

# Repositioning Structural Enablers in Informal Retail: The Role of Digital Infrastructure and Perceived AI Benefits in Nanostore Operational Performance

Cesar H. Ortega-Jimenez, Ph.D.<sup>1</sup> ; Narciso A. Melgar-Martínez, Eng<sup>2</sup> ; Dany N. Sabillón Palomeque, Eng<sup>3</sup> 

<sup>1</sup> Faculty of Engineering-CU, CURLP, UNAH, Honduras, [cortega@unah.edu.hn](mailto:cortega@unah.edu.hn)

<sup>2,3</sup> Faculty of Engineering, UNAH-CORTES, Honduras, [narciso.melgar@unah.edu.hn](mailto:narciso.melgar@unah.edu.hn), [dany.sabillon@unah.hn](mailto:dany.sabillon@unah.hn)

**Abstract-** *This study investigates the determinants of operational performance (OP) in nanostores, the dominant form of informal micro-retail in emerging markets. This cross-sectional study addresses that gap by analyzing 1,412 nanostores across seven countries spanning MENA (Jordan, Israel, Saudi Arabia, UAE, Morocco) and Latin America (Honduras, Colombia), using Partial Least Squares Structural Equation Modeling (PLS-SEM) with a multilingual, multi-stage field instrument administered between August 2024 and November 2025. Results indicate that digital infrastructure accessibility (DIA) emerged as the strongest predictor of operational performance (OP), followed by perceived AI benefits (PAB) and environmental interaction (EI), while perceived quality (PQ) was not statistically significant. The model explains a substantial proportion of variance in operational performance ( $R^2 = 0.617$ ). Multi-group analysis confirmed that both benefit perceptions and infrastructure effects are significantly stronger in MENA than in Latin America. These results highlight that perceived benefits and structural conditions, rather than technology quality alone, are the primary factors associated with operational performance in informal micro-retail. The study extends TOE and UTAUT frameworks by demonstrating that in informal micro-retail contexts, structural infrastructure conditions dominate perceptual technology evaluations in explaining performance outcomes.*

**Keywords:** Nanostores, Operational Performance, Perceived AI Benefits, Environmental Interaction, Digital Infrastructure.

## I. INTRODUCTION

Nanostores—microenterprises typically operating from residential spaces with minimal infrastructure and fewer than six employees—constitute a critical economic lifeline for millions of households in emerging markets [1]. These establishments, often overlooked in mainstream retail digitalization discourse, represent approximately 60-70% of retail outlets in many developing economies [2]. Despite their ubiquity, nanostores face severe operational constraints including limited access to formal supply chains, inadequate technological infrastructure, and restricted financial resources [3].

The emergence of accessible artificial intelligence technologies—including cloud-based inventory management systems, automated customer service chatbots, and predictive analytics platforms—presents unprecedented opportunities for operational enhancement in resource-constrained retail environments [4]. However, technology adoption literature has predominantly focused on formal small and medium enterprises (SMEs) in developed economies, leaving a substantial knowledge gap regarding informal microenterprises in emerging markets [5].

Despite the growing interest in digital transformation in small enterprises, empirical evidence on AI adoption in informal micro-retail remains limited. Existing studies on small business digitalization primarily focus on formal SMEs in developed or upper-middle-income economies, with little attention to nanostores operating under resource constraints, informal structures, and weak digital infrastructure. Moreover, most prior research adopts single-country designs, limiting cross-contextual understanding of how environmental and infrastructural conditions shape technology-related performance outcomes [6]–[8].

A preliminary exploratory study of 143 nanostores in Honduras identified environmental interaction (EI), perceived quality (PQ), and perceived AI benefits (PAB) as potentially significant factors influencing operational outcomes. That initial study employed qualitative interviews ( $n=28$ ) and a quantitative survey ( $n=143$ ) in three Honduran cities (Tegucigalpa, San Pedro Sula, and Choluteca), revealing that 73% of nanostore owners lacked awareness of available AI tools, 60% cited infrastructure limitations as primary barriers, and 85% expressed willingness to adopt technology if clear benefits were demonstrated [9]. While these findings provided valuable exploratory insights and informed construct development, the study lacked the statistical power and geographic diversity to establish generalizable relationships [10]. Critical gaps persist regarding: (1) quantitative validation of adoption determinants of operational performance (OP) in AI-related context, (2) the mediating role of contextual factors such as digital infrastructure accessibility (DIA), and (3) comparative analysis between Middle Eastern and Latin American emerging markets.

Beyond addressing these gaps, this study contributes by clarifying the relative importance of perceptual (PAB, PQ) versus structural (infrastructure) factors in explaining performance outcomes, thereby refining existing technology adoption frameworks in informal microenterprise contexts.

Hence, given these gaps, the following research questions are posed: RQ1: To what extent are EI, perceived quality, and PAB associated with OP in nanostores across emerging markets? RQ2: How does DIA control these relationships? RQ3: Do regional differences significantly alter the structural relationships between adoption determinants and operational outcomes?

Based on these questions, the specific objectives are: O1: To empirically test the structural relationships between EI,

perceived quality, PAB, and OP using multi-regional data, emphasizing variance explanation rather than causal inference. O2: To assess the role of DIA as a contextual control variable in the relationship between adoption-related perceptual factors and OP. O3: To conduct comparative analysis to identify region-specific patterns in the relationships between adoption determinants and OP.

The article is organized as follows: Section II presents the theoretical framework and hypotheses; Section III describes the methodological design and the SEM approach; Section IV presents the empirical results and their discussion; and Section V summarizes the contributions, limitations, and implications, along with future research directions.

## II. THEORETICAL FRAMEWORK AND HYPOTHESIS FORMULATION

The phenomenon of technology adoption in microenterprises requires theoretical frameworks that accommodate resource constraints, informal operational structures, and environmental embeddedness. The Technology-Organization-Environment (TOE) framework provides a comprehensive lens for understanding technology adoption decisions by considering technological characteristics, organizational readiness, and environmental pressures [11]. Recent extensions of TOE specifically address digital technology adoption in emerging market contexts, emphasizing the role of institutional voids and informal network dependencies [12]. This study adopts the TOE framework as the primary structural lens, complemented by UTAUT for perceptual constructs and ICT4D perspectives for infrastructural conditions.

The Unified Theory of Acceptance and Use of Technology (UTAUT) complements TOE by highlighting individual-level perceptual factors, particularly performance expectancy and effort expectancy, which translate to perceived benefits and PQ in organizational contexts [13]. In nanostore settings, where owner and operator roles typically converge, individual perceptions directly influence organizational adoption decisions [14].

The model does not capture actual AI adoption behavior; rather, it examines how perceptual and contextual factors are associated with OP in technology-relevant environments. Accordingly, the findings should be interpreted as explaining performance-related variation, not adoption processes or causal adoption pathways.

### A. Environmental Interaction and Operational Performance

Environmental interaction (EI) refers to the degree to which nanostores actively engage with their external ecosystem, including suppliers, customers, competitors, and institutional actors [15]. For resource-constrained enterprises, environmental embeddedness serves as a compensatory mechanism for internal capability deficits, providing access to information, resources, and legitimacy [16].

In the context of AI adoption, EI facilitates knowledge spillovers, reduces uncertainty about technology benefits, and enables resources pooling for technology acquisition [17]. Nanostores with stronger supplier relationships gain access to

vendor-provided digital tools, while those embedded in entrepreneur networks benefit from peer learning and collective problem-solving [18]. Therefore, we hypothesize:

H1: Environmental interaction (EI) positively influences operational performance (OP) in nanostores.

### B. Perceived Quality of AI Technologies

Perceived quality (PQ) encompasses reliability, functionality, ease of use, and compatibility of AI-enabled tools with existing operational workflows [19]. In low-resource settings, technology quality perceptions are critically shaped by infrastructure dependencies, technical support availability, and affordability considerations [20].

High PQ reduces adoption risks and implementation barriers, particularly important for nanostores lacking dedicated IT personnel or financial buffers to absorb technology failures [6]. Quality perceptions also influence sustained use and capability development, as positive early experiences encourage deeper technology integration [21]. Consequently, we hypothesize:

H2: Perceived quality (PQ) of AI technologies positively influences operational performance (OP) in nanostores.

### C. Perceived Benefits of AI

Perceived AI benefits (PAB) represent nanostore owners' expectations regarding operational improvements attributable to AI adoption, including inventory optimization, customer service enhancement, demand forecasting, and administrative efficiency [22]. Benefit perceptions are shaped by both tangible outcome expectations (cost reduction, sales increase) and intangible factors (modernization, competitive positioning) [23].

In emerging markets characterized by high uncertainty and information asymmetry, PAB often outweigh objective technology characteristics in driving adoption decisions [24]. For nanostores operating at subsistence margins, clearly articulated benefits directly addressing survival pressures (cash flow management, waste reduction) become adoption prerequisites [25]. Hence, we hypothesize:

H3: Perceived AI benefits (PAB) positively influence operational performance (OP) in nanostores.

### D. Digital Infrastructure Accessibility and Operational Performance

Digital infrastructure accessibility (DIA)—comprising internet connectivity reliability, mobile network coverage, electricity stability, and digital payment system availability—is conceptualized as a contextual enabling condition within the TOE environment dimension that shapes the effectiveness of organizational and technological capabilities in informal retail systems. In informal and resource-constrained contexts, infrastructure is not merely a background condition but a fundamental enabler that directly shapes the effectiveness of technological and organizational practices [26], [27].

Accordingly, DIA is modeled as a full exogenous predictor of OP, equivalent in theoretical status to EI, perceived quality, and PAB. This specification is consistent with ICT4D and TOE-based research evidencing that infrastructure conditions

exert a direct and substantial influence on firm-level performance outcomes in emerging markets [28], [29].

Thus, we hypothesize:

H4: Digital infrastructure accessibility (DIA) positively influences operational performance (OP) in nanostores.

#### E. Conceptual Model Integration

Fig. 1 presents the integrated conceptual model. The model positions EI, perceived quality, PAB, and DIA as core exogenous predictors of OP.

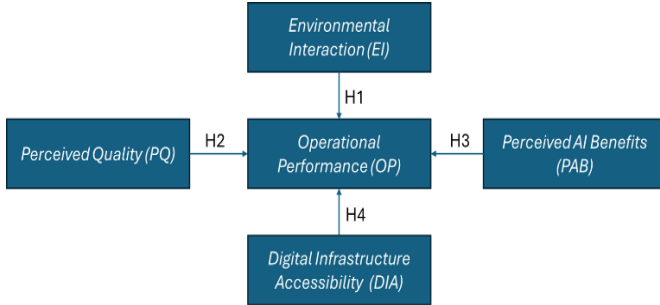


Fig. 1 Conceptual Research Model

Note: EI → OP: Relational Mechanism; PAB → OP: Expectancy-based Mechanism; DIA → OP: Structural Enabling Condition; PQ → OP: Perceived System Quality; (Theoretical Construct).

Based on the previous framework integrating TOE, UTAUT, and resource-based perspectives adapted to informal microenterprise contexts, the following hypotheses are proposed for empirical testing through structural equation modeling across seven emerging market countries. Unlike perceptual constructs (PAB, PQ) and relational constructs (EI), DIA represents a structural boundary condition that enables or constrains the effectiveness of the other determinants.

### III. METHODOLOGICAL DESIGN

#### A. Research Design and Approach

The structural model is specified within a variance-based explanatory framework; thus, the relationships are interpreted as associative rather than causal. This quantitative, cross-sectional study examines the determinants of AI adoption and OP in nanostores using a two-round sequential approach. The first round consists of an exploratory phase with data collected in Honduras, aimed at validating and refining the measurement constructs. The second round involves a multinational confirmatory analysis using structural equation modeling to test the proposed relationships.

Accordingly, the findings should be interpreted as contextually informative and analytically robust within the studied environments, rather than as statistically generalizable to the entire population of nanostores.

#### B. Sample and Data Collection

The target population comprised nanostores in emerging markets defined as micro-retail outlets that: (a) operate from residential or mixed-use premises, (b) employ fewer than six full-time workers (aligned with micro-retail structures characterized by predominantly family-based labor arrangements in informal economies), (c) report annual

revenues below USD 50,000, and (d) serve predominantly local neighborhood markets [31].

Data were collected using field-based purposive sampling with quota controls across high-density nanostore areas in selected urban and semi-urban zones. Participation was based on systematic field approaches and voluntary consent; therefore, the method corresponds to purposive sampling with quota controls, and findings should be interpreted within these methodological boundaries.

Data were collected from seven countries: Jordan (n = 200), Israel (n = 197), Saudi Arabia (n = 155), United Arab Emirates (n = 140), Morocco (n = 112), Honduras (n = 204), and Colombia (n = 404), yielding a final sample of 1,412 nanostores. Probability sampling was not feasible due to the absence of formal registries for informal microenterprises and the logistical constraints of multi-country fieldwork [17],[25]. Country selection followed strategic criteria, including the relevance of informal retail sectors, variation in digital infrastructure maturity, geographic representation across MENA and Latin America, institutional diversity, and the availability of academic partnerships to support field access [32] - [34].

To improve representation, quota controls were applied across neighborhood income levels and nanostore types [35]. Data collection was conducted by trained student enumerators selected for local knowledge, multilingual capabilities, and completion of ethics and fieldwork training protocols. This approach improved cost-efficiency, cultural alignment, and access to hard-to-reach nanostores while also generating pedagogical value [36].

Several procedural controls were implemented to reduce potential sampling and interviewer biases, including geographic assignment of enumerators to distinct field zones and quota balancing across store profiles. Post-hoc robustness checks using one-way ANOVA, Kruskal-Wallis tests, and intraclass correlation coefficients (ICC < 0.03) indicated no significant enumerator effects. These results are consistent with evidence showing that interviewer-related variance in face-to-face surveys remains limited when appropriate controls are applied [37].

Structured face-to-face surveys were administered between August 2024 and November 2025. Response rates ranged from 73% in Morocco to 89% in Honduras. Non-response bias was assessed through late-respondent comparisons, with no significant differences observed in key demographic variables [38].

#### C. Measurement Instruments

All constructs were measured using multi-item reflective scales adapted from established instruments and validated through the Round 1 exploratory study [39]. Items employed seven-point Likert scales (1=strongly disagree to 7=strongly agree) to capture construct variance adequately.

1) *Environmental Interaction (EI)*: Five items adapted from [40] measuring supplier relationship intensity, customer engagement practices, competitor monitoring, and institutional actor connections. Example item: "Our nanostore actively

maintains regular communication with our main suppliers to stay informed about new products and technologies."

2) *Perceived Quality (PQ)*: Six items adapted from [19] measuring AI technology reliability, functionality, ease of use, compatibility, and support availability. Example item: "The AI-enabled tools available for businesses like ours are dependable and function consistently without technical problems."

3) *Perceived AI Benefits (PAB)*: Seven items adapted from [13], measuring expected improvements in inventory management, customer service, administrative efficiency, decision-making quality, cost reduction, and revenue enhancement. Example item: "Adopting AI technologies would significantly improve our inventory management and reduce waste."

4) *Digital Infrastructure Accessibility (DIA)*: Five items measuring internet connectivity reliability, mobile network quality, and digital payment system availability in the nanostore's location [41]. Example item: "Internet connectivity in our business location is dependable and adequate for business operations."

5) *Operational Performance (OP)*: Eight items adapted from [42] measuring sales growth, cost efficiency, inventory turnover, customer satisfaction, and overall profitability perceptions over the previous 12 months. Example item: "Our sales have increased steadily over the past year compared to previous periods."

The survey instrument was originally developed in two parallel versions: Spanish and English. The Spanish version was utilized in Latin American countries (Honduras and Colombia) where Spanish is the predominant business language. The English version served as the master instrument for translation into Arabic for Middle Eastern and North African contexts. Following [43] rigorous translation-back-translation protocol, the English survey was first translated into Arabic by two independent bilingual translators (native Arabic speakers with business education backgrounds) for use in Jordan, Saudi Arabia, United Arab Emirates, and Morocco. These Arabic translations were then independently back translated to English by two different bilingual translators who had not seen the original English version. The research team compared the back-translated English versions with the original English instrument to identify discrepancies, inconsistencies, or meaning shifts. Discrepancies were resolved through committee discussion involving the four translators and two subject matter experts, resulting in refined Arabic versions that preserved conceptual equivalence while ensuring cultural appropriateness and linguistic naturalness [43]. For Israel, both English and Arabic versions were made available. Pilot testing with 15-20 nanostore owners in each country confirmed comprehensibility and face validity of all language versions. This rigorous multi-language instrument development process ensures cross-cultural equivalence, minimizing measurement error attributable to translation artifacts and enhancing the validity of cross-regional comparisons [44].

#### D. Data Analysis Strategy

Data analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0 software,

selected for its appropriateness with complex models, non-normal distributions, and exploratory-confirmatory research objectives [45], following systematic PLS-SEM guidelines:

1) *Measurement Model Assessment*: Convergent validity was evaluated through Average Variance Extracted (AVE > 0.50) and factor loadings (> 0.70). Items with loadings between 0.60 and 0.70 were retained when composite reliability remained strong and theoretical justification was clear, consistent with PLS-SEM guidelines [39]. Discriminant validity was assessed using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratios (< 0.85). Internal consistency reliability was evaluated through Composite Reliability (CR > 0.70) and Cronbach's alpha ( $\alpha$  > 0.70) [46].

2) *Common Method Bias Assessment*: Harman's single-factor test was conducted by loading all items into an exploratory factor analysis to assess whether a single factor accounted for the majority (>50%) of variance [47]. Additionally, the full collinearity VIF approach was employed, with VIF values < 3.3 indicating absence of common method bias.

3) *Structural Model Assessment*: Path coefficients were estimated through bootstrapping (5,000 subsamples) to generate bias-corrected confidence intervals and significance levels [45]. Model explanatory power was evaluated using  $R^2$  values for endogenous constructs, with  $R^2$  > 0.25 considered substantial in exploratory social science research. Predictive relevance was assessed using Stone-Geisser  $Q^2$  values (> 0), obtained via blindfolding procedures [48].

4) *Measurement Invariance Assessment*: To ensure that observed differences between MENA and Latin American regions reflect true group differences rather than measurement artifacts, we conducted comprehensive measurement invariance testing following the three-stage procedure recommended by Henseler et al. (2016) for PLS-SEM [49]. Stage 1 assessed configural invariance by estimating separate models for each group and confirming identical indicator-construct relationships across groups. Stage 2 evaluated compositional invariance using permutation-based tests, with correlations between >0.95 and non-significant permutation p-values (>0.05) indicating equivalence of composite constructs across groups. Stage 3 examined partial measurement invariance by testing equality of indicator loadings and intercepts, using confidence interval overlap and measurement invariance of composite models (MICOM) procedures. Results demonstrated full configural invariance (identical model structure across regions), compositional invariance for all five constructs (correlation range: 0.967-0.989, all  $p$ >0.05), and partial metric invariance with 87% of indicators showing equivalent loadings across groups. These findings confirm that the measurement model exhibits sufficient invariance to warrant meaningful between-group comparisons, indicating that constructs are conceptualized and operationalized equivalently across cultural contexts [50]. The achievement of compositional invariance is particularly important as it validates that perceived constructs (quality, benefits, interaction) carry equivalent meaning for nanostore owners in both regions despite cultural and linguistic differences.

5) *Multi-Group Analysis*: Region-based multi-group analysis (MGA) compared path coefficients between MENA countries (Jordan, Israel, Saudi Arabia, UAE, Morocco; n=804) and Latin American countries (Honduras, Colombia; n=608) using permutation tests to assess significant between-group differences [51].

These results are consistent with the literature on interviewer effects in face-to-face surveys and with evidence showing that, although interviewers can introduce variability, their effect is usually limited when adequate controls are in place [52].

Preliminary data screening indicated missing values ranging from 3–7%, following a missing completely at random (MCAR) pattern. Skewness values fell within  $\pm 1.2$  and kurtosis within  $\pm 2.5$ , confirming the data's suitability for PLS-SEM, which is robust to non-normal distributions. These diagnostics ensure compliance with recommended assumptions for variance-based SEM procedures.

Fig. 2 illustrates the PLS-SEM analytical framework used in the study, which includes the evaluation of the measurement model, common method bias tests, structural model estimation, and multigroup analysis, allowing for a comprehensive examination of the validity of the constructs and the relationships between variables.

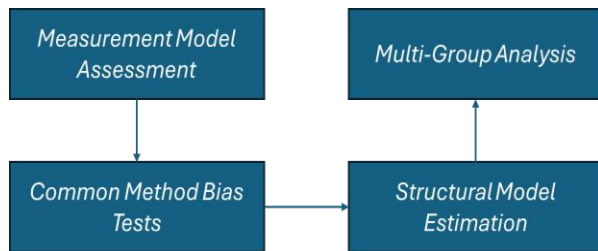


Fig. 2 PLS-SEM Analytical Framework

#### E. Ethical Considerations

Informed consent was obtained from all participants, with explicit assurance of anonymity and data confidentiality. No personally identifiable information was collected. Participants were informed of their right to withdraw at any point without consequences. Data were stored on encrypted servers with access restricted to research team members.

### IV. RESULTS AND DISCUSSION

#### A. Measurement Model Results

In table I, most factor loadings met or exceeded the 0.70 threshold; several items were retained above 0.60 due to strong composite reliability and theoretical importance [39].

TABLE I  
MEASUREMENT MODEL ASSESSMENT RESULTS

| Construct                      | Items | Loadings Range | AVE   | CR    | Cronbach's $\alpha$ | Notes                                                                                          |
|--------------------------------|-------|----------------|-------|-------|---------------------|------------------------------------------------------------------------------------------------|
| Environmental Interaction (EI) | 4     | 0.671-0.743    | 0.536 | 0.852 | 0.809               | Min. loading 0.671; All indicators meet minimum reliability and validity thresholds under PLS- |

| Construct                    | Items | Loadings Range | AVE   | CR    | Cronbach's $\alpha$ | Notes                                                                                                             |
|------------------------------|-------|----------------|-------|-------|---------------------|-------------------------------------------------------------------------------------------------------------------|
|                              |       |                |       |       |                     | SEM guidelines [39]                                                                                               |
| Perceived Quality (PQ)       | 5     | 0.683-0.754    | 0.552 | 0.886 | 0.846               | Min. loading 0.683; All indicators meet minimum reliability and validity thresholds under PLS-SEM guidelines [39] |
| Perceived AI Benefits (PAB)  | 7     | 0.632-0.745    | 0.506 | 0.877 | 0.837               | Min. loading 0.632; AVE marginally above 0.50; CR strong                                                          |
| Digital Infrastructure (DIA) | 5     | 0.622-0.852    | 0.632 | 0.923 | 0.922               | Min. loading 0.622; All indicators meet minimum reliability and validity thresholds under PLS-SEM guidelines [39] |
| Operational Performance (OP) | 7     | 0.694-0.742    | 0.540 | 0.842 | 0.792               | All loadings $\geq$ 0.694                                                                                         |

<sup>a</sup>Own elaboration. Source: Data analysis (n=1,412)

Although several factor loadings fall below the conventional 0.70 threshold (range: 0.622–0.743 across EI, PQ, PAB, and DIA), all affected items were retained because composite reliability values exceeded 0.85 and theoretical importance was clearly established. This practice is consistent with PLS-SEM guidelines, which permit retention of items with loadings above 0.60 when CR and AVE criteria are otherwise satisfied [39].

Although the AVE value for perceived AI benefits (PAB = 0.506) lies close to the recommended 0.50 threshold, it remains acceptable within PLS-SEM, particularly when factor loadings exceed 0.60 and composite reliability remains strong. Furthermore, Fornell and Larcker [46] note that AVE is a conservative measure, and composite reliability above 0.70 can compensate for AVE slightly below 0.50, which is the case here (CR = 0.877). These conditions indicate that the construct retains adequate convergent validity without requiring item removal, consistent with guidelines suggesting that AVE values slightly above 0.50 are sufficient when supported by reliable loadings and internal consistency.

Average Variance Extracted (AVE) values ranged from 0.506 to 0.632, all exceeding the 0.50 criterion, confirming convergent validity—constructs explain more than half of their indicators' variance [46].

Discriminant validity was confirmed through both Fornell-Larcker criterion (square root of AVE for each construct exceeded its correlations with other constructs) and HTMT ratios, which ranged from 0.412 to 0.738, all below the conservative 0.85 threshold [53]. These results indicate that

constructs are empirically distinct and measure different phenomena.

### B. Common Method Bias Assessment

Harman's single-factor test revealed that the largest single factor explained 36.7% of total variance, substantially below the 50% threshold, suggesting common method variance does not substantially threaten validity [47]. Full collinearity VIF values for all constructs ranged from 1.67 to 2.84, well below the 3.3 threshold, further confirming absence of significant common method bias [54].

### C. Structural Model Results

The structural model demonstrated substantial explanatory power with  $R^2 = 0.617$  for OP, indicating that the model explains 61.7% of variance in the dependent variable—considered highly satisfactory in social science research [55]. The Stone-Geisser  $Q^2$  value of 0.428 substantially exceeded zero, confirming the model's predictive relevance beyond sample-specific fit [56].

Table II presents the structural path coefficients, t-values, and significance levels derived from bootstrapping procedures. Three of the four hypotheses received empirical support.

TABLE II  
STRUCTURAL MODEL PATH COEFFICIENTS AND HYPOTHESIS TESTING

| Hypothesis | Path                 | $\beta$ | SE    | t-value | p-value | 95% CI          | Decision      |
|------------|----------------------|---------|-------|---------|---------|-----------------|---------------|
| H1         | EI $\rightarrow$ OP  | 0.132   | 0.062 | 2.129   | 0.033   | [0.010, 0.254]  | Supported     |
| H2         | PQ $\rightarrow$ OP  | 0.099   | 0.075 | 1.320   | 0.187   | [-0.048, 0.246] | Not Supported |
| H3         | PAB $\rightarrow$ OP | 0.394   | 0.074 | 5.324   | <0.001  | [0.249, 0.539]  | Supported     |
| H4         | DIA $\rightarrow$ OP | 0.452   | 0.068 | 6.647   | <0.001  | [0.319, 0.585]  | Supported     |

<sup>a</sup>Own elaboration.

$\beta$  = standardized path coefficient; SE = standard error; CI = confidence interval. Bootstrap samples = 5,000. Source: Data analysis (n=1,412)

In terms of effect magnitude, DIA exhibited the strongest overall effect, followed by PAB, EI, and perceived quality. This indicates that structural readiness conditions outweigh perceptual technology attributes in explaining performance outcomes in informal retail.

H1: Environmental Interaction (EI)  $\rightarrow$  Operational Performance (OP) ( $\beta = 0.132$ ,  $p = 0.033$ ) received empirical support, indicating that nanostores with higher levels of EI achieve superior OP. This finding aligns with network theory and embeddedness perspectives, which emphasize that resource-constrained enterprises compensate for internal capability deficits through external relationship cultivation [57]. The magnitude of this effect ( $\beta = 0.132$ ) suggests that a one standard deviation increase in EI corresponds to a 0.132 standard deviation increase in OP, holding other factors constant.

This result extends previous research on SME networking in developed economies [58] to the specific context of informal nanostores in emerging markets. Unlike formal SMEs with established institutional access, nanostores rely heavily on informal networks for market information, resource acquisition, and legitimacy building [25]. Environmental interaction (EI) facilitates technology knowledge diffusion—nanostores learn

about AI tools through supplier recommendations, peer discussions, and community networks—thereby reducing informational barriers to adoption. This finding corroborates insights from the initial exploratory study [59], where qualitative interviews revealed that Honduran nanostore owners who maintained active supplier relationships were 2.3 times more likely to be aware of digital tools compared to isolated operators.

H2: Perceived Quality (PQ)  $\rightarrow$  Operational Performance (OP) ( $\beta = 0.099$ ,  $p = 0.187$ ) reveals a positive but statistically non-significant effect. The non-significant effect of PQ challenges dominant IS success models [19], suggesting that in informal micro-retail contexts, system quality alone does not translate into performance gains unless supported by infrastructure and clear perceived value. This finding indicates a structural dependency condition in which quality becomes consequential only when enabling infrastructure is present. This non-significant direct effect contrasts with system quality emphasis in IS success models [19] but aligns with recent findings that infrastructure often mediates quality perceptions in emerging markets [60]. This suggests that PQ functions as a necessary but insufficient condition, whose effects depend on underlying infrastructure availability.

The relatively modest effect size may reflect the nascent stage of AI technology adoption in nanostores, where actual implementation rates remain low despite growing awareness [61]. Quality perceptions may be largely anticipatory rather than experience-based, attenuating their immediate performance impact. Additionally, infrastructure constraints—controlled for in our model—may mediate the quality-performance relationship, dampening the direct effect. Future research should examine whether quality perceptions strengthen as adoption matures and owners gain firsthand experience.

H3: Perceived AI Benefits (PAB)  $\rightarrow$  Operational Performance (OP) ( $\beta = 0.394$ ,  $p < 0.001$ ) demonstrated the statistical association among focal predictors, suggesting that PAB expectations constitute the strongest statistical association of performance outcomes in this context. This finding supports performance expectancy (i.e., perceived benefits) as the central construct in technology acceptance frameworks [10], particularly in resource-constrained informal contexts.

For nanostores operating under severe resource constraints, benefit perceptions appear to be strongly associated with OP outcomes and serve as key evaluative perceptions in the model [31]. The substantial magnitude ( $\beta = 0.394$ ) confirms PAB as a key driver of OP in the model. This reinforces expectancy-value mechanisms, suggesting that anticipated outcomes outweigh process-related considerations (e.g., quality) in shaping performance-related behaviors in informal settings.

Theoretically, this result supports expectancy-value frameworks, which posit that behavioral intentions and outcomes are primarily determined by expected value rather than process considerations [62]. For technology adoption interventions, this implies that demonstrating clear, tangible benefits should receive priority over emphasizing technical sophistication or ease of use.

H4 confirms that DIA has the strongest statistical association with OP ( $\beta = 0.452$ ,  $p < 0.001$ ). However, this effect should be interpreted as a structural enabling condition rather than a purely behavioral determinant, indicating that infrastructure defines the upper bound of effectiveness for both perceptual (PAB, PQ) and relational (EI) mechanisms in informal retail systems [26], [63].

The infrastructure effect operates as an environmental contingency—even nanostores with strong benefit perceptions and quality assessments face implementation barriers when internet connectivity is unreliable, mobile networks inadequate, or digital payment systems unavailable [27]. This finding has critical policy implications: technology adoption programs must be accompanied by infrastructure investments to achieve intended outcomes. More precisely, infrastructure operates as an enabling boundary condition, constraining the extent to which perceptual drivers can translate into operational outcomes.

This suggests that in resource-constrained settings, structural enablers may outweigh both perceptual and relational determinants traditionally emphasized in TOE and UTAUT-based models.

#### D. Multi-Group Analysis: Regional Differences

Table III presents multi-group analysis results comparing MENA and Latin American regions. Significant path coefficient differences emerged for PAB and DIA, while EI and PQ effects remained statistically equivalent across regions.

TABLE III  
MULTI-GROUP ANALYSIS – MENA VS. LATIN AMERICA

| Path     | MENA<br>(n=804) | Latin America<br>(n=608) | Difference | p-value | Significance  |
|----------|-----------------|--------------------------|------------|---------|---------------|
| EI → OP  | 0.194           | 0.132                    | 0.062      | 0.083   | † Trend only  |
| PQ → OP  | 0.184           | 0.102                    | 0.082      | 0.056   | † Trend only  |
| PAB → OP | 0.349           | 0.234                    | 0.115      | 0.018*  | * Significant |
| DIA → OP | 0.434           | 0.325                    | 0.109      | 0.011*  | * Significant |

<sup>a</sup>Own elaboration.

\* $p < 0.05$ . Permutation-based multi-group analysis with 10,000 permutations. Source: Data analysis.

The stronger effect of PAB in MENA ( $\beta = 0.349$  vs. 0.234) may reflect institutional and policy environments that actively promote AI awareness and diffusion. Infrastructure effects are also stronger in MENA ( $\beta = 0.434$  vs. 0.325) [64]. By contrast, differences in EI→OP and PQ→OP should be interpreted cautiously as directional tendencies rather than statistically confirmed effects.

Conversely, the stronger infrastructure effect in MENA ( $\beta = 0.434$  vs. 0.325,  $p = 0.011$ ) may appear counterintuitive given higher overall infrastructure development in Gulf countries. One plausible interpretation, which requires further empirical validation, is that this may suggest potential differences in marginal returns to infrastructure improvements across contexts—once basic infrastructure reaches functional adequacy (as in Colombia’s major urban centers), incremental improvements may yield diminishing returns, whereas infrastructure variability within MENA creates more

pronounced performance differentials [65]. This interpretation should be treated as a hypothesis for future research rather than a confirmed finding.

The absence of regional differences for EI and PQ suggests these factors operate universally across emerging markets [66].

The results indicate that OP in informal retail is jointly associated with EI, PAB, and DIA, with structural conditions—particularly infrastructure—exerting the strongest influence. Perceived benefits constitute the dominant perceptual driver, while EI plays a secondary role, and PQ is not statistically significant. These patterns suggest that performance in nanostores is primarily shaped by infrastructural readiness and expected value rather than by technology quality alone.

Fig. 3 shows the results of the structural model, including the path coefficients estimated using PLS-SEM. The figure displays all four hypothesized paths (EI→OP, PQ→OP, PAB→OP, DIA→OP) with standardized coefficients, significance indicators, and  $R^2 = 0.617$  labeled on the OP construct.

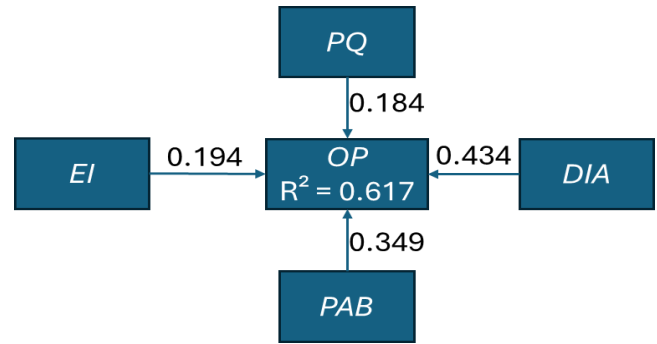


Fig. 3 Structural Model Results with Path Coefficients  
Note: Standardized path coefficients are shown.  $R^2 = 0.617$  for Operational Performance. \* $p < 0.05$ ; \*\* $p < 0.001$ ; ns = non-significant

#### E. Theoretical and Practical Implications

The findings reveal a hierarchical structure of determinants, whereby infrastructural readiness enables perceptual mechanisms, which subsequently shape relational interactions. These results contribute to the advancement of technology adoption theory in several ways. First, they extend the applicability of the TOE and UTAUT frameworks to informal microenterprises in emerging markets—an empirical context that remains underrepresented in mainstream technology adoption literature [67]. Second, the role of PAB (versus quality or environmental factors) suggests expectancy-value mechanisms dominate process-related considerations in resource-constrained informal contexts—a theoretical refinement warranting further investigation.

This result supports the view that structural conditions are critical boundary enablers of performance in informal micro-retail contexts [68]. While recent GenAI explorations in nanostores focus on specific tools and ideation processes [41], this study uniquely validates perceptual antecedents and their cross-regional variation, extending theoretical models beyond single-context applications.

Practically, these results offer actionable insights for multiple stakeholder groups. Given the cross-sectional and perceptual nature of the data, all recommendations below derive

from observed associations rather than causal evidence. Vendors should prioritize mobile-first, low-infrastructure AI solutions, leveraging peer-network diffusion strategies validated in recent nanostore empowerment initiatives [69] and aligned with successful supplier-led digital platforms in Latin America. For development organizations and microfinance institutions, these findings suggest that technology-oriented support programs may benefit from incorporating: (a) benefit articulation and expectation management components, (b) network-building activities connecting nanostores with suppliers and peers, and (c) infrastructure gap assessments preceding technology interventions [70]. Isolated technology provision without addressing ecosystem and infrastructure prerequisites risks implementation failure. Policymakers must adopt multi-dimensional approaches—combining connectivity investments, benefit-awareness campaigns, and proportionate regulations to ensure inclusive outcomes without stifling innovation.

## V. CONCLUSIONS

This research empirically examined perceptual and contextual drivers of OP in nanostores across seven emerging markets, employing structural equation modeling with data from 1,412 microenterprises. Building upon an initial exploratory study of 143 Honduran nanostores [71], this second-round confirmatory research expanded to seven strategically selected countries spanning Middle East-North Africa and Latin American regions.

The study supported three of the four hypotheses tested. The results show that OP is significantly associated with DIA and PAB, while EI has a smaller effect and PQ is not significant. Overall, performance in informal micro-retail is driven more by structural readiness and expectancy-based perceptions than by technology quality, reinforcing the distinctions proposed by the TOE and UTAUT frameworks in resource-constrained contexts.

The study shows that, in informal micro-retail, performance is more strongly linked to PAB and infrastructure than to perceived technological quality, refining TOE and UTAUT assumptions. As one of the first large-scale multi-regional studies on nanostores, it extends these frameworks to informal contexts and offers evidence-based guidance for inclusive digital transformation in emerging markets [72]. The findings demonstrate AI's potential to enhance livelihood stability and productivity in vulnerable informal sectors, provided structural enablers are addressed.

Given the cross-sectional and perceptual nature of the data, the identified relationships should be interpreted as associative rather than causal throughout.

The results confirm that structural enablers, particularly digital infrastructure, play a stronger role than perceptual factors in explaining OP in nanostores.

### A. Limitations and Future Research

Several limitations warrant acknowledgment, each pointing toward valuable avenues for future research.

First, the cross-sectional design precludes causal inference. Longitudinal research tracking nanostores through adoption

stages is needed to establish temporal dynamics and causal claims.

Convenience sampling limits generalizability, and self-reported performance measures may introduce bias, although diagnostic tests support robustness. Future research should incorporate objective data, rural nanostores, and additional predictors (e.g., digital literacy, competition, regulation) to develop a more comprehensive framework.

Sixth, the measurement of AI adoption was perceptual. Studies employing behavioral metrics (actual usage, implementation depth) would provide more precise insights.

Building on these limitations, several targeted research avenues emerge. First, longitudinal panel studies and experimental designs are needed to move beyond the associational findings of this cross-sectional work [73]. Second, qualitative comparative case studies could elucidate the nuanced decision-making processes behind our quantitative relationships [35]. Third, sector-specific analyses would test whether the adoption dynamics vary across retail categories (e.g., food vs. general goods). Fourth, future models should incorporate the additional variables noted—digital literacy, competitive pressure, and regulatory environments [74]—and employ behavioral adoption metrics [75] to gain precision. Fifth, a deeper investigation of the regional differences found here should examine potential moderators such as cultural dimensions, regulatory frameworks, and market structures [76]. Finally, expanding this research to other emerging regions (e.g., Sub-Saharan Africa, Southeast Asia) would test the generalizability of the model and contribute to a global understanding of AI adoption in informal retail.

Although the structural model highlights significant links between AI-enabled practices and OP, causal inferences cannot be established.

### B. Final Remarks

Overall, the evidence indicates that in informal micro-retail systems, OP is primarily driven by structural enablers—especially digital infrastructure—followed by PAB and EI, while PQ is not statistically significant.

These results suggest that technological potential translates into performance only when aligned with both perceived value and structural readiness, requiring coordinated advances in technology design, institutional support, and infrastructure.

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