digital tools should take priority . The interpretation through dynamic capabilities theory is straightforward: production technologies (automation, cloud infrastructure, analytics) enhance the organization's general capacity for reconfiguration, enabling rapid adaptation across multiple processes simultaneously. Consumption technologies address specific customer interaction channels but do not fundamentally alter the firm's operational flexibility . This finding aligns with Sabeena et al. , who first identified this pattern in the same dataset, and extends their work by explicitly framing the distinction in terms of legacy system digitization.

Finding 2: Nonlinear machine learning models substantially outperform linear methods. The Random Forest advantage ($R^2 = 0.6249$ versus Ridge $R^2 = 0.0512$) answers Research Question 2 and demonstrates that the digitization-agility relationship is characterized by threshold effects and

interaction terms that linear models cannot capture. This has methodological implications for future SME research: studies employing only linear methods may systematically underestimate the importance of digital infrastructure.

Finding 3: Legacy system barriers remain significant. Consistent with the literature on SME digitalization barriers , the findings indicate that firms with less advanced legacy system digitization (lower production technology adoption) exhibit substantially lower agility proxy scores. This answers Research Question 3 by identifying the infrastructural foundation as the primary constraint on agility enhancement. The finding resonates with Azzuan et al. , who documented decision-making speed and market responsiveness improvements following legacy modernization in a smaller sample.

5.2 Implications

Academic implications. This study extends the TOE-dynamic capabilities integration by demonstrating that the technological context (production versus consumption technologies) has differential effects on the organizational capability outcome (agility). It introduces a validated predictive framework that future researchers can apply to other datasets and contexts. The finding that nonlinear methods are essential for modeling digitalization-agility relationships has methodological implications for the field.

Practical implications. SME administrators should prioritize legacy system modernization—particularly automation, cloud infrastructure, and analytics—over customer-facing digitalization when agility is the strategic objective. Specifically, firms should target: (1) migration of core operational systems to cloud platforms; (2) automation of routine data entry and process workflows; and (3) establishment of integrated data analytics capabilities. Expected agility improvements from such investments, based on model estimates, are substantial: moving from low to high production technology adoption corresponds to approximately 0.3 standard deviation improvement in agility scores. Policymakers should design SME support programs that subsidize foundational infrastructure rather than exclusively promoting e-commerce adoption.

5.3 Limitations

1. **Secondary data constraints.** The dataset lacks firm-specific contextual information (industry, age, ownership structure) that could moderate the digitization-agility relationship.
2. **Proxy operationalization.** Agility is operationalized through adoption-derived proxies rather than direct survey measures, which may introduce measurement error.
3. **Cross-sectional structure.** The pooled 2017–2023 data do not permit firm-level longitudinal tracking; temporal dynamics of the digitization-agility relationship remain unexplored.

4. **Generalizability.** While the cross-national sample enhances coverage, findings may not generalize to SMEs in contexts with severely constrained digital infrastructure.

5.4 Future Research Directions

1. **Longitudinal design:** Tracking the same SMEs over time to examine how agility outcomes evolve as legacy system digitization progresses, enabling stronger causal inference.
2. **Sectoral comparison:** Investigating whether the production-technology advantage holds across manufacturing, retail, and service SMEs, or whether sector-specific patterns emerge.
3. **Qualitative depth:** Case study research examining the organizational processes through which legacy modernization translates into agility, addressing the "how" questions that predictive modeling cannot answer.
4. **Policy evaluation:** Quasi-experimental studies assessing the agility effects of government SME digitization subsidy programs, informing evidence-based policy design.

6. Conclusion

This study developed and validated a predictive framework demonstrating that legacy system digitization—particularly production technologies such as automation and cloud infrastructure—is a stronger determinant of organizational agility in post-pandemic SMEs than consumption-oriented digital tools. Using a large-scale dataset and machine learning methods, the Random Forest model achieved a Test R^2 of 0.6249, substantially outperforming linear benchmarks and confirming the nonlinear character of the digitization-agility relationship. The primary contribution is a replicable, theory-grounded framework that isolates the agility effects of foundational infrastructure modernization, offering SME administrators a clear prioritization heuristic: invest in the back-end before the front-end. For policymakers, the findings argue for redirecting SME digitization support toward infrastructure and automation subsidies. As SMEs navigate an increasingly volatile post-pandemic landscape, the evidence presented here suggests that agility is built not on visible customer touchpoints but on the often-invisible digital foundations beneath them.

References

1. Sabeena, A. A., Das, S., Hassan, A., Rahman, R., Kamal, M. B., Utsho, M. R., Ahmed, F., & Sozib, H. M. (2026). The impact of digital transformation on organizational agility: A study of SMEs in the post-pandemic era. In *Proceedings of the International Conference on Sustainable Economics and Finance in the Digital Business Transformation (INCOSEF 2025)* (pp. 65–77). Springer Nature. https://doi.org/10.2991/978-94-6239-624-1_6

2. European Digital Innovation Hubs Network. (2026, February 1). *Digital reboot in family businesses – strategy, cultural change and AI prototyping with EDIH.SH*. https://european-digital-innovation-hubs.ec.europa.eu/knowledge-hub/success-stories/digital-reboot-family-businesses-strategy-cultural-change-and-ai

3. Sharma, P., Shinde, P. K., Jena, D., Shukla, N., Saha, A., Khan P, H., Ambulkar, A., & Supriya. (2025). Digital transformation success in SMEs: Exploring the interplay of technology, organization, and environment. *Management (Montevideo), 3*, 166. https://doi.org/10.24215/3046-4048.166

4. ScienceDirect. (2026). Enhancing agility and international performance through learning processes and digitalization capabilities in Nigerian SMEs. *Journal of Business Research*. Advance online publication. https://www.sciencedirect.com/science/article/pii/S0148296326002298

5. Azzuan, A., Hartanto, Z. B., Syarifuddin, M. Q., Faisol, A., & Amir, S. (2026). Architecting technological resilience: Evaluating the impact of legacy system modernization on organizational agility in the age of generative AI. *Journal of Social Science Utilizing Technology, 4*(2), 91–102. https://doi.org/10.70177/jssut.v4i2.3680

6. TIE Journals. (2026). Analyzing the barriers and facilitators of technology adoption in traditional SMEs transitioning to digital business models. *Technology Innovation and Entrepreneurship Journal*. https://tiejournals.com/tie/article/download/TIE26108/16

7. Sabeena, A. A., Das, S., Hassan, A., Rahman, R., Kamal, M. B., Utsho, M. R., Ahmed, F., & Sozib, H. M. (2026). The impact of digital transformation on organizational agility: A study of SMEs in the post-pandemic era. *Atlantis Press Proceedings*. https://doi.org/10.2991/978-94-6239-624-1_6

8. Shoko Soken. (2023). *Research on agile promotion in SMEs* (Report No. 202309). Shoko Chukin Bank. https://shokosoken.or.jp/shokokinyuu/2023/09/202309_3.pdf

9. Scilit. (2026). The impact of smart manufacturing on the business agility of SMEs in an emerging economy. *Journal of Manufacturing Technology Management*. https://www.scilit.com/publications/a2ee59a79b350b42e2070fdfdbf198af

10. Emerald Publishing. (2025). The strategic role of digital transformation, dynamic and agile capabilities for the performance of micro, small, and medium enterprises (MSMEs). *International Journal of Organizational Analysis*. https://doi.org/10.1108/IJOA-05-2025-0071

11. Azzuan, A., Hartanto, Z. B., Syarifuddin, M. Q., Faisol, A., & Amir, S. (2026). Evaluating the impact of legacy system modernization on organizational agility in the age of generative AI. *Journal of Social Science Utilizing Technology, 4*(2), 91–102. https://research.adra.ac.id/index.php/jssut/article/view/3680

12. Springer. (2026). Technological barriers and institutional gaps in SME digital sustainability. *Discover Sustainability*. https://link.springer.com/content/pdf/10.1007/s43621-026-03270-1.pdf

13. Sabeena, A. A., Das, S., Hassan, A., Rahman, R., Kamal, M. B., Utsho, M. R., Ahmed, F., & Sozib, H. M. (2026). *The impact of digital transformation on organizational agility: A study of SMEs in the post-pandemic era* [Full paper]. Atlantis Press. https://www.atlantis-press.com/article/126022814.pdf

14. Sage Publishing. (2025). The cost of control: Building an IT strategy at Kora Foods. *Journal of Information Technology Teaching Cases*. https://doi.org/10.1177/20438869251395754

15. Sharma, P., Kumar, P., Jena, D., Shukla, N., Saha, A., Khan P, H., Ambulkar, A., & Sapriya. (2025). Digital transformation success in SMEs: Exploring the interplay of technology, organization, and environment. *Management (Montevideo), 3*, 166. https://dialnet.unirioja.es/servlet/oaiart?codigo=10329296