Smart Manufacturing Adoption and Its Effect on Operational Agility: Evidence from Post-Pandemic Industrial SMEs

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Abstract

The post-pandemic period has compelled industrial small and medium-sized enterprises (SMEs) to reconfigure operations for heightened responsiveness, yet the extent to which smart manufacturing adoption translates into operational agility remains inadequately quantified. Existing studies have examined Industry 4.0 readiness or agility independently, but few have modelled the predictive relationship between specific smart manufacturing capabilities and agility outcomes using robust analytical approaches. This study addresses this gap by developing and validating a predictive framework linking smart manufacturing adoption dimensions—digital process integration, real-time data utilisation, and automated production control—to operational agility in post-pandemic industrial SMEs. Using survey data from 312 manufacturing SMEs and employing partial least squares structural equation modelling (PLS-SEM) complemented by machine learning-based feature importance analysis, the study identifies digital process integration as the strongest predictor of agility ($\beta = 0.42$, $p < 0.001$), followed by real-time data utilisation ($\beta = 0.31$, $p < 0.01$). The integrated model achieves 89.4% classification accuracy in predicting high versus low agility performers. Financial access significantly moderates the smart manufacturing–

agility relationship, with resource-constrained firms exhibiting weaker conversion of adoption into agility. The findings suggest that SMEs should prioritise foundational data integration capabilities over advanced automation to achieve agility gains. Practically, the framework offers a diagnostic tool for SME managers to assess adoption priorities, while academically it extends dynamic capabilities theory by specifying the capability pathways through which smart manufacturing generates agility.

Keywords: Smart manufacturing, operational agility, industrial SMEs, post-pandemic recovery, digital transformation

1. Introduction

1.1 Background

The COVID-19 pandemic exposed profound vulnerabilities in manufacturing supply chains and production systems, particularly among small and medium-sized enterprises (SMEs) that lacked the resource buffers and technological infrastructure of larger firms . As economies entered recovery phases, operational agility—the capacity to sense and respond rapidly to market shifts, supply disruptions, and demand volatility—emerged as a critical determinant of SME survival and competitiveness . Concurrently, smart manufacturing technologies, encompassing digital process integration, real-time data acquisition, and automated control systems, have been promoted as enablers of such agility .

The theoretical appeal of smart manufacturing rests on its promise of enhanced visibility, responsiveness, and adaptive capacity. Industry 4.0 technologies enable firms to collect and analyse production data in real time, reconfigure processes with minimal downtime, and synchronise operations with supply chain partners . For SMEs, however, adoption remains uneven and often superficial. Surveys indicate that basic technologies such as enterprise resource planning systems predominate, while advanced applications like machine learning and digital twins remain rare . This pattern raises a fundamental question: does smart manufacturing adoption, at the levels actually achievable by SMEs, deliver the operational agility benefits that the literature and policy discourse promise?

1.2 Problem Statement

Prior research has established correlations between digital technology adoption and organisational agility, but three limitations constrain both theoretical understanding and practical guidance. First, most studies treat smart manufacturing as a monolithic construct, failing to distinguish between foundational capabilities (data integration, process monitoring) and advanced applications (automation, predictive analytics) that impose vastly different resource requirements on SMEs . Second, the mechanisms through which adoption translates into agility are under-specified; studies report associations without modelling the mediating pathways or the moderating conditions,

particularly financial constraints, that shape whether adoption yields agility gains . Third, empirical evidence specific to the post-pandemic context remains scarce; existing frameworks were largely developed under pre-pandemic conditions that did not account for the structural disruptions and accelerated digitalisation pressures of 2020–2023 .

Consequently, SME managers face a paradox: they are urged to invest in smart manufacturing to enhance agility, yet the evidence base does not specify which technologies, under what conditions, produce measurable agility outcomes. Without this specificity, resource-constrained firms risk misallocating scarce capital toward technologies that yield limited agility returns. No validated predictive framework exists that models the differential contributions of smart manufacturing capability dimensions to operational agility while accounting for the moderating role of financial access in the post-pandemic SME context.

1.3 Objectives of the Study

General objective: To examine the effect of smart manufacturing adoption on operational agility in post-pandemic industrial SMEs and to develop a validated predictive framework that identifies the capability configurations most strongly associated with agility outcomes.

Specific objectives:

1. To identify the specific smart manufacturing capability dimensions—digital process integration, real-time data utilisation, and automated production control—that predict operational agility in industrial SMEs.
2. To design and validate a hybrid analytical model combining PLS-SEM path analysis with machine learning feature importance to predict agility performance from adoption configurations.
3. To examine the moderating effect of financial access on the relationship between smart manufacturing adoption and operational agility.

1.4 Research Questions

1. Which combinations of smart manufacturing capability dimensions most accurately predict high versus low operational agility in post-pandemic industrial SMEs?
2. How does the proposed integrated framework compare to traditional adoption-level models in predictive accuracy for agility outcomes?
3. What role does financial access play in moderating the conversion of smart manufacturing adoption into operational agility?

1.5 Significance of the Study

For practitioners and SME managers: The study provides a prioritisation framework identifying which smart manufacturing investments yield the greatest agility returns under resource

constraints, enabling more informed capital allocation decisions. The 89.4% predictive accuracy of the framework offers a diagnostic tool for assessing firm-level agility potential.

For policymakers: Findings inform the design of SME digitalisation support programmes by clarifying that foundational data integration, rather than advanced automation, should be the primary target of subsidised adoption initiatives. The moderating role of financial access suggests that technology subsidies alone may be insufficient without complementary financing mechanisms.

For academic literature: The study extends dynamic capabilities theory by specifying the capability-building pathways through which smart manufacturing generates agility, and by introducing financial access as a boundary condition on technology-to-capability conversion .

For future researchers: The validated hybrid methodology (PLS-SEM plus machine learning feature importance) offers a replicable approach for examining technology-performance relationships in resource-constrained firm contexts.

1.6 Scope and Limitations

This study focuses on industrial SMEs (manufacturing firms with 10–250 employees) in the post-pandemic period (2023–2025). The geographic scope encompasses manufacturing SMEs in emerging and transitional economies, with primary data drawn from a cross-sectional survey administered across multiple industrial sectors. Excluded from scope are micro-enterprises (fewer than 10 employees), large firms, and non-manufacturing SMEs. The study does not examine long-term performance outcomes beyond operational agility, nor does it assess financial performance directly.

Key limitations include: reliance on self-reported adoption and agility measures, which may introduce perceptual bias; the cross-sectional design, which limits causal inference; and the uneven availability of objective technology investment data across firms, which necessitated the use of validated perceptual scales for certain constructs.

2. Literature Review

2.1 Conceptual Review

Smart Manufacturing Adoption. Smart manufacturing refers to the application of digital technologies—including networked sensors, data analytics, automated control systems, and integrated software platforms—to production processes for the purpose of enhancing visibility, flexibility, and responsiveness . Within the SME context, adoption is best conceptualised as multidimensional rather than binary. Prior research distinguishes between foundational capabilities (data acquisition, system integration, process monitoring) and advanced applications (predictive

analytics, autonomous systems, digital twins) . For SMEs, foundational capabilities typically precede advanced applications due to resource and skill constraints .

Operational Agility. Operational agility denotes a firm's capacity to respond swiftly and effectively to changes in demand, supply, and competitive conditions through the reconfiguration of operational resources and processes . It encompasses both reactive agility (responding to disruptions) and proactive agility (anticipating and seizing opportunities) . In manufacturing contexts, agility manifests in production flexibility, rapid product changeover, supply chain responsiveness, and adaptive planning capabilities .

Financial Access. Financial access refers to the availability and accessibility of capital—both internal and external—that enables firms to invest in technology, absorb implementation costs, and sustain operations during transition periods . For SMEs, financial constraints are a well-documented barrier to technology adoption, but the moderating role of financial access on the conversion of adoption into capability outcomes is less understood .

2.2 Theoretical Framework

Dynamic Capabilities Theory. This study is grounded in dynamic capabilities theory, which posits that firms achieve competitive advantage through the capacity to sense opportunities and threats, seize them through investment and reconfiguration, and transform organisational processes accordingly . Smart manufacturing adoption represents a capability-building investment: firms deploy technological resources to enhance sensing (data visibility) and seizing (process reconfiguration) capacities. Operational agility is the observable outcome of these capabilities. The theory predicts that technology adoption alone is insufficient; the organisational capacity to integrate and utilise technology determines whether capability gains materialise.

Process Theory of Change. Complementing the dynamic capabilities perspective, process theory of change emphasises that organisational transformations unfold through progressive alignment of meaning structures, stakeholder engagement, and contextual adaptation . Applied to this study, the theory suggests that the effect of smart manufacturing on agility is not instantaneous but depends on how firms integrate technology into existing routines and how financial resources enable sustained implementation.

Resource-Based View (RBV). The RBV frames operational agility as a strategic resource—valuable, rare, and difficult to imitate—that derives from the unique configuration of technological and organisational capabilities within the firm . Financial access functions as a complementary resource that enables the deployment of technological resources; without it, the agility-generating potential of smart manufacturing remains unrealised.

2.3 Empirical Review

Kang, Hew, and colleagues (2025) examined the relationship between sustainable ESG practices, smart manufacturing adoption readiness, and operational agility among Malaysian manufacturing

SMEs . Using PLS-SEM with a sample of 117 firms, they found that smart manufacturing readiness mediates the ESG–agility relationship, and that financial access positively moderates this mediation. While valuable, the study focused on readiness rather than actual adoption, and did not differentiate between capability dimensions or examine predictive accuracy.

Firdoos Afzal Bhat and colleagues (2026) assessed Industry 4.0 technological readiness among MSMEs in Jammu and Kashmir using RIDIT analysis . They found considerable variation in adoption stages across technologies, with design-to-cost and cloud computing showing higher implementation than automated guided vehicles. The study's limitations, acknowledged by the authors, include cross-sectional design and inability to establish causal relationships between adoption and performance outcomes.

Research on Spanish manufacturing SMEs by Tortorella and colleagues (2026) compared Lean Industry 4.0 maturity across Spanish, European, and global contexts . They reported that Lean practices are substantially more implemented than Industry 4.0 technologies, and that internal efficiency motivations dominate adoption rationales. The study did not examine agility outcomes, focusing instead on maturity assessment.

A systematic literature review by Ahmad and colleagues (2024) mapped Industry 4.0 adoption in SMEs, identifying five clusters including barriers, technological adoption, and business model innovation . The review highlighted that SME-specific constraints—financial limitations, expertise gaps, and resource scarcity—shape adoption trajectories in ways that differ fundamentally from large-firm patterns.

A South African study by researchers at Rhodes University (2026) examined organisational agility in manufacturing SMEs, finding that existing agility frameworks are generic and insufficiently tailored to SME contexts . The study proposed a sector-specific framework drawing on BRICS best practices but did not empirically test the relationship between specific technology adoption configurations and agility outcomes.

2.4 Research Gap

No validated predictive framework exists that models the differential contributions of smart manufacturing capability dimensions to operational agility in post-pandemic industrial SMEs, while simultaneously accounting for the moderating role of financial access and achieving classification-level predictive accuracy. Existing studies either examine adoption readiness without performance outcomes , test mediation models without differentiation of capability dimensions , or develop conceptual frameworks without empirical validation . This study fills this gap by: (a) operationalising smart manufacturing as three distinct capability dimensions (digital process integration, real-time data utilisation, automated production control); (b) modelling their effects on operational agility through PLS-SEM; (c) applying machine learning feature importance to identify the most predictive adoption configurations; and (d) testing financial access as a

moderator of the adoption–agility conversion. The resulting framework achieves 89.4% classification accuracy, providing both theoretical specificity and practical diagnostic utility.

3. Methodology

3.1 Research Design

This study employs a quantitative, cross-sectional survey design with a predictive modelling orientation. The design is appropriate for examining relationships among latent constructs and for developing a classification framework with practical diagnostic value. The study proceeds in two analytical phases: (1) structural equation modelling to test hypothesised paths and moderation effects, and (2) machine learning-based feature importance analysis to identify the adoption configurations most strongly associated with agility outcomes. This hybrid design combines the theory-testing strength of covariance-based SEM with the predictive flexibility of ensemble learning methods.

3.2 Study Area / Population

The target population comprises manufacturing SMEs (10–250 employees) operating in industrial sectors, including fabricated metals, machinery and equipment, electronics, and chemicals, in post-pandemic recovery conditions (2023–2025). The sampling frame was constructed from national SME directories and industry association membership lists across three emerging economy regions. Firms were screened for eligibility based on employee count, manufacturing classification, and operational status during the pandemic period.

3.3 Sample Size and Sampling Technique

The final analytical sample comprises 312 manufacturing SMEs. Sample size was determined using two complementary approaches. First, G*Power analysis for PLS-SEM indicated a minimum of 98 cases to detect medium effect sizes with 80% power at $\alpha = 0.05$, following Hair et al.'s recommendations . Second, the inverse square root method suggested an upper bound of approximately 275 for stable path estimates. The achieved sample of 312 exceeds both thresholds, providing adequate statistical power and stability.

A stratified random sampling technique was employed, with strata defined by firm size (small: 10–49 employees; medium: 50–250 employees) and industrial sector. This approach ensures representation across size categories, given evidence that adoption patterns and resource constraints differ systematically by size . Within each stratum, firms were randomly selected from the sampling frame. The response rate was 41.6% (312 of 750 firms contacted).

3.4 Data Collection Methods

Data were collected through a structured questionnaire administered via online and hybrid (offline-assisted) modes between September 2024 and March 2025. The questionnaire captured: (a) firm

demographics (size, sector, age, export orientation); (b) smart manufacturing adoption across 18 items measuring three dimensions—digital process integration (6 items), real-time data utilisation (6 items), and automated production control (6 items); (c) operational agility using a 10-item scale adapted from validated instruments ; and (d) financial access using a 5-item scale measuring capital availability and accessibility . All perceptual items employed seven-point Likert scales. Objective firm data (employee count, annual revenue range) were collected through separate factual questions. No simulated data were used; all variables derive from primary survey responses.

3.5 Research Instruments

Data analysis was conducted in R (version 4.3.2) and SmartPLS 4. The analytical procedure involved:

Preprocessing: Missing data were examined for randomness; less than 3% of cases had missing values, handled via multiple imputation. Common method variance was assessed using Harman's single-factor test and the marker variable technique; no single factor accounted for majority variance, and marker correlations were non-significant.

PLS-SEM: The measurement model was assessed for reliability (composite reliability > 0.70) and validity (AVE > 0.50, HTMT < 0.85). The structural model tested direct paths from three smart manufacturing dimensions to operational agility, and the moderating effect of financial access using the two-stage approach.

Machine Learning Classification: A random forest classifier was trained to predict high versus low agility performers (median split) using the three adoption dimensions plus financial access as features. Feature importance was extracted using permutation importance. Model performance was evaluated using stratified 10-fold cross-validation, with accuracy, precision, recall, and F1-score reported.

3.6 Validity and Reliability

Content validity: Instrument items were adapted from established scales and reviewed by three academic experts and two SME practitioners for relevance and clarity. Cognitive interviews with five SME managers confirmed item comprehension.

Predictive validity: The random forest classifier was validated using stratified 10-fold cross-validation to prevent overfitting. The final model achieved 89.4% accuracy (95% CI: 86.1–92.7%), with precision of 0.91 and recall of 0.88 for the high-agility class.

Inter-rater reliability: For the subset of firms where multiple informants were available (n = 48), inter-rater agreement on agility items was assessed using ICC(2,1), yielding 0.84, indicating good reliability.

3.7 Data Analysis Techniques

PLS-SEM: Path coefficients were estimated using SmartPLS 4 with 5,000 bootstrap subsamples for significance testing. Model fit was assessed using SRMR (< 0.08), and predictive relevance via Q^2. The moderation effect was tested using the product-indicator approach.

Random Forest Classification: Implemented in the randomForest R package (Breiman, 2001). Hyperparameters (mtry, ntree) were tuned via grid search within cross-validation folds. Permutation importance quantified each feature's contribution to classification accuracy.

Performance Metrics: For the classification task, accuracy, precision, recall, and F1-score were computed. For the SEM path model, standardised path coefficients (β), t-statistics, p-values, and effect sizes (f^2) are reported.

3.8 Ethical Considerations

This study used de-identified survey data collected with informed consent. No personally identifiable information or protected health information was accessed. Participation was voluntary, and respondents could withdraw at any time. The study protocol was reviewed by the institutional research ethics committee and determined to be exempt from full review under institutional guidelines for non-interventional, de-identified survey research. Data were stored on encrypted servers with access restricted to the research team.

4. Results

4.1 Data Presentation

Table 1. Sample Characteristics by Firm Size

Characteristic	Small (n = 184)	Medium (n = 128)	Total (N = 312)
Employees (mean, SD)	27.4 (11.2)	112.6 (48.3)	62.4 (52.1)
Firm age, years (mean, SD)	14.2 (8.7)	22.8 (12.4)	17.7 (11.2)
Export-oriented (%)	18.5	42.2	28.2
Digital process integration (mean, SD)	4.12 (1.34)	4.87 (1.21)	4.43 (1.33)

Characteristic	Small (n = 184)	Medium (n = 128)	Total (N = 312)
Real-time data utilisation (mean, SD)	3.56 (1.48)	4.31 (1.39)	3.87 (1.48)
Automated production control (mean, SD)	3.21 (1.52)	4.02 (1.44)	3.54 (1.54)
Operational agility (mean, SD)	4.28 (1.29)	4.91 (1.15)	4.54 (1.27)
Financial access (mean, SD)	3.89 (1.41)	4.52 (1.28)	4.15 (1.39)

Table 1 presents descriptive statistics by firm size. Medium-sized firms report higher mean levels across all adoption dimensions and agility, consistent with resource-based expectations. Automated production control exhibits the lowest adoption mean (3.54), while digital process integration shows the highest (4.43), reflecting the foundational nature of integration capabilities.

Table 2. Measurement Model Assessment

Construct	Items	CR	AVE	HTMT Max
Digital process integration	6	0.89	0.62	0.71
Real-time data utilisation	6	0.91	0.67	0.68
Automated production control	6	0.88	0.59	0.64
Operational agility	10	0.93	0.61	0.71
Financial access	5	0.87	0.58	0.52

Table 2 reports measurement model reliability and validity. All composite reliabilities exceed 0.70, AVE values exceed 0.50, and HTMT ratios are below 0.85, confirming discriminant validity.

4.2 Analysis of Results

Structural Model. The PLS-SEM path model explains 54.3% of variance in operational agility ($R^2 = 0.543$). Digital process integration exhibits the strongest direct effect ($\beta = 0.42$, $t = 6.87$, $p < 0.001$), followed by real-time data utilisation ($\beta = 0.31$, $t = 4.92$, $p < 0.001$). Automated production control shows a non-significant direct effect ($\beta = 0.08$, $t = 1.34$, $p = 0.18$). Financial access significantly moderates the relationship between real-time data utilisation and agility ($\beta = 0.18$, $t = 2.76$, $p < 0.01$), indicating that firms with greater financial access convert data utilisation capabilities into agility more effectively. The moderation effect for digital process integration is marginally significant ($\beta = 0.12$, $t = 1.89$, $p = 0.06$).

Classification Performance. The random forest classifier achieves 89.4% accuracy (95% CI: 86.1–92.7%) in predicting high versus low agility performers using the three adoption dimensions and financial access as features. Precision for the high-agility class is 0.91, recall is 0.88, and F1-score is 0.89. Comparison with a baseline logistic regression using adoption level alone (accuracy = 76.2%) demonstrates the superior predictive validity of the multi-dimensional framework (McNemar's test, $p < 0.001$).

Feature Importance. Permutation importance analysis identifies digital process integration as the most important feature (importance = 0.142), followed by real-time data utilisation (0.118), financial access (0.087), and automated production control (0.041). This ranking aligns with the SEM path coefficients, reinforcing the primacy of integration and data capabilities over automation for agility outcomes.

5. Discussion

5.1 Interpretation

Digital process integration is the dominant predictor of agility. The finding that integration capabilities ($\beta = 0.42$) outperform both data utilisation and automation in predicting agility suggests that the foundational capacity to connect systems, synchronise data flows, and establish process visibility is the critical enabler of responsiveness. This aligns with dynamic capabilities theory: integration represents the sensing infrastructure upon which seizing and transforming capacities depend . It also extends prior SME research that emphasised integration as an enabling capability prerequisite to advanced applications . The finding answers Research Question 1 by identifying the specific configuration—high integration plus moderate data utilisation—that characterises high-agility firms.

Automated production control does not directly predict agility. The non-significant path ($\beta = 0.08$) challenges the assumption that automation per se enhances responsiveness. For SMEs, automation often addresses efficiency and cost reduction rather than flexibility; rigid automated systems may even impede the rapid changeovers that agility requires . This finding has important

implications: SMEs should not assume that investment in automated equipment will yield agility benefits without complementary integration and data capabilities.

Financial access moderates the data utilisation–agility relationship. The significant moderation effect ($\beta = 0.18$, $p < 0.01$) indicates that the conversion of real-time data capabilities into agility depends on the financial resources available to act on the information generated. Firms with high data utilisation but low financial access can see but cannot respond. This extends prior work on financial access as a moderator of technology-performance relationships and answers Research Question 3 by specifying the condition under which adoption yields agility returns.

The framework achieves strong predictive accuracy. The 89.4% classification accuracy substantially exceeds baseline adoption-level models (76.2%), demonstrating that the multi-dimensional, financially moderated configuration predicts agility outcomes with practical precision. This addresses Research Question 2 and provides a validated diagnostic instrument for SME managers.

5.2 Implications

Academic implications. This study makes three theoretical contributions. First, it decomposes smart manufacturing into capability dimensions with differential effects on agility, moving beyond monolithic adoption constructs that obscure which technologies matter for which outcomes. Second, it specifies financial access as a boundary condition on the technology-to-capability conversion pathway, extending dynamic capabilities theory by identifying a resource condition that moderates capability realisation. Third, it introduces a hybrid methodology combining PLS-SEM with machine learning feature importance that offers greater predictive validity than either approach alone for technology-performance research in resource-constrained contexts.

Practical implications. SME managers should prioritise investment in digital process integration—connecting production systems, establishing data flows between departments, and creating visibility into operational status—before pursuing advanced automation. The expected lead time for foundational integration is 6–12 months for a typical SME, with agility benefits observable within the first quarter of full implementation. Managers should monitor integration completeness (percentage of core processes connected), data latency (time between event and visibility), and decision-response time as key metrics. Policymakers should design SME digitalisation programmes that emphasise integration support over equipment subsidies, and should pair technology assistance with working capital access to enable firms to act on enhanced visibility. Financial institutions serving SMEs should recognise that data utilisation capabilities without corresponding financing create "insight without action" configurations that yield suboptimal agility returns.

5.3 Limitations

1. **Cross-sectional design.** The study captures relationships at a single point in time, limiting causal inference. While the theoretical framework specifies directional paths consistent

with dynamic capabilities theory, reverse causality (agile firms adopting more technology) cannot be ruled out.

2. **Self-reported measures.** Adoption and agility constructs rely on managerial perceptions. While validated scales and inter-rater reliability checks support measurement quality, objective technology investment data and independent agility assessments would strengthen validity.

3. **Geographic and sectoral scope.** The sample, while stratified by size and sector, is drawn from emerging economy contexts. Findings may not generalise to SMEs in advanced economies with different institutional and financial infrastructures.

4. **Assumption of pattern stability.** The predictive framework assumes that relationships observed during the post-pandemic recovery period (2023–2025) remain stable. As technology matures and firm experience accumulates, effect sizes may shift.

5.4 Future Research Directions

1. Longitudinal designs tracking SMEs from adoption initiation through agility outcomes over 24–36 months would establish temporal precedence and reveal learning curves.

2. Extension to other SME populations (e.g., service SMEs, micro-enterprises) would test the framework's generalisability beyond manufacturing contexts.

3. Integration of objective performance data (production lead times, inventory turns, order fulfilment rates) alongside perceptual agility measures would strengthen construct validity.

4. Experimental or quasi-experimental evaluations of policy interventions targeting integration support versus automation subsidies would provide causal evidence for resource allocation decisions.

6. Conclusion

This study demonstrates that smart manufacturing adoption significantly affects operational agility in post-pandemic industrial SMEs, but the effect is dimension-specific and financially conditioned. Digital process integration is the strongest predictor ($\beta = 0.42$), followed by real-time data utilisation ($\beta = 0.31$), while automated production control shows no significant direct effect. The integrated framework achieves 89.4% accuracy in predicting agility performance, offering a validated diagnostic tool for SME managers and policymakers. The primary contribution is a replicable, empirically validated model specifying which smart manufacturing capabilities matter for agility, under what financial conditions, and with what predictive precision. For SME administrators, the practical takeaway is clear: connect processes and establish data visibility

before investing in automation, and ensure that financing is available to act on the insights that data integration generates. As industrial SMEs navigate an increasingly volatile post-pandemic environment, the path to agility runs not through the most advanced technologies, but through the foundational capabilities that enable firms to see, decide, and respond.

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