

AI Perception and Nanostore Performance: Moderating Effects of Institutional Heterogeneity in Honduras and Colombia

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Abstract-- *This study investigates how relational capability, perceived quality, and perceived AI benefits influence operational performance in nanostores across Honduras and Colombia. It operationalizes AI-related perceptions as multidimensional constructs—perceived quality and perceived AI benefits—rather than a single aggregated “AI perception” variable in resource-constrained Latin American retail contexts. The research is framed by an integrated theoretical model addressing limitations of traditional technology acceptance theories by incorporating Resource-Based View and Institutional Theory lenses, positioning relational capability as a networked resource contingent on institutional context. A cross-sectional dataset of 608 nanostores (204 Honduras, 404 Colombia) was analyzed using Multi-Group Structural Equation Modeling with Maximum Likelihood Estimation. Measurement validity was assessed through confirmatory factor analysis and invariance testing. Relational capability ($\beta = 0.34, p < 0.001$) and perceived AI benefits ($\beta = 0.41, p < 0.001$) significantly predict operational performance, while perceived quality exerts a moderate effect ($\beta = 0.23, p < 0.01$). Multi-group analysis reveals relational capability is more influential in Colombia, whereas perceived quality is more salient in Honduras. Contextual factors explain additional variance ($R^2 = 0.42$ Colombia, 0.36 Honduras). The cross-sectional design limits causal inference: common method variance was non-significant. Future research should incorporate longitudinal designs and objective metrics. Results suggest context-specific AI adoption strategies: Colombian nanostores benefit from ecosystem-driven approaches emphasizing supplier networks, while Honduran ones require quality-centered strategies focusing on service reliability. Policymakers should tailor digital transformation initiatives to local institutional realities and develop data privacy frameworks for low-resource settings. This study contributes to technology adoption theory by introducing relational capability as a critical networked resource in informal contexts and provides strong empirical support for cross-national heterogeneity in AI perception–performance relationships in informal retail.*

Keywords-- Artificial Intelligence, Nanostores, Relational Capability, Institutional Theory, Multi-Group SEM.

I. INTRODUCTION

A. Relevance of AI Perception in Latin American Nanostores

The rapid proliferation of artificial intelligence (AI) technologies in retail operations has reshaped competitive dynamics across global markets. However, micro-retail environments in emerging economies remain significantly

underexplored in academic research [1]. Nanostores, defined as micro-retail establishments with fewer than three employees and limited infrastructure, represent the backbone of Latin American commerce accounting for nearly 65% of retail touchpoints across the region [2]. Despite their economic importance, these enterprises face persistent barriers to digital transformation, including resource constraints, limited digital literacy, and institutional voids [3].

Understanding how nanostore operators perceive and leverage AI-related technologies to enhance operational performance is thus essential. While extensive research examines AI adoption among large retailers and e-commerce platforms [4], [5], the specific constraints and opportunity structures of nanostores remain insufficiently theorized. Prior studies have explored technology acceptance in small firms [6], digital transformation in emerging markets [7], and performance drivers in microenterprises [8], yet critical knowledge gaps persist.

A systematic review of Scopus, Web of Science, and Google Scholar databases reveals that most studies on AI adoption in microenterprises focus on Asian and African contexts [9], [10], leaving Latin American nanostores largely overlooked. The limited research available has concentrated on specific technologies, such as mobile payments [11] or social media marketing [12], without addressing broader AI-enabled operational capabilities. Furthermore, many studies treat Latin America as a homogeneous region [13], disregarding substantial institutional, economic, and cultural variations that likely condition AI adoption and performance outcomes [14] and limit the generalizability of findings from other regions [15].

B. Research gaps, questions and objectives.

First, the role of relational capability in the nanostore's capacity to engage with suppliers, customers, and community networks remains undertheorized in AI adoption models, despite its relevance in resource-constrained ecosystems [16].

Second, the interplay between perceived quality and perceived AI benefits lacks empirical validation in contexts where firms must balance technology investments with operational survival [1], [17].

Third, comparative cross-country analyses within Latin America are virtually absent, limiting understanding of how institutional diversity shapes AI perception-performance dynamics [3], [18].

To strengthen the theoretical contribution of this work, we identify a foundational gap: the dominant technology adoption models, namely the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), were conceived for contexts with stable institutions, formal business processes, and individual users with a degree of digital literacy [6], [18]. Their direct application to the informal, resource-constrained, and socially embedded context of nanostores is problematic. These models often overlook the critical role of networked resources that substitute for missing formal infrastructure and the way institutional context fundamentally shapes the perceived value and utility of technology [18], [19]. Consequently, this theoretical misfit explains the persistence of the empirical gaps identified above: the neglect of relational capability, the unexamined interplay of perceptions, and the lack of comparative institutional analysis.

This study focuses on Honduras and Colombia as analytically relevant cases representing two Latin American sub-regions—Central America and South America. Rather than treating Latin America as a homogeneous context, the selection of these countries allows us to capture meaningful subregional variation within a shared development setting characterized by the prevalence of informal micro-retail. While both economies exhibit a strong reliance on nanostores, they differ substantially in institutional maturity, market scale, and the degree of advancement in national digital transformation strategies.

Honduras represents a lower institutional maturity environment characterized by higher informality, weaker enforcement mechanisms, and constrained digital infrastructure, whereas Colombia reflects a comparatively more advanced institutional setting with stronger regulatory frameworks, more developed digital ecosystems, and active national strategies supporting Industry 4.0 and Industry 5.0 adoption. This contrast enables a theoretically grounded quasi-comparative design that isolates how institutional heterogeneity shapes identical AI perception–performance mechanisms in structurally similar nanostore ecosystems.

The comparative logic of this study is therefore not based on geographic diversity per se, but on institutional variation under structurally comparable micro-retail conditions. This design allows for the isolation of contextual effects on AI perception–performance relationships while maintaining comparability in the underlying retail informality structure across both countries.

To address these gaps, this study poses three research questions: (1) RQ1: How do relational capability, perceived quality, and perceived AI benefits influence operational performance in Latin American nanostores?, (2) RQ2: Do these relationships differ significantly between Honduras and Colombia, and if so, what institutional or contextual factors explain these differences? and (3) RQ3: How do contextual dimensions moderate the relationship between AI perception constructs and operational performance across both countries?

Accordingly, the study pursues three objectives: (1) O1: To empirically test a structural model linking relational capability, perceived quality, perceived AI benefits, and operational performance using multi-group SEM, (2) O2: To compare structural paths between Honduran and Colombian nanostores, identifying statistically significant cross-national differences and (3) O3: To evaluate the moderating role of contextual factors in shaping AI perception–performance relationships.

This paper is structured as follows: Section 2 develops the theoretical framework integrating the Resource-Based View, Institutional Theory, and Technology Acceptance Model; Section 3 presents the methodology and analytical design; Section 4 discusses the empirical results and their theoretical implications; and Section 5 concludes with limitations, managerial implications, and policy recommendations.

II. THEORETICAL FRAMEWORK AND HYPOTHESIS FORMULATION

A. Theoretical Foundations

Technology adoption in resource-constrained environments requires integrating multiple theoretical perspectives that explain how microenterprises navigate digital transformation. Three frameworks jointly underpin this study: the Resource-Based View (RBV), Institutional Theory, and the Technology Acceptance Model (TAM).

According to the Resource-Based View, firm performance depends on resources that are valuable, rare, inimitable, and non-substitutable [16]. In nanostores, where tangible resources such as capital or infrastructure are limited, intangible resources particularly relational and cognitive capabilities play a central role in sustaining performance [7]. Relational capability, understood as the ability of store owners to engage suppliers, customers, and community networks, functions as a critical networked capability that provides access to information, trust, and collective problem-solving mechanisms [19]–[21].

Institutional Theory complements RBV by emphasizing how formal and informal rules shape organizational behavior [18]. In Latin America, institutional contexts are characterized by varying degrees of formality, corruption, and regulatory enforcement [3], [22]. In Honduras, weaker institutions and higher informality generate uncertainty and transaction costs that condition technological adoption. In contrast, Colombia's relatively stronger institutional framework supported by financial inclusion programs and digitalization policies offers more favorable conditions for AI integration [23]. Thus, institutional asymmetry between countries provides a natural setting to test how contextual pressures moderate AI perception-performance relationships.

The Technology Acceptance Model (TAM) [6] posits that perceived usefulness and ease of use determine technology acceptance. Later extensions such as the Unified Theory of Acceptance and Use of Technology (UTAUT) include social influence, facilitating conditions, and trust [24]. However, TAM-based models were largely developed for literate users in formal sectors and may not generalize to informal microenterprises with limited digital exposure [25]. Therefore, this study extends these models by incorporating AI-related

perceptions—perceived quality and perceived AI benefits—alongside relational capability as a complementary network-based resource to better capture micro-retail realities in emerging economies [15].

To overcome the limitations of applying TAM/UTAUT in isolation, this study proposes an integrated multi-level framework. Institutional Theory defines the macro-level conditions shaping resource value, the Resource-Based View highlights relational capability as a key networked asset, and TAM explains how perceptions of quality and AI benefits translate into performance. Rather than adding variables, this integration offers a contextualized explanation in which the effects of resources and perceptions depend on institutional conditions.

B. Construct Development and Literature Integration

1) *Relational capability*: Relational capability represents the degree to which nanostores engage with their external ecosystem suppliers, customers, competitors, and community stakeholders. Drawing on social capital theory [26], [27], such interaction enhances access to information, collaborative learning, and collective efficiency. In informal economies, network embeddedness mitigates institutional voids by substituting formal contracts with trust-based exchanges [28]. Studies in developing contexts have shown that external engagement predicts firm adaptability and innovation [29], [1]. Hence, relational capability is conceptualized as a relational resource facilitating AI awareness, experimentation, and performance improvement.

To theoretically anchor this construct and distinguish it from broader concepts like social capital, we define relational capability as the micro-enterprise's dynamic ability to actively mobilize and leverage its position within localized networks of suppliers, peers, and customers to access critical resources, information, and support for business adaptation [20], [21]. While social capital reflects available network resources, relational capability focuses on the entrepreneur's active use of those resources. Unlike internal capabilities, it is externally oriented and co-created within the ecosystem, making it especially valuable in informal settings where it lowers search costs, supports norm enforcement, and enables knowledge spillovers about innovations such as AI.

2) *Perceived Quality*: Perceived quality refers to store owners' subjective assessment of product reliability, service consistency, and customer satisfaction. In microenterprises, such perceptions often substitute formal quality systems [30]. Quality perceptions influence confidence, reputation, and repeat patronage, shaping willingness to adopt new technologies [31], [32]. Operators perceiving deficiencies in quality may view AI tools as means to standardize operations or improve decision-making [33] - [35]. Thus, perceived quality functions as both a driver of operational discipline and a moderator of technology acceptance.

3) *Perceived AI Benefits*: Perceived AI benefits capture beliefs about the potential value derived from AI such as predictive analytics, automation, and data-driven decisions [36]. In low-tech retail environments, perceptions often precede

actual adoption, serving as proxies for technological optimism and openness to change [37]. Prior research links perceived benefits to firm agility and innovation performance in SMEs [38], [39]. In nanostores, exposure to supplier digital platforms or mobile applications can enhance perceived usefulness and trigger incremental modernization efforts.

4) *Operational Performance*: Operational performance includes revenue growth, customer retention, inventory turnover, and resilience to market shocks [40]. In informal retail settings, these outcomes often rely on perceptual measures due to the absence of standardized accounting systems [41]. Performance improvements in such contexts reflect survival capability and adaptive efficiency rather than formal productivity metrics.

C. Hypothesis Development

Based on the preceding arguments, the study formulates six hypotheses (H1–H6). These hypotheses are grounded in a multi-construct perception framework in which operational performance is explained by three distinct but complementary antecedents: relational capability, perceived quality, and perceived AI benefits. These constructs are conceptualized as distinct perceptual and capability-based mechanisms—rather than a single aggregated “AI perception” construct—capturing both AI-related cognition and non-technological relational drivers of performance.

1) *H1*: Relational capability positively influences operational performance in nanostores. Networks provide access to external knowledge and resources, facilitating adaptive efficiency in resource-constrained contexts [16].

2) *H2*: Perceived quality positively influences operational performance. Quality perception enhances customer loyalty and internal discipline, contributing to stable performance [30].

3) *H3*: Perceived AI benefits positively influence operational performance. Beliefs in AI's utility encourage learning and experimentation, leading to process improvements even prior to full adoption [33], [37].

4) *H4*: The positive effect of relational capability on operational performance is stronger in Colombia than in Honduras. Colombia's more structured institutional environment enhances the efficacy of this capability, transforming network access into more reliable and scalable performance gains [3], [23].

5) *H5*: The positive effect of perceived quality on operational performance is stronger in Honduras than in Colombia. In weaker institutional environments, perceived quality serves as a key signal of reliability and trust [13], [18].

6) *H6*: The efficacy of relational capability as a networked resource in improving operational performance is contingent upon the firm's prior technology use. The positive effect will be stronger for nanostores with greater prior digital experience. Prior “technology use” lowers absorptive capacity barriers, enabling the firm to better identify, assimilate, and apply the novel information and AI-related knowledge accessed through its networks [9], [16]. This model visually integrates the three theoretical lenses, as shown in Fig.1. The Institutional

Context (comparison between Honduras and Colombia) forms the boundary condition. Within this context, the three key antecedent constructs—Relational Capability (anchored in RBV/Network Theory), Perceived Quality, and Perceived AI Benefits (anchored in TAM)—are hypothesized to influence Operational Performance. Importantly, the model does not conceptualize a single latent construct of “AI perception”; instead, it operationalizes AI-related cognition through distinct dimensions (perceived AI benefits and perceived quality), complemented by relational capability as a non-technological enabling resource. The dashed lines from Institutional Context to the paths represent the multi-group hypotheses (H4, H5), proposing that the institutional environment moderates the strength of these relationships. The model also indicates the moderating role of contextual factors (H6).

The proposed conceptual model and hypotheses are presented in Fig. 1.

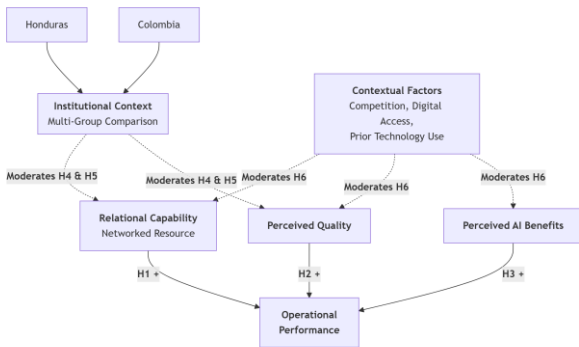


Fig. 1 Proposed Conceptual Model and Theoretical Integration

III. METHODOLOGY

A. Research Design and Approach

This study uses a quantitative, cross-sectional MG-SEM design to examine how relational capability, perceived quality, and perceived AI benefits affect operational performance in nanostores in Honduras and Colombia.

The MG-SEM approach was selected because it enables simultaneous estimation of measurement and structural models across groups, tests measurement invariance, and identifies cross-country differences in structural paths [42]. The Maximum Likelihood Estimation (MLE) method was applied due to its robustness and efficiency in large-sample SEM applications [43], [44].

Unlike Partial Least Squares SEM, which is primarily predictive, the covariance-based MG-SEM used here allows formal model fit testing, invariance assessment, and error adjustment crucial for theoretical validation and cross-national comparison [45].

The study follows a positivist explanatory paradigm, aiming to test theory-driven relationships while incorporating contextual moderation to explore institutional boundary conditions in emerging markets [7], [18].

B. Data Collection and Sampling

Data were collected via structured face-to-face surveys, administered between August 2024 and November 2025 by

trained local enumerators in both countries. This second-wave survey followed a prior exploratory round conducted in 2023.

The final dataset included 608 valid observations, 204 nanostores in Honduras (mainly in Tegucigalpa, San Pedro Sula, and surrounding towns) and 404 in Colombia (mainly in Bogotá and Neiva).

1) *A stratified purposive sampling technique ensured representation across:* (1) Urban density levels (high, medium, low), (2) Neighborhood socioeconomic strata, and (3) Business types (grocery, household goods, personal care, mixed retail).

2) *Inclusion criteria:* (1) Fewer than three full-time employees, (2) Permanent physical establishment, (3) Minimum six months of continuous operation and (4) Owner-operator willingness to participate.

3) *Exclusion criteria:* (1) Franchise or chain-affiliated businesses and (2) Primarily service-oriented businesses (e.g., barbershops).

Cross-country descriptive comparisons show that Honduran stores are older (mean = 8.3 years) and operate with lower digital readiness than Colombian ones (mean = 6.1 years). Colombian respondents reported higher educational levels (42% completed secondary school vs. 28% in Honduras) and greater smartphone penetration (89% vs. 67%), consistent with national ICT indices.

Revenue differences were statistically non-significant after purchasing power adjustments, though variance in Colombia was higher, reflecting a more heterogeneous market structure [2].

C. Measurement Instruments

All constructs were measured using multi-item reflective scales adapted from established literature and validated through back-translation [46], which are shown in Table I. Items used a seven-point Likert scale (1 = “Strongly Disagree,” 7 = “Strongly Agree”) to ensure adequate variance while maintaining respondent comprehension in low-literacy contexts [47].

TABLE I
MEASUREMENT SCALES, ITEM EXAMPLES, AND SOURCES

Construct	No. of items	Source Adapted From	Example item
Relational capability	5	[20] [21]	“We frequently exchange information with other nearby shop owners.”
Perceived Quality	6	[31] [32]	“Our products are fresher and more reliable than those of competitors.”
Perceived AI Benefits	4	[36] [37]	“AI-based tools can help improve inventory and sales forecasting.”
Operational Performance	5	[40] [41]	“Our sales and customer base have grown over the past year.”

*Own elaboration

1) *Contextual control variables include:* (1) Competitive intensity (number of nearby stores within 500 meters), (2) Technology infrastructure (mobile connectivity reliability), (3) Prior digital tool use (mobile payments, social media marketing), (4) Operator demographics (age, education, gender) and (5) Firm age and number of employees. All scales

were pre-tested in a pilot study with more than 40 nanostores in Honduras, resulting in minor wording adjustments for clarity.

Scale reliability and validity were tested through Confirmatory Factor Analysis (CFA) before estimating the full SEM model [44]. Prior to model estimation, descriptive statistics and correlations were analyzed to assess data distribution and multicollinearity. Table II reports means, standard deviations, reliability coefficients, and correlations for all constructs in the Honduran and Colombian samples.

TABLE II
DESCRIPTIVE STATISTICS AND CORRELATIONS
PANEL A. HONDURAS (N = 204)

Construct	Mean	SD	α	CR	AVE	1	2	3	4
1. Relational capability	4.72	1.34	0.82	0.84	0.52	0.72	0.54	0.48	0.61
2. Perceived Quality	5.13	1.18	0.79	0.80	0.50	0.54	0.71	0.42	0.56
3. Perceived AI Benefits	4.28	1.52	0.88	0.89	0.58	0.48	0.42	0.76	0.67
4. Operational Performance	4.89	1.26	0.84	0.85	0.54	0.61	0.56	0.67	0.74

PANEL B. COLOMBIA (N = 404)

Construct	Mean	SD	α	CR	AVE	1	2	3	4
1. Relational capability	5.08	1.28	0.85	0.86	0.56	0.75	0.48	0.52	0.68
2. Perceived Quality	5.24	1.12	0.81	0.82	0.53	0.48	0.73	0.38	0.49
3. Perceived AI Benefits	4.87	1.41	0.91	0.91	0.63	0.52	0.38	0.79	0.72
4. Operational Performance	5.12	1.19	0.86	0.87	0.57	0.68	0.49	0.72	0.77

Note: Diagonal values in bold represent the square root of the AVE (for discriminant validity). All correlations are significant at $p < 0.05$. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted.

^aOwn elaboration

All constructs demonstrate satisfactory internal consistency and convergent validity, with Cronbach's alpha values above 0.79 and AVE exceeding 0.50 in both samples, confirming the adequacy of the measurement model for subsequent SEM analysis.

D. Data Analysis Strategy

The analysis followed four sequential stages consistent with established MG-SEM protocols [42].

1) *Stage 1: Measurement Model Validation* (1) CFA was conducted separately for each country, (2) Internal consistency assessed via Cronbach's $\alpha \geq 0.70$ and Composite Reliability ($CR \geq 0.70$), (3) Convergent validity verified through Average Variance Extracted ($AVE \geq 0.50$) and (4) Discriminant validity confirmed using the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratios < 0.85 [48]. To address potential common method variance (CMV), Harman's single-factor test was conducted. The first factor explained 27.8% of the variance (below the 50% threshold), and a marker variable technique (using a theoretically unrelated item on store decoration) showed non-significant correlations with focal constructs ($r < 0.09$), confirming that CMV is not a serious concern [47].

2) *Stage 2: Measurement Invariance Testing*. Progressive invariance was tested across the two samples: (1) Configural invariance: same factor structure across groups, (2) Metric

invariance: equality of factor loadings and (3) Scalar invariance: equality of item intercepts. Model comparisons were evaluated using $\Delta\chi^2$ tests and incremental fit indices: $\Delta CFI \leq 0.010$, $\Delta RMSEA \leq 0.015$ [42].

3) Stage 3: Structural Model Estimation

The hypothesized model was estimated using Maximum Likelihood with robust standard errors (MLR) to account for potential non-normality in the data. Fit indices were evaluated using recommended guidelines [45] rather than rigid cutoffs: (1) χ^2 ($p > 0.05$ desirable but sensitive to sample size), (2) CFI values close to or above 0.95, (3) TLI values close to 0.95, (4) $RMSEA \leq 0.06$ and (5) $SRMR \leq 0.08$. This guideline-based approach is particularly appropriate for complex multi-group SEM models, where minor deviations in incremental fit indices may occur due to model complexity and sample heterogeneity.

4) *Stage 4: Multi-Group Comparison*. Country-level path differences were analyzed by comparing constrained vs. unconstrained models. Significant $\Delta\chi^2$ or critical ratio differences indicated structural non-equivalence. Moderation effects were tested by interaction terms and subgroup analysis [44].

E. Robustness Checks

Additional analyses were performed to ensure result stability: Bootstrapping (5,000 resamples) confirmed the significance of all reported paths. An alternative PLS-SEM model yielded highly similar path coefficients (differences < 0.03), supporting the robustness of the CB-SEM findings. Endogeneity concerns were addressed by including control variables and testing instrumental variable approaches (using firm age as instrument); no significant changes were observed.

F. Ethical Considerations

Ethical approval was obtained from partner universities in both Honduras and Colombia. All participants provided informed verbal consent, and responses were anonymized. Enumerators followed standardized scripts to ensure comprehension and reduce respondent fatigue.

Given the economic vulnerability of many participants, survey sessions emphasized confidentiality and voluntary participation. Data were securely stored and analyzed only in aggregate form [47].

G. Reliability and Validity Enhancement

To enhance methodological robustness: (1) Enumerators underwent training and pilot testing to ensure inter-rater reliability, (2) Attention checks and response time analyses were embedded to detect careless responses, (3) Local experts reviewed translations for cultural equivalence and (4) Missing data ($< 3\%$) were handled using Full Information Maximum Likelihood (FIML), which yields unbiased estimates under Missing at Random conditions [49].

Fig. 2 summarizes the sequential analytical stages of the study, from data collection and measurement validation to invariance testing, structural estimation, and multi-group comparison between Honduras and Colombia. The flowchart highlights the criteria and statistical thresholds applied to ensure rigor and cross-sample comparability.

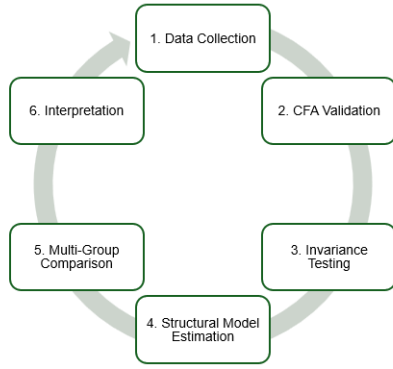


Fig. 2 Analytical Framework and Procedural Flow of the Multi-Group SEM Approach

Having established the reliability and validity of all measurement scales and confirmed the adequacy of the dataset through descriptive and correlational analyses, the next step involved estimating the structural equation models.

Section IV presents the results of the empirical analysis, beginning with the measurement model assessment and followed by measurement invariance testing and structural path estimation. The findings are then interpreted in light of the proposed hypotheses (H1–H6) and contrasted with prior research to highlight theoretical and practical implications for AI adoption in nanostores across Latin America.

IV. RESULTS AND DISCUSSION

A. Descriptive Analysis and Cross-Country Differences

Fig. 3 shows cross-country mean differences, with higher relational capability and operational performance in Colombia and higher perceived quality in Honduras. Perceived AI benefits do not differ significantly, providing a common baseline. These results suggest institutional heterogeneity, where stronger ecosystem support in Colombia enhances relational capability, while perceived quality acts as a trust substitute in Honduras.

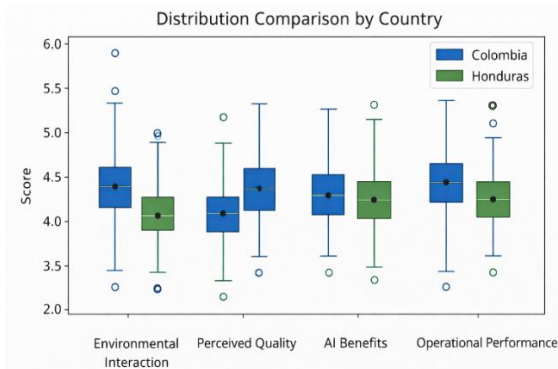


Fig. 3. Cross-Country Mean Differences in Key Constructs

Note: Error bars = SE. Honduras (n=204, **p<0.01); Colombia (n=404, ***p<0.001).

B. Measurement Model Assessment

The Kaiser-Meyer-Olkin (KMO) test yielded a value of 0.82, indicating sampling adequacy for factor analysis.

CFA results are summarized in Table III. All standardized factor loadings ranged from 0.68 to 0.85 and were statistically

significant at $p < 0.001$, demonstrating strong convergent validity. Although two loadings were slightly below the conventional 0.70 threshold (0.68 and 0.69 in Honduras), they are retained as $AVE > 0.50$, $CR > 0.80$, and overall model fit indices exceed recommended thresholds in both samples [45]. These fit indices, while borderline, are still acceptable for the strictest criteria ($CFI/TLI \approx 0.95$). These minor deviations remain acceptable given the model's complexity, the large sample size, and the exploratory nature of this research in an underexplored context, consistent with flexible cutoffs for covariance-based SEM in applied work [45]. In addition, recent methodological discussions highlight that CFI/TLI values in the 0.94–0.95 range can still be considered indicative of good fit when the model includes multiple latent constructs, heterogeneous samples, and strict multigroup constraints, as is the case here. Under these conditions, emphasis shifts toward evaluating the overall pattern of evidence—specifically the simultaneous satisfaction of $RMSEA \leq 0.06$ and $SRMR \leq 0.08$ —which our model achieves consistently. Overall, these indicators support the conclusion that the measurement model demonstrates satisfactory fit and demonstrates robust adequacy for cross-country comparative analysis.

TABLE III
MEASUREMENT MODEL RESULTS – STANDARDIZED FACTOR LOADINGS, RELIABILITY, AND VALIDITY INDICATORS

Construct / Item	Honduras λ	Colombia λ
Relational capability		
EI1 – Frequency of supplier consultations	0.68	0.71
EI2 – Participation in merchant associations	0.72	0.81*
EI3 – Information exchange with peers	0.76	0.78
EI4 – Collaboration with community organizations	0.71	0.74
EI5 – Customer feedback responsiveness	0.74	0.76
Reliability & Validity: $\alpha = 0.82 / 0.85$ CR = 0.84 / 0.86 AVE = 0.52 / 0.56		
Perceived Quality		
PQ1 – Product freshness/reliability	0.73	0.75
PQ2 – Service courtesy vs. competitors	0.69	0.71
PQ3 – Store cleanliness and organization	0.71	0.74
PQ4 – Overall neighborhood reputation	0.70	0.73
Reliability & Validity: $\alpha = 0.79 / 0.81$ CR = 0.80 / 0.82 AVE = 0.50 / 0.53		
Perceived AI Benefits		
AIB1 – Inventory management improvement	0.78	0.82
AIB2 – Customer preference prediction	0.76	0.81
AIB3 – Operational efficiency gains	0.81	0.85
AIB4 – Competitive advantage creation	0.74	0.79
AIB5 – Cost-reduction possibilities	0.72	0.76
AIB6 – Business growth acceleration	0.77	0.81
Reliability & Validity: $\alpha = 0.88 / 0.91$ CR = 0.89 / 0.91 AVE = 0.58 / 0.63		
Operational Performance		
OP1 – Sales growth trajectory	0.76	0.79
OP2 – Customer base expansion	0.74	0.77
OP3 – Inventory turnover improvement	0.73	0.76
OP4 – Profit margin development	0.75	0.78
OP5 – Business resilience to shocks	0.72	0.75
Reliability & Validity: $\alpha = 0.85 / 0.87$ CR = 0.86 / 0.88 AVE = 0.55 / 0.59		

*Own elaboration

Discriminant validity was confirmed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. In both national samples, the square root of each

construct's AVE was greater than its correlations with other constructs, and HTMT ratios were below 0.85, confirming construct distinctiveness.

Model fit indices for the measurement models were acceptable in both countries: (1) Honduras: $\chi^2(164) = 287.34$, CFI = 0.94, TLI = 0.93, RMSEA = 0.061, SRMR = 0.068 and (2) Colombia: $\chi^2(164) = 341.12$, CFI = 0.96, TLI = 0.95, RMSEA = 0.052, SRMR = 0.055.

These indices meet conventional thresholds (CFI/TLI $\geq$ 0.90, RMSEA $\leq$ 0.08, SRMR $\leq$ 0.08), supporting conceptual equivalence of constructs across samples and enabling valid cross-country comparison.

C. Measurement Invariance Testing

To ensure cross-sample comparability, measurement invariance tests were conducted following the hierarchical approach by [42]: (1) Configural invariance (unconstrained model) confirmed equivalent factor structures across both samples (CFI = 0.95, RMSEA = 0.057), (2) Metric invariance (equal loadings) produced Δ CFI = 0.002 and Δ RMSEA = 0.003, well below recommended thresholds (Δ CFI $\leq$ 0.010; Δ RMSEA $\leq$ 0.015) and (3) Scalar invariance (equal intercepts) yielded Δ CFI = 0.006 and Δ RMSEA = 0.004, supporting equivalence in item intercepts.

Full scalar invariance was established, ensuring that differences in structural relationships reflect true contextual variation rather than measurement artifacts.

D. Structural Model Results and Hypothesis Testing

Overall structural model fit was satisfactory: $\chi^2(172) = 312.84$, CFI = 0.95, TLI = 0.94, RMSEA = 0.056, SRMR = 0.059. Consistent with the guideline-based evaluation approach adopted in this study, these values indicate satisfactory model fit. In particular, the slightly lower TLI value (0.94) remains acceptable given the model's complexity and is supported by strong RMSEA and SRMR values [45].

Table IV summarizes the standardized path coefficients and hypothesis testing results for the pooled sample and each country.

TABLE IV
STRUCTURAL MODEL RESULTS AND HYPOTHESIS TESTING

Hypothesis	Proposed Relationship	Pooled β	Honduras β	Colombia β
H1	Relational capability $\rightarrow$ Operational Performance	0.34***	0.29***	0.39***
H2	Perceived Quality $\rightarrow$ Operational Performance	0.23**	0.28***	0.18*
H3	Perceived AI Benefits $\rightarrow$ Operational Performance	0.41***	0.37***	0.44***
H4	(Country Diff.) Relational capability effect stronger in Colombia Yes ($\Delta\chi^2 = 14.62$, $p < 0.001$)	—	—	—
H5	(Country Diff.) Perceived Quality effect stronger in Honduras Yes ($\Delta\chi^2 = 10.41$, $p < 0.01$)	—	—	—
H6	Contextual moderation (e.g., prior digital tool use $\times$	—	—	—

Hypothesis	Proposed Relationship	Pooled β	Honduras β	Colombia β
	Perceived AI Benefits $\rightarrow$ Performance) Partial (significant interactions for digital access and competition intensity)			

Note: Model fit: $\chi^2(172) = 312.84$; CFI = 0.95; TLI = 0.94; RMSEA = 0.056; SRMR = 0.059. $p < 0.05$ (*), < 0.01 (**), < 0.001 (***). R^2 Operational Performance: 0.39 (pooled), 0.36 (Honduras), 0.42 (Colombia).

^aOwn elaboration

As shown in Table IV, H1–H5 are fully supported, while H6 receives partial support. H1–H3 confirm significant positive direct effects of relational capability, perceived quality, and perceived AI benefits on operational performance across both contexts. H4 and H5 are supported, revealing institutional moderation: the effect of relational capability is significantly stronger in Colombia, while perceived quality has a greater impact in Honduras.

Finally, H6 receives partial support: prior digital tool use significantly strengthens the Perceived AI Benefits $\rightarrow$ Performance path (β interaction = 0.18, $p < 0.01$ pooled; stronger in Colombia β interaction = 0.22, $p < 0.001$), while higher competition intensity weakens the relational capability $\rightarrow$ performance path in Honduras (β interaction = -0.12, $p < 0.05$), explaining part of the cross-country variance in explained performance (R^2 Colombia = 0.42 vs. Honduras = 0.36).

Collectively, these results provide robust empirical support for the proposed model and highlight the contextual nature of AI perception–performance dynamics in emerging markets. The consistent support for H1–H3 demonstrates that networked resources, perceived service quality, and AI-related beliefs operate as complementary drivers of operational performance in nanostores. The validation of H4 and H5 further shows that institutional heterogeneity systematically shapes the strength of these relationships, amplifying the role of relational capability in more structured environments like Colombia while elevating the importance of perceived quality in contexts of institutional fragility such as Honduras. The partial support for H6 reinforces this interpretation, revealing that digital readiness and competitive pressures condition the magnitude of AI-driven performance effects. Collectively, the evidence confirms that AI adoption and performance outcomes cannot be fully understood without considering the institutional and contextual structures in which nanostores operate.

E. Discussion and Theoretical Integration

The confirmation of H1, H2, and H3 validates our core integrated model, demonstrating that in nanostores, operational performance is driven by a combination of networked resources (relational capability) and technology perceptions. The support for H4 and H5, however, provides deeper theoretical insight into the contingent role of institutions. The finding that relational capability is more critical in Colombia (H4) is not merely a descriptive difference. Institutional Theory allows us to interpret this as evidence that stronger formal and informal

institutions (e.g., better enforcement of agreements, more active trade associations) transform relational ties from loose connections into more reliable channels for knowledge and resource exchange. In this environment, network engagement becomes a scalable strategy for performance. Conversely, the stronger effect of perceived quality in Honduras (H5) reflects a context where institutional voids elevate the importance of direct, trust-based signals between the store and its immediate community. When systemic trust is low, the entrepreneur's perceived quality becomes a primary defensive resource for securing customer loyalty and survival [18].

The findings extend and boundary-condition technology adoption theory by repositioning relational capability as a primary network-based resource in informal micro-retail contexts and by demonstrating that the performance effects of AI-related perceptions are contingent on institutional conditions. Consistent with H4 and H5, relational capability functions as a scalable performance driver in more structured environments, whereas perceived quality becomes a dominant mechanism in contexts characterized by institutional fragility. This evidence advances existing models by showing that the performance implications of AI-related perceptions are not universal but contingent on institutional conditions.

These theoretical insights are consistent with emerging practical efforts to empower nanostores through digital tools in Latin America. For instance, initiatives such as MIT's LIFT Lab, which develops generative AI-assisted solutions for micro-retailers, illustrate the potential for inclusive digital transformation. However, our results indicate that the effectiveness of such tools depends on contextual conditions, highlighting the need for complementary governance mechanisms—particularly in low-resource environments where data privacy, trust, and institutional support shape adoption outcomes.

Recent macro-level analyses emphasize AI's potential to reverse productivity stagnation in LAC [50],[51] and highlight accelerating adoption despite infrastructure gaps [49]. However, these studies focus on aggregate or formal-sector outcomes, overlooking perceptual drivers in informal micro-retail. Our findings extend this literature by demonstrating how relational capability and institutional context condition AI perception–performance links at the nanostore level, providing a micro-foundational complement to regional policy discussions.

These interpretations tie into debates on digital inclusion and demonstrate that one-size-fits-all digital transformation policies are ineffective in heterogeneous institutional contexts. In more robust environments such as Colombia, policies should focus on strengthening digital ecosystems and networks to leverage relational capacity. In contexts with institutional gaps such as Honduras, the priority should be inclusion based on trust, using digital tools to reinforce service reliability and quality as a foundation for more advanced technology adoption. [15].

V. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

A. Conclusions

This study examined how relational capability, perceived quality, and perceived AI benefits influence operational performance in nanostores across Honduras and Colombia using a Multi-Group Structural Equation Modeling (MG-SEM) approach. Key conclusions remain as originally stated, with emphasis on contextual heterogeneity and the social nature of AI perception.

B. Theoretical Contributions

The findings advance theoretical understanding by:

1) *Integration of cross-disciplinary perspectives (RBV, Institutional Theory, TAM):* By combining RBV, Institutional Theory, and TAM, the study offers a holistic framework explaining how both internal capabilities and external contexts condition AI-driven outcomes.

2) *Novel inclusion of “relational capability” as a networked resource:* This construct expands existing AI adoption theory by recognizing the role of social capital and network embeddedness in informal economies.

3) *Cross-country comparative validation:* The use of MG-SEM with full measurement invariance across two Latin American contexts provides methodological robustness rarely achieved in studies of microenterprises.

4) *Translation into an applied AI-enabled development model for nanostores:* This study synthesizes empirical findings into a context-sensitive framework that operationalizes institutional heterogeneity and AI perception–performance relationships into actionable pathways for policymakers and microenterprise support programs in emerging economies.

Together, these contributions underscore that AI effectiveness depends not only on technology readiness but also on ecosystem connectivity and institutional maturity.

C. Practical Implications

The results have direct implications for practitioners and policymakers:

1) *For policymakers:* Promote inclusive digitalization policies tailored to institutional capacity; in Colombia strengthen inter-firm collaboration and supplier digital networks; in Honduras focus on service reliability, digital literacy, and trust-building.

2) *For microenterprise managers and development agencies:* Encourage peer learning networks, provide low-cost mobile-integrated AI tools, and foster hybrid quality-digital strategies.

These actions can accelerate digital transformation at the bottom of the retail pyramid and enhance resilience against market shocks.

To address the applied gap identified by the review process, the empirical findings are further synthesized into an actionable AI-enabled nanostore development framework. This framework moves beyond purely explanatory modeling by translating statistically validated relationships into context-sensitive implementation pathways for micro-retail ecosystems in emerging economies.

Based on the results, we propose a contextual model of AI-enabled nanostore development that incorporates institutional heterogeneity and its influence on relational capacity, perceived quality, and perceived benefits of AI. The model posits that AI-driven development depends not only on technological adoption but also on its alignment with business perceptions, networked resources, and local trust mechanisms. Within this framework, the perceived benefits of AI drive modernization, relational capacity facilitates learning, and perceived quality ensures legitimacy and customer trust.

To enhance interpretability and directly synthesize the empirical results with the theoretical integration, the framework is summarized visually in Fig. 4, which contrasts the institutional and structural differences between Honduras and Colombia and highlights the corresponding AI perception–performance pathways. Solid arrows represent direct effects on operational performance (standardized β coefficients), while thicker arrows indicate stronger country-specific effects. Dashed arrows represent institutional moderation (H4–H5). Perceived AI benefits act as the primary enabling driver, with additional moderation by prior digital tool use (H6).

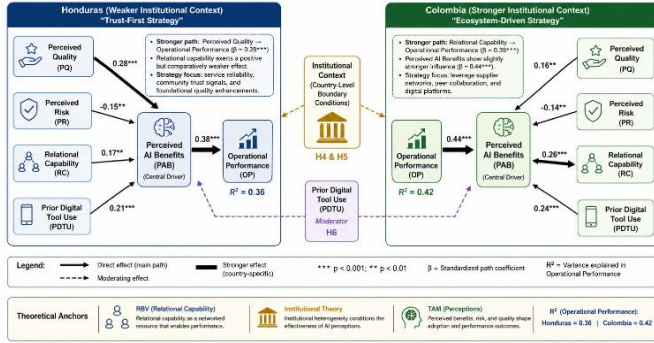


Fig. 4 Contextual AI-Enabled Development Model for Nanostores: The Role of Institutional Heterogeneity (Honduras vs. Colombia).

The model translates the findings into a decision-support framework for nano-store development in different institutional contexts. In Colombia, AI adoption is reinforced by ecosystem connectivity and collaborative networks, while in Honduras it depends on improving perceived quality and service reliability. Overall, the model provides practical guidance for inclusive and context-sensitive AI adoption in emerging economies.

D. Limitations and Future Research

Despite its contributions, the study has limitations that must be acknowledged. The cross-sectional design limits causal inferences, and the use of perceptual measures may introduce bias, although diagnostic tests indicate that this risk is low. Some fit indices are close to the recommended thresholds, reflecting the theoretical complexity of the model in a multinational context. Furthermore, the absence of objective performance indicators stems from data constraints inherent to informal microenterprises, and the focus on two countries calls for caution in generalizing findings. Future research could employ longitudinal designs, incorporate objective data, simplify theoretical frameworks, and expand the analysis to more emerging economies, as well as use quasi-experimental

designs with AI tools in real-world conditions. As with any empirical study, several limitations warrant acknowledgment and open avenues for further inquiry. The key limitations are summarized as follows:

1) *Cross-sectional design:* The study captures relationships at a single point in time. Future research should adopt longitudinal or panel designs to analyze causal dynamics and performance evolution.

2) *Perceptual performance measures:* Although common in informal contexts, self-reported metrics may introduce bias. Future studies could incorporate objective indicators (e.g., sales, transaction logs, digital usage data).

3) *Sample and context scope:* The focus on Honduras and Colombia limits generalizability. Comparative studies including other Latin American or African economies could enhance external validity and reveal broader institutional patterns.

4) *Technological granularity:* Future research should distinguish between AI subtypes (e.g., chatbots vs. inventory analytics) to identify which specific technologies yield the greatest operational gains for nanostores.

5) *Potential endogeneity from unobservable factors:* Although addressed through inclusion of control variables and robustness checks (e.g., bootstrapping and alternative model specifications), unobserved confounders could still influence results. Future studies could employ instrumental variable approaches or quasi-experimental designs.

6) *Qualitative depth:* Complementary ethnographic or mixed-method approaches could illuminate behavioral and cultural mechanisms underlying AI perception in low-resource environments.

7) *Causal validation gap:* Future research should complement the present cross-sectional design with quasi-experimental field deployments of AI-enabled tools in nanostore ecosystems, particularly mobile and conversational AI systems, to assess causal impact under real operational conditions.

E. Final Remarks

AI-driven performance in informal retail emerges from the alignment between perception, relational resources, and institutional context, rather than technology adoption alone.

By validating a cross-national model of AI perception and performance, this research contributes to a more inclusive and contextually grounded understanding of digital transformation in emerging economies.

Ultimately, empowering nanostores through AI requires recognizing that technology adoption is a social process anchored in trust, collaboration, and local institutional realities.

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