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Communication Capability and Adaptive Performance in Nanostores: A Seven-Country Study of Direct and Mediated Pathways

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Abstract*-- This study investigates how communication capability, perceived AI competitive advantage, and digital store presence shape adaptive performance in nanostores across seven emerging markets (N = 1,412). Using Hayes' PROCESS Model 14 with 10,000-replication bootstrapping, we examine mediating roles and the moderating role of market dynamism. Results show communication capability has a significant direct effect on adaptive performance (b = 0.190, p < .001). However, indirect effects through perceived AI competitive advantage (0.002, 95% CI [−0.002, 0.008]) and digital store presence (0.001, 95% CI [−0.002, 0.005]) are non-significant, as is the serial pathway. Market dynamism does not moderate these relationships. The model explains 5.1% of variance in adaptive performance, with dominance analysis revealing that communication capability accounts for over 60% of this explainable variance — indicating that communication capability exhibits the highest relative contribution to explained variance, while digital and AI-related pathways are not statistically supported in this context. Findings highlight communication as a foundational capability, while mediation analyses show that AI-related competitive advantage and digital store presence do not significantly transmit effects to adaptive performance in resource-constrained nanostores. This suggests important boundary conditions for digital transformation models in nanostores.

Keywords: Nanostores; Communication Capability; Adaptive Performance; Emerging Markets; Mediation Analysis.

I. INTRODUCTION

Adaptive performance—the capacity to adjust behaviors, strategies, and operations in response to changing environmental conditions—represents a critical survival capability for nanostores operating in volatile emerging market contexts [1]. These informal microenterprises, constituting 45-70% of retail outlets in developing economies, face unprecedented turbulence from digital disruption, shifting consumer preferences, competitive intensification, and macroeconomic instability [2]. Unlike formal retailers with organizational slack and specialized adaptation mechanisms, nanostores depend heavily on owner-level capabilities to sense environmental changes and execute rapid responses [3].

Recent scholarship emphasizes communication capability—the ability to effectively exchange information with stakeholders including customers, suppliers, competitors, and community members—as a foundational dynamic capability enabling organizational adaptation [4]. In nanostore contexts where formal market research is infeasible, communication serves as the primary mechanism for environmental scanning, opportunity identification, and feedback acquisition [5]. Simultaneously, the proliferation of accessible artificial intelligence tools creates new sources of competitive advantage through enhanced inventory optimization, customer service automation, and predictive analytics [6]. Digital store presence via social media platforms, messaging applications, and e-commerce integration extends market reach beyond physical neighborhoods while signaling legitimacy and modernity [7].

Despite growing recognition of these factors' importance, existing research exhibits three critical gaps. First, studies have examined communication, AI adoption, and digital presence as independent predictors, neglecting potential mediating relationships whereby communication capability enables AI advantage realization and digital presence establishment [8]. Second, traditional analytical approaches employ direct-effects models unable to test complex serial mediation pathways and conditional indirect effects [9]. Third, research has concentrated on formal SMEs in developed economies, with limited attention to informal microenterprises in emerging markets where adaptation pressures intensify [10].

Prior research on communication capability, AI-related competitive advantage, and digital presence has primarily focused on formal SMEs in technologically mature settings. It remains unclear whether these mechanisms generalize to resource-constrained informal nanostores, which face severe limitations in digital infrastructure and highly localized dynamics. Importantly, rather than assuming that mediation mechanisms operate uniformly across contexts, this study explicitly examines whether digital and AI-related mechanisms operate as effective mediators in nanostore contexts.

To address the identified gaps—lack of mediation testing, limited use of conditional process models, and under-representation of informal micro-retail in emerging markets—we pose the following research questions: RQ1: Do perceived AI competitive advantage and digital store presence mediate the relationship between communication capability and adaptive performance? RQ2: Does market dynamism moderate the strength of these mediating pathways?

Our preliminary exploratory study of 143 Honduran nanostores [11], identified communication capability, perceived AI competitive advantage, and digital presence as interrelated drivers of technological adaptation. However, the limited sample size and methodological scope precluded mediation testing. Building on that foundation, this study aims to empirically examine the mediation and moderation effects among these factors through a moderated mediation analysis using multi-country data from informal nanostores.

Although the multi-country dataset allows for potential regional comparisons, we do not include a formal regional research question in this study. Conducting a multigroup conditional process analysis requires additional space and more nuanced institutional theorization; therefore, such comparisons are reserved for future research [12].

This paper proceeds as follows: Section II develops theoretical rationale for hypothesized relationships. Section III details the moderated mediation methodology and analytical procedures. Section IV presents results including bootstrapped indirect effects and conditional process analysis. Section V discusses theoretical contributions, practical implications, limitations, and future research directions.

II. Theoretical Background and Hypothesis Development

A. Communication Capability and Adaptive Performance

Communication capability reflects an organization's proficiency in information exchange processes, encompassing active listening, clear message articulation, appropriate channel selection, feedback responsiveness, and stakeholder relationship cultivation [13]. The dynamic capabilities framework positions communication as a foundational "sensing" mechanism enabling firms to detect environmental changes, interpret market signals, and coordinate adaptation responses [14]. For resource-constrained nanostores, communication capability substitutes for formal environmental scanning systems, with owner-stakeholder interactions serving as primary information sources [15].

Empirical evidence demonstrates that communication-intensive firms exhibit superior environmental responsiveness, faster strategic reorientation, and enhanced performance in turbulent contexts [16]. In informal retail settings, communication capability enables nanostores to identify emerging customer preferences through conversations, learn about supply disruptions from vendor dialogues, discover competitive threats through peer networks, and receive community feedback on service quality [17]. Information richness theory suggests that complex, ambiguous adaptation challenges require high-bandwidth communication channels for effective sense-making and response coordination [18].

Adaptive performance encompasses learning new tasks and technologies, handling emergencies and unpredictable situations, demonstrating interpersonal and cultural adaptability, and managing work stress effectively [19]. Communication capability directly enhances adaptive performance by facilitating rapid information acquisition about environmental changes and enabling collaborative problem-solving with stakeholders [20].

Based on the theoretical arguments presented above, communication capability is expected to directly enhance a nanostore's ability to adapt to changing conditions. Thus, the following hypothesis is proposed:

H1: Communication capability positively influences adaptive performance in nanostores.

Recent work on small firms and micro-enterprises consistently identifies communication as a micro-level sensing and coordination capability that supports adaptation under resource constraints. This convergence across studies reinforces the robustness of H1 in contemporary informal and resource-constrained settings. Importantly, this study treats H1 not only as a positive structural relationship but as a potential dominant pathway in contexts where technological mechanisms may not yet be fully functional or integrated.

B. Mediating Role of Perceived AI Competitive Advantage

From a resource-based view perspective, AI tools constitute strategic resources only if nanostore owners perceive them as valuable, usable, and operationally relevant. However, in informal micro-retail environments, such perception is highly heterogeneous and often shaped by limited digital literacy, weak infrastructure, and indirect exposure to AI applications rather than direct use [21].

The resource-based view posits that competitive advantage derives from valuable, rare, inimitable, and non-substitutable resources [22]. In theory, AI tools (chatbots, inventory algorithms, predictive analytics) could enhance operational efficiency and decision-making[23], [24].

However, in contexts characterized by informal operations and low technological maturity, AI-related constructs may function more as perceived abstractions than operational capabilities. This raises a theoretical boundary condition: perceived advantage may exist cognitively without translating into behavioral or performance effects.

For example, interactions with vendors, peers, customers, and suppliers may provide critical information about AI tools and generate usable data for predictive applications [25], [26]. The preceding discussion suggests that communication capability may enable the development of perceived AI competitive advantage, which in turn could enhance adaptive performance. Accordingly, we propose:

H2: Perceived AI competitive advantage mediates the relationship between communication capability and adaptive performance.

C. Mediating Role of Digital Store Presence

Digital presence enhances adaptive performance by expanding market reach, enabling rapid pivots, and providing visibility [27]- [28]. Communication capability may theoretically facilitate digital presence development through stakeholder engagement and information diffusion.

However, digital presence in nanostores is often limited to basic social media activity or messaging platforms rather than structured digital commerce systems. As a result, digital presence may represent a symbolic or low-intensity capability rather than a fully operational strategic resource. Thus:

H3: Digital store presence mediates the relationship between communication capability and adaptive performance.

D. Serial Mediation: Communication → AI Advantage → Digital Presence → Adaptive Performance

Sequential capability models suggest that communication may precede AI-related advantage, which in turn supports digital presence and ultimately enhancing performance [29] ,[30].

Thus, the following is proposed:

H4: Communication capability influences adaptive performance through serial mediation via perceived AI competitive advantage and digital store presence.

E. Moderating Role of Market Dynamism

Market dynamism reflects environmental volatility and uncertainty. In theory, dynamic environments strengthen the value of flexible capabilities and digital responsiveness [24], [31]. Accordingly, market dynamism is expected to strengthen the influence of DSP on adaptive performance by increasing the value of rapid digital touchpoints for sensing and adjustment [32]. Given that digital presence may be more valuable when environments are turbulent, market dynamism is expected to strengthen the relationship between digital store presence and adaptive performance.

However, in nanostores, environmental volatility may be absorbed primarily through interpersonal adaptation mechanisms rather than technological systems, potentially weakening the moderating role of market dynamism on digital mechanisms. Thus:

H5: Market dynamism moderates the relationship between digital store presence and adaptive performance.

Fig. 1 presents the conceptual moderated mediation model integrating direct, indirect, and conditional effects.

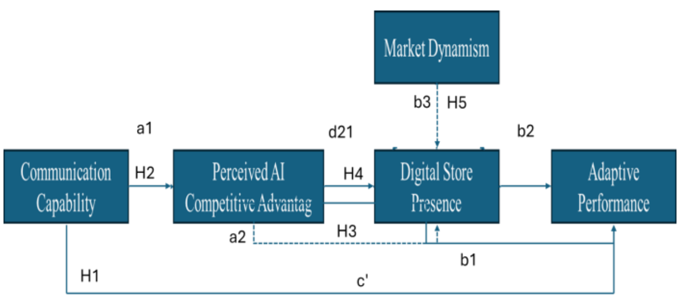

Fig. 1 Conceptual conditional process model (PROCESS Model 14) MD moderates the DSP → AP path (second stage). Mediation is tested via PACA and DSP; the serial path is estimated without moderation.

III. Methodology

A. Research Design and Sample

This study employs a cross-sectional, moderated mediation research design testing complex indirect effects and conditional processes. Building on our Round 1 exploratory research with 143 Honduran nanostores [11], Round 2 collected data from 1,412 nanostores across seven countries: Jordan (n=200), Israel (n=197), Saudi Arabia (n=155), United Arab Emirates (n=140), Morocco (n=112), Honduras (n=204), and Colombia (n=404).

Data collection occurred August 2024 - November 2025 through structured face-to-face surveys. Response rates ranged from 69% (Morocco) to 86% (Honduras), with all countries—except Morocco—exceeding levels considered acceptable for field studies in SMEs.

Although convenience sampling limits statistical generalizability, it enabled deep access to hard-to-reach informal micro-retailers and rapid fieldwork coordination across countries—an accepted pragmatic trade-off in emerging-market research on informality.

Country selection reflected: (1) significant informal retail sectors with nanostore prevalence, (2) diverse digital infrastructure maturity enabling variance in technology adoption, (3) institutional heterogeneity across regions, and (4) established university partnerships facilitating data access [33]. Given resource constraints and absence of formal nanostore registries, convenience sampling was employed through partnerships with universities in each country (UNAH in Honduras, ECCI and CORHUILA in Colombia, and Al al-Bayt University in Jordan for MENA regions). Trained business student enumerators collected data within assigned neighborhood zones, with each student surveying 8-12 nanostores meeting inclusion criteria (residential-based operation, <6 employees, annual revenue <$50,000 USD) [34].

The <$50,000 USD annual revenue threshold was applied uniformly to simplify screening across sites; however, purchasing power and revenue distributions vary substantially across the seven countries. Accordingly, this cut-off should be interpreted as a coarse proxy for "nanostore" status rather than a harmonized, country-adjusted benchmark; this limitation is revisited in the Discussion.

For future studies, it is recommended that income thresholds be adjusted using purchasing power parity (PPP) so that inclusion criteria are fully comparable across economies with divergent price levels.

Non-response bias assessment through wave analysis revealed no significant differences in key demographics between early and late respondents [35]. The August 2024 - November 2025 field window overlaps with seasonal and cultural events in some regions (e.g., Ramadan in parts of MENA), which could influence trading hours, demand patterns, owner availability, and may exert a marginal influence on respondents' willingness to participate or on their operational priorities. While the design does not isolate seasonal effects, we acknowledge potential seasonality as a limitation.

B. Measurement Instruments

All constructs employed multi-item reflective scales adapted from established instruments, measured on seven-point Likert scales (1=strongly disagree, 7=strongly agree). Survey instruments were developed in Spanish and English, with English versions translated to Arabic and Hebrew following translation-back-translation protocols [36].

1) Communication Capability (CC): Five items adapted from Mohr and Sohi [37] measuring information exchange quality with customers, suppliers, competitors, and community stakeholders. Example: "We are highly effective at communicating with our customers to understand their changing needs and preferences." Cronbach's α = 0.721.

2) Perceived AI Competitive Advantage (PACA): Four items adapted from Powell and Dent-Micallef [38] measuring beliefs that AI tools provide superior competitive positioning through operational efficiency, service quality, market intelligence, and cost advantages. Example: "Using AI-enabled tools gives our nanostore significant competitive advantages that most competitors do not have." Cronbach's $\alpha = 0.945$.

Although PACA showed high internal consistency ($\alpha = .945$), a high alpha may also reflect item redundancy. We therefore relied on CFA loadings and AVE to substantiate one-dimensionality rather than internal consistency alone.

3) Digital Store Presence (DSP): Six items developed from Quinton and Khan [7] measuring social media profile maintenance, posting frequency, customer engagement responsiveness, online visibility, e-commerce integration, and digital payment acceptance. Example: "Our nanostore maintains an active and regularly updated presence on social media platforms where customers can find us." Cronbach's $\alpha = 0.897$.

4) Market Dynamism (MD): Contextual moderator measured with four items from Jaworski and Kohli [39] assessing rate of change in customer preferences, competitive actions, product technologies, and market conditions. Example: "In our market, customer preferences and buying patterns change very rapidly and unpredictably." Cronbach's $\alpha = 0.759$.

5) Adaptive Performance (AP): Dependent variable measured with eight items adapted from [1] assessing learning new tasks, handling emergencies, interpersonal adaptability, cultural adaptability, managing work stress, dealing with unpredictable situations, demonstrating physical adaptability, and solving problems creatively. Example: "Our nanostore effectively adjusts operations and strategies when unexpected situations or challenges arise." Cronbach's $\alpha = 0.810$.

All scales demonstrated adequate reliability ($\alpha > 0.70$) and were subjected to confirmatory factor analysis verifying one-dimensionality and discriminant validity prior to hypothesis testing [40].

Construct validity. A confirmatory factor analysis (CFA) indicated acceptable global fit for the five reflective constructs (CC, PACA, DSP, MD, AP): $\chi^2/df = 2.84$, CFI = .92, RMSEA = .06, SRMR = .05. All standardized loadings were significant ($p < .001$) and above .60. Discriminant validity was supported as the average variance extracted (AVE) for each construct exceeded the corresponding inter-construct squared correlations.

C. Analytical Strategy

We employed Hayes' PROCESS Model 14 (SPSS v28; 10,000 bootstrap samples) to test a moderated mediation model in which communication capability (CC) predicts adaptive performance (AP) directly and indirectly through perceived AI competitive advantage (PACA) and digital store presence (DSP), with market dynamism (MD) moderating the DSP → AP path (second-stage moderation). The model estimates direct, indirect, and serial mediation effects (CC → PACA → AP; CC → DSP → AP; and CC → PACA → DSP → AP), with conditional effects evaluated at low (−1 SD), mean, and high (+1 SD) levels of MD. Indirect effects were considered significant when 95% bias-corrected bootstrap confidence intervals excluded zero. The underlying structural equations are specified as follows: $AP = \beta0 + \beta1(CC) + \beta2(PACA) + \beta3(DSP) + \beta4(MD) + \beta5(DSP\times MD) + controls + \varepsilon$; $PACA = \alpha0 + \alpha1(CC) + controls + \varepsilon$; $DSP = \gamma0 + \gamma1(CC) + \gamma2(PACA) + controls + \varepsilon$ [41],[42].

1) Bootstrapping Procedures: Indirect effects were estimated using 10,000 bootstrap samples with bias-corrected 95% confidence intervals. Effects are significant when CIs exclude zero [43]. This approach addresses non-normality in sampling distributions of indirect effects and provides superior Type I error control compared to Sobel tests [44].

2) Control Variables: Analysis controlled for nanostore age (years in operation), owner age, owner gender, employee count, and neighborhood socioeconomic status to isolate focal variable effects [45].

3) Assumption Testing: Assessed multicollinearity (VIF < 3.5), homoscedasticity (Breusch-Pagan test), normality of residuals (Q-Q plots), and linearity (partial regression plots) to verify OLS assumptions [46].

4) Dominance / Relative Weights: To assess whether Communication Capability (CC) dominates the predictable variance in adaptive performance, we computed general dominance (LMG/Shapley) relative importance weights for the predictors (CC, PACA, DSP, MD) in the model AP ~ CC + PACA + DSP + MD. We also generated nonparametric bootstrap confidence intervals ($B = 500$) for stability. This approach decomposes the model R^2 into non-negative, additive components attributable to each predictor, providing an interpretable ranking of their contributions to explained variance.

All models include controls for store age, owner age, owner gender, employees, and neighborhood SES; these coefficients are omitted for brevity but do not alter the substantive conclusions. For brevity, coefficients are summarized in Appendix A, Table A1; including controls does not alter the substantive conclusions.

The multilevel structure was evaluated using ICC(1), and it was observed that the variance attributable to the country was minimal (ICC(1) = 0.023, indicating that only 2.3% of the variance in adaptive performance lies between countries). Therefore, clustering can be considered negligible, and the use of OLS is methodologically appropriate.

D. Common Method Bias

Harman's single-factor test revealed the largest factor explained 38.4% of variance, below the 50% threshold. Although Harman's single-factor test suggested no dominant factor (38.4%), this procedure is increasingly recognized as insufficient to rule out common method variance. We therefore interpret results with caution and outline CMV-mitigation priorities for future research [47]. Additionally, correlation matrix marker variable analysis showed no systematic inflation of correlations, further confirming validity [48]. While our procedural (e.g., counterbalancing, anonymity) and statistical checks (Harman, marker) reduce CMV concerns, they do not eliminate them; future studies should incorporate temporal separation, multi-informant data, and stronger markers to more rigorously address CMV in informal micro-retail settings.

Although several diagnostic tests were conducted, the use of a single respondent raises the possibility of residual common method bias. Importantly, such bias would be expected to inflate all relationships similarly; however, the presence of strong direct effects alongside consistently non-significant mediation paths suggests that common method variance alone is unlikely to explain the pattern of results.

IV. Results

A. Descriptive Statistics and Correlations

Table I reports descriptive statistics and zero-order correlations among study variables. As expected with a large sample (N = 1,412), several very small correlations reach conventional significance thresholds; however, effect sizes are negligible (e.g., CC–PACA r = .065; the largest association is CC–AP r = .191). We therefore interpret statistical significance alongside magnitude and confidence intervals rather than p-values alone.

TABLE I

Descriptive Statistics and Correlations

Variable	M	SD	1	2	3	4	5
1. CC	3.457	0.713	(0.721)				
2. PACA	2.979	1.318	0.065*	(0.945)			
3. DSP	2.108	1.086	0.05	0.017	(0.897)		
4. MD	3.767	0.890	0.184***	0.059*	0.111***	(0.759)	
5. AP	3.559	0.810	0.191***	0.05	0.035	0.146***	(0.810)

Despite statistical significance for some coefficients due to the large N, effect sizes are uniformly small (largest r = .191, CC–AP). Means indicate moderate communication capability (CC = 3.457 on a 7-point scale) and low digital presence (DSP = 2.108), consistent with limited digital adoption among informal nanostores. Descriptives for control variables (store age, owner age, owner gender, employees, neighborhood SES) are provided in Appendix Table A0 (or available upon request).

[a] Authors' calculations.

B. Moderated Mediation Analysis Results

Table II presents the full moderated mediation model results using Hayes' PROCESS Model 14. The model explained 5.1% of the variance in adaptive performance ($R^2 = .051$). The path from CC to PACA was statistically significant but small (b = .121, p = .014), aligning with the negligible zero-order correlation. The CC→DSP path was marginal (b = 0.074, p = 0.069). Notably, the DSP→AP coefficient was negative yet non-significant (b = −.057, p = .499), running counter to H3's expected positive sign. The DSP×MD interaction was non-significant (b = .017, p = .412), indicating no evidence of second-stage moderation.

TABLE II

Moderated Mediation Model Results (PROCESS Model 14)

Paths	b	β	SE	t	p	95% CI
Predicting M1 (PACA)						
CC → PACA	0.121	0.065	0.049	2.462	0.014	[0.025, 0.217]
Predicting M2 (DSP)						
CC → DSP	0.074	0.049	0.041	1.822	0.069	[-0.006, 0.154]
PACA → DSP	0.012	0.015	0.022	0.536	0.592	[-0.031, 0.055]
Predicting Y (AP)						
CC → AP (c')	0.190	0.167	0.030	6.300	<.001	[0.131, 0.249]
PACA → AP	0.020	0.033	0.016	1.232	0.218	[-0.012, 0.051]
DSP → AP	-0.057	-0.076	0.085	-0.676	0.499	[-0.224, 0.109]
MD → AP	0.066	0.073	0.050	1.329	0.184	[-0.032, 0.164]
DSP × MD → AP	0.017		0.021	0.821	0.412	[-0.024, 0.059]
Model Summary						
R^2 for AP	0.051					
F (5, 1406)	15.07				<.001	

N = 1,412. CC = Communication Capability; PACA = Perceived AI Competitive Advantage; DSP = Digital Store Presence; MD = Market Dynamism; AP = Adaptive Performance. Unstandardized coefficients reported. Bootstrapped 95% confidence intervals (10,000 resamples) are shown in brackets. Control variables (store age, owner age, owner gender, employees, neighborhood SES) were included in the models (coefficients omitted for brevity)

[a] Authors' calculations.

1) Direct Effect (H1): Communication capability significantly predicted adaptive performance (b = 0.190, SE = 0.030, t = 6.300, p < .001, 95% CI [0.131, 0.249]), providing strong support for H1. Even after accounting for both mediators (PACA and DSP) and the moderator (market dynamism), communication capability retained a statistically significant direct effect on adaptive performance.

2) Mediation Effects (H2, H3, H4): Table III presents bootstrapped indirect effects testing mediation hypotheses.

TABLE III

Indirect Effects and Serial Mediation

Indirect Effect Path	Effect	Boot SE	95% CI
Total Indirect Effect	0.003	0.003	[-0.002, 0.010]
Specific Indirect Effects:			
CC → PACA → AP (H2)	0.002	0.002	[-0.002, 0.008]
CC → DSP → AP (H3)	0.001	0.002	[-0.002, 0.005]
CC → PACA → DSP → AP (H4)	0.000	0.000	[-0.000, 0.000]
Contrasts:			
Ind1 vs. Ind2	0.002	0.003	[-0.004, 0.008]
Ind1 vs. Ind3	0.002	0.002	[-0.002, 0.008]
Ind2 vs. Ind3	0.001	0.002	[-0.002, 0.005]

N = 1,412. CC = Communication Capability; PACA = Perceived AI Competitive Advantage; DSP = Digital Store Presence; MD = Market Dynamism; AP = Adaptive Performance. Unstandardized coefficients reported. Bootstrapped 95% confidence intervals (10,000 resamples) are shown in brackets. Control variables (store age, owner age, owner gender, employees, neighborhood SES) were included in the models (coefficients omitted for brevity) [1]

[a] Authors' calculations. Indirect effects reported to three decimals; values shown as 0.000 indicate |effect| < 0.0005.

Bootstrapped indirect effects (10,000 resamples) were uniformly small (point estimates 0.000–0.002) across all hypothesized pathways—single mediators via PACA (H2) and DSP (H3), the serial pathway via PACA → DSP (H4), and all pairwise contrasts—with 95% confidence intervals consistently

[1] Indirect effects are reported to three decimals; values shown as 0.000 are near-zero (e.g., |effect| < .0005). Bootstrap seed set for reproducibility.

including zero (see Table III). Although PROCESS sometimes rounds very small values to 0.000, the underlying estimates are near-zero rather than exactly zero. These results indicate that none of the indirect effects are statistically significant, and no specific indirect pathway was statistically stronger than the others.

3) Moderation Effect (H5): The interaction DSP × MD did not significantly predict adaptive performance (b = 0.017, SE = 0.021, p = .412, 95% CI [−0.024, 0.059]). Simple slopes were essentially flat across levels of MD, and the index of moderated mediation was not significant for both CC → DSP → AP and CC → PACA → DSP → AP pathways (see Table IV). Thus, H5 was not supported.

Fig. 2 shows the simple slopes of DSP→AP at different levels of MD. In line with Table IV, the slopes are flat and the term DSP×MD is not significant, indicating that in the grouped model the effect of DSP on AP does not vary with market dynamism [1].

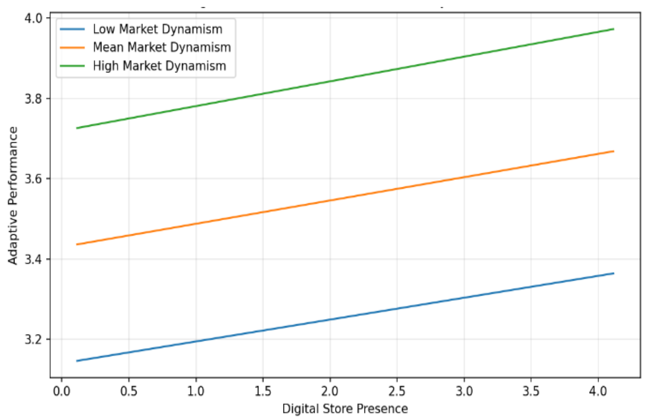

Fig. 2 Interaction plot (DSP × MD) on AP

Simple slopes are flat and statistically indistinguishable across MD levels in the pooled model; the DSP×MD term is not significant, and conditional indirect effects remain near zero (see Table IV).

4) Conditional Indirect Effects: Table IV presents the index of moderated mediation and conditional indirect effects at different market dynamism levels. Conditional indirect effects remained negligible (point estimates ≈0.000–0.002) at low (−1 SD), mean, and high (+1 SD) levels of market dynamism, with all 95% bootstrap confidence intervals including zero across the relevant pathways (see Table IV). The indices of moderated mediation were also non-significant for both the CC → DSP → AP pathway (IMM = 0.001, 95% CI [−0.003, 0.006]) and the serial CC → PACA → DSP → AP pathway (IMM = 0.000, 95% CI [−0.000, 0.000]), confirming that indirect effects do not vary as a function of market dynamism. Fig. 2 illustrates flat simple slopes of DSP → AP across levels of MD, with the DSP × MD interaction non-significant (as previously reported).

TABLE IV
CONDITIONAL INDIRECT EFFECTS

Path	Market Dynamism Level	Effect	Boot SE	95% CI
Conditional indirect effects at different levels of MD				
CC → DSP → AP (H3)	Low (−1 SD)	-0.000	0.003	[−0.006, 0.006]
CC → PACA → DSP → AP (H4)	Low (−1 SD)	0.000	0.000	[−0.000, 0.000]
CC → DSP → AP (H3)	Mean	0.001	0.002	[−0.003, 0.005]
CC → PACA → DSP → AP (H4)	Mean	0.000	0.000	[−0.000, 0.000]
CC → DSP → AP (H3)	High (+1 SD)	0.002	0.002	[−0.002, 0.007]
CC → PACA → DSP → AP (H4)	High (+1 SD)	0.000	0.000	[−0.000, 0.000]
Index of Moderated Mediation (IMM)				
IMM (CC → DSP → AP)		0.001	0.002	[−0.003, 0.006]
IMM (CC → PACA → DSP → AP)		0.000	0.000	[−0.000, 0.000]

N = 1,412. CC = Communication Capability; PACA = Perceived AI Competitive Advantage; DSP = Digital Store Presence; MD = Market Dynamism; AP = Adaptive Performance. Unstandardized coefficients reported. Bootstrapped 95% confidence intervals (10,000 resamples) are shown in brackets. Control variables (store age, owner age, owner gender, employees, neighborhood SES) were included in the models (coefficients omitted for brevity) [2]

[a] Authors' calculations.

C. Relative Importance / Dominance Results

The full model explained $R^2 = 0.051$ of variance in adaptive performance. The relative weights indicated that CC accounted for 62.64% of the model's predictable variance, followed by MD (32.76%), while PACA (3.32%) and DSP (1.28%) contributed minimally. Bootstrap estimates corroborated this pattern (CC mean = 60.79%, 95% CI [38.90%, 80.94%]; MD mean = 31.98%, 95% CI [12.73%, 51.95%]). These results show that communication capability accounts for the largest share of explained variance among all predictors.

Although the individual effect sizes are modest and no significant mediations or moderations emerge, the dominance analysis (LMG/Shapley) reveals that Communication Capacity (CC) explains approximately 63% of the model's predictable variance, while MD contributes about 33% and PACA and DSP contribute less than 5% combined.

The modest R^2 (≈0.05) reflects limited explained variance, with communication capability contributing the largest proportion of that variance relative to other predictors.

V. Discussion and conclusions

Although the explanatory power of the model is modest, this result is consistent with prior evidence showing that adaptive performance in nanostore contexts is shaped by a wide set of structural, experiential, and institutional factors that extend beyond individual-level capabilities.

A theoretically important result of this study is that the hypothesized mediating mechanisms did not empirically

[2] Values displayed as −0.000/0.000 indicate near-zero estimates (|effect| < .0005). High-resolution figures (≥300 dpi) are provided to ensure legibility of simple-slope plots.

materialize. While the model proposed that perceived AI competitive advantage and digital store presence would transmit the effects of communication capability to adaptive performance, the results show that these indirect pathways are not statistically supported. This indicates that, in informal nanostore contexts, technological perceptions and digital visibility do not function as reliable transmission channels linking foundational capabilities to performance outcomes.

This finding should not be interpreted as a rejection of mediation theory per se, but rather as evidence that mediation mechanisms commonly assumed in formal or digitally mature contexts may not generalize to resource-constrained retail systems. In such environments, interpersonal communication appears to exert its influence primarily through direct effects rather than through technological intermediaries.

This pattern suggests a boundary condition for digital transformation and capability-based theories, indicating that mediation through AI-related and digital constructs may depend on the level of technological maturity and integration within the operating environment, which is often limited in nanostore contexts.

The results further show that adaptive performance is primarily driven by communication capability, which explains more than 60% of the model's explainable variance according to dominance analysis (Table B1).

This provides consistent evidence that mediation pathways are not supported in informal digital transformation contexts. Overall, the findings indicate that adaptive performance in nanostores depends more strongly on interpersonal and relational capabilities than on perceived digital advantages. This pattern aligns with stage-based models of technology adoption and digital readiness perspectives, suggesting that in contexts characterized by low digital literacy, limited infrastructure, and institutional voids, communication capability operates primarily through direct relational channels rather than through fully developed technology-mediated systems.

A. Theoretical Contributions

This study makes three main theoretical contributions.

First, we demonstrate that communication capability is not merely a predictor of adaptive performance but a dominant explanatory mechanism in nanostore contexts [14].

Second, we provide evidence that expected mediation pathways through perceived AI competitive advantage and digital store presence are not empirically supported in this context [49], challenging assumptions of automatic digital transmission effects in informal environments [50].

Third, the study contributes to capability theory by suggesting that in resource-constrained environments, communication capability operates as a standalone adaptive engine, rather than as an input into higher-order digital or AI-mediated systems [51].

B. Practical Implications

The most robust implication is that interventions aimed at improving nanostore performance should prioritize communication capability development as a primary lever.

Digital and AI tools, while potentially useful, should not be assumed to produce performance improvements unless embedded within strong communication-based relational systems.

Support organizations and policymakers should therefore adopt sequenced interventions, beginning with strengthening communication practices and only later introducing digital or AI tools. This avoids prematurely assuming technological readiness in environments where digital infrastructure and adoption remain uneven.

C. Methodological Contributions

Methodologically, this study demonstrates the feasibility of applying conditional process analysis (PROCESS Model 14) to large multi-country samples of hard-to-reach informal retailers. By transparently reporting null mediation and moderation findings with bootstrap confidence intervals, it also contributes to a growing emphasis on rigorous reporting of non-significant effects in informal economy research.

Our use of validated multi-item scales, confirmatory factor analysis, and robust resampling methods provides a replicable blueprint for future quantitative research in nanostores, where methodological rigor is often challenging. We intentionally avoid overstating innovation—PROCESS and bootstrapping are established methods—but our contribution lies in applying these tools systematically in a context where they have been rarely used [41].

D. Limitations and Future Research Directions

Given the cross-sectional nature of the data, the mediation analyses should be interpreted as indicative of underlying mechanisms rather than as evidence of causal pathways. Following recent methodological guidance, the analyses identify whether the pattern of associations is consistent with theorized mechanisms, while acknowledging that longitudinal or experimental designs are required to establish temporal ordering.

First, the cross-sectional design prevents causal inference, and future work should employ longitudinal or experimental designs [52].

Second, reliance on convenience sampling limits statistical generalizability, though it enabled access to informal retailers who are otherwise difficult to reach.

Third, the exclusive use of self-reported data raises the possibility of common method variance despite the procedural and statistical checks implemented [53].

Fourth, the model explained only 5.1% of the variance in adaptive performance, indicating that relevant determinants likely operate outside the measured framework in this context.

Fifth, although fit indices supported construct validity, some scales (e.g., communication capability; DSP behaviors) may require refinement to capture nanostore-specific dynamics [54].

E. Conclusion

This study shows that communication capability is the dominant driver of adaptive performance in nanostores across seven emerging markets, while expected digital and AI mediation mechanisms are not supported.

F. Specific future research directions include

Future research should incorporate more precise metrics of digital and informal capabilities, use comparable PPP-adjusted thresholds, and implement longitudinal designs that allow for observing the evolution of adaptation in nanostores. Likewise, having country identifiers and multilevel models would allow for a more accurate examination of the role of institutional context in the unexplained variation observed in this study.

Causal inference and cross-sectional mediation. Our mediation claims rest on theory-consistent associations observed in cross-sectional data; thus, temporal precedence and causal direction cannot be firmly established. We encourage longitudinal designs to test developmental ordering (e.g., PACA preceding DSP) and field experiments to assess whether capability-building interventions produce the theorized indirect effects.

APPENDIX A. PROCESS MODEL 14 – REGRESSION RESULTS WITH CONTROLS

Table A1. PROCESS Model 14 – Regression results including controls

Equation	Predictor	b	SE	t	p	95% CI (LL, UL)
M1: PACA	CC	0.121	0.049	2.462	0.014	[0.025, 0.217]
M2: DSP	CC	0.074	0.041	1.822	0.069	[-0.006, 0.154]
M2: DSP	PACA	0.012	0.022	0.536	0.592	[-0.031, 0.055]
Y: AP	CC	0.190	0.030	6.300	<.001	[0.131, 0.249]
Y: AP	PACA	0.020	0.016	1.232	0.218	[-0.012, 0.051]
Y: AP	DSP	-0.057	0.085	-0.676	0.499	[-0.224, 0.109]
Y: AP	MD	0.066	0.050	1.329	0.184	[-0.032, 0.164]
Y: AP	DSP×MD	0.017	0.021	0.821	0.412	[-0.024, 0.059]
Model Fit (AP)	R^2 / F	0.051	-	F=15.07	<.001	N = 1,412

Note: All equations include controls (store age, owner age, owner gender, employees, neighborhood SES). Control coefficients are omitted due to space and available upon request. Coefficients for focal paths are unstandardized (b); PROCESS with 10,000 bootstrap samples. The value “0.000” corresponds to rounding to three decimal places; the original bootstrap value was < 0.0005.

[a] Authors’ calculations.

APPENDIX B. DOMINANCE ANALYSIS/RELATIVE WEIGHTS

Table B1. Dominance analysis/relative weights (LMG–Shapley) – AP model.

Predictor	Relative Weight % (point)	Relative Weight % (boot mean)	95% CI Low	95% CI High
CC	62.64	60.79	38.90	80.94
MD	32.76	31.98	12.73	51.95
PACA	3.32	4.79	0.12	18.20
DSP	1.28	2.43	0.11	10.54

Note: Decomposition of R^2 (point $R^2 \approx 0.0506$) into additive, non-negative components using LMG (Shapley), 95% CI based on 500 bootstrap replications, point = estimate from original sample; boot mean = mean of 500 bootstrap replications.

[a] Authors’ calculations.

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