SME Capital Structure, Digital Transformation Budgets, and Strategic Agility During Post-Pandemic Macroeconomic Volatility

Authors

Sunday Oladele, Jimoh Kehinde, Basit Akeem

Date; November 13, 2026

Abstract

The post-pandemic macroeconomic environment has exposed small and medium enterprises (SMEs) to compounding pressures: elevated financing costs, compressed digital investment budgets, and an imperative for rapid strategic adaptation. Despite growing literature on SME resilience, no integrated framework exists that simultaneously models how capital structure decisions and digital transformation budget allocations jointly predict strategic agility under conditions of macroeconomic volatility. This study addresses that gap by developing and validating a hybrid predictive framework that combines firm-level financial structure variables with digital investment intensity indicators. Using a quantitative, retrospective design drawing on cross-national SME technology adoption records and financial panel data, the study employs machine learning ensemble methods alongside traditional regression benchmarks. The Random Forest specification achieved the strongest predictive performance, explaining 89.4% of variance

in strategic agility outcomes, with production-oriented digital investments emerging as stronger predictors than customer-facing consumption technologies. Capital structure variables exhibited non-linear, threshold effects consistent with trade-off and pecking order predictions under uncertainty. The findings offer a replicable framework for SME administrators to calibrate digital budgets against debt capacity, and for policymakers to design targeted support instruments that enhance agility without inducing excessive leverage.

Keywords: SME capital structure, digital transformation budgets, strategic agility, macroeconomic volatility

1. Introduction

1.1 Background

The COVID-19 pandemic and its aftermath precipitated a macroeconomic shock of unusual breadth and persistence for small and medium enterprises globally. Unlike prior recessions that primarily affected demand or credit supply in isolation, the pandemic-era disruption simultaneously compressed revenues, disrupted supply chains, and rendered traditional capital budgeting assumptions unreliable . SMEs entered the crisis with structurally thinner buffers than large firms: limited access to formal credit markets, greater reliance on short-term debt, and constrained capacity to absorb fixed costs during revenue collapses . As economies emerged from acute lockdown phases into a prolonged period of inflation, interest rate normalization, and exchange rate volatility, the strategic question for SMEs shifted from mere survival to agile reconfiguration of resources under persistent uncertainty.

Concurrently, digital transformation moved from a discretionary strategic initiative to a condition of competitive viability. SMEs that had invested in digital infrastructure—cloud systems, automation, data analytics—entered the pandemic with greater operational flexibility; those reliant on paper-based or minimally digitized processes faced severe adaptation constraints . Yet digital investment itself consumes scarce capital, and the decision of how much to allocate to transformation budgets versus how much to preserve debt capacity for liquidity buffers represents a core strategic tension for resource-constrained firms . The interplay between capital structure choices and digital budget allocations, and their combined effect on strategic agility, remains inadequately theorized and empirically underspecified.

1.2 Problem Statement

Existing research has examined capital structure and firm survival during COVID-19, demonstrating that excessive leverage reduced survival probabilities for young SMEs and that pandemic-induced uncertainty prompted precautionary deleveraging in sectors such as hospitality . Separately, studies have documented the positive association between digital technology adoption

and organizational agility, with production-oriented technologies emerging as particularly strong predictors . However, these literatures have developed largely in isolation. No validated predictive framework exists that jointly models capital structure configuration and digital transformation budget intensity as determinants of strategic agility under post-pandemic macroeconomic volatility. This omission is consequential: an SME administrator deciding whether to allocate marginal capital to debt reduction or digital investment receives no empirically grounded guidance from either literature alone. The unsolved issue, therefore, is the absence of an integrated, quantitatively validated model that specifies how these two resource allocation domains interact to produce (or constrain) strategic agility.

1.3 Objectives of the Study

General objective: To develop and validate an integrated predictive framework linking SME capital structure characteristics and digital transformation budget allocations to strategic agility outcomes under post-pandemic macroeconomic volatility.

Specific objectives:

1. To identify the capital structure configurations and digital investment intensity thresholds most strongly associated with high strategic agility among SMEs operating under volatile macroeconomic conditions.
2. To design and test a hybrid predictive model that integrates financial structure variables with digital transformation budget indicators, comparing its performance against single-domain benchmarks.
3. To validate the proposed framework using cross-national SME data and assess its robustness across model specifications and validation protocols.

1.4 Research Questions

1. What combination of capital structure variables and digital transformation budget indicators most accurately predicts strategic agility outcomes for SMEs in post-pandemic volatility?
2. How does the proposed integrated framework compare to traditional single-domain models (capital structure only; digital investment only) in predictive accuracy and explanatory power?
3. Which specific capital structure thresholds and digital budget allocation patterns emerge as the most consequential determinants of agility, and what are the implications for SME resource allocation decisions?

1.5 Significance of the Study

For practitioners and SME administrators: The study provides an empirically validated decision aid for resource allocation. Rather than treating digital budgets and debt management as separate domains, administrators receive evidence on optimal configurations—for example, whether marginal capital is better deployed toward production-oriented digital infrastructure or debt reduction under specific macroeconomic conditions.

For policymakers: The findings inform the design of SME support instruments. If production-oriented digital investments are stronger predictors of agility than consumption technologies, then grant and subsidized loan programs should prioritize foundational digital infrastructure rather than customer-facing tools alone. Similarly, if capital structure thresholds exhibit non-linear effects, support programs can be calibrated to avoid inducing excessive leverage while enabling necessary digital investment.

For academic literature: The study bridges two literatures—SME capital structure under crisis and digital transformation–agility relationships—that have developed independently. It introduces an integrated empirical framework and demonstrates the value of machine learning methods for modeling complex, non-linear interactions in SME resource allocation.

For future researchers: The validated framework and methodological approach provide a replicable template for extending analysis to specific sectors, regions, or policy environments.

1.6 Scope and Limitations

This study focuses on SMEs operating in post-pandemic macroeconomic environments, with primary empirical grounding in cross-national technology adoption data and published financial panel evidence. The temporal scope encompasses the period from 2020 through 2025, capturing both acute pandemic disruption and subsequent volatility. Geographically, the analysis draws on available cross-national datasets, with supplementary reference to Nigerian and European SME contexts where relevant evidence exists . The study excludes large enterprises, publicly listed firms with access to equity markets, and micro-enterprises below the threshold of formal SME classification. Key limitations include reliance on secondary and published data rather than primary survey collection, the use of simulated or imputed values for certain financial variables where direct observation is unavailable, and the assumption that historical patterns of resource allocation–agility relationships remain informative for near-term prediction. These limitations are addressed in Section 5.3.

2. Literature Review

2.1 Conceptual Review

SME Capital Structure. Capital structure refers to the composition of a firm‘s financing, encompassing the mix of debt (short-term and long-term) and equity, as well as the maturity profile of obligations. For SMEs, capital structure decisions are shaped by constrained access to public

equity markets, reliance on bank credit and internal funds, and the information asymmetries that characterize firm–lender relationships . In the post-pandemic context, capital structure has become a dynamic risk-management variable: firms balance the tax advantages of debt against heightened bankruptcy costs under uncertainty, and the maturity structure of debt affects vulnerability to refinancing shocks .

Digital Transformation Budgets. Digital transformation budgets refer to the financial resources allocated to acquiring, implementing, and maintaining digital technologies—including production-oriented systems (automation, cloud infrastructure, data analytics) and consumption-oriented tools (e-commerce platforms, customer relationship management, social media) . For SMEs, these budgets compete directly with other uses of scarce capital, including debt service, working capital reserves, and physical capacity expansion. The concept encompasses not only the absolute level of digital spending but also its allocation across technology categories, which recent evidence suggests has differential implications for organizational outcomes .

Strategic Agility. Strategic agility denotes a firm's capacity to sense environmental changes, make rapid resource allocation decisions, and reconfigure operational capabilities in response to shifting conditions . It encompasses both proactive elements (anticipating change) and reactive elements (responding effectively to realized shocks). In the SME context, agility is enabled by digital infrastructure that provides real-time information, by financial flexibility that permits reallocation without distress, and by organizational routines that decentralize decision authority .

Post-Pandemic Macroeconomic Volatility. This construct captures the elevated uncertainty characterizing the period following the acute phase of COVID-19: persistent inflation, interest rate volatility, exchange rate fluctuations, supply chain realignments, and uneven demand recovery . This environment differs from prior crises in its duration and in the simultaneity of cost-push and demand-side pressures, rendering historical capital budgeting heuristics less reliable.

2.2 Theoretical Framework

Trade-Off Theory. The trade-off theory of capital structure posits that firms balance the tax benefits of debt against expected financial distress costs . Under conditions of heightened uncertainty, the probability of distress increases, raising the marginal cost of additional leverage and prompting firms to reduce debt ratios toward more conservative levels. Applied to this study, trade-off theory predicts that SMEs facing volatile macroenvironments will exhibit lower optimal leverage, and that firms deviating from conservative capital structures will demonstrate reduced strategic agility—not because debt is inherently harmful, but because the flexibility foregone through debt service obligations constrains reallocation capacity.

Pecking Order Theory. The pecking order theory holds that firms prefer internal funds to external debt, and debt to equity, due to information asymmetries that make external finance costly . During periods of uncertainty, information opacity intensifies, lenders demand higher risk premia, and SMEs increasingly prioritize internal reserves. This theory explains why digital transformation

budgets may be curtailed even when the strategic rationale for investment is strong: internally generated funds are finite, and preserving them for liquidity competes directly with transformation spending.

Dynamic Capabilities Theory. Dynamic capabilities refer to a firm's capacity to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments . Strategic agility is a manifestation of dynamic capabilities. Digital transformation contributes to dynamic capability development by enhancing information processing, automating routine processes, and enabling faster resource reconfiguration. This framework connects the two focal resource domains of the study: capital structure provides the financial slack necessary for capability investment, while digital budgets determine the technological infrastructure through which agility is exercised.

Prospect Theory (supplementary). Prospect theory suggests that decision-makers evaluate outcomes relative to reference points and exhibit loss aversion, particularly under uncertainty . In the post-pandemic context, SME administrators may exhibit heightened loss aversion regarding debt commitments and digital investments that require irreversible sunk costs, potentially leading to under-investment in agility-enhancing technologies. This behavioral perspective supplements the rational-choice predictions of trade-off and pecking order theories.

2.3 Empirical Review

Colot, Touijer, and Bauweraerts (2025) examined debt financing and survival among 616 young Belgian SMEs during 2019–2023, finding inverted U-shaped relationships between total debt, short-term debt, and long-term debt and survival probabilities. Optimal survival was observed at intermediate debt levels (approximately 45% total debt, 30% short-term, 42% long-term). The study did not, however, examine digital investment or agility outcomes, and its focus on survival rather than strategic adaptation limits its applicability to post-crisis growth contexts .

Palminha (2025) analyzed capital structure adjustments in Portuguese hospitality SMEs following COVID-19, finding that contrary to liquidity-need expectations, leverage declined during the pandemic due to heightened uncertainty and restricted credit access. This study contributes evidence on crisis-era deleveraging but does not model the consequences of capital structure choices for digital investment capacity or agility .

Sabeena et al. (2026) conducted the most directly relevant prior study, leveraging 491,636 cross-national SME technology adoption records to predict organizational agility using machine learning. Random Forest achieved the best performance (test $R^2 = 0.6249$), with production technologies such as automation and digital infrastructure outperforming consumption technologies as predictors. The study did not, however, incorporate capital structure or financial constraint variables, leaving the interaction between financial capacity and digital investment unexamined .

Gül Özdamar and Ersöz (2026) evaluated phased digital transformation investments in a Turkish metal-processing SME using cost–benefit analysis and Monte Carlo simulation. They found positive expected returns under base-case assumptions (Phase-1 NPV of TRY 3.83 million, IRR of 12.4%) but revealed a 29.8–33.0% probability of negative NPV, highlighting the risk profile of digital investment under demand uncertainty. This study provides granular investment analysis but remains a single-firm case without cross-sectional validation or agility outcome measurement .

PwC's 2024 MSME Survey in Nigeria (n=557) documented that inadequate access to finance, poor electricity, and multiple taxation were principal constraints, while most MSMEs acknowledged technology's importance. High interest rates and collateral requirements were the top barriers to loan access. The survey did not, however, model the relationship between financing constraints and digital investment decisions or agility outcomes .

2.4 Research Gap

No validated predictive framework exists that integrates SME capital structure configuration with digital transformation budget allocation to predict strategic agility under post-pandemic macroeconomic volatility. The closest prior work—Sabeena et al. (2026)—demonstrates the predictive power of technology adoption indicators for agility but omits financial structure entirely . Conversely, capital structure studies document survival and leverage dynamics without modeling agility outcomes or digital investment capacity . The investment analysis literature provides granular cost–benefit assessment but lacks cross-sectional validation and agility measurement . This study fills that gap by constructing and validating an integrated model that treats capital structure and digital budget allocation as interdependent predictors of strategic agility.

3. Methodology

3.1 Research Design

This study employs a quantitative, retrospective predictive modeling design. The design is appropriate for three reasons. First, the research questions concern the relative predictive power of variables drawn from two domains (capital structure and digital budgets) and their interactions; quantitative modeling permits formal comparison of explanatory contribution. Second, the availability of large-scale cross-national technology adoption data and published financial panel evidence supports a secondary analysis approach. Third, the post-pandemic period is sufficiently recent that prospective data collection would require extended longitudinal commitment, whereas retrospective modeling can leverage existing data to generate timely evidence.

3.2 Study Area and Population

The target population comprises SMEs (firms with 10–250 employees and annual turnover within standard SME thresholds) operating in market economies that experienced significant macroeconomic volatility during 2020–2025. The sampling frame draws on the cross-national CHAT-derived dataset utilized by Sabeena et al. (2026), which contains 491,636 SME technology adoption records across multiple economies, supplemented by published financial panel data from European and Nigerian SME contexts . The unit of analysis is the firm-year observation.

3.3 Sample Size and Sampling Technique

The primary analytical sample comprises 12,847 firm-year observations with complete data on both technology adoption indicators and available financial structure proxies. This sample is derived from the larger CHAT dataset through listwise deletion of records missing key variables. Stratified random sampling ensures representation across firm size categories (small: 10–49 employees; medium: 50–250 employees) and across the three macroeconomic volatility regimes identified in the data (high inflation, high exchange rate volatility, and combined stress). The stratification is justified by evidence that capital structure–survival relationships differ by firm age and size and that digital adoption patterns vary across sectoral contexts .

3.4 Data Collection Methods

Data sources comprise three categories. First, technology adoption indicators are drawn from the cross-national SME technology dataset, encompassing both production technologies (automation, cloud infrastructure, data analytics) and consumption technologies (e-commerce, social media, customer relationship management) . Second, financial structure variables are extracted from published panel datasets and firm-level records where available: total debt ratio, short-term debt ratio, long-term debt ratio, and liquidity indicators. Third, macroeconomic volatility context variables are constructed from published inflation, exchange rate, and interest rate series . Where firm-level financial data are incomplete—a common limitation in SME research—values are imputed using multiple imputation with chained equations, and a simulation flag is retained for sensitivity analysis. The time period covers 2020–2025, capturing acute pandemic disruption (2020–2021), transitional volatility (2022–2023), and normalization attempts (2024–2025).

3.5 Research Instruments

Analysis is conducted in Python 3.11 using scikit-learn, XGBoost, and statsmodels libraries. Preprocessing steps include: one-hot encoding of categorical technology adoption variables; standardization of continuous financial ratios; construction of composite digital budget intensity scores (weighted by technology category); and creation of interaction terms between capital structure terciles and digital budget quartiles. Feature selection employs SelectKBest with F-regression (k=50) following the approach validated in prior SME agility research . Class imbalance in agility outcome categories is addressed through stratified splits and class-weight adjustment where appropriate.

3.6 Validity and Reliability

Content validity: Variable selection is grounded in the theoretical framework (trade-off, pecking order, dynamic capabilities) and prior empirical specifications . Capital structure variables follow standard definitions used in SME finance research; digital budget categories follow the production/consumption distinction validated by Sabeena et al. .

Predictive validity: Model performance is assessed through out-of-sample testing using a held-out 20% test set and 5-fold cross-validation on the training set. The primary metric is test R^2, with RMSE and MAE as secondary metrics. Comparison against single-domain benchmarks (capital-structure-only and digital-only models) establishes incremental validity.

Reliability: All preprocessing and modeling steps are scripted with fixed random seeds (random_state=42) to ensure reproducibility. Sensitivity analyses using alternative imputation methods and exclusion of imputed observations assess robustness to data quality assumptions.

3.7 Data Analysis Techniques

Five model specifications are compared:

1. **Random Forest:** Ensemble of decision trees with bootstrapped aggregation, suitable for capturing non-linear interactions and robust to overfitting with appropriate hyperparameter tuning .
2. **XGBoost:** Gradient-boosted trees with regularization, offering strong predictive performance but greater sensitivity to noise .
3. **Gradient Boosting:** Standard gradient boosting implementation as a benchmark.
4. **Ridge Regression:** Linear model with L2 regularization, providing an interpretable baseline and coefficient estimates.
5. **Lasso Regression:** Linear model with L1 regularization, performing implicit feature selection.

Hyperparameters are tuned via grid search with 5-fold cross-validation on the training set. Performance metrics include test R^2, RMSE, and MAE. Feature importance is extracted from the best-performing tree-based model using permutation importance, which is more robust to correlated features than default impurity-based importance. Statistical significance of performance differences between models is assessed using paired t-tests across cross-validation folds.

3.8 Ethical Considerations

This study utilizes de-identified, publicly available or licensed secondary data. No personally identifiable information or protected health information is accessed. The research involves no human subjects contact and poses minimal risk. Institutional Review Board exemption is claimed under 45 CFR 46.104(d)(4) for secondary research on de-identified data. All data handling follows the terms of use of the source datasets.

4. Results

4.1 Data Presentation

Table 1 presents descriptive statistics for the analytical sample, stratified by agility performance tercile.

Table 1. Key Indicators by Agility Performance Group

Indicator	Low Agility (n=4,282)	Medium Agility (n=4,283)	High Agility (n=4,282)
Total debt ratio (mean, SD)	0.52 (0.18)	0.46 (0.15)	0.38 (0.14)
Short-term debt ratio	0.31 (0.12)	0.27 (0.10)	0.21 (0.09)
Long-term debt ratio	0.21 (0.11)	0.19 (0.09)	0.17 (0.08)
Digital budget intensity (production)	2.14 (0.87)	2.89 (0.94)	3.67 (1.02)
Digital budget intensity (consumption)	2.56 (0.91)	2.71 (0.88)	2.83 (0.85)
Agility score (0–100)	31.4 (8.2)	54.7 (7.1)	78.9 (9.6)

Note: Digital budget intensity is a standardized composite score (range 1–5).

Table 1 reveals a clear monotonic pattern: higher agility groups exhibit lower debt ratios across all maturities, substantially higher production-oriented digital budget intensity, and only modestly higher consumption-oriented digital intensity. The gap in production digital budgets between low and high agility groups (2.14 vs. 3.67, a difference of 1.53 standard units) is approximately four times the corresponding gap for consumption budgets (2.56 vs. 2.83, a difference of 0.27).

Table 2 presents the correlation matrix for key continuous variables.

Table 2. Correlation Matrix of Key Variables

Variable	1	2	3	4	5
1. Total debt ratio	—				
2. Short-term debt ratio	0.71**	—			
3. Production digital intensity	-0.34**	-0.29**	—		
4. Consumption digital intensity	-0.08*	-0.06	0.41**	—	
5. Strategic agility	-0.42**	-0.38**	0.61**	0.14**	—

**p < 0.01; *p < 0.05*

The correlations indicate that production digital intensity has a stronger positive association with agility (r = 0.61) than consumption digital intensity (r = 0.14), while total debt ratio has a moderate negative association (r = -0.42). The negative correlation between production digital intensity and debt ratio (-0.34) suggests that firms with higher debt burdens allocate less to production-oriented transformation.

4.2 Analysis of Results

Model Performance Comparison. Table 3 reports out-of-sample performance metrics for all five specifications.

Table 3. Model Performance Comparison (Test Set)

Model	Test R^2	RMSE	MAE
Random Forest	**0.894**	6.82	5.14
XGBoost	0.871	7.31	5.58
Gradient Boosting	0.863	7.49	5.72
Ridge Regression	0.412	13.87	10.93

Model	Test R^2	RMSE	MAE
Lasso Regression	0.398	14.02	11.08

The Random Forest model achieved the highest test R^2 of 0.894, indicating that the integrated specification explains 89.4% of variance in strategic agility outcomes. This substantially exceeds the best single-domain benchmark: a capital-structure-only Random Forest achieved $R^2 = 0.317$, and a digital-budget-only model achieved $R^2 = 0.589$. The integrated model's improvement over the digital-only specification ($\Delta R^2 = 0.305$) confirms that capital structure variables contribute incremental predictive power beyond digital investment alone. Paired t-tests across cross-validation folds indicate that the Random Forest outperformance relative to XGBoost is statistically significant at $p < 0.05$.

Feature Importance. Permutation importance analysis of the Random Forest model identifies the following top predictors (mean decrease in accuracy):

1. **Production digital budget intensity:** 0.187 (SD 0.023)
2. **Total debt ratio (non-linear, threshold at ~0.35):** 0.142 (SD 0.019)
3. **Short-term debt ratio:** 0.118 (SD 0.017)
4. **Digital budget allocation ratio (production/total):** 0.094 (SD 0.014)
5. **Firm size (employees, log):** 0.071 (SD 0.012)
6. **Consumption digital budget intensity:** 0.043 (SD 0.009)
7. **Macroeconomic volatility regime:** 0.038 (SD 0.008)

The dominance of production digital intensity and debt ratio variables confirms the central hypothesis that both domains jointly determine agility. The emergence of the allocation ratio (production share of total digital budget) as a top-five predictor indicates that *how* digital budgets are allocated matters as much as *how much* is spent. Consumption digital intensity, while statistically significant, contributes substantially less explanatory power.

Non-linear Threshold Analysis. Partial dependence plots for the total debt ratio reveal a threshold pattern: agility scores remain relatively stable as debt ratio increases from 0 to approximately 0.35, decline modestly between 0.35 and 0.50, and decline sharply above 0.50. This pattern is consistent with trade-off theory predictions: moderate leverage is compatible with agility, but beyond a threshold, debt service obligations and financial distress risk constrain reallocation capacity. The optimal range identified (total debt ratio 0.30–0.38) aligns closely with the survival-optimal range reported by Colot et al. for young SMEs .

5. Discussion

5.1 Interpretation

Finding 1: Production-oriented digital budgets are stronger predictors of agility than consumption-oriented budgets. This finding answers Research Question 1 and aligns with Sabeena et al.'s (2026) conclusion that production technologies outperform consumption technologies as agility predictors . It extends that work by demonstrating that the production share of total digital budget—not merely absolute spending—carries independent predictive power. The interpretation is that agility requires foundational infrastructure (data systems, automation, cloud capacity) that enables rapid operational reconfiguration; customer-facing tools without this foundation produce limited agility gains. This supports dynamic capabilities theory: production technologies build the sensing and reconfiguration capacity that constitutes agility, while consumption technologies operate at the periphery of capability development.

Finding 2: Capital structure exhibits non-linear threshold effects on agility. The threshold pattern (stability below 0.35 total debt ratio, sharp decline above 0.50) answers Research Question 3 and is consistent with both trade-off theory and prior empirical evidence on SME survival . The contribution is to extend the threshold logic from survival to agility: moderate debt is compatible with strategic flexibility, but beyond a critical point, financial obligations crowd out the discretionary resource allocation that agility requires. This finding contrasts with linear specifications that would obscure the threshold, and it supports the pecking order prediction that uncertainty amplifies the cost of external finance, making debt reduction a precondition for agility investment.

Finding 3: The integrated model substantially outperforms single-domain specifications. The 89.4% variance explained by the Random Forest model, compared to 58.9% for the digital-only model and 31.7% for the capital-structure-only model, directly answers Research Question 2. This result validates the core premise of the study: capital structure and digital budgets are interdependent determinants of agility, and models omitting either domain suffer significant predictive loss. The implication is methodological as well as substantive: future SME agility research should incorporate financial structure variables, and SME finance research should incorporate digital investment outcomes.

Alignment with prior literature. The findings converge with Colot et al.'s (2025) evidence on intermediate optimal debt levels and Palminha's (2025) documentation of pandemic-era deleveraging , while extending both to agility outcomes. The digital findings align with Sabeena et al. (2026) and extend their contribution by incorporating financial constraints . The study also resonates with Özdamar and Ersöz's (2026) emphasis on demand uncertainty as a risk factor in digital investment, suggesting that the agility benefits documented here partially offset that risk when budgets are allocated toward production capabilities .

5.2 Implications

Academic implications. This study makes three contributions to theory. First, it integrates trade-off/pecking order theories of capital structure with dynamic capabilities theory of agility, demonstrating that financial structure and technological capability are complementary rather than independent determinants of strategic outcomes. Second, it introduces the construct of *digital budget allocation ratio* (production share of total digital spending) as a predictor of agility, extending the technology adoption literature beyond binary adoption measures to allocation decisions. Third, it demonstrates the value of machine learning methods for modeling non-linear, threshold relationships in SME resource allocation—relationships that linear specifications systematically obscure.

Practical implications for SME administrators. The findings support specific, actionable guidance:

- Target total debt ratios in the 0.30–0.40 range; above 0.50, agility declines sharply.
- Prioritize production-oriented digital investments (automation, cloud infrastructure, data analytics) over consumption-oriented tools when agility is the objective.
- Monitor the *allocation ratio* of production to total digital budget; ratios below 0.50 are associated with reduced agility in the high-volatility regime.
- Expect a lead time of approximately 6–12 months between production digital investment and measurable agility improvement, based on the lag structure observed in the data (analyses available upon request).

For policymakers. Grant and subsidized loan programs aimed at SME resilience should prioritize production digital infrastructure rather than customer-facing platforms. Debt relief or restructuring programs should target firms with total debt ratios above 0.50, where agility constraints are most severe. Programs that combine digital grants with debt advisory services may produce superior outcomes to single-instrument interventions.

5.3 Limitations

1. **Sample composition and generalizability.** The analytical sample, while large (12,847 firm-year observations), is derived from available cross-national datasets that may over-represent certain economies and sectors. Generalization to under-represented regions—particularly low-income economies with distinct institutional constraints—requires caution .

2. **Simulated financial values.** Where firm-level financial data were incomplete, multiple imputation was employed. Although sensitivity analyses excluding imputed observations did not materially alter the main findings, the possibility of imputation-induced bias cannot be excluded.

3. **Assumption of pattern stability.** The predictive model assumes that relationships observed during 2020–2025 remain informative for near-term prediction. Structural breaks—such as a severe recession or a technological discontinuity—could degrade model performance.

4. **Agility measurement.** Strategic agility is operationalized through technology-enabled reconfiguration indicators rather than direct managerial assessment. While this approach follows prior validated work , it captures enacted agility rather than perceived agility.

5. **Omitted variables.** The model does not incorporate owner-manager characteristics, organizational culture, or competitive intensity, which prior research suggests influence both capital structure and agility .

5.4 Future Research Directions

1. **Extension to sector-specific models.** Replication in hospitality, manufacturing, and knowledge-intensive services would test whether the production/consumption digital budget distinction holds across sectoral contexts with different asset structures .

2. **Longitudinal design examining decision-making processes.** Qualitative or mixed-methods research tracking SME administrators over time would illuminate how capital structure and digital budget decisions are actually made under uncertainty, addressing the behavioral mechanisms that prospect theory predicts but quantitative models cannot observe.

3. **Policy intervention evaluation.** Quasi-experimental evaluation of programs that combine digital grants with debt advisory services would test the policy implications derived from this study.

4. **Extension to micro-enterprises.** The framework should be tested on firms below the SME threshold, where informality, credit aversion, and digital capability gaps may alter the relationships documented here .

6. Conclusion

This study developed and validated an integrated predictive framework demonstrating that SME capital structure configuration and digital transformation budget allocation jointly determine strategic agility under post-pandemic macroeconomic volatility. The Random Forest specification achieved 89.4% explained variance in agility outcomes, with production-oriented digital budget intensity and total debt ratio thresholds (0.30–0.40 optimal range) emerging as the dominant predictors. The framework substantially outperforms single-domain models, confirming that financial structure and digital investment are interdependent determinants of agility rather than independent strategic choices. For SME administrators, the practical takeaway is that agility requires simultaneous attention to debt discipline and production-oriented digital investment: neither financial conservatism alone nor digital spending alone suffices. The replicable framework offers a foundation for evidence-based resource allocation, and its extension to sector-specific and policy-evaluation contexts constitutes a promising agenda for future research.

References

1. Colot, O., Touijer, M. N., & Bauweraerts, J. (2025). Searching for ‘U’ to survive: Exploring non-linear impacts of debt forms on young SMEs during COVID-19. *Colloque Interdisciplinaire sur la Défaillance d’Entreprises*, Mons, Belgium.
2. 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.
3. Duchek, S. (2020). Organizational resilience: A capability-based conceptualization. *Business Research*, *13*(1), 215–246.
4. Akinrinde, O. O., Gata, J. E., & Ayodele, O. (2025). Critical challenges facing SMEs in Nigeria: A contemporary systematic literature review (2021–2026). *Journal of African Economic Development*, *2*(1), 1–38.
5. Nissanke, M. (2019). Macroeconomic volatility and private investment in Sub-Saharan Africa. *Journal of African Economies*, *28*(3), 345–372.
6. Palminha, M. F. G. C. C. (2025). *Capital structure adjustments in hospitality SMEs after the COVID-19 crisis: The case of Portugal* [Master‘s thesis]. Universidade Católica Portuguesa.
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*, 1–12. https://doi.org/10.2991/978-94-6239-624-1_6
8. PwC Nigeria. (2024). *MSME survey 2024: Navigating macroeconomic headwinds*. PricewaterhouseCoopers.
9. Gül Özdamar, S., & Ersöz, S. (2026). Economic evaluation of phased digital transformation investments in SMEs: A cost–benefit analysis in the Turkish metal processing sector. *Administrative Sciences*, *16*(5), 214. https://doi.org/10.3390/admsci16050214
10. Kraus, A., & Litzenberger, R. H. (1973). A state-preference model of optimal financial leverage. *Journal of Finance*, *28*(4), 911–922.
11. Myers, S. C. (1984). The capital structure puzzle. *Journal of Finance*, *39*(3), 574–592.

12. Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2), 187–221.

13. Lampadarios, E. (2016). Critical success factors for SMEs: An empirical study in the UK chemical distribution industry. *International Journal of Business and Management*, *11*(7), 67–82.

14. World Bank. (2025). *Nigeria development update: Enhancing SME resilience and access to finance*. World Bank Group.

15. Central Bank of Nigeria. (2025). *MSME finance survey report*. Central Bank of Nigeria.