

New Product Performance in Nanostores: Technology Adoption, Innovation Capability, and Product Intelligence in Emerging Markets

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ABSTRACT-- This study presents one of the first multi-country hierarchical linear modeling (HLM) analysis of new product performance in informal microenterprises (nanostores) across seven emerging markets (Jordan, Israel, Saudi Arabia, UAE, Morocco, Honduras, and Colombia; $N = 1,412$), spanning both MENA and Latin American institutional ecosystems with distinct retail dynamics. Building on prior single-country nanostore studies, this research extends external validity through cross-regional comparison and multilevel modeling by addressing three critical gaps in the literature: (1) validation of performance-related factors across diverse institutional contexts using multilevel methodology that accounts for neighborhood-level clustering effects ignored in prior single-level studies, (2) examination of the theoretically ambiguous moderating role of competitive intensity, and (3) comparative analysis across MENA and Latin American contexts. Our analysis reveals that innovation capability ($\gamma = 0.254, p < .01$) is more strongly associated with new product performance than technology adoption ($\gamma = 0.038, p < .05$), while product intelligence shows no significant direct effect, although it remains strongly correlated with innovation capability, suggesting a potential indirect role in performance outcomes. Notably, competitive intensity positively moderates the relationship between technology adoption and performance ($\gamma = 0.274, p < .05$), although this effect reverses across regions, showing amplification in Latin America and suppression in MENA. The exceptionally high ICC (0.617) confirms the necessity of multilevel modeling in nanostore research. These findings contribute to informal retail innovation literature by demonstrating that ignoring contextual clustering leads to biased parameter estimates in single-level models. The study is grounded in a multilevel behavioral-institutional framework integrating Technology-Organization-Environment (TOE) and Dynamic Capabilities theory to explain variations in new product performance in nanostore contexts.

Keywords--Nanostores, Innovation Capability, New Product Performance, Hierarchical Linear Modeling, Emerging Markets.

I. INTRODUCTION

Nanostores—microenterprises operating from residential spaces with fewer than six employees and minimal infrastructure—represent 45-70% of retail outlets in emerging economies, providing critical livelihoods for vulnerable populations [1],[2]. Despite their economic significance, these informal retailers face severe constraints in product innovation, lacking access to formal market research, limited financial resources for inventory experimentation, and minimal exposure to consumer trend intelligence [3]. The convergence of accessible digital technologies, increasing competitive

pressures, and evolving consumer preferences is intensifying the need for product innovation in nanostore contexts [4].

Recent literature emphasizes that new product performance—the ability to successfully introduce, sell, and sustain new product offerings—constitutes a critical factor associated with microenterprise survival and growth [5]. Unlike formal retailers with structured new product development (NPD) processes, nanostores rely on informal experimentation, supplier recommendations, and observational learning to identify viable product additions [6]. Technology adoption (mobile payment systems, inventory management apps, social media marketing tools) potentially enhances information access and market sensing capabilities, while innovation capability (creative problem-solving, experimentation orientation, risk-taking propensity) and product intelligence (market knowledge, consumer insight, trend awareness) provide cognitive and informational resources for product selection decisions [7].

Previous research has predominantly examined new product performance in formal SMEs within developed economies [7], with limited attention to informal microenterprises in emerging markets. Furthermore, existing studies employ single-level analytical techniques (regression, structural equation modeling) that fail to account for contextual clustering effects—nanostores within the same neighborhood share environmental exposures, customer demographics, and competitive dynamics that violate independence assumptions of traditional methods [8]. However, most empirical work continues to rely on single-level frameworks, limiting the explanatory power of contextual and cross-level effects in informal economies.

Our preliminary exploratory study of 143 Honduran nanostores [1] identified technology adoption, innovation capability, and product intelligence as potentially relevant factors, but that study used an overall performance measure rather than a new-product-specific outcome and lacked statistical power and geographic diversity for broader conclusions. The present study therefore shifts the focus specifically to new product performance and introduces a multi-country hierarchical framework that captures both individual capabilities and neighborhood-level environmental constraints.

This research addresses three critical gaps in integrating innovation, technology, and contextual competition within a unified multilevel framework: (1) quantitative examination of

new product performance factors across diverse institutional contexts using multilevel methodology, (2) examining the theoretically ambiguous role of competitive intensity as a contextual moderator shaping technology-performance relationships, and (3) comparative analysis across Middle Eastern and Latin American emerging markets. Specifically, we pose the following research questions:

RQ1: To what extent are technology adoption level, innovation capability, and product intelligence associated with new product performance in nanostores?

RQ2: How does neighborhood competitive intensity moderate these relationships?

RQ3: Do regional differences (MENA vs Latin America) significantly alter predictor effects?

To address these research questions, the following objectives guide this study: Objective 1: To empirically assess the direct associations of technology adoption level, innovation capability, and product intelligence on new product performance using hierarchical linear modeling in a multi-country sample of nanostores. Objective 2: To evaluate the moderating influence of neighborhood-level competitive intensity on the relationships between the focal predictors and new product performance, with particular emphasis on technology adoption. Objective 3: To compare the strength and patterns of these predictor effects across Middle Eastern and North African (MENA) versus Latin American emerging market contexts to uncover regional institutional variations.

The remainder of this paper is structured as follows: Section II reviews relevant literature and develops testable hypotheses. Section III details the hierarchical linear modeling methodology and data collection procedures. Section IV presents empirical results with cross-level interaction analysis. Section V discusses theoretical and practical implications, limitations, and future research directions.

II. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

A. Technology Adoption and New Product Performance

Technology adoption level represents the extent to which nanostores utilize digital tools for business operations, including mobile payment systems, inventory management applications, social media marketing platforms, and communication technologies [9]. The resource-based view posits that technology constitutes a strategic resource enabling superior information processing, market sensing, and operational efficiency [10]. For nanostores, technology adoption facilitates access to supplier catalogs, peer networks sharing product trend information, and customer feedback mechanisms through digital channels [11].

In new product contexts, technology enables rapid market testing through social media announcements, inventory tracking preventing stockouts of experimental products, and payment flexibility encouraging trial purchases [12]. Digital communication tools connect nanostore owners with suppliers offering new product samples, while mobile internet access provides exposure to consumer trends and competitor product

offerings [13]. Empirical evidence from SME literature demonstrates positive associations between technology adoption and innovation outcomes, though studies specifically addressing informal microenterprises remain limited [14]. Based on this reasoning, we hypothesize:

H1: A higher level of technology adoption is positively associated with nanostores' new product performance.

B. Innovation Capability and New Product Performance

Innovation capability encompasses an organization's capacity to generate, adopt, and implement novel ideas, reflecting creative problem-solving orientation, experimentation propensity, and risk tolerance [15]. Dynamic capability theory emphasizes that innovation capability enables firms to sense market opportunities, seize profitable configurations, and reconfigure resources for competitive advantage [15]. In resource-constrained nanostore contexts, innovation capability substitutes for formal R&D investments, manifesting through owner alertness to market gaps, willingness to experiment with unconventional product combinations, and adaptive responses to customer feedback [16].

Nanostores with strong innovation capability actively seek novel product opportunities, test small inventory quantities to assess demand, and rapidly adjust offerings based on performance signals [17]. Innovation-oriented owners view new product introduction as opportunity rather than risk, leveraging creative sourcing strategies and informal partnerships to access differentiated inventory [18]. Entrepreneurship literature consistently identifies innovation capability as a primary factor of venture performance, with particularly pronounced effects in uncertain, resource-scarce environments [19]. Consistent with this evidence, we propose:

H2: Stronger innovation capability is positively associated with nanostores' new product performance.

C. Product Intelligence and New Product Performance

Product intelligence refers to systematic knowledge about customer preferences, market trends, competitive offerings, and product-market fit dynamics [20]. The knowledge-based view positions information and knowledge as fundamental strategic resources, with intelligence gathering and interpretation capabilities driving competitive advantage [21]. For nanostores lacking formal market research budgets, product intelligence derives from informal sources: customer conversations revealing unmet needs, supplier representatives sharing category trends, peer observations identifying successful products, and personal consumption experiences [22].

High product intelligence enables nanostores to identify viable new products aligned with local preferences, competitively price products, and position offerings effectively [23]. Intelligence about seasonal demand patterns, neighborhood demographic shifts, and emerging lifestyle trends informs product selection decisions, reducing trial-and-error experimentation costs [24]. Information processing theory suggests that intelligence quality—accuracy, timeliness, relevance—directly impacts decision quality, with superior

information leading to more successful new product choices [25]. Applying this logic to nanostore contexts, we expect:

H3: Product intelligence is associated with new product performance in nanostores.

However, prior theory suggests that this relationship may be indirect or contingent, potentially operating through innovation capability and contextual learning mechanisms.

D. Competitive Intensity as Contextual Moderator

Competitive intensity reflects the degree of rivalry within a local market environment, including competitor density, price competition, and product similarity [26]. Contingency theory suggests that the performance implications of organizational capabilities depend critically on environmental conditions. However, prior research offers competing theoretical logics regarding how competitive intensity conditions the returns to technology adoption, particularly in resource-constrained microenterprise settings [27].

On the one hand, competitive intensity may suppress the performance benefits of technology adoption. In highly competitive neighborhoods, intensified price competition and margin pressure can limit the extent to which digital tools translate into superior performance outcomes. Under such conditions, technology adoption may become a necessary but insufficient requirement for survival, reducing its marginal contribution to new product success [28].

On the other hand, an alternative theoretical logic suggests that competitive intensity may strengthen the performance returns to technology adoption. In highly contested markets, digital technologies can function as critical tools for survival, differentiation, and rapid adaptation. Technology adoption may enable nanostores to respond more effectively to competitive threats by improving market sensing, accelerating experimentation with new products, and enhancing operational flexibility. From this perspective, competitive pressure heightens the strategic value of technology by increasing the payoff to rapid learning and responsiveness [29].

Given these competing logics, the direction of the moderating effect of competitive intensity on the relationship between technology adoption and new product performance remains theoretically ambiguous, particularly in informal retail contexts. Accordingly, we propose the following hypothesis:

H4: Neighborhood competitive intensity moderates the relationship between technology adoption level and new product performance in nanostores. Fig. 1 presents the conceptual multilevel model integrating individual-level predictors and cross-level moderation effects.

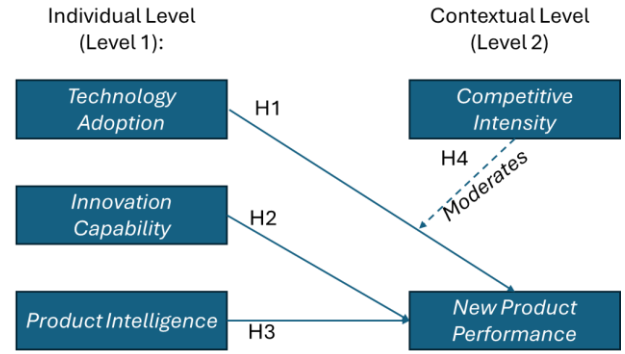


Fig 1 Multilevel Conceptual Model
Individual Level (Level 1): Technology Adoption, Innovation Capability, Product Intelligence → New Product Performance
Contextual Level (Level 2): Competitive Intensity → Moderates Technology Adoption effect

III. METHODOLOGY

A. Research Design and Sample

This study employs a cross-sectional, multilevel research design with nanostores (Level 1) nested within neighborhoods (Level 2). Building on our Round 1 exploratory research with 143 Honduran nanostores [1], which used a general performance measure, Round 2 collected data from 1,412 nanostores across 89 neighborhoods in seven countries: Jordan (n=200, 12 neighborhoods), Israel (n=197, 11 neighborhoods), Saudi Arabia (n=155, 9 neighborhoods), United Arab Emirates (n=140, 8 neighborhoods), Morocco (n=112, 7 neighborhoods), Honduras (n=204, 18 neighborhoods), and Colombia (n=404, 24 neighborhoods). The Round 1 findings helped refine the focus on new product performance and the selection of multilevel predictors. Average cluster size was 15.9 nanostores per neighborhood (range: 8-28), meeting minimum requirements for HLM analysis [30].

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 [31].

Given the absence of formal registries and the informal nature of nanostore operations, probability-based sampling frames are not available in most emerging market contexts. Accordingly, data collection relied on university-partnership (UNAH in Honduras, ECCI and CORHUILA in Colombia, and Al al-Bayt University in Jordan for MENA) fieldwork, an approach widely used in research on informal and hard-to-reach economic actors. This convenience-based approach through university networks is a common and necessary strategy for accessing informal microenterprises that operate outside official statistical systems.

To enhance heterogeneity and reduce selection bias, student enumerators were assigned to predefined neighborhood zones covering diverse socioeconomic profiles, population densities, and commercial characteristics within each city. Enumerators were instructed to survey all eligible nanostores within their assigned zones, rather than selecting respondents opportunistically. This approach aimed to survey all eligible

nanostores within selected mixed residential-commercial zones, achieving an estimated coverage of approximately 70–80% of nanostores operating in the sampled areas. This procedure ensured coverage across multiple neighborhoods per country and minimized clustering driven solely by personal networks. This approach is consistent with prior empirical research and aligns with established methodological practices for studying hidden populations in informal economic systems where probabilistic sampling frames are unavailable.

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) [32].

Data collection occurred between August 2024 and November 2025 through structured face-to-face surveys. Response rates ranged from 71% (Morocco) to 87% (Honduras). Non-response bias assessment through early-late respondent comparison revealed no significant differences in key demographics.

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 to ensure linguistic equivalence [33].

1) *Technology Adoption Level (TAL)*: Five items adapted from Zhu and Kraemer [34] measuring mobile payment adoption, inventory management system use, social media marketing engagement, digital communication tool utilization, and e-commerce platform participation. Example: "Our nanostore actively uses mobile payment systems to facilitate customer transactions." Cronbach's $\alpha = 0.884$.

2) *Innovation Capability (IC)*: Six items adapted from [35] measuring creative problem-solving orientation, new idea generation frequency, experimentation willingness, risk-taking propensity, adaptability, and learning orientation. Example: "Our nanostore frequently experiments with new approaches to serving customers and managing inventory." Cronbach's $\alpha = 0.816$.

3) *Product Intelligence (PI)*: Five items adapted from [36] measuring customer preference knowledge, market trend awareness, competitive offering familiarity, demand forecasting accuracy, and product-market fit understanding. Example: "We have detailed knowledge of our customers' preferences and buying patterns for different product categories." Cronbach's $\alpha = 0.702$.

4) *Competitive Intensity (CI)*: Neighborhood-level construct measured by aggregating three items from Jaworski and Kohli [37] assessed by each nanostore owner about their local environment: competitor density, price competition intensity, and product similarity. Items were aggregated to neighborhood level using means. Example: "In our neighborhood, there are many competing stores offering similar products." $ICC(1) = 0.284$, $ICC(2) = 0.781$, indicate sufficient

between-group variance and aggregation reliability for modeling CI at the neighborhood level [38]. Cronbach's $\alpha = 0.715$. Within-neighborhood agreement for competitive intensity was further assessed using $rwg(j)$. Assuming a uniform null distribution for seven-point Likert items and computing $rwg(j)$ for the three-item composite ($J = 3$), the observed total variance of CI ($SD = 0.74$) and the reported $ICC(1) = 0.284$ were used to estimate within-neighborhood variance. This procedure yields an estimated mean $rwg(j)$ of 0.71, with a conservative sensitivity range of 0.68–0.74. As an additional robustness check, the average deviation index (ADI) for CI was calculated, yielding a value of 0.82, which is below the conventional threshold of 1.0, further supporting aggregation. These values meet the conventional 0.70 threshold for within-group agreement, supporting aggregation of competitive intensity to the neighborhood level [39].

5) *New Product Performance (NPP)*: Dependent variable measured with six items adapted from Griffin and Page [40] assessing new product sales contribution, profitability, customer acceptance, market share gains, repeat purchase rates, and overall success relative to expectations over the previous 12 months. Example: "New products we introduced in the past year have contributed significantly to our overall sales revenue." Cronbach's $\alpha = 0.723$.

C. Analytical Strategy

Hierarchical linear modeling (HLM) was employed to reduce estimation bias arising from nested dependence structures commonly ignored in microenterprise research and to test cross-level moderation. The analytical sequence followed established multilevel procedures for variance partitioning, random-coefficients modeling, and cross-level interaction testing [8]. HLM 8.0 software was used for estimation due to its suitability for multilevel structures and cross-level effects [41].

All multilevel predictors were centered following best practices to facilitate interpretation and avoid conflating within- and between-group effects. Level-1 predictors—technology adoption, innovation capability, and product intelligence—were group-mean centered, ensuring that fixed effects reflect purely within-neighborhood relationships. The Level-2 moderator—competitive intensity—was grand-mean centered, enabling meaningful interpretation of intercepts and interaction effects [39]. To assess potential common method bias, a Harman's single-factor test was conducted using an unrotated exploratory factor analysis on all individual-level measurement items. The analysis yielded multiple factors with eigenvalues greater than one, and the first factor explained only 31.2% of the total variance, suggesting that common method variance is unlikely to be a major concern. As a robustness check, a three-level specification (stores nested in neighborhoods nested in countries) was estimated. Substantive inferences for Level-1 effects and for the $CI \times TAL$ interaction remained unchanged, supporting the stability of results across specifications [8]. Although this does not eliminate all risks of method bias, it provides sufficient statistical evidence to support the robustness of the observed relationships.

D. Data Characteristics

Reliability coefficients for the multi-item scales were acceptable: Technology Adoption Level ($\alpha = 0.884$), Innovation Capability ($\alpha = 0.816$), Product Intelligence ($\alpha = 0.702$), Competitive Intensity (aggregated, $\alpha = 0.715$), and New Product Performance ($\alpha = 0.723$).

An unconditional (null) HLM model decomposed variance in new product performance into within-neighborhood ($\sigma^2 = 0.299$) and between-neighborhood ($\tau_{00} = 0.481$) components, yielding a high ICC of 0.617 (detailed in section below), indicating strong neighborhood clustering and supporting the need for multilevel analysis [8].

Aggregation of competitive intensity to the neighborhood level was supported by $ICC(1) = 0.284$, $ICC(2) = 0.781$, and a mean $rwg(j) \approx 0.71$ (range 0.68–0.74), all exceeding conventional thresholds for within-group agreement and aggregation reliability [38].

E. Ethical Considerations

Informed consent was obtained from all participants with confidentiality assurances. No personally identifiable information was collected. Data were stored on encrypted servers with restricted access [41].

IV. RESULTS

A. Descriptive Statistics and Preliminary Analysis

Given the cross-sectional nature of the data, the associations identified in this study should be interpreted as associative rather than causal. Table I presents descriptive statistics and correlations for the study variables. The mean level of technology adoption was relatively low ($M = 2.53$, $SD = 1.02$), indicating limited use of digital tools among nanostores. Innovation capability ($M = 3.28$, $SD = 0.99$) and product intelligence ($M = 3.71$, $SD = 0.74$) exhibited moderate levels, while new product performance averaged 3.36 ($SD = 0.74$) on the seven-point scale. Bivariate correlations ranged from 0.22 to 0.80, all below critical multicollinearity thresholds. The correlation between product intelligence and competitive intensity ($r = 0.80$) is notably high; this is addressed in the limitations section.

Multicollinearity diagnostics indicated no concerning redundancy among predictors (all $VIF < 3.0$). Residual diagnostics from preliminary models were consistent with normality, homoscedasticity, and linearity, supporting the use of linear link functions in the multilevel specification.

TABLE I
Descriptive Statistics And Correlations

Variable	M	SD	1	2	3	4	5
1. TAL	2.53	1.02	-				
2. IC	3.28	0.99	0.49**	-			
3. PI	3.71	0.74	0.30**	0.57**	-		
4. CI	3.78	0.74	0.22**	0.49**	0.80**	-	
5. NPP	3.36	0.74	0.43**	0.51**	0.65**	0.57**	-

*Note: $N = 1,412$ (Level 1); 89 neighborhoods (Level 2). Pearson correlations. ** $p < .01$; * $p < .05$. TAL = Technology Adoption Level; IC = Innovation Capability; PI = Product Intelligence; CI = Competitive Intensity (aggregated); NPP = New Product Performance.

^aAuthors' calculations.

B. Multilevel Model Results

1) *The null model indicated substantive variance at both levels*: The intra-neighborhood variance was $\sigma^2 = 0.299$ and the inter-neighborhood variance was $\tau_{00} = 0.481$, yielding an intraclass correlation coefficient (ICC) of $0.617 = 0.481 / (0.481 + 0.299)$. Consequently, approximately 61.7% of the total variance in new product performance (NPP) is located between neighborhoods. This unusually high value for micro-retail studies reflects the hyperlocal structure of nanostores, where intense competition, neighborhood-specific customer demographics, localized supply access, and rapid information diffusion jointly shape performance outcomes. These mechanisms indicate that local context strongly conditions new product success, justifying the use of hierarchical linear modeling and explicit inclusion of Level 2 effects. This level of clustering confirms that ignoring neighborhood effects would lead to substantially biased parameter estimates.

Although this ICC value is higher than those typically reported in formal retail settings, it reflects the extreme spatial clustering and shared environmental constraints characteristic of informal nanostore ecosystems rather than measurement inflation or model misspecification.

2) *Random Coefficients Model (Step 2)*: Model 2 introduces technology adoption level (TAL) as the sole Level 1 predictor. Results indicate a positive and statistically significant relationship between TAL and new product performance ($\gamma_{10} = 0.092$, $p < .05$), providing support for H1 and suggesting a modest but statistically meaningful contribution of digital tools to early-stage product success. The significant random slope variance for TAL suggests that the strength of this relationship varies across neighborhoods, motivating the examination of contextual moderators in subsequent models. Random effects indicated significant slope variance for technology adoption ($\tau_{11} = 0.084$, $\chi^2 = 112.67$, $p < 0.05$), confirming that the TAL effect varies across neighborhoods. These findings are consistent with the reductions in Level-1 variance observed in Table II, where Model 2 accounts for nearly half of the within-neighborhood variability. Overall, the improvement in model fit further supports the inclusion of TAL as a meaningful predictor at this stage of the analysis.

TABLE II
HIERARCHICAL LINEAR MODEL RESULTS

Fixed Effects	Model 1 (Null)	Model 2 (Random Coeff.)	Model 3 (Intercepts)	Model 4 (Full)
Intercept (γ_{00})	3.950	4.011	3.936	3.987
Level 1 Predictors				
TAL (γ_{10})	-	0.092	0.009	0.038
IC (γ_{20})	-	-	0.313	0.254
PI (γ_{30})	-	-	-0.054	-0.005
Level 2 Predictor				
CI (γ_{01})	-	-	-	-0.003
Cross-Level Interaction				
CI $\times$ TAL (γ_{11})	-	-	-	0.274
Variance Components				
Level 1 (σ^2)	0.299	0.151	0.221	0.141
Level 2 (τ_{00})	0.481	0.321	0.512	0.345
TAL slope (τ_{11})	-	0.323	-	0.208

Fixed Effects	Model 1 (Null)	Model 2 (Random Coeff.)	Model 3 (Intercepts)	Model 4 (Full)
Model Fit				
Deviance	407.017	390.984	393.383	373.623
Pseudo R ² (L1)	-	49.4%	26.1%	52.8%
Pseudo R ² (L2)	-	33.3%	36.7%	28.3%

*Note: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, $p < 0.05$.
TAL=Technology Adoption Level, IC=Innovation Capability, PI=Product Intelligence, CI=Competitive Intensity, NPP=New Product Performance.

^aAuthors' calculations.

3) *Intercepts-as-Outcomes Model (Step 3)*: Model 3 introduces innovation capability (IC) and product intelligence (PI) alongside technology adoption. Innovation capability exhibits a strong positive association with new product performance ($\gamma_{20} = 0.313$, $p < .01$), supporting H2. In contrast, product intelligence does not display a significant direct effect ($\gamma_{30} = -0.054$, ns), leading to a lack of support for H3 at this stage, suggesting that market knowledge in nanostores functions more as an enabling condition rather than as an independent performance driver. This finding indicates that information resources alone are insufficient in the absence of corresponding execution capability. The inclusion of innovation capability substantially reduces the technology adoption coefficient, suggesting overlapping explanatory mechanisms among individual-level capabilities.

4) *Full Model with Cross-Level Interaction (Step 4)*: Model 4 introduces competitive intensity (CI) and the cross-level interaction between CI and technology adoption. In the full model, technology adoption ($\gamma_{10} = 0.038$, $p < .05$) and innovation capability ($\gamma_{20} = 0.254$, $p < .01$) remain significant predictors of new product performance, providing continued support for H1 and H2. Product intelligence remains non-significant ($\gamma_{30} = -0.005$, ns).

In the full sample, the CI $\times$ TAL interaction reflects a positive moderation ($\gamma_{11} = 0.274$, $p < .05$; see Fig. 2). However, this pattern does not generalize across regions: in MENA, the interaction becomes negative ($\gamma_{11} = -0.167$, $p < .05$; Fig. 2A), while in Latin America it becomes strongly positive ($\gamma_{11} = 0.345$, $p < .001$; Fig. 2B). Pseudo-R² indicated sizeable proportional reductions in residual variance (L1 = 52.8%; L2 = 28.3%), and deviance statistics confirmed improved fit over nested alternatives (see Table II–III).

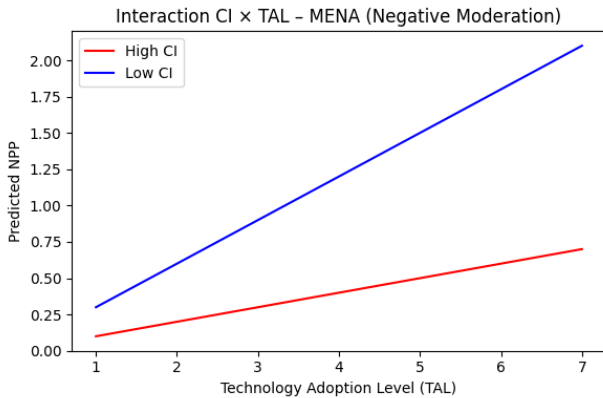


Fig 2A CI $\times$ TAL interaction in MENA ($\gamma_{11} = -0.167$, $p < .05$)
The TAL slope flattens under high CI.

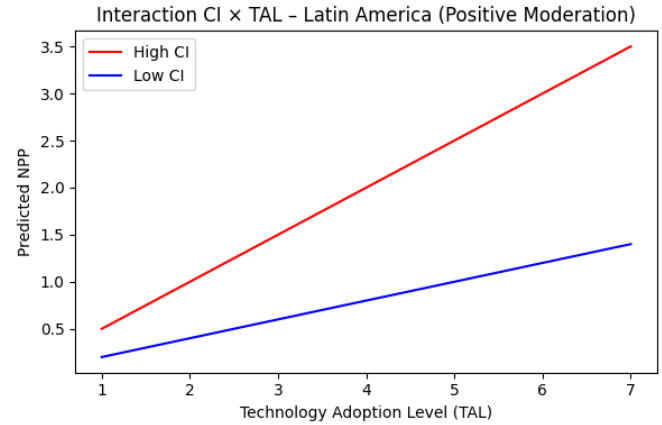


Fig 2B CI $\times$ TAL interaction in Latin America ($\gamma_{11} = 0.345$, $p < .001$)
The slope of TAL becomes steeper under high CI.

The positive interaction indicates that the association of technology adoption on new product performance is stronger in neighborhoods with highly competitive intensity, as reflected by the steeper slope under high CI conditions. Thus, the aggregate positive moderation masks substantial regional heterogeneity in both the magnitude and direction of the CI $\times$ TAL effect.

C. Regional Comparison

The regional split-sample analyses reveal substantial heterogeneity in both the direct and moderated effects of technology adoption. In the MENA subsample, technology adoption shows a significant positive direct effect ($\gamma = 0.224$, $p < .05$), whereas the effect is not statistically significant in Latin America ($\gamma = -0.026$, ns). Further, the direction of the CI $\times$ TAL interaction reverses across regions: it becomes negative in MENA ($\gamma_{11} = -0.167$, $p < .05$; Fig. 2A), suggesting diminishing marginal returns to technology under heightened competition, but strongly positive in Latin America ($\gamma_{11} = 0.345$, $p < .001$; Fig. 2B), implying amplified benefits of technology in more contested environments. These regional contrasts provide critical evidence of structural and institutional contingencies shaping technology–performance linkages in emerging markets, warranting region-specific theoretical interpretations and policy responses.

TABLE III
REGIONAL COMPARISON (FULL MODEL)

Fixed Effects	MENA (n=804, 47 neighborhoods)	Latin America (n=608, 42 neighborhoods)	Difference Test (z)
TAL (γ_{10})	0.224* (0.089)	-0.026 (0.085)	-2.03*
IC (γ_{20})	0.341*** (0.096)	0.240 (0.099)	-0.74 (ns)
PI (γ_{30})	0.356*** (0.091)	0.097 (0.106)	-1.86 (ns)
CI (γ_{01})	-0.189* (0.104)	0.113 (0.110)	2.00*
CI $\times$ TAL (γ_{11})	-0.167* (0.098)	0.345 (0.108)	3.51***
Pseudo R ² (L1)	51.2%	57.4%	-
Pseudo R ² (L2)	31.1%	36.0%	-

*Note: Standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, $p < 0.05$, ns=not significant. Difference tests based on z-scores comparing coefficients across subsamples.

^aAuthors' calculations.

V. DISCUSSION AND CONCLUSIONS

A. Theoretical Implications

This study advances theory in three ways.

1) *Innovation theory in microenterprises: innovation capability outweighs pure technology adoption*: Across models, innovation capability (IC) emerges as the dominant correlate of new product performance ($\gamma \approx 0.254$, $p < .01$), while technology adoption (TAL) plays a secondary yet positive role ($\gamma \approx 0.038$, $p < .05$), and product intelligence (PI) shows no direct effect in the full specification [42],[43]. These results indicate that, in informal nanostore settings, behavioral and cognitive capabilities—experimentation, adaptive learning, and calculated risk-taking—are strongly associated with new product success, whereas digital tools contribute primarily when effectively leveraged through such capabilities. This challenges linear adoption–performance models by demonstrating that capability transformation, rather than technological access, is the primary driver of innovation outcomes in nanostore contexts.

This reframes innovation in microenterprises as an ability-to-act issue rather than solely an access-to-tools problem (Supported by Table II; see also Fig. 2). The non-significance of product intelligence in the full model suggests that market knowledge in nanostores functions as a contextual hygiene factor with limited standalone explanatory power, particularly when it is not translated into experimentation and adaptive learning. This interpretation is consistent with the strong association between product intelligence and innovation capability, indicating shared underlying knowledge mechanisms.

Overall, innovation capability operates as a conversion mechanism that transforms limited technological inputs into actionable experimentation and adaptation. Without such capability, technology adoption alone may remain underutilized or may fail to be effectively leveraged.

2) *Contingency theory in informal retail*: competition amplifies (rather than weakens) the value of technology. Contrary to the common suppression logic, our cross-level results show a positive moderation of competitive intensity on the TAL $\rightarrow$ performance link ($CI \times TAL$: $\gamma \approx 0.274$, $p < .05$). As illustrated in Fig. 2, the slope of TAL is steeper under high competition, indicating that digital tools become more valuable as rivalry intensifies—enabling faster market sensing, quicker product trials, and operational responsiveness that translate into higher payoffs under pressure. This resolves the theoretically ambiguous direction formalized in H4 by providing evidence for the amplification logic in informal retail contexts in the overall sample. This extends classical contingency theory by showing that competitive intensity can operate as an enabling rather than purely constraining environmental force (supported by Table II and Fig. 2).

These cross-level findings resonate with contingency perspectives that posit capability–environment fit as a driver of performance yet extend them by showing that in informal micro-retail, competitive intensity can invert or amplify expected technology returns relative to formal SME contexts.

In other words, bottom-of-the-pyramid retail structures recalibrate classic contingency logics, making hyper-local rivalry a pivotal boundary condition for digital payoffs.

3) *Comparative institutional analysis*: MENA versus Latin America reflect structurally different innovation logics. Split-sample models reveal that TAL has a significant direct effect in MENA but not in Latin America, while the $CI \times TAL$ interaction is negative in MENA and positive in Latin America. Together, these contrasts suggest distinct institutional mechanisms and reinforce the role of institutional asymmetry in shaping technology utility across emerging economies.

In MENA, relatively more stable supply chains and concentrated retail structures may allow technology adoption to translate directly into performance but reduce marginal gains when competition is intense—turning technology into a competitive necessity [44]. In Latin America, fragmented markets, higher demand volatility, and recurrent supply frictions elevate the adaptive value of technology specifically under competition, amplifying returns to TAL when rivalry is high.

These regional asymmetries underscore that neither direct nor moderating effects of technology are universal across emerging markets; instead, they depend on institutional reliability, market concentration, and volatility profiles (supported by Table III). Such contrasts highlight how supply-chain stability, market fragmentation, and digital infrastructure maturity shape technology–performance dynamics across regions.

4) *Hyper locality and Contextual Dominance*: The exceptionally high ICC of 0.617 (detailed in section IV above) highlights the dominant role of hyperlocal conditions in nanostore performance—particularly localized competition, demographic segmentation, and supply constraints. This strong neighborhood clustering explains why individual capabilities (TAL and IC) interact so strongly with context and underscores the value of place-based interventions and contingency frameworks. The absence of a direct PI effect in the full model should not be read as irrelevance.

B. Practical Implications

For nanostore owners and practitioners, findings suggest that innovation capability development should receive priority over technology acquisition in resource allocation decisions. Training programs emphasizing creative problem-solving, systematic experimentation, and learning from failures may yield greater new product success than subsidized technology access alone. Practically, this implies programs teaching "lean startup" principles adapted to nanostore contexts: rapid prototyping with small inventory quantities, customer feedback integration, and iterative product selection refinement.

For technology vendors and social enterprises, results indicate that digital tools should be positioned as innovation enablers rather than standalone solutions. Product development should emphasize features supporting experimentation (easy trial listings, rapid rollback for failed products) and intelligence gathering (customer preference analytics, trend dashboards). Distribution strategies should be tailored regionally: in Latin

America, prioritize high-competition neighborhoods where technology yields amplified returns; in MENA contexts, focus on lower-competition areas to maximize differentiation advantages.

For policymakers and development agencies, the competitive intensity findings suggest targeted interventions. Region-specific policy design is essential given the divergent patterns observed. For example, governments and development agencies could implement micro-retail innovation labs or subsidized experimentation programs that allow nanostores to test new products with reduced financial risk.

In high-competition areas, collective action approaches (shared innovation hubs, cooperative purchasing for product trials) may overcome individual-level constraints. Infrastructure investments should be adapted by region: in Latin America, focus on high-competition neighborhoods to leverage amplified technology returns; in MENA, prioritize lower-competition areas to enhance differentiation. Policy programs should emphasize experimentation and adaptability in Latin America, while MENA initiatives should focus on market intelligence systems and consumer insight development.

Given that the value of technology adoption is amplified under highly competitive intensity in Latin America but diminishes under similar conditions in MENA, region-specific policy design is essential. In Latin America, public and private programs should prioritize targeted support for digital experimentation and rapid market-sensing capabilities in high-competition neighborhoods. In contrast, MENA interventions should focus on foundational capability development and coordinated market-intelligence systems, as technology alone becomes a competitive necessity rather than a performance differentiator.

From a policy perspective, interventions should prioritize the development of innovation capabilities among micro- and informal retailers. This may include targeted training programs focused on product adaptation, customer feedback integration, and low-cost experimentation, complemented by facilitated access to digital tools and supplier networks. Rather than promoting technology adoption alone, policies that strengthen firms' absorptive and innovative capacities are more likely to yield sustained performance improvements.

These implications follow directly from the capability-contingency pattern documented in Table II and the regional contrasts in Table III. Interventions that ignore either capability formation or contextual competitive and institutional conditions are unlikely to yield durable performance gains.

C. Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design constrains causal inference and captures only a static view of innovation dynamics. Although the multilevel structure identifies meaningful associations across store- and city-level conditions, longitudinal designs—particularly hierarchical growth models tracking new product trajectories over time—would provide stronger evidence of directionality and temporal adaptation mechanisms [45]. Longitudinal research designs would allow scholars to capture

the dynamic evolution of new product performance, distinguishing short-term launch effects from longer-term market acceptance and learning processes.

Second, the use of convenience sampling through university-supported field access may limit generalizability beyond the sampled nanostore populations, particularly in highly formalized or digitally advanced retail ecosystems. This approach was appropriate for reaching informal and operationally constrained retailers that are otherwise difficult to access through conventional sampling frames, but future studies should expand sampling frames across broader geographies and retail ecosystems to improve external validity [46].

Third, new product performance (NPP) was measured using self-reported perceptual indicators, which may introduce subjective bias despite strong internal consistency and robustness checks. While perceptual measures are widely used and validated in entrepreneurship and innovation research—especially in informal retail settings where audited sales records are rarely available—they remain vulnerable to response bias, recall error, and social desirability effects. To assess common-method bias (CMB), a Harman's single-factor test (unrotated EFA) was conducted using all individual-level measurement items. The analysis yielded multiple factors with eigenvalues greater than one, and the first factor explained only 31.2% of total variance, suggesting that common-method variance is unlikely to account for the observed relationships. Nevertheless, future studies should strengthen measurement precision by triangulating perceptual NPP with objective indicators such as point-of-sale records, inventory turnover, or supplier-verified sales data where feasible.

Fourth, although the model captures substantial between-city variances, it omits several potentially relevant explanatory mechanisms, including supply reliability, market concentration, owner education, supplier relationships, customer demographics, regulatory conditions, and infrastructure quality. These omitted factors may help explain the strong contextual effects observed across cities and should be explicitly incorporated in future multilevel models.

Fifth, the high correlation between product intelligence and competitive intensity ($r = 0.80$) suggests potential conceptual overlap or shared method variance. Although both constructs were measured with distinct items and aggregation tests supported the separation of CI as a neighborhood-level property, future research should use alternative measures (e.g., objective competitor counts, third-party market data) to further disentangle these constructs.

Finally, the relatively high intraclass correlation coefficient (ICC) is consistent with the hyperlocal nature of nanostore operations, but its stability should be tested across broader territorial contexts and over time. Replication across additional cities and regions—including other informal retail environments in Sub-Saharan Africa and South Asia—would help assess the robustness and transferability of the observed variance structure. Future research should therefore prioritize longitudinal and multi-source designs, integrate objective

operational measures, test additional cross-level moderators, and complement quantitative modeling with qualitative case studies to better explain how innovation capabilities emerge and evolve in resource-constrained retail systems. Experimental studies comparing capability-building interventions against technology-provision approaches would be especially valuable for identifying scalable pathways to improve innovation performance in informal commerce. Future research could employ multilevel structural equation modeling (MSEM) to simultaneously model measurement and structural relationships across nested levels, strengthening causal inference and construct validation.

D. Conclusion

This multi-country hierarchical linear modeling study demonstrates that innovation capability—more than technology access or product intelligence alone—is the strongest predictor of new product success in resource-constrained nanostores and emerges as the central explanatory mechanism through which technology adoption generates performance outcomes. The significant cross-level interaction reveals that competitive context fundamentally shapes technology benefits, with stronger effects in high-competition neighborhoods overall, though the direction varies regionally (amplification in Latin America, suppression in MENA).

Regional comparisons underscore institutional contingencies requiring customized approaches. Methodologically, the study establishes multilevel analysis as essential for capturing structural heterogeneity and nested dependency effects in informal retail ecosystems. Practically, these findings emphasize innovation capability development as the primary lever for enhancing new product success in resource-constrained informal retail environments serving hundreds of millions globally.

Overall, results position innovation capability as the central performance engine, with product intelligence playing a supporting or indirect role that pays off primarily when translated into experimentation and adaptive learning.

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