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Digital Adoption and Digital Maturity in Ecuadorian SMEs: A Cross-Sectional Econometric Analysis of the 2021 National Digital Skills Survey

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Abstract

The post-pandemic acceleration of digital tools has reshaped how small and medium-sized enterprises (SMEs) in Latin America compete, yet the resulting maturity gains remain poorly understood in individual emerging-market economies. Ecuador exemplifies this gap: SMEs account for over ninety per cent of the formal business register but appear in few econometric studies, most based on convenience samples. This study asks how strongly digital adoption is associated with the digital maturity of Ecuadorian SMEs and which tools best predict e-commerce engagement. The analysis draws on the National Digital Skills Survey (ENHD, Encuesta Nacional de Habilidades Digitales), administered by Ecuador's Ministry of Telecommunications (MINTEL), covering 847 SMEs in 2021. A ten-indicator Digital Adoption Index (DAI) is related to the ENHD maturity score through least squares regression with robust standard errors, and a binary logit model with multicollinearity diagnostics identifies the tools that predict e-commerce adoption. The DAI explains over half of the variance in digital maturity, robust to firm-size and sector controls. Website presence exerts the largest marginal effect on e-commerce adoption, followed by cloud services. Top adopters score twice as high as non-adopters, consistent with cumulative advantage. Policy implications include subsidised digital-foundations bundles for laggard micro-enterprises.

Keywords: digital transformation; SME performance; e-commerce adoption; Digital Adoption Index; Resource-Based View; emerging markets; Ecuador

JEL Classification: O33; L25; O54; L86



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1. Introduction

Ecuador's small and medium-sized enterprise sector occupies a paradoxical position in the national economy. Firms with fewer than two hundred employees account for more than ninety per cent of registered enterprises and generate close to sixty per cent of private-sector employment (INEC, 2023). Yet structural fragility persists. The 2022 Structural Business Survey reported a 3.7 per cent contraction in SME value added, with per-worker productivity at approximately USD 39,000—well below the OECD average of USD 107,000 (INEC, 2023; OECD, 2021). The COVID-19 pandemic forced an abrupt

acceleration of digitalisation across Latin America (CEPAL, 2021), and four years on, the distribution of digital capabilities across Ecuadorian firms remains deeply unequal.

This inequality—the digital divide—functions not merely as a technology gap but as a structural economic fault line separating firms capable of accessing wider markets through digital channels from those confined to informal, low-productivity activities. Three dimensions are well documented in the regional and Ecuadorian literature (OECD/CAF, 2019; MINTEL, 2023). First, geographic heterogeneity divides the country: broadband penetration in Pichincha and Guayas exceeds sixty per cent, while several Amazonian provinces fall below twenty per cent. Second, sectoral variation places service firms ahead of agricultural and artisanal manufacturing producers. Third, scale effects leave micro-enterprises without the capital required to deploy integrated digital systems even when connectivity is available.

The post-pandemic period beginning in 2021 constitutes a critical inflexion point for the Ecuadorian SME landscape. The National Digital Agenda 2021–2025 introduced obligations on electronic invoicing for formal SMEs, the SRI fiscal authority deployed an online tax-filing infrastructure, and consumer demand patterns shifted permanently toward digital purchase channels (MINTEL, 2023). Despite this institutional context, rigorous econometric evidence on whether digital adoption translates into measurable maturity improvements for Ecuadorian SMEs remains scarce.

A synthetic reading of the current state of research identifies three convergent strands and one persistent gap. The first strand, anchored in the productivity literature, establishes that information and communication technology (ICT) adoption is associated with positive but heterogeneous output effects: in their meta-analytic review of 150 firm-level studies, Cardona et al. (2013) report ICT-productivity elasticities of 0.05 to 0.10 and identify firm size, country development level, and complementary organisational change as the principal moderators. The second strand, originating in the dynamic-capabilities and digital-transformation literature, conceptualises digital tools as resource amplifiers rather than productivity inputs (Nambisan et al., 2017; Verhoef et al., 2021; Hanelt et al., 2021), and the systematic review of 119 articles by de Mattos et al. (2024) identifies human capital, institutional support, and competitive pressure as the dominant moderators of digital-transformation outcomes in SMEs. The third strand, focused on emerging-market evidence, documents that the magnitude and direction of digital effects diverges from the OECD pattern: Cirera et al. (2021) find sector-specific technology adoption gaps in Brazilian firms; Alderete (2019) shows in Argentine manufacturing SMEs that e-commerce adoption raises sales only when accompanied by sufficient ICT-use intensity; and Espina-Romero et al. (2024) demonstrate, in a structural model of 307 SMEs in Lima, Peru, that digital competencies mediate the transformation-sustainability link; and Heredia et al. (2022), using firm-level data from Latin American economies, show that digital capabilities improve performance only through the technological capabilities they enable, underscoring the mediated nature of digital returns in the region. The persistent gap is that the Ecuadorian case has been studied almost exclusively through convenience-sample descriptive work (Galarza-Sánchez, 2023; Ortiz-Choez et al., 2024), leaving the central questions of magnitude, mechanism, and moderator structure open for systematic econometric treatment.

This paper addresses the gap with two research questions. RQ1 asks how strongly digital adoption is associated with the digital maturity of Ecuadorian SMEs and whether the association is robust to the joint inclusion of firm-size and sector controls. RQ2 asks which specific digital tools most strongly predict the probability of engaging in e-commerce, the most direct observable indicator of market expansion. The contribution is threefold. First, a ten-indicator Digital Adoption Index is constructed and validated against an independently scored maturity instrument, using the 2021 ENHD survey of 847 Ecuadorian SMEs. Second,

an OLS regression with HC3 robust standard errors quantifies the strength and robustness of the association between adoption and maturity. Third, a binary logit model identifies which specific tools shift the probability of e-commerce engagement, with variance inflation factor diagnostics ruling out multicollinearity as a confounder.

The remainder of the paper is organised as follows. Section 2 presents the theoretical background, anchored in the Resource-Based View and recent extensions to dynamic and digital capabilities, and reviews comparative evidence from Latin American SME studies. Section 3 describes the data source, the construction of the Digital Adoption Index, and the econometric specification. Section 4 reports the descriptive, regression, and logit results, together with multicollinearity diagnostics. Section 5 discusses the findings against the international literature, addresses the cumulative-advantage dynamic observed between adoption groups, and acknowledges the limitations of the cross-sectional design. Section 6 concludes with policy and managerial implications.

2. Theoretical Background

2.1. Resource-Based View, Dynamic Capabilities, and Digital Resources

The Resource-Based View (RBV) provides the foundational theoretical lens for analysing how digital tools influence firm performance. Barney (1991) established that competitive advantage arises from resources that are valuable, rare, imperfectly imitable, and non-substitutable. Teece et al. (1997) extended this framework by introducing the concept of dynamic capabilities—the firm’s ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. Teece (2007) subsequently disaggregated dynamic capabilities into three micro-foundations: sensing opportunities, seizing them through resource commitments, and transforming the organisational architecture accordingly.

Bharadwaj (2000) was the first to translate this logic to information technology (IT), conceptualising IT capability as a bundle of IT infrastructure, human IT skills, and IT-enabled intangibles, and demonstrating that high-IT-capability firms sustain superior profitability over multi-year horizons. More recent work has refined this argument in the context of digital transformation specifically. Warner and Wäger (2019) show, through a qualitative process model of incumbent firms, that digital transformation is best understood as an ongoing process of strategic renewal in which sensing, seizing, and transforming capabilities are built incrementally rather than acquired in a single step. Mikalef and Gupta (2021) operationalise artificial-intelligence capability as a higher-order construct combining tangible, human, and intangible resources, and show in a sample of 56 studies that the construct is robustly associated with organisational creativity and firm performance. de Mattos et al. (2024), in a systematic review of 119 articles on technological transformation in SMEs, identify three recurrent moderators—human-capital quality, institutional support, and competitive pressure—that align closely with the dynamic-capabilities micro-foundations. In volatile post-pandemic environments, digital tools enable rapid resource reconfiguration—new e-commerce channels, cloud-based operational architectures, and digital payment rails—that constitutes the empirical expression of strategic agility (Kraus et al., 2021).

Three implications follow for the Ecuadorian SME context. First, the RBV framework predicts that firms accumulating a broader set of digital resources should display higher digital maturity. Second, the dynamic-capabilities extension implies that strategy formulation—captured in the present analysis by the existence of a formal digital-transformation plan—should matter beyond the mere possession of individual tools. Third, the moderators identified in the international literature suggest that firm size and sector

may either amplify or attenuate the adoption–performance relationship, motivating the inclusion of those controls in the empirical specification.

2.2. Digital Maturity Models and Their Measurement

Westerman et al. (2014) proposed a digital maturity model classifying firms along two axes—digital intensity (the extent of investment in customer experience, operations, and business models) and transformation management intensity (leadership vision, governance, and engagement). Their analysis of 391 corporations across multiple industries identified that the firms scoring high on both axes (“Digital Masters”) outperformed industry peers by 26 per cent in profitability. Subsequent contributions have extended the maturity-model approach to SME contexts in particular. Müller et al. (2018) develop an Industry 4.0 readiness framework for German manufacturing SMEs and link specific drivers (digital strategy, ICT integration, employee skills) to performance outcomes. Espina-Romero et al. (2024) apply a maturity-based structural equation model to a sample of 307 SMEs in Lima, Peru, and find that digital competencies mediate the relationship between digital transformation and organisational sustainability.

CEPAL (2021) adapts the maturity logic to Latin American conditions, documenting the region’s gaps in broadband access, in the adoption of digital technologies in production, and in e-commerce, and explicitly accommodates the lower baseline and higher heterogeneity characteristic of emerging-market SMEs. Ecuador’s MINTEL maturity scoring instrument, deployed in the ENHD survey that underpins the present analysis, draws directly from this framework, which makes the resulting score internationally comparable while remaining contextually grounded. The accumulation of evidence linking maturity to performance is now substantial: Verhoef et al. (2021) formalise the maturity logic as a three-stage sequence—digitization, digitalization, and digital transformation—in which each stage requires progressively deeper organisational assets and delivers progressively larger strategic returns. The cross-country evidence in Myovella et al. (2020) confirms that digitalisation contributes positively to economic growth in both Sub-Saharan Africa and OECD economies, with stronger effects observed where the institutional environment is more developed.

2.3. The Ecuadorian Context and Hypotheses

Two contextual features of the Ecuadorian SME landscape sharpen the analytical predictions. First, the simplified RISE tax regime is widely used by micro-enterprises and exempts them from issuing electronic invoices. The exemption creates a structural incentive misalignment because most e-commerce platforms require electronic invoicing for integration, effectively excluding a large fraction of the micro-enterprise base from the digital channel even when basic connectivity is available (MINTEL, 2023). Second, the dollarised economy eliminates exchange-rate risk from cross-border digital transactions but reduces the price competitiveness of Ecuadorian exports. Domestic digital market expansion therefore emerges as the immediate strategic priority for SMEs that have crossed the basic digital threshold (Galarza-Sánchez, 2023; Ortiz-Choez et al., 2024).

Comparative regional evidence reinforces three moderators that are particularly salient for the Ecuadorian case. Human-capital quality determines whether digital tools yield returns once installed (OECD/CAF, 2019). Institutional and infrastructural reliability affects the perceived risk of digital investments (Cirera et al., 2021, in their Brazilian firm-level evidence). Market structure conditions the competitive pressure that pushes laggards toward adoption (OECD/CAF, 2019). Cluster geography and increasing returns offer an additional theoretical anchor: Krugman’s (1991) increasing-returns geography and the industrial-district literature applied to digital ecosystems (Götz & Jankowska, 2017)

predict that the concentration of digital infrastructure and skills in particular regions should produce divergent adoption trajectories across Ecuadorian provinces.

Three testable hypotheses follow, each anchored in the empirical literature reviewed above. H1 states that the Digital Adoption Index is positively and significantly associated with the digital maturity score among Ecuadorian SMEs, and that the association is robust to the joint inclusion of firm-size and sector controls; this prediction extends to the Ecuadorian case of the resource-to-digitalisation pathway documented by [Eller et al. \(2020\)](#), who show for European SMEs that information technology, employee skills, and an explicit digital strategy jointly drive digitalisation and, through it, financial performance. H2 predicts that foundational digital tools—website presence and cloud services—exert significant positive marginal effects on the probability of e-commerce adoption, consistent with the resource-amplifier characterisation of platforms in the digital innovation literature ([Nambisan et al., 2017](#)) and with the case-based evidence of [Li et al. \(2018\)](#), who show that resource-constrained SMEs build e-commerce capabilities incrementally on foundational platform infrastructure rather than through enterprise-level systems. H3 predicts that the digital maturity gap between early adopters and laggards is large in magnitude and statistically robust, consistent with the cumulative-advantage dynamic theorised by [Myrdal \(1957\)](#), with the process view of digital transformation in which early strategic responses compound over time ([Vial, 2019](#)), and with the firm-level evidence of [Cirera et al. \(2021\)](#), who document that technology gaps are systematically wider among smaller firms.

3. Materials and Methods

3.1. Data Source and Sample Construction

The empirical analysis draws on a single primary data source: the Encuesta Nacional de Habilidades Digitales (ENHD), administered by Ecuador's Ministerio de Telecomunicaciones y Sociedad de la Información (MINTEL) and published under a Creative Commons CC-BY 4.0 licence through the National Digital Observatory. The dataset used is the 2021 business-entity component (file identifier MINTEL_ENHD_DCD_2021), which comprises 1291 valid responses across seven organisational categories: large firms, ciudadanos (individuals), government entities, pymes (small and medium-sized firms), microempresarios, artesanos, and organisations of the Popular and Solidarity Economy (EPS). Sector-level data from [INEC \(2023\)](#) and the MINTEL Digital Agenda 2021–2025 progress report ([MINTEL, 2023](#)) are used in the introduction for context but do not enter the econometric models, which rely exclusively on the ENHD micro-data.

The working sample is constructed in two stages. First, all entities classified as productive units in one of four broad SME categories—microempresarios, pymes, artesanos, or organisations of the Popular and Solidarity Economy (EPS)—are retained. This broad definition is substantively important. In Ecuador, the legal-administrative distinction between these four categories reflects regulatory and tax regimes (RISE, RUEPS, RUC) more than economic substance: all four groups are productive units with fewer than two hundred employees, competing in the same product markets and facing the same digital-adoption decisions. Restricting the sample to the formally registered PYME or microempresario categories alone would discard the artesanos ($n = 189$) and EPS ($n = 16$) records, both of which are economically equivalent to micro-pymes. After applying this category filter, the sample contains 851 entities (microempresarios = 573, pymes = 73, artesanos = 189, EPS = 16).

Second, a consistency check is applied to reconcile self-reported organisational type with the self-reported workforce-size band. Four respondents who declared their organisation as microempresario, pyme, or artesano simultaneously reported workforce size in the GRANDE band (more than two hundred employees), which contradicts the SME defini-

tion and likely reflects a data-entry error. These four records are removed. The resulting working sample is $N = 847$ SMEs (microempresarios = 571, pymes = 72, artesanos = 188, EPS = 16).

Two further data-quality steps complete the sample construction. The ten DAI indicators are coded as binary 0/1 variables based on a ‘Sí’/‘No’ question stem. Within the working sample of 847 SMEs, nine of the ten indicators have effectively no missing responses (≤ 0.5 per cent missing). The electronic-invoicing indicator (col 16 of the raw file) presents a higher non-response rate (approximately 60 per cent of records report no answer), which is consistent with the structure of the RISE/RUEPS tax regimes that exempt most micro-enterprises and artesanos from the obligation to issue electronic invoices and therefore rarely prompt them to answer the question. Following the standard convention for self-reported digital-adoption surveys (OECD/CAF, 2019), non-response is treated as non-adoption rather than as informative missingness: in a self-administered instrument, a respondent who does not answer a digital-adoption question is far more likely to be a non-adopter than to be a silent adopter, and the conservative coding minimises false positives in the index. The full pattern of missingness per indicator, together with the binary coding rule, is documented in Appendix A. Interquartile-range outlier analysis applied to the digital maturity score identifies no extreme values requiring removal: all values fall within 1.5 IQR of the first and third quartiles. Because every record in the final working sample carries a complete vector of recoded variables, listwise deletion is vacuous and the working N of 847 is preserved through every subsequent model.

The final sample of 847 SMEs is dominated by micro-enterprises with one to nine employees ($n = 787$, 92.9 per cent), followed by small firms with ten to forty-nine employees ($n = 51$, 6.0 per cent), medium-A firms ($n = 7$), and medium-B firms ($n = 2$). Sectorally, the sample is concentrated in agriculture, livestock and fisheries (28 per cent); other services (28 per cent); and a long tail of trade, hospitality, manufacturing, construction, and ICT (the remaining 44 per cent). Twenty of Ecuador’s twenty-four provinces appear in the sample.

3.2. Variables and Index Construction

3.2.1. Digital Adoption Index

The Digital Adoption Index (DAI) is constructed as the unweighted arithmetic mean of ten binary indicators drawn from the ENHD instrument, each scored 1 when the respondent reports adoption and 0 otherwise. The ten indicators capture: online sales activity; presence of a business website; use of electronic invoicing; dedicated e-commerce personnel; use of electronic signatures; existence of a formalised digital investment plan; ownership of operational technology solutions; existence of a formal digital-transformation strategy; adoption of cloud services; and awareness or use of Internet of Things technologies. The selection of indicators follows the digitalisation dimensions that CEPAL (2021) identifies for Latin American production—connectivity, adoption of digital tools in production and sales channels, and e-commerce—and the maturity-model logic synthesised by Westerman et al. (2014). The unweighted aggregation is preferred for parsimony, interpretability, and resistance to sample-specific variance inflation; this is the same scheme adopted by Cardona et al. (2013) in their ICT-productivity index. The DAI ranges from 0 (complete non-adoption) to 1 (full adoption across all ten indicators).

$$DAI_i = (1/10) \cdot \sum_j \text{Digital}_{[j,i]}, \quad j = 1, \dots, 10 \quad (1)$$

3.2.2. Outcome Variables

Two outcome variables are used. The digital maturity score (Y1) is the composite “Puntuación” produced by the ENHD scoring instrument and ranges in this sample from

42 to 204 points (theoretical maximum 326). The score functions as a continuous proxy for firm-level digital performance and is independently computed from the DAI inputs, which makes it a valid construct-validity benchmark for the index. E-commerce adoption (Y2) is a binary indicator equal to 1 if the respondent reports conducting online sales and 0 otherwise.

3.2.3. Control Variables

Firm size enters the analysis in two specifications. Specification A uses an ordinal 1–4 variable corresponding to micro, small, medium-A, and medium-B categories. Specification B uses three size dummy variables with micro-enterprises as the reference category. Sector is encoded as a set of dummy variables corresponding to the five most frequent categories—agriculture (reference), other services, trade and retail, hospitality, and a “not applicable” category for respondents who did not classify their activity—with all remaining sectors absorbed into the constant. The gender of the respondent is recorded but not entered in the main models because the response is at the individual respondent rather than the firm level.

3.3. Econometric Specification

Three models are estimated. Model 1 is an ordinary least squares (OLS) regression of the digital maturity score on the DAI and firm size (specification A), estimated with heteroskedasticity-consistent type-3 (HC3) standard errors (MacKinnon & White, 1985). HC3 is preferred over HC0 and HC1 in small-to-moderate samples because it inflates the residuals using the leverage values, providing a more conservative inference.

$$Score_i = \beta_0 + \beta_1 \cdot DAI_i + \beta_2 \cdot Size_i + \varepsilon_i \quad (2)$$

Model 2 extends Model 1 by jointly including the DAI together with three size dummies and five sector dummies. This combined specification allows the adoption effect and the structural controls to be evaluated within a single model, so that the marginal contribution of firm size and sector can be read directly against the DAI coefficient.

$$Score_i = \gamma_0 + \gamma_1 \cdot DAI_i + \sum_s \gamma_s \cdot Size_s + \sum_k \gamma_k \cdot Sector_k + u_i \quad (3)$$

Model 3 is a binary logit specification for e-commerce adoption. The link function is the standard logistic Λ , and average marginal effects (AMEs) are reported alongside the estimated coefficients to allow interpretation in probability units (Cameron & Trivedi, 2005). The set of predictors is selected via backward elimination using the Bayesian Information Criterion (BIC), retaining variables that materially improve the model fit. Variance inflation factor (VIF) diagnostics are computed for all retained predictors to rule out multicollinearity.

$$P(e_{sales,i} = 1) = \Lambda(\delta_0 + \delta_1 \cdot website_i + \delta_2 \cdot cloud_i + \delta_3 \cdot invest_{plan,i} + \delta_4 \cdot strategy_i + \delta_5 \cdot Size_i) \quad (4)$$

All analyses are performed in Python 3.12 using the statsmodels 0.14 package. The full replication code and the cleaned working dataset are provided in the Supplementary Materials.

4. Results

4.1. Descriptive Statistics and Adoption Profile

Table 1 reports descriptive statistics for the principal study variables. The mean DAI of 0.160 (SD = 0.182) indicates that the average Ecuadorian SME in the sample has adopted approximately 1.6 of the ten digital indicators. The standard deviation is wide because the underlying distribution is bimodal: a substantial cluster of firms registers a DAI of zero,

while a smaller cohort of early adopters exceeds 0.30. Among the individual indicators, e-commerce activity (40.0 per cent) and cloud adoption (30.5 per cent) are the most prevalent, while electronic invoicing (5.8 per cent) and dedicated e-commerce personnel remain rare. The wide gap between basic and advanced tool adoption foreshadows the cumulative-advantage dynamic documented in Section 4.5.

Table 1. Descriptive statistics for principal study variables. $N = 847$.

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Digital Adoption Index (DAI)	847	0.160	0.182	0.000	0.000	0.100	0.200	1.000
Digital Maturity Score	847	84.812	30.341	42.000	57.000	82.000	106.000	204.000
E-Commerce Adoption (binary)	847	0.400	0.490	0	0	0	1	1
Website Presence	847	0.128	0.334	0	0	0	0	1
Cloud Adoption	847	0.305	0.461	0	0	0	1	1
Electronic Invoicing	847	0.058	0.234	0	0	0	0	1
Digital Strategy	847	0.125	0.331	0	0	0	0	1
Investment Plan	847	0.090	0.286	0	0	0	0	1
Firm Size (1–4 scale)	847	1.084	0.328	1	1	1	1	4

Note. The DAI is the unweighted mean of ten binary digital-adoption indicators (Equation (1)). The digital maturity score is the ENHD composite “Puntuación” metric. The binary indicators (e-commerce adoption through investment plan) are coded 0 = no, 1 = yes; their mean is therefore the sample adoption rate and their standard deviation is the corresponding binomial spread. Firm size is an ordinal 1–4 encoding (1 = micro, 2 = small, 3 = medium-A, 4 = medium-B); a sample mean of 1.08 reflects the dominance of micro-enterprises in the working sample. Quartile values of 0 or 1 for the binary variables reflect their concentration at one of the two endpoints rather than missing data.

4.2. Correlation Structure

Figure 1 displays the Pearson correlation matrix for the digital-adoption variables and the maturity score. The DAI correlates strongly with the maturity score ($r = 0.72$, $p < 0.001$), providing initial support for H1. Among individual indicators, e-commerce adoption and cloud adoption show the highest bivariate associations with the maturity score. Website presence, though adopted by only 12.8 per cent of firms, correlates strongly with e-commerce adoption ($r \approx 0.52$), foreshadowing the large website effect identified in the logit results. Firm size shows only a modest positive correlation with the DAI ($r \approx 0.10$), which indicates that digital heterogeneity persists across size categories and is not reducible to scale effects.

4.3. OLS Regression Results

Table 2 reports the OLS estimates for Models 1 and 2. In Model 1, the DAI coefficient is 119.11 (HC3 SE = 4.73, $p < 0.001$): each 0.10-unit increase in the DAI corresponds to an increase of approximately 11.9 points on the digital maturity score, which is substantively meaningful relative to the outcome standard deviation of 30.3. Firm size is not statistically significant ($\beta = 2.92$, $p = 0.213$), which indicates that digital adoption rather than organisational scale drives the variance in performance. Model 1 explains 51.6 per cent of the outcome variance, providing direct support for H1.

Model 2 adds the size dummies and sector dummies jointly with the DAI in a single specification, permitting a direct comparison of the adoption effect and the structural controls. The DAI coefficient is essentially unchanged ($\beta = 118.80$, $p < 0.001$), and no size or sector dummy achieves conventional statistical significance (all $p > 0.14$). The adjusted R-squared moves only marginally, which confirms that the DAI absorbs essentially all of the explained variation in digital maturity once it is in the model. The cross-sector robustness aligns with Kraus et al. (2021), who report stable digital-transformation effects across manufacturing and service SMEs in their international sample.

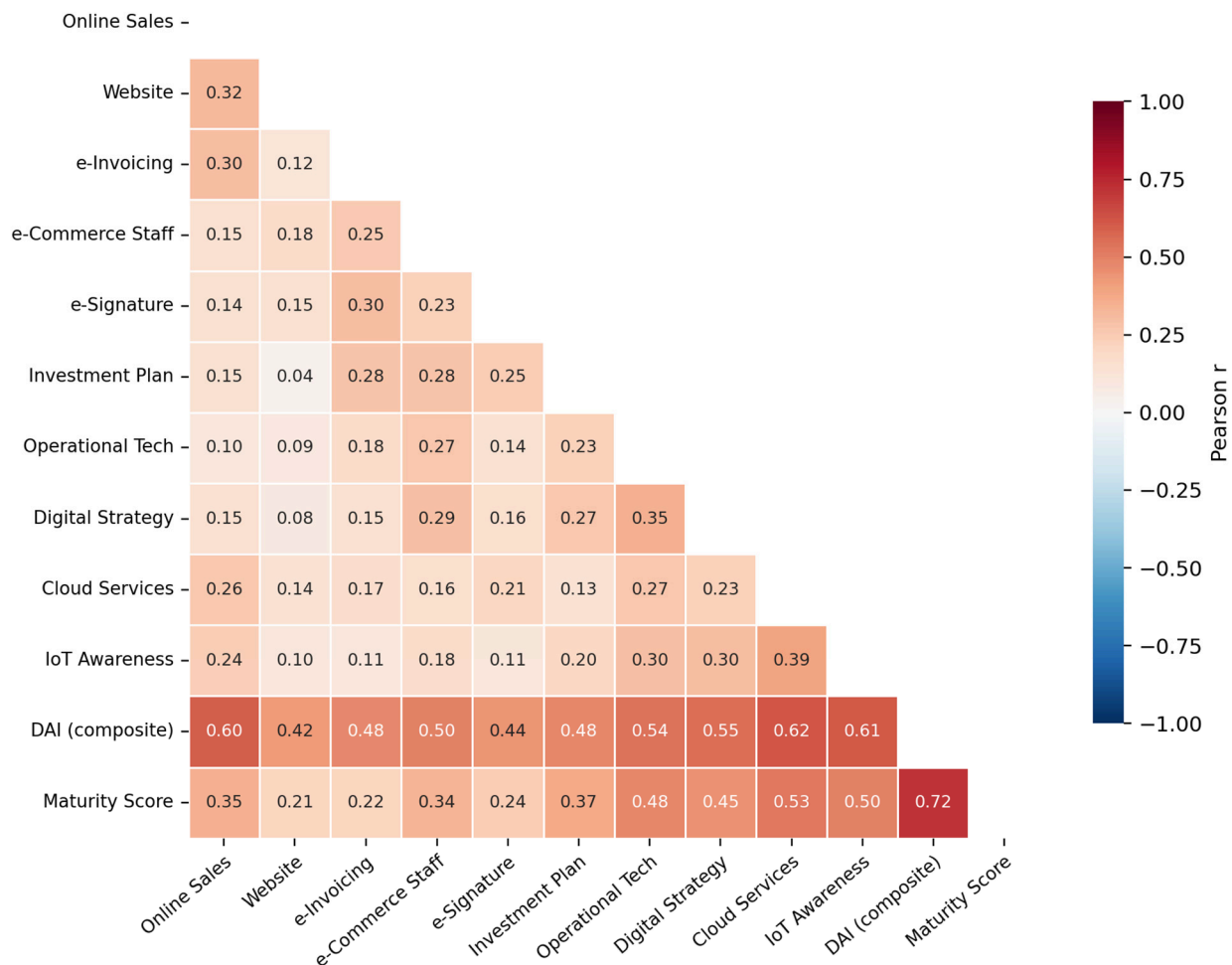


Figure 1. The Pearson correlation matrix for the ten DAI components, the composite DAI, and the digital maturity score ($N = 847$). Cell values are Pearson correlation coefficients; the lower triangle is shown to avoid redundant display.

Table 2. OLS regression results. Dependent variable: digital maturity score. HC3 heteroskedasticity-consistent standard errors in parentheses. The coefficients in column 2 (Model 1) and column 4 (Model 2) are unstandardised regression slopes expressed in maturity-score points per unit change in the predictor.

Variable	Model 1: Coefficient (HC3 SE)	<i>p</i> -Value	Model 2: Coefficient (HC3 SE)	<i>p</i> -Value
Intercept	62.54 (2.73)	<0.001	65.90 (1.27)	<0.001
Digital Adoption Index	119.11 (4.73)	<0.001	118.80 (4.76)	<0.001
Firm Size (ordinal)	2.92 (2.35)	0.213	—	—
Size: Small (dummy)	—	—	4.06 (2.79)	0.146
Size: Medium-A (dummy)	—	—	4.09 (10.28)	0.690
Size: Medium-B (dummy)	—	—	1.71 (33.35)	0.959
Sector: Other Services	—	—	−0.86 (1.77)	0.628
Sector: Trade/Retail	—	—	3.65 (3.25)	0.262
Sector: Hospitality	—	—	−0.61 (3.43)	0.859
Sector: N/A	—	—	−2.37 (2.19)	0.280
R ²	0.516		0.518	
Adjusted R ²	0.515		0.513	
F-statistic	318.2		81.3	
N	847		847	

Note. Reference categories: micro-enterprise size; agriculture sector. Coefficients are unstandardised regression slopes; column 2 reports Model 1 estimates and column 4 reports Model 2 estimates, with HC3 robust standard errors in parentheses. Exact *p*-values are reported in columns 3 and 5.

Figure 2 visualises the two core estimates: panel (a) plots the bivariate relationship between the DAI and the digital maturity score underlying Model 1, and panel (b) displays the average marginal effects from the logit model of e-commerce adoption reported below.

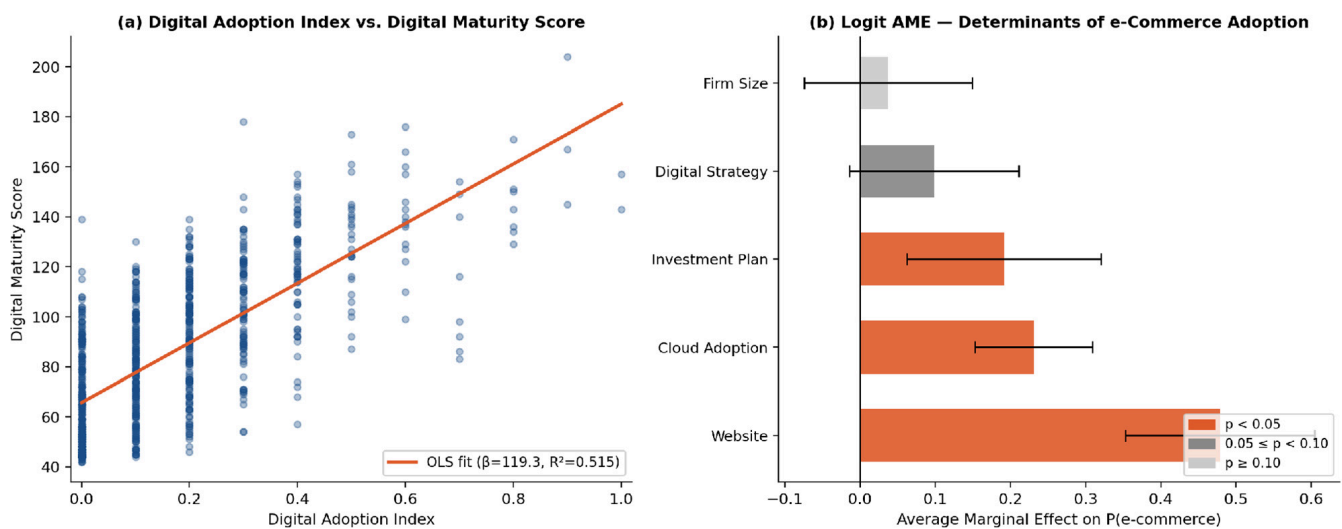


Figure 2. Panel (a) shows the bivariate relationship between the Digital Adoption Index and the digital maturity score ($N = 847$). The orange line is the OLS regression fit. Panel (b) reports the average marginal effects from the binary logit model predicting e-commerce adoption (Equation (4)). Error bars represent 95 per cent confidence intervals.

4.4. Logit Results and Multicollinearity Diagnostics

Table 3 presents the logit coefficients, AMEs, and 95 per cent confidence intervals for the e-commerce adoption model. Website presence exerts the largest marginal effect: firms with an active website are approximately 47.9 percentage points more likely to conduct online sales than firms without one (AME = 0.479, $p < 0.001$; 95 per cent confidence interval [CI]: [0.353, 0.604]). Given an unconditional adoption probability of approximately 40.0 per cent, this implies that website presence more than doubles the likelihood of e-commerce engagement, providing direct support for H2. Cloud adoption follows with an AME of 0.231 ($p < 0.001$), and the existence of a formal investment plan raises the adoption probability by 19.1 percentage points (AME = 0.191, $p = 0.004$). A formal digital strategy approaches but does not cross conventional significance (AME = 0.099, $p = 0.086$), and firm size is not statistically significant ($p = 0.512$), confirming that scale is not the binding constraint on digital market participation in this sample.

To rule out multicollinearity among the logit predictors, variance inflation factors (VIFs) were computed for all five regressors. The maximum VIF is 1.54 (cloud adoption) and the mean is 1.34, both well below the conventional thresholds of 5 (mild concern) and 10 (serious concern) recommended by Cameron and Trivedi (2005). The bivariate correlations among the logit predictors are all below 0.30. Multicollinearity is therefore not a concern in the present specification, and the standard errors reported in Table 3 are not artefactually inflated.

Figure 3 complements the regression evidence with two descriptive patterns: panel (a) ranks the adoption rates of the eight digital indicators, and panel (b) compares the mean DAI across economic sectors.

Table 3. The binary logit results. Dependent variable: e-commerce adoption (1 = conducts online sales; 0 = does not). The average marginal effects (AMEs) were computed at sample means. The VIF column reports the variance inflation factor for each predictor.

Variable	Coefficient	Std. Error	AME	AME SE	VIF	<i>p</i> -Value (AME)
Intercept	−1.248	0.277	—	—	—	<0.001
Website Presence	1.995	0.262	0.479	0.064	1.17	<0.001
Cloud Adoption	0.963	0.167	0.231	0.040	1.52	<0.001
Investment Plan	0.798	0.275	0.191	0.066	1.19	0.004
Digital Strategy	0.411	0.240	0.099	0.057	1.29	0.086
Firm Size (ordinal)	0.156	0.237	0.037	0.057	1.54	0.512
McFadden Pseudo- R^2	0.127					
Log-Likelihood	−497.8					
N	847					
Max VIF	1.54	(threshold of concern: 5)				

Note. AME = average marginal effect. SE = standard error. VIF = variance inflation factor. The maximum VIF is well below the conventional threshold of 5 (Cameron & Trivedi, 2005). Exact *p*-values are reported for each coefficient.

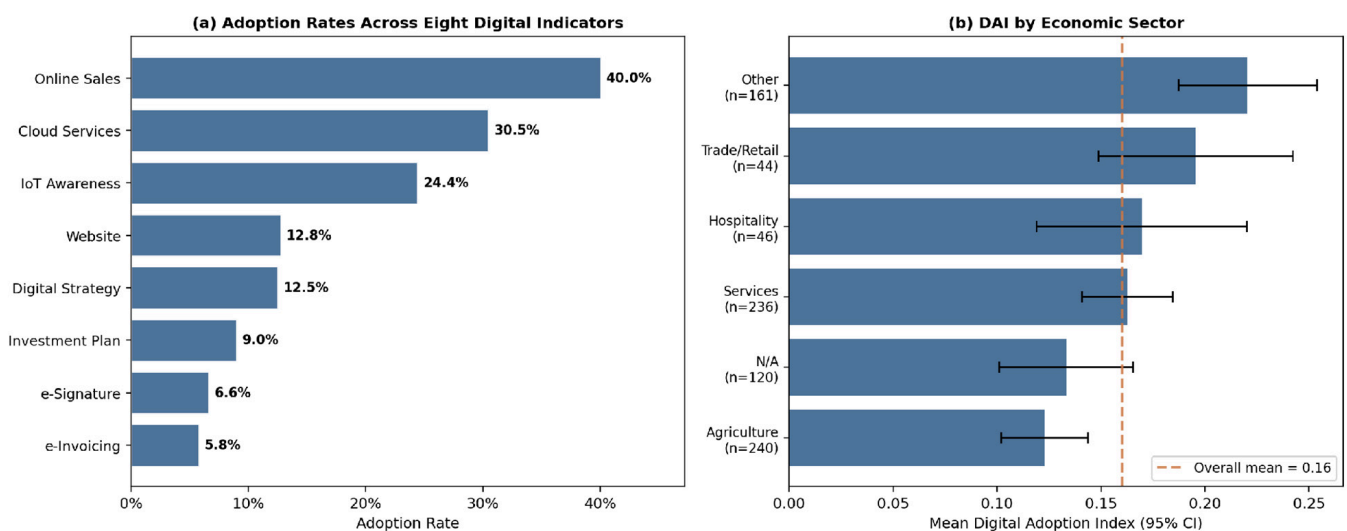


Figure 3. Panel (a) reports the adoption rate for eight digital indicators ($N = 847$). Panel (b) shows the mean Digital Adoption Index by economic sector, with 95 per cent confidence intervals; the dashed orange line marks the overall sample mean.

4.5. Cumulative Adoption Gap

Classifying SMEs into four adoption groups based on the DAI distribution yields a systematic gradient in digital maturity. Group Q1 (laggards, $DAI = 0$, $n = 310$) records a mean maturity score of 63.0, Q2 (low adoption, $0 < DAI \leq 0.10$, $n = 180$) averages 78.8, Q3 (moderate adoption, $0.10 < DAI \leq 0.30$, $n = 236$) averages 96.8, and Q4 (early adopters, $DAI > 0.30$, $n = 121$) averages 126.3. The difference between Q4 and Q1 is 63.3 points, equivalent to a 100.5 per cent higher mean score for early adopters than for laggards. The difference is highly statistically robust (Welch $t = 25.47$, $p < 0.001$, Cohen's $d = 2.90$), confirming H3. The magnitude of the gap—approximately three standard deviations of the outcome variable—indicates that the digital-adoption divide in Ecuador is not a marginal heterogeneity but a structural cleavage in firm-level capabilities.

5. Discussion

5.1. Digital Adoption as a Performance Determinant

The OLS finding that the DAI alone accounts for 51.6 per cent of the variance in digital maturity, with the coefficient essentially unchanged when size and sector controls are jointly added in Model 2, is notable for a cross-sectional design. For comparison, Cardona et al. (2013) report mean ICT-productivity elasticities of 0.05 to 0.10 in European samples, and Müller et al. (2018) achieve R-squared values of approximately 0.44 in German Industry 4.0 samples. The substantially higher explanatory power obtained here is consistent with the greater within-sample heterogeneity of emerging-market SME populations: the difference between firms with zero digital tools and firms with five tools is far more consequential for the outcome than the marginal differences typically observed in advanced-economy studies (de Mattos et al., 2024).

The sector-level null findings warrant particular attention. Unlike studies in Brazil (Cirera et al., 2021) and Chile (Alderete, 2019) that identify sector-specific digital performance differentials, the present data reveal no sector dummy with conventional statistical significance once the DAI is in the model. Given that approximately 28 per cent of the sample is in agriculture—where digital adoption is constrained by rural connectivity deficits rather than by sector-specific economic logic—the sector indicator likely absorbs infrastructure limitations rather than productivity mechanisms intrinsic to the sector. The implication for policy is that rural connectivity investment may be a more efficient lever for agricultural SMEs than sector-specific digitalisation programmes.

5.2. The Primacy of Foundational Tools

The logit marginal effects reveal a hierarchy of digital catalysts that diverges from the European pattern. In Cardona et al. (2013) and Müller et al. (2018), enterprise resource planning integration and data analytics emerge as the primary performance drivers. For Ecuadorian SMEs, the most impactful predictors are foundational rather than advanced: an active website (48 percentage points) and cloud service access (23 percentage points). For a micro-enterprise with revenues below USD 100,000, a website transforms the addressable market from a local cluster to the national e-commerce ecosystem, and cloud adoption removes the single largest financial barrier to e-commerce infrastructure by eliminating the need for capital-intensive hardware (Espina-Romero et al., 2024).

These findings are consistent with the resource-amplifier characterisation in Nambisan et al. (2017) and with the cumulative-advantage logic identified in Kraus et al. (2021), whereby the highest marginal returns to digitalisation accrue to firms at early adoption stages precisely because foundational tools unlock entire capability cascades. The investment-plan effect deserves separate emphasis. The mere existence of a formalised investment plan—the variable least dependent on capital availability and most dependent on managerial intent—raises adoption probability by 19 percentage points. Strategic intentionality, not incidental tool acquisition, appears to be a prerequisite for commercial digital transformation in the Ecuadorian context.

5.3. The Cumulative Digital Divide

The 100 per cent maturity gap between Q4 early adopters and Q1 laggards, combined with the long right tail of the maturity distribution in Q4 (Figure 4b), is consistent with a self-reinforcing cumulative-causation dynamic of the kind theorised by Myrdal (1957) and operationalised in modern increasing-returns geography (Krugman, 1991; Götz & Jankowska, 2017). Digital revenues generate data, data enable personalisation, personalisation raises conversion rates, and conversion rates produce additional revenues. Without

deliberate policy intervention to lift the laggards across the basic adoption threshold, the loop appears likely to widen the intra-sector divide.

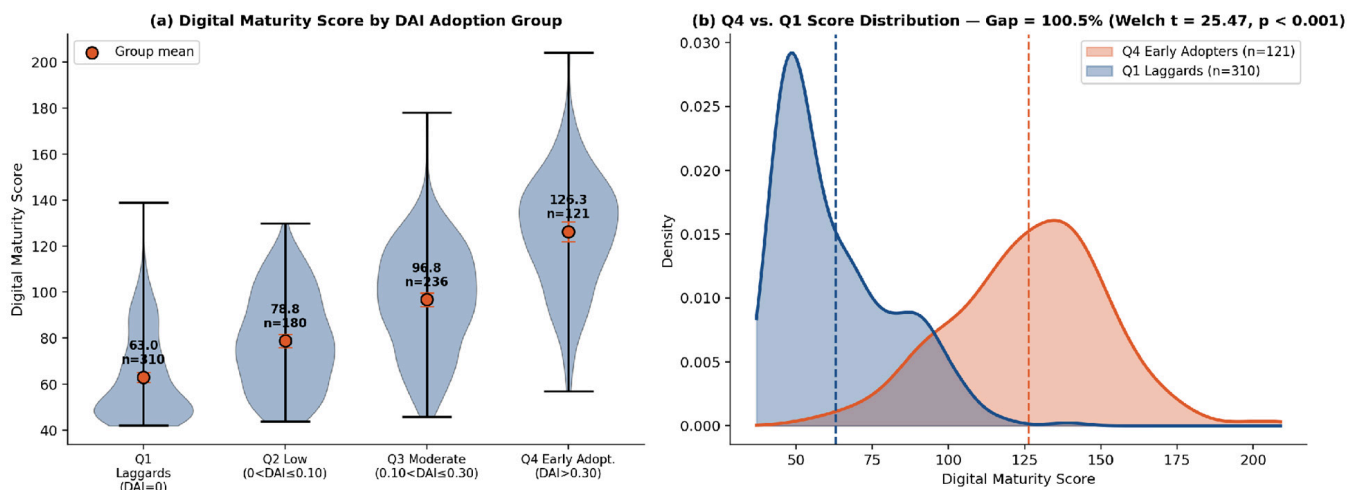


Figure 4. Panel (a) shows the distribution of the digital maturity score by DAI adoption group (Q1 laggards through Q4 early adopters; $N = 847$); the orange points and bars denote group means with 95 per cent confidence intervals. Panel (b) overlays the kernel density estimates of the maturity-score distribution for Q4 versus Q1, with dashed vertical lines marking group means.

Peru's SME Digitisation Programme (2020–2023), which combined subsidised cloud subscriptions with mandatory digital skills training, achieved a 17-percentage-point increase in SME e-commerce adoption in its first two years (ProInversión, 2023), and offers a directly relevant benchmark for Ecuadorian policy designers. The 40.0 per cent overall e-commerce rate observed here masks a bimodal distribution where a substantial fraction of firms remain at DAI = 0 across all ten indicators. The implication is that general-purpose digitalisation campaigns will likely be less effective than targeted, needs-segmented interventions calibrated to the specific gap profile of each adoption group.

5.4. Limitations

Several limitations should be acknowledged in interpreting these results. First, and most importantly, the ENHD dataset is cross-sectional: all observations correspond to the 2021 wave, which precludes panel-based causal identification and limits the ability to distinguish temporal dynamics from cohort effects. The post-pandemic contextual framing in the abstract and introduction should therefore be interpreted as a contextual qualifier rather than as evidence of longitudinal estimation. Future research should link successive ENHD waves at the firm level and integrate the INEC ENESEM financial performance data to estimate the digital-adoption to financial-performance link directly. Second, the cross-sectional design does not allow the exclusion of reverse causality in the logit results: a website and cloud services raise the probability of e-commerce adoption, but firms that already engage in e-commerce may simultaneously invest in those resources to support their existing online operations. The associations reported in Table 3 should therefore be read as conditional predictive relationships rather than as identified causal effects. An instrumental-variables strategy using exogenous variation in regional broadband rollout would be a natural next step.

Third, the ENHD does not record financial-performance variables such as revenue, profit margin, or employment growth. The outcome variable used here is therefore a digital-maturity proxy rather than a direct economic performance indicator. Although the maturity score is constructed from a validated MINTEL instrument and correlates

strongly with the DAI, the inference that maturity translates into financial performance ultimately rests on the supporting evidence from [Eller et al. \(2020\)](#), [Mikalef and Gupta \(2021\)](#), and the wider international literature rather than on direct evidence from the present dataset. Fourth, the DAI uses an unweighted equal-weighting scheme that does not capture potential complementarities between digital tools. A Cobb–Douglas digital-capability aggregation, or a confirmatory factor analysis with empirically estimated weights, would provide a more theoretically grounded index in future iterations of this work.

Finally, with respect to the question of whether the use of artificial-intelligence tools generated limitations for this study: as disclosed in the Acknowledgments, a large language model was employed for code assistance and language editing. Because every statistical output was independently verified and every numerical result was re-computed from the cleaned data before inclusion, the authors assess that this use introduces no methodological limitation beyond those already stated in this section.

6. Conclusions and Policy Implications

This study has examined the relationship between digital adoption and digital maturity in 847 Ecuadorian SMEs surveyed by MINTEL in 2021. The empirical analysis combines a ten-indicator Digital Adoption Index, an OLS specification with heteroskedasticity-consistent standard errors, and a binary logit model for e-commerce adoption with variance inflation factor diagnostics. Three empirical conclusions follow.

First, the Digital Adoption Index displays strong construct validity, with a Pearson correlation of approximately 0.72 with the independently scored MINTEL maturity score, and the index alone explains 51.6 per cent of the variance in digital maturity. The effect is robust to the joint inclusion of firm-size and sector dummies in the combined specification of Model 2, where neither size nor sector achieves statistical significance once the DAI is in the model. Second, website presence, cloud adoption, and the existence of a formalised investment plan emerge as the three strongest predictors of e-commerce engagement, with average marginal effects of approximately 48, 23, and 19 percentage points respectively. Third, the adoption gap between top-quartile and laggard firms reaches three standard deviations of the maturity score, which suggests that the divide is structural rather than marginal and is therefore unlikely to close without deliberate policy intervention.

These findings both confirm and refine the picture that emerged from the literature review conducted for this study. The review indicated that the international evidence on information technology and productivity reports moderate explanatory power, with firm size, development level, and organisational complements as the principal moderators; our results show that in a population where a large share of firms operates with no digital tools at all, a parsimonious ten-indicator adoption index can by itself account for over half of the variance in digital maturity, a considerably higher share than is typical in European firm samples. The review also suggested that in emerging markets foundational tools matter more than enterprise-level systems; our logit estimates confirm this ordering for Ecuador, with website presence and cloud services dominating the marginal-effect ranking while firm size adds no predictive power once the digital variables are in the model. Finally, the review anticipated a cumulative-advantage dynamic in which early adopters pull away from laggards; the doubling of the maturity score between the bottom and top adoption groups documented here provides direct empirical support for that dynamic in the post-pandemic Ecuadorian context.

The policy implications follow naturally from these patterns. For MINTEL and the Ministry of Production, the most immediate priority is to design a national SME Digital Maturity Benchmark Programme that uses the ENHD scoring instrument as the baseline and publishes sector- and province-specific reports on an annual basis. Such an instrument

would provide both diagnostic clarity for policymakers and a benchmarking reference for the firms themselves. A second policy priority is the design of a subsidised digital-foundations package targeted at laggard micro-enterprises, defined as those with a DAI of zero. The package should bundle a pre-configured e-commerce storefront with one year of subsidised cloud hosting, a digital payment module compatible with the SRI electronic-invoicing system, and a forty-hour digital-skills training programme delivered through the SECAP. The Peruvian programme cited above offers a directly relevant template. A third priority is to incentivise early-stage digital investment through SRI tax credits tied to the formalisation of digital investment plans, given that the existence of such a plan is associated with a nineteen-percentage-point increase in e-commerce adoption probability and is the variable least dependent on capital availability.

For SME owners, three managerial implications can be drawn from the evidence. Website development and cloud migration should be prioritised before more complex tools, given that their marginal returns on the probability of e-commerce engagement substantially exceed those of enterprise-level systems in the Ecuadorian context. The formalisation of a digital-transformation plan, even a single-page document, is associated with a measurable increase in e-commerce adoption probability and should be undertaken before significant capital is committed to tools. Finally, engagement with sectoral chambers and associations is a low-cost route to collective purchasing arrangements for cloud services, training, and digital-marketing support, which reduces per-unit costs and diffuses adoption knowledge across firms in the same productive ecosystem.

Three directions for future research emerge from the limitations identified in Section 5.4. The most pressing is the construction of a panel by linking successive ENHD waves at the firm level, which would enable the use of fixed-effects or difference-in-differences designs to identify causal effects net of time-invariant firm heterogeneity. A second is the integration of the INEC ENESEM financial performance data with the MINTEL maturity data, which would substitute revenue, profit, or productivity for the maturity score as the outcome and would strengthen the inferential chain from digital adoption to economic performance. A third is the development of weighted DAI specifications—using confirmatory factor analysis or Cobb–Douglas aggregation—that capture complementarities between digital tools and may reveal heterogeneity masked by the unweighted index used here.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/econometrics14030041/s1>, File S1, the complete Python replication code for all econometric models and figures; File S2, the cleaned 2021 ENHD SME subset (N = 847) in CSV format. All references cited in the Supplementary Materials are also cited and listed in the main text.

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Abbreviations

The following abbreviations are used in this manuscript:

AME	Average Marginal Effect
BIC	Bayesian Information Criterion
CEPAL	Comisión Económica para América Latina y el Caribe
CI	Confidence Interval
CIIU	Clasificación Industrial Internacional Uniforme
DAI	Digital Adoption Index
ENHD	Encuesta Nacional de Habilidades Digitales
EPS	Economía Popular y Solidaria
ENESEM	Encuesta Estructural Empresarial
HC3	Heteroskedasticity-Consistent Covariance Matrix (MacKinnon-White type 3)
ICT	Information and Communication Technology
INEC	Instituto Nacional de Estadísticas y Censos
IT	Information Technology
JEL	Journal of Economic Literature
MINTEL	Ministerio de Telecomunicaciones y Sociedad de la Información
OLS	Ordinary Least Squares
PYME	Pequeña y Mediana Empresa
RBV	Resource-Based View
RISE	Régimen Impositivo Simplificado Ecuatoriano
RUC	Registro Único de Contribuyentes
RUEPS	Registro Único de los Actores de la Economía Popular y Solidaria
SECAP	Servicio Ecuatoriano de Capacitación Profesional
SME	Small and Medium-sized Enterprise
SRI	Servicio de Rentas Internas
VIF	Variance Inflation Factor
VRIN	Valuable, Rare, Imperfectly Imitable, Non-substitutable

Appendix A. Missingness Pattern and Binary Coding Rule

This appendix reports the missingness pattern for the ten Digital Adoption Index (DAI) indicators and the maturity score within the working sample of 847 Ecuadorian SMEs. The appendix documents the data-quality steps described in Section 3.1 so that the treatment of missing responses can be verified and replicated.

Table A1 reports, for each modelling variable, the count and percentage of records with no answer to the raw question stem, before the binary recoding rule is applied. Nine of the ten DAI indicators carry effectively zero missing responses in the working sample. The electronic-invoicing indicator presents 508 non-responses (≈ 60 per cent), a pattern that is consistent with the structure of the RISE and RUEPS tax regimes that exempt micro-enterprises and artesanos from issuing electronic invoices and therefore rarely prompt them to answer the question. The maturity score is fully observed.

Table A1. The missingness pattern for the ten DAI indicators, the maturity score, and firm size in the working sample ($N = 847$).

Variable	N Missing	% Missing
Online Sales	0	0.00%
Website Presence	0	0.00%
Electronic Invoicing	508	59.98%
E-Commerce Staff	0	0.00%
Electronic Signature	0	0.00%
Digital Investment Plan	0	0.00%
Operational Technology	0	0.00%
Digital Strategy	0	0.00%
Cloud Adoption	0	0.00%
IoT Awareness	0	0.00%
Digital Maturity Score	0	0.00%
Firm Size	0	0.00%

The binary recoding rule for the ten DAI indicators is the following: a value of 1 is assigned when the raw response equals ‘Si’ (or a contextually equivalent affirmative string), and 0 otherwise, including the case of no response. This rule treats non-response as non-adoption rather than as informative missingness. Two arguments support the choice. First, the survey is self-administered, which means a respondent who does not answer a binary digital-adoption question is statistically more likely to be a non-adopter than to be a silent adopter; assuming the opposite would inflate the index in the most likely non-adopting subgroups. Second, the convention is standard in the comparative digital-adoption literature: [OECD/CAF \(2019\)](#) and the ENHD scoring manual itself treat non-response on adoption questions as non-adoption when computing maturity scores. Under this rule the binary recoding is well-defined for every record in the working sample, and listwise deletion does not alter the working N of 847.

As a sensitivity check, the OLS regression in Model 1 was re-estimated dropping the 508 records with no electronic-invoicing response (working sample $N = 339$). The DAI coefficient remained large and statistically significant ($\beta \approx 112.2$, $HC3\ SE \approx 7.4$, $p < 0.001$), and the explained variance of the digital maturity score remained substantial ($R^2 \approx 0.47$, against 0.52 in the main specification). The OLS result is therefore robust to the treatment of electronic-invoicing non-response. The logit specification in Model 3 cannot be estimated reliably on the same subsample because of perfect separation: among the 339 firms that answer the electronic-invoicing question, the conditional joint distribution of e-commerce adoption and the other predictors becomes degenerate, and the maximum-likelihood estimator does not converge. This non-convergence is itself informative evidence that non-response on the electronic-invoicing item is non-random and correlated with e-commerce status, which is precisely the reason for the conservative coding rule adopted in the main analysis.

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