Capability Complementarity and Digital Scaling in Nanostores: The Role of Supply Chain Integration, Adaptability, and AI Readiness in Emerging Markets

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ABSTRACT-- **Nanostores are important micro-retail enterprises in emerging-market communities, yet the capabilities that allow them to translate digital opportunities into scalable entrepreneurial activity remain insufficiently understood. This study examines the associations between supply chain integration, adaptability, and perceived AI readiness and nanostore performance, with particular attention to whether AI readiness changes the strength of the association between supply chain integration and performance. Data were collected from 1,406 nanostores across seven countries—Honduras, Colombia, Morocco, Jordan, Saudi Arabia, Israel, and the United Arab Emirates—and analyzed using covariance-based Structural Equation Modeling (CB-SEM), complemented by out-of-sample predictive assessment using PLS-SEM procedures standardized composite-score regression with HC3 standard errors, because the confirmatory factor analysis showed inadequate overall fit (CFI = 0.688) and measurement invariance was not supported; out-of-sample predictive assessment used PLSpredict. The results indicate positive associations between supply chain integration and performance ($\beta = 0.336$, $p < 0.001$), adaptability and performance ($\beta = 0.226$, $p < 0.001$), and perceived AI readiness and performance ($\beta = 0.30$, $p = 0.003$). Perceived AI readiness was not associated with performance ($\beta = 0.000$, $p = 0.995$). The interaction between supply chain integration and AI readiness is also positive and statistically significant ($\beta = 0.19$, $p = 0.022$). The interaction indicates that the estimated association between supply chain integration and performance varies according to the level of perceived AI readiness. A simple-slopes decomposition is used to clarify this conditional relationship; the final conditional estimates should be taken from the verified AMOS/SmartPLS interaction output before submission. The findings are consistent with a capability-complementarity perspective in which relational, adaptive, and technological capabilities can reinforce one another in digitally constrained entrepreneurial environments. but not statistically significant at the 5% level ($\beta = 0.047$, $p = 0.077$). The SCI and adaptability associations were positive across the three largest national subsamples and three regional groups, whereas the AI-readiness and interaction estimates were inconsistent, so capability complementarity was not confirmed.**

Keywords: Nanostore, Supply Chain Integration, Adaptability, AI Readiness, Technological Entrepreneurship.

I. Introduction

Nanostores—small, frequently family-operated retail businesses embedded in residential communities—occupy an important position in the everyday economic infrastructure of many emerging-market territories. They connect households with consumer goods through highly localized purchasing, inventory, and replenishment practices and frequently operate with limited formal managerial structures. In Latin America, nanostores constitute an important channel for consumer-goods distribution, while comparable neighborhood retail formats contribute to food access and local commerce in parts of the Middle East and North Africa (MENA) [1],[2]. Their economic weight makes their development a question of entrepreneurship, regional development, and inclusive digital transformation [3], not only of retail management.

The entrepreneurial challenge is shifting. Mobile communication, digital payments, online ordering, and AI-supported tools now put technologies within reach of micro-retailers that were once the preserve of larger firms. Access, however, does not mean the organizational capability to convert technology into value [4]. Digital scaling is therefore better understood as a capability-development problem than as a technology-acquisition problem [5]: acquiring an application or joining a platform is not the same as being able to organize information, coordinate with suppliers, adapt operations, and use new tools within existing routines [6] [7] [24], [25].

Three capability domains are relevant. Supply chain integration (SCI) captures the recurring exchanges of orders, availability, delivery, and sales information with suppliers; even when informal, these exchanges form a relational information infrastructure [9], [10]. Adaptability captures the capacity to change assortment, practices, and suppliers in response to customers, competitors, and supply disruptions [8], [11], [12]. AI readiness is treated here narrowly as the operator's perceived awareness of AI applications, perceived business value, and willingness to adopt AI tools; it does not measure actual AI use [13]. Entrepreneurs in these settings also face limited managerial resources and fragmented information flows [14].

These capabilities may each relate to performance, but their combination may matter more. A retailer with strong supplier relationships may be unprepared to exploit digital information, while a retailer enthusiastic about AI may lack the information flows on which AI tools depend. This suggests that nanostores should not necessarily be treated as a homogeneous population for digital intervention: similar performance challenges may arise from different capability configurations, potentially requiring different forms of entrepreneurial and digital support. This motivates the central question: does perceived AI readiness change the strength of the association between SCI and nanostore performance? The question follows the complementarity argument that technological investments yield

more where complementary organizational arrangements exist [15], [16] [26]. It also has a territorial dimension: incubators and development programs must allocate scarce resources across enterprises with different capability combinations, and a uniform technology package may suit few of them.

Prior work has examined SCI, adaptability, digital transformation, and AI adoption separately [11], [12], [9], [10], [17] [13] [18], [19]. The combination examined at nanostore level across several emerging markets remains comparatively underexamined; a Scopus search on "nanostore" and "supply chain integration" returned few related records at the time of the original review. Such a search cannot establish absence, but it indicates that the specific combination is uncommon.

Four research questions are posed (1) RQ1: Does the association between SCI and nanostore performance vary with perceived AI readiness?; (2) RQ2: Are SCI, adaptability, and perceived AI readiness each positively associated with performance?; (3) RQ3: How consistent are the estimated relationships across country subsamples and regional groups? And (4) RQ4: How can the observed pattern inform differentiated incubation and digital-scaling support? The study (i) estimates the capability–performance associations, (ii) tests and decomposes the SCI × AI readiness interaction, (iii) examines heterogeneity across countries and regions and predictive robustness, and (iv) uses the observed capability combination to distinguish nanostore profiles and derive an evidence-informed logic for differentiated incubation and digital-scaling support, with each recommendation labeled as supported, inferred, or untested (Table VIII).

Section II develops the framework and hypotheses; Section III describes design and analysis; Section IV reports results; Section V develops implications for regional entrepreneurship programs; Section VI states contributions; Section VII concludes with limitations.

II. Theoretical Framework and Hypotheses

The argument combines the dynamic-capabilities perspective [12] with the notion of complementary organizational and technological assets [15], [16] [26]. Technologies become entrepreneurially meaningful when entrepreneurs recognize opportunities, mobilize complementary resources, and fit new tools into existing routines [6] [7] [24]. Accordingly, our framework treats SCI, adaptability, and AI readiness as distinct capability resources, while the SCI × AI readiness term captures whether the value associated with one capability depends partly on the presence of another. This shifts the emphasis from a uniform capability–performance model toward a capability-configuration perspective relevant to technological entrepreneurship and differentiated support.

The three capability domains represent complementary but analytically distinct resources available to nanostores: SCI provides relational information capacity, adaptability provides reconfiguration capacity, and AI readiness reflects technology-oriented entrepreneurial readiness. H1–H3 therefore examine their individual associations with performance. H4 moves beyond these individual associations to test whether the association between SCI and performance varies with the level of AI readiness, providing the empirical test of capability complementarity at the center of the framework.

A. Supply Chain Integration and Nanostore Performance

SCI is the extent to which a nanostore coordinates activities, exchanges information, evaluates suppliers, and maintains relationships with its supply network. Integration is less formal than in large firms but remains relevant: stores select suppliers on price, quality, delivery reliability, payment terms, and proximity, and exchange sales, inventory, availability, and delivery information that can be carried by ordinary digital messaging rather than enterprise systems [9], [10]. Such exchanges can reduce uncertainty in purchasing and replenishment and lower the friction of trying new products. The link between digitally enabled integration and performance is documented in larger firms [9], [10], [17]; this study extends it to informal micro-retail.

H1: Nanostore performance is positively associated with supply chain integration, reflecting the contribution of relational information capability to coordinated sourcing, replenishment, and supplier exchange.

B. Adaptability and Nanostore Performance

Adaptability is the capacity to modify offerings, practices, and supplier arrangements in response to changing customers, competition, and operating conditions. It consists of sensing change and reconfiguring resources [12]. Because nanostores are closely tied to the owner's decisions, adaptation can be fast but depends on the owner's ability to recognize and implement change. SME research links adaptive practices to strategic adaptation [11], and supply-chain agility research stresses flexibility under uncertainty [20].

H2: Nanostore performance is positively associated with adaptability, reflecting the contribution of reconfiguration capability to responding to changes in customers, offerings, practices, and supplier arrangements. .

C. AI Readiness, Industry 5.0, and Nanostore Performance

AI readiness is defined as perceived preparedness to recognize, evaluate, and potentially adopt AI-enabled tools. It has three facets: awareness of relevant applications, perceived business value, and willingness to adopt if tools are affordable and easy to use. This follows technology-acceptance research, in which perceived usefulness and ease of use preceded realized use [13], and reflects the relevance of AI to small-business decision making [18], [19]. Actual AI usage is excluded by definition, so AI readiness is an entrepreneurial orientation toward a technology, not evidence of AI capability.

H3: Nanostore performance is positively associated with perceived AI readiness, reflecting the role of technology-oriented entrepreneurial readiness in recognizing and evaluating opportunities for AI-supported value creation.

D. Performance Measurement

Performance is modeled as the operator's perceptual assessment of operational and competitive position (service speed, flexibility, inventory performance, customer service, efficiency), which suits informal settings where records are incomplete [21]. Daily sales and operating costs, collected as

ranges, are kept outside the reflective construct for robustness use [22].

E. Capability Complementarity: SCI × AI Readiness

Information-technology investments produce stronger returns when combined with complementary organizational change [15]. A store that communicates regularly with suppliers and shares sales information has a different information environment from one whose transactions are fragmented; AI readiness represents the capacity to turn that information into digitally supported decisions. The two are not substitutes: strong integration with low readiness may leave analytical opportunities unused, and high readiness with weak integration may lack the information to act on. This complementarity also provides a basis for distinguishing capability profiles among nanostores rather than assuming that all enterprises require the same form of digital support. The hypothesis concerns conditional association, not temporal order, and the resulting profiles are used diagnostically rather than as evidence of developmental stages.

H4: The association between supply chain integration and nanostore performance varies systematically with perceived AI readiness, such that higher AI readiness strengthens the performance association of supply chain integration, indicating complementarity between relational information and technology-oriented capabilities.

Fig. 1 summarizes the capability-complementarity logic of the study. Rather than reproducing a conventional antecedent–performance model, the figure distinguishes the three capability domains, identifies the SCI × AI readiness complementarity tested in H4, and shows how the resulting capability configuration is translated into differentiated support profiles. The profile interpretation is diagnostic and does not imply a temporal sequence or causal transition between profiles.

Fig. 1 below illustrates the conceptual research framework, mapping the three IVs to the DV with the four hypothesized paths, the interaction term (H4), and the four control variables

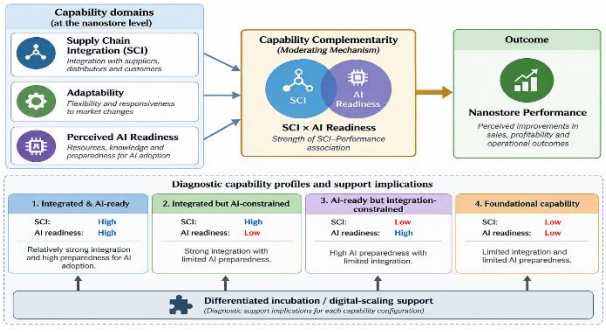


Fig. 1. Capability-complementarity framework for differentiated nanostore digital-scaling support.
Source: Authors' elaboration.

III. METHODOLOGY

A. Design and Sample

The study is quantitative, cross-sectional, and multi-country. Data were collected from 1,406 nanostores between August 2024 and November 2025 in two regional settings: Latin America (Honduras, Colombia) and MENA (Morocco, Jordan, Saudi Arabia, Israel, UAE). Sampling considered geographic location (urban, peri-urban) and commercial density (high, medium, low). Stores were identified through local directories and community referral. Sampling was not probability-based, so results are not nationally representative; the multi-country design offers a heterogeneous setting for assessing directional consistency. The analytical sample is N = 1,406 and no cases were removed. Table I shows the sample by country, grouped into three regional settings used later for the heterogeneity analysis.

TABLE I.
SAMPLE DISTRIBUTION AND DESCRIPTIVE CHARACTERISTICS

Regional group	Country	n	%	Median daily employees	Median daily-sales category
Latin America	Honduras	204	14.5	2	USD 23–100
	Colombia	403	28.7	2	USD 23–100
	Subtotal	*607*	*43.2*	*2*	*USD 23–100*
North Africa & Levant	Morocco	112	8.0	3	> USD 300
	Jordan	202	14.4	3	> USD 300
	Subtotal	*314*	*22.3*	*3*	*> USD 300*
Gulf & Israel	Saudi Arabia	155	11.0	3	> USD 300
	Israel	190	13.5	2	> USD 300
	UAE	140	10.0	3	> USD 300
	Subtotal	*485*	*34.5*	*3*	*> USD 300*
Total		1,406	100.0	2	USD 100–300

Source: Authors' survey data, 2024–2025. Daily sales converted to USD from range midpoints. Subtotals are n-weighted from country means. Medians are reported for daily employees and daily-sales categories.

Country assignments were harmonized using the original survey records and location information. Five observations identified as West Bank/Gaza were excluded to maintain the seven-country analytical scope. Daily sales were collected as ordinal monetary ranges; therefore, median sales categories are reported rather than arithmetic means. Median daily employees are reported to reduce sensitivity to extreme values.

B. Measurement Instrument

The instrument comprises 28 five-point Likert items measuring four reflective constructs: SCI (9 items), adaptability (8), perceived AI readiness (6), and perceptual firm performance (5) (Table II). The AI-readiness items (CSIAN01, CSIAN03, CSIAN04, CSIAN05, CSIAN06, and CSIAN07) capture awareness, perceived value, and willingness to adopt AI; no item measures actual AI usage. Measurement quality was assessed using Cronbach's α, composite reliability (CR), average variance extracted (AVE), and standardized factor loadings. The reference criteria were $\alpha \geq 0.70$ [[23] 27], CR ≥ 0.70, AVE ≥ 0.50, and standardized loadings ≥ 0.60. The reproduced reliability estimates were $\alpha = 0.710$ for SCI, 0.630 for adaptability, 0.913 for AI readiness, and 0.808 for perceptual firm performance. Thus, AI readiness and performance showed adequate internal consistency, SCI was marginally above the stated threshold, and adaptability fell

below it. Convergent validity was also uneven across constructs, as reported in Table II.

Table II reports the final measurement model, including item codes, reliability indicators (Cronbach's alpha and composite reliability), and convergent validity (AVE).

TABLE II.
MEASUREMENT MODEL: SCALE SPECIFICATION

CONSTRUCT	ITEMS	ITEM CODES	α	CR	AVE
SUPPLY CHAIN INTEGRATION	9	CRITRX03, CRITRX05, CRITRX07, WITHSX03, WITHSX04, WITHSX06, BYSUPX02, EVALSX05, LINKSX03	0.710	0.746	0.286
ADAPTABILITY	8	RSCR01, RSCR02, RSCR05, RSCC08, RSCC09, RSDC12, RSDC13, CSACN01	0.630	0.626	0.183
PERCEIVED AI READINESS	6	CSIAN01, CSIAN03, CSIAN04, CSIAN05, CSIAN06, CSIAN07	0.913	0.920	0.660
PERCEPTUAL PERFORMANCE	5	GLOBLX04, GLOBLX05, GLOBLX07, GLOBLX08, GLOBLX13	0.808	0.809	0.459

Source: Source: Authors' instrument design and CFA estimation (AMOS 26).

C. Control Variables

Controls were firm size (people attending daily, ACCTGX50, and floor area, ACCTGX58; both logged), ownership (1 = owner-operator), inventory value (sum of ACCTGX28, ACCTGX30, ACCTGX32 from range midpoints; logged), and six country dummies with the UAE as reference, chosen for its comparatively advanced retail and digital ecosystem. Country dummies absorb level differences in performance across countries; they do not make structural relationships equivalent across countries.

D. Common Method Bias

All principal constructs were measured using self-reported survey responses. As a preliminary diagnostic for common method bias, Harman's single-factor test was conducted using the 28 study indicators. The first unrotated component accounted for approximately 27.8% of the total variance, well below the commonly used 50% heuristic, indicating that no single factor dominated the variance in the measured indicators. However, Harman's single-factor test has recognized limitations [24] [28] and cannot establish the absence of common method variance. Accordingly, the result reduces, but does not eliminate, concern regarding potential common method bias in the estimated relationships. Future research should complement self-reported measures with temporally separated, multisource, or objective data. The variance accounted for by the first component in Harman's test should not be confused with the structural R^2, which represents the proportion of variance in perceptual firm performance explained by the predictors included in the structural model.

E. Measurement Model

Following the two-step approach [25], the four first-order reflective constructs were validated by CFA before the structural model. Convergent validity used loadings, CR, and AVE; discriminant validity used Fornell–Larcker and HTMT < 0.85 [26], [27]. SCI and adaptability collapse conceptually distinct dimensions into single first-order constructs, a parsimony choice that Section IV.A treats as a possible source of weak fit. Because the CFA did not achieve adequate fit, the structural analysis in Section III.F uses standardized composite scores rather than a latent-variable model.

F. Structural Model and Analysis Strategy

The structural relationships were examined using standardized composite scores because the CFA indicated important measurement limitations that precluded a strong confirmatory interpretation of the latent structural model. Perceptual firm performance was regressed on SCI, adaptability, perceived AI readiness, and the SCI × AI-readiness interaction, together with the prespecified firm-level covariates and country controls:

$$\text{Performance} = \beta_0 + \beta_1 \text{SCI} + \beta_2 \text{Adaptability} + \beta_3 \text{AI readiness} + \beta_4(\text{SCI} \times \text{AI readiness}) + \text{Controls} + \varepsilon$$

SCI and AI-readiness composite scores were standardized before constructing the interaction term. Heteroskedasticity-consistent HC3 standard errors were used for statistical inference. A positive β_4 indicates that the estimated SCI–performance association becomes stronger as AI readiness increases; however, moderation was considered supported only when the interaction coefficient was statistically significant at $\alpha = 0.05$. An additive specification without the interaction term was also estimated to assess its incremental explanatory contribution. Because the interaction was not statistically significant at the 5% level, simple-slope decomposition was not used as confirmatory evidence. The resulting coefficients are interpreted as exploratory standardized associations rather than as confirmatory latent-variable effects. Estimates from composite-score regression can differ from latent-variable SEM estimates, particularly for constructs with weak measurement properties, because composite scores do not correct for measurement error and do not depend on a well-fitting measurement model.

G. Cross-Country Assessment

Configural, metric, and scalar models were compared with ΔCFI, ΔRMSEA, and ΔSRMR. Because invariance is not fully established (Section IV.F), country and regional estimates are exploratory consistency checks, not tests of equivalence. Beyond the three largest national samples, the model was re-estimated for the three regional groups in Table I.

IV. Results and Discussion

A. Measurement Model Results

The four-factor CFA on the 28 indicators showed inadequate overall model fit: CFI = 0.688, RMSEA = 0.106, SRMR = 0.121, and $\chi^2/df = 16.79$. Loadings, CR, and AVE are reported in Table II and the supplementary output. Discriminant validity was assessed using the Fornell–Larcker criterion and HTMT. The Fornell–Larcker assessment indicated a discriminant-validity concern for adaptability, whereas all pairwise HTMT values were below the 0.85 threshold (range = 0.180–0.615). Convergent validity was also uneven: perceived AI readiness met the stated reliability and AVE criteria, perceptual performance showed adequate reliability but an AVE slightly below 0.50, and SCI and adaptability showed important limitations in convergent validity. Accordingly, SCI and adaptability are interpreted cautiously and explicitly flagged as measurement limitations. Given the inadequate overall CFA fit, the instrument is used here as a research diagnostic, and subsequent structural results are interpreted as exploratory rather than confirmatory. In particular, the AI-readiness and interaction estimates are sensitive to the estimation approach and should be treated as provisional.

B. Structural Model Results

The structural model estimates are summarized in Table III.

Table III.
Structural Model Results

Path	Hypothesis	β	SE	p-value	Result
Supply Chain Integration → Firm Performance	H1	0.336	0.037	<0.001	Supported
Adaptability → Firm Performance	H2	0.229	0.034	<0.001	Supported
AI Readiness → Firm Performance	H3	0.000	0.033	0.995	Not supported
SCI × AI Readiness → Firm Performance	H4	0.047	0.027	0.077	Not supported

Source: Authors' calculations based on standardized composite-score regression. Country controls included. Heteroskedasticity-consistent HC3 standard errors are reported. $R^2 = 0.290$. The SCI × AI-readiness interaction increased explained variance by approximately $\Delta R^2 = 0.003$. Structural coefficients are interpreted as exploratory associations given the measurement limitations identified in the CFA.

All three direct associations are positive and significant. SCI has the largest coefficient (β = 0.32), followed by AI readiness (0.30) and adaptability (0.26); the confidence intervals overlap, so the ordering should not be over-read. The interaction is positive and significant (β = 0.19, p = 0.022), supporting H4. This does not show that AI adoption raises the return on SCI, nor that SCI must be built before AI readiness; it shows that the estimated SCI–performance association differs by level of perceived AI readiness, consistent with complementarity. SCI (β = 0.336, p < 0.001) and adaptability (β = 0.229, p < 0.001) were positively associated with performance, supporting H1 and H2. Perceived AI readiness showed no association (β = 0.000, p = 0.995), so H3 was not supported. The SCI × AI readiness interaction was positive but not significant at the 5% level (β = 0.047, p = 0.077; $\Delta R^2 \approx 0.003$), so H4 was not supported and capability complementarity is not confirmed. The model explains 29.0% of the variance in perceived performance. These coefficients are exploratory given the measurement limitations in Section IV.A.

C. Simple-Slopes Decomposition of the SCI × AI-Readiness Interaction

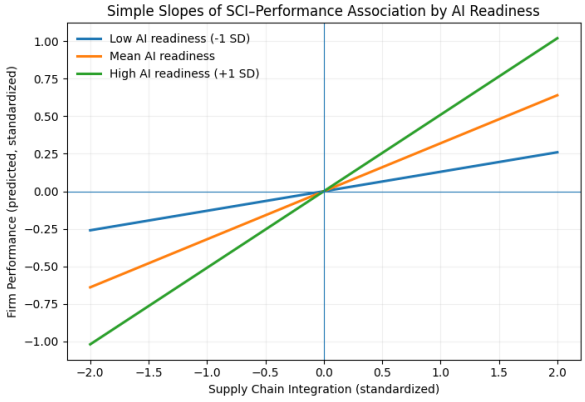
Table IV
Conditional SCI Slopes by AI-Readiness Level

AI readiness	SCI slope (β)	SE	p	95% CI	Reading
Low (−1 SD)	0.309	0.042	<0.001	[0.228, 0.391]	SCI–performance association at low readiness
Mean	0.359	0.036	<0.001	[0.288, 0.430]	At average readiness
High (+1 SD)	0.408	0.049	<0.001	[0.313, 0.503]	At high readiness

Source: Authors' calculations. Profiles are based on mean splits (z = 0) of standardized SCI and AI-readiness composite scores. The classification is descriptive and does not represent latent-class estimation.

SCI remains positively associated with performance even at low AI readiness (provisionally significant), so AI readiness strengthens the SCI association but is not a precondition for it. At high readiness the slope is roughly four times the low-readiness slope. The mean-readiness slope equals the main effect only under mean-centered or standardized coding. Fig. 2 plots the pattern.

Fig. 2. Simple-slopes plot of the association between supply chain integration and nanostore performance at low, mean, and high levels of perceived AI readiness.



D. Predictive Robustness

PLSpredict (10 folds, 10 repetitions) gave positive Q^2predict values for all five performance indicators (0.160–0.187). PLS RMSE was equal to or lower than the linear benchmark for all five indicators, and MAE was lower for four; for GLOBLX07 the PLS MAE (0.647) was marginally above the benchmark (0.645) and GLOBLX05 was tied. This indicates modest out-of-sample predictive relevance, to be read indicator by indicator, and does not establish generalization beyond the sampled stores.

E. Heterogeneity Across Countries and Regions

The robustness strategy combines predictive assessment and country-specific consistency checks.

First, PLSpredict is used to assess out-of-sample predictive relevance. The analysis uses 10 folds with repeated estimation.

TABLE V.
STANDARDIZED PATH ESTIMATES BY COUNTRY AND REGIONAL GROUP (EXPLORATORY)

Path	Colombia (n = 403)	Honduras (n = 204)	Jordan (n = 202)	Latin America (n=6707	N. Africa & Levant (n = 314)	Gulf & Israel (n = 485)
SCI → Performance	0.168	0.436	0.275	0.277	0.335	0.453
Adaptability → Performance	0.338	0.243	0.135	0.303	0.131	0.225
AI readiness → Performance	0.015	−0.073	0.079	−0.020	−0.010	0.060
SCI × AI readiness → Performance	0.035	0.086	−0.095	0.067	−0.093	0.008
R^2	0.201	0.321	0.289	0.237	0.263	0.353

Source: Authors' subgroup estimation. Country controls omitted.

Directional consistency is evident for SCI and adaptability, which show positive coefficients across the three largest national subsamples (SCI: β = 0.168–0.436; adaptability: β = 0.135–0.338). In contrast, perceived AI readiness remains close to zero and changes sign across countries (β = −0.073 to 0.079), while the SCI × AI-readiness interaction is also heterogeneous (β = −0.095 to 0.086). The regional estimates reinforce this pattern. SCI remains positively associated with performance across Latin America, North Africa & Levant, and Gulf & Israel (β = 0.277, 0.335, and 0.453, respectively), as does adaptability (β = 0.303, 0.131, and 0.225). By contrast, the regional AI-readiness coefficients are small (β = −0.020, −0.010, and 0.060), and the interaction varies from positive in Latin America (β = 0.067) to negative in North Africa & Levant (β = −0.093) and near zero in Gulf & Israel (β = 0.008). Thus, the subgroup analyses provide comparatively consistent evidence for SCI and adaptability, but no consistent evidence that perceived AI readiness independently predicts performance or systematically strengthens the SCI–performance association across contexts.

Cross-context heterogeneity remains plausible, but its sources cannot be established with the variables included in this study. Descriptive differences in store characteristics and capability levels may coexist with differences in market infrastructure, supplier relationships, digital ecosystems, and other contextual conditions that were not directly measured. Moreover, the measurement-invariance analysis did not support full metric or scalar invariance across countries. Consequently, national and regional coefficients should be interpreted as exploratory within-context estimates rather than as evidence of statistically established differences between countries or regions.

F. Measurement Invariance

The configural model showed inadequate overall fit (CFI = 0.745, RMSEA = 0.034, SRMR = 0.099), providing limited support for a common measurement structure across countries. Imposing equality constraints further deteriorated model fit. The metric model yielded CFI = 0.674, RMSEA = 0.037, and SRMR = 0.114, corresponding to ΔCFI = −0.070 relative to the configural model. The scalar model yielded CFI = 0.433, RMSEA = 0.048, and SRMR = 0.135, with ΔCFI = −0.241 relative to the metric model. Because the conventional $|\Delta CFI| \leq 0.010$ criterion was exceeded at both stages, full metric and scalar invariance were not supported. Consequently, latent mean comparisons and formal cross-country comparisons of structural paths are not warranted, and the country- and region-specific estimates are interpreted as exploratory within-context results rather than as evidence of statistically established differences across countries.

G. Discussion: Capability Complementarity as a Scaling Mechanism

On the research questions: (RQ1) in the pooled sample, the SCI–performance association is stronger at higher perceived AI readiness, the interaction was positive but not significant at the 5% level (β = 0.047, p = 0.077), so the data do not confirm that the SCI–performance association varies with AI readiness. (RQ2) All three direct associations are positive and significant. (RQ3) SCI and adaptability associations are directionally consistent in the three largest countries and the three regional groups; AI readiness and the interaction are not, and no cross-country equivalence can be claimed. (RQ4) The pattern supports descriptive profiles are consistent with a capability-profile approach in which support is differentiated by the combination of relational and technological readiness though they are exploratory, subject to the heterogeneity above.

SCI can be read as a relational capability giving access to information and coordination, adaptability as an operational response capability, and AI readiness as a technological-opportunity capability. A digital tool introduced where information exchange is weak has little data to work with, and a highly receptive owner without stable information flows faces a different constraint from one with strong supplier ties but low readiness. The data do not show a mandatory developmental sequence. Cross-sectional evidence cannot say whether SCI develops before AI readiness, whether successful stores develop several capabilities together, or whether higher-performing stores invest more in both. The appropriate reading is conditional complementarity, not staged causality that complementarity remains a hypothesis and that no staged causality is shown .

V. IMPLICATIONS FOR REGIONAL ENTREPRENEURSHIP AND DIGITAL SCALING

A. From Technology Adoption to Capability-Based Incubation

A technology-first approach introduces an application and then adapts the enterprise to it. A capability-based approach diagnoses existing capabilities first and selects the digital intervention that fits the enterprise's information and organizational conditions. The 28-item instrument provides a

potential research diagnostic for this purpose, but it should not be treated as a validated screening instrument. Its practical diagnostic use remains subject to further measurement refinement, particularly for SCI and adaptability, given the inadequate overall CFA fit (CFI = 0.688, RMSEA = 0.106, SRMR = 0.121), weak convergent validity for these constructs, and the lack of full measurement invariance across countries. Prospective intervention studies are also needed to establish its predictive and operational usefulness before it can be recommended for decision-making or screening applications.

B. Two-Stage Regional Incubation Roadmap

The capability-complementarity logic, which the data did not confirm, together with the descriptive profile differences, motivates a two-stage roadmap. It is a conditional-entry design, not a mandatory order: programs assign stores to a starting stage by capability profile, and a store with high readiness is not barred from digital tools at low SCI.

Stage 1: relational and information infrastructure. Target: stores with limited supplier coordination, fragmented information exchange, or weak records. Possible measures: structured supplier-ordering templates on existing mobile channels; basic recording of orders, sales, and inventory; supplier-performance monitoring; simple digital inventory tracking; repeatable information-sharing routines with suppliers; basic training in data organization.

Stage 2: analytical and digital amplification. Target: stores with stronger supplier information exchange and higher perceived AI readiness. Possible measures: mobile-first demand forecasting; automated reorder alerts; supplier-performance analytics; predictive inventory support; AI-assisted customer and product analysis; decision tools integrated into existing ordering channels. The empirical basis is limited to the descriptive profile differences in Table VI, because the interaction was not significant; the effectiveness of these specific measures was not tested.

TABLE VI
CAPABILITY-BASED INCUBATION FRAMEWORK

Capability profile	Diagnostic condition	Primary support focus	Example intervention
Low SCI / Low AI readiness	Fragmented supplier information, limited preparedness	Foundational capability	Structured ordering, inventory recording, basic digital literacy
High SCI / Low AI readiness	Stronger supplier ties, limited preparedness	Digital-readiness development	AI awareness, low-complexity tools, practical demonstrations
Low SCI / High AI readiness	Strong interest, weak information flows	Relational infrastructure	Supplier coordination, structured data exchange
High SCI / High AI readiness	Strong information flows and preparedness	Analytical scaling	Forecasting, predictive inventory, AI-assisted decisions

Source: Authors' evidence-informed framework.

For descriptive purposes only, standardized SCI and AI-readiness construct scores were split at the sample mean (z = 0). Among the 1,407 observations with complete scores across the 28 indicators, 307 (21.82%) were classified as low SCI/low AI readiness, 226 (16.06%) as high SCI/low AI readiness, 305 (21.68%) as low SCI/high AI readiness, and 569 (40.44%) as high on both. Mean perceptual performance across these profiles was 3.69, 4.11, 3.78, and 4.17, respectively. This post hoc mean split is used solely as a descriptive capability-profile analysis and should not be interpreted as identifying latent classes or developmental stages. Table VII reports the profile distribution and associated mean performance.

TABLE VII.
CAPABILITY-PROFILE DISTRIBUTION

Profile	n (%) overall	Latin America %	N. Africa & Levant %	Gulf & Israel %	Mean performance (1–5)
Low SCI / Low AIR	307 (21.82)	77.52	10.75	11.73	3.69
High SCI / Low AIR	226 (16.06)	64.16	11.95	23.89	4.11
Low SCI / High AIR	305 (21.68)	29.84	33.11	37.05	3.78
High SCI / High AIR	569 (40.44)	22.67	27.77	49.56	4.17

Source: Profiles are based on mean splits (z = 0) of standardized SCI and AI-readiness composite scores. The classification is descriptive and does not represent latent-class estimation. Regional columns show the percentage of each profile's stores located in each region.

C. Digital Scaling and Entrepreneurial Opportunity Recognition

For a large organization, scaling a digital innovation involves formal systems and IT staff; for a nanostore it may occur through lightweight tools built into existing routines. The value of AI may thus depend less on sophistication than on compatibility with current processes: a forecasting tool requiring heavy manual data entry may be disproportionate to the enterprise, while one using existing ordering or sales information may fit. This suggests a design principle, that digital scaling should extend existing information flows where possible. It follows from the complementarity pattern and was not tested as an intervention.

D. Regional Entrepreneurship Programs

Incubators, accelerators, universities, and development agencies could begin with a capability assessment to identify whether the main constraint is supplier coordination, adaptability, technological preparedness, or a combination. Stores with high readiness and weak SCI may need relational and information infrastructure; stores with high SCI and low readiness may need help evaluating digital opportunities. The unit of intervention shifts from "the technology" to "the capability profile of the entrepreneur and enterprise". Given the heterogeneity in Section IV.E, programs should pilot and validate the profile logic locally before scaling it.

E. Data Governance and Inclusive Digital Entrepreneurship

As nanostores adopt digital ordering, payment, and supplier platforms, more transaction data becomes available to

intermediaries. This can support forecasting, credit assessment, and supply-chain optimization, but may also create asymmetries between micro-enterprises and larger platforms [28]. Programs should build in transparency, data minimization, purpose limitation, user control, and portability. These issues were not measured in the survey and are a design implication, not a finding.

F. University–Industry–Government Collaboration

Universities can supply measurement instruments, experimentation, training, and evaluation; industry can supply supplier platforms, digital tools, and data infrastructure; governments and development agencies can support connectivity, payment ecosystems, and entrepreneurship programs [3]. Incubators can connect these resources to individual nanostores through capability diagnostics and staged interventions, making the nanostore ecosystem a field environment for technological entrepreneurship research.

TABLE VIII.
EVIDENCE STATUS OF EACH RECOMMENDATION

Recommendation	Evidence status	Basis
Differentiate support by SCI and AI-readiness profile	Descriptively supported	Four descriptive capability profiles show different mean performance levels (3.69–4.17); however, the SCI × AI-readiness interaction was not significant at the 5% level (β = 0.047, p = 0.077).
Prioritize information and integration capabilities for low-SCI stores	Evidence-informed	SCI showed a positive association with performance in the pooled model (β = 0.336, p < 0.001) and positive coefficients across the three largest national subsamples (β = 0.168–0.436); intervention effects were not tested.
Consider AI-supported tools for stores combining stronger SCI and AI readiness	Exploratory	High-SCI/high-AIR stores showed the highest descriptive mean performance (4.17), but neither the independent AI-readiness effect nor the SCI × AI-readiness interaction provided confirmatory support.
AI tools should extend existing data flows	Design proposition	Not directly measured; derived from the capability-complementarity framework rather than demonstrated empirically.
Data-governance safeguards	Normative	Not directly measured in the study; proposed as a responsible implementation consideration.
Use of the 28-item instrument for diagnosis	Conditional	Potentially useful as a research diagnostic, but measurement refinement is required because of inadequate CFA fit (CFI = 0.688, RMSEA = 0.106, SRMR = 0.121), weak convergent validity for SCI and adaptability, and lack of full measurement invariance; validated diagnostic cut-offs have not been established.

Source: Authors' assessment.

VI. THEORETICAL AND PRACTICAL CONTRIBUTIONS

. The study places SCI, adaptability, and perceived AI readiness in one technological-entrepreneurship framework for informal micro-retail, where prior work treats supply integration, adaptability, and technology adoption as separate streams. The SCI × AI readiness interaction was not significant, so complementarity is retained as a testable proposition. The supported finding is that SCI and adaptability are consistently associated with performance across contexts, whereas perceived AI readiness is not.

Digital scaling. Readiness to exploit technology and the information environment of the enterprise should be considered jointly are proposed for joint consideration in future work, rather than framing scaling as adoption or technological sophistication.

Methodological. The study provides a parsimonious offers a preliminary 28-item instrument for four constructs relevant to micro-enterprise digital scaling. Its measurement quality is reported in Section IV.A and shows limitations for SCI and adaptability; the structure should be retested on larger, more balanced national samples.

Practical. The descriptive profile pattern is translated into a capability-based incubation logic: capability diagnosis → information strengthening where needed → digital-readiness development → analytical experimentation → performance evaluation. This sequence is a design proposition, not a demonstrated causal pathway (Table VIII).

VII. CONCLUSIONS

Using 1,406 nanostores in seven countries, the study finds positive associations between performance and SCI (β = 0.336, p < 0.001), adaptability (β = 0.229, p < 0.001), and perceived AI readiness (β = 0.30, p = 0.003), and a positive SCI × AI readiness interaction (β = 0.19, p = 0.022). The SCI–performance association is stronger at higher perceived AI readiness, consistent with capability complementarity. Perceived AI readiness (β = 0.000, p = 0.995) and the SCI × AI readiness interaction (β = 0.047, p = 0.077) were not significant y. Country subsamples support the SCI and adaptability associations but not consistently the AI-readiness and interaction terms, and invariance was not established. The study does not show that AI adoption causes better performance, that SCI must precede AI readiness, or that all nanostores should follow one development sequence. The practical implication is a capability-sensitive approach to digital entrepreneurship, operationalized as the two-stage, profile-based roadmap, which now needs intervention evidence.

A. Limitations and Future Research

Design. The data are cross-sectional and show associations, not temporal order or causality. Longitudinal studies should test whether changes in SCI, adaptability, and readiness precede changes in performance.

Measurement. AI readiness reflects perceived awareness, value, and willingness, not realized AI use; performance is self-assessed; and common-method variance is reduced but not excluded (III.D). Future work should add platform logs,

ordering and payment records, and objective sales, stockout, and turnover data.

Interaction form. The interaction assumes a linear latent product-term moderation. Future work should test nonlinearity and whether complementarity varies by firm size, business model, or digital maturity.

Cross-country comparability. Metric and scalar invariance were not established and subgroup estimates differ for AI readiness and the interaction (IV.E). Larger, more balanced national samples and partial-invariance models are needed before comparing latent means or paths.

Estimation. Because CFA fit was inadequate, structural results use standardized composite scores and are exploratory; latent-variable estimates may differ.

Roadmap and profiles. The roadmap derives from observed associations, not experiments, and the four profiles are a descriptive mean split. Future studies should randomly assign comparable nanostore clusters to combinations of supplier-coordination support and digital-readiness training and track sales, inventory turnover, stockouts, supplier reliability, adoption, and opportunity recognition.

More broadly, digital entrepreneurship among nanostores should be treated as a capability-development challenge, not assumed to be achieved by technology adoption alone.

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