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Digital Infrastructure and the Performance of Logistics Startups and Smes in Silicon Mountain, Cameroon: The Mediating Role of Organisational Culture

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ABSTRACT: This study examines the relationship between digital infrastructure and the performance of logistics startups and small and medium-sized enterprises (SMEs) in Silicon Mountain, Cameroon's technology cluster in Fako Division, and tests whether organisational culture mediates that relationship. Drawing on the resource-based view and dynamic capabilities theory, the study proposes that digital infrastructure provides the technology base on which organisational practices of skill development, coordination, and information sharing are built, and that these cultural practices in turn drive logistics performance. Data were collected from 308 logistics firms through a cross-sectional survey and analysed using partial least squares structural equation modelling (PLS-SEM). The results show that digital infrastructure is positively related to logistics performance both directly ($\beta = 0.270$, $p < .001$) and indirectly through organisational culture ($\beta = 0.310$, $p < .001$), with culture accounting for approximately 53% of the total effect. Digital infrastructure was strongly associated with organisational culture ($\beta = 0.659$, $p < .001$), and culture was positively related to logistics performance ($\beta = 0.470$, $p < .001$). The model explained 43.4% of the variance in organisational culture and 46.1% in logistics performance. The mediation is complementary (partial), indicating that infrastructure supports performance through both direct system reliability benefits and indirect organisational practices. The findings contribute to the dynamic capabilities literature by positioning organisational culture as a channel through which technology infrastructure affects performance rather than only as a moderator, and they extend digital transformation research to an understudied Central African context. Practical implications suggest that infrastructure investment by founders, ecosystem organisers, and policymakers should be paired with support for organisational practices and skills development. The study is limited by its cross-sectional design, self-reported measures, and incomplete discriminant validity between culture and performance (HTMT = 0.924), which qualify the interpretation of the mediation results.

KEYWORDS: digital infrastructure, logistics performance, organisational culture, Silicon Mountain, SMEs, startups, Cameroon, PLS-SEM

1. INTRODUCTION

Logistics is basically where an economy's trade objectives and goals meet its physical and informational limits (Gani, 2017). In the World Bank's 2023 Logistics Performance Index (LPI), Cameroon scored 2.1 on a five-point scale and ranked 134th of 139 economies (Jean-François Arvis, Lauri Ojala,Ben Shepherd, 2023), World Bank report, 2023. In this study, the lowest component score was for tracking and tracing (1.8, ranked 136th), and it placed 138th on timeliness (World Bank, 2023). This shortfall is neither purely a matter of roads and ports but something much more. Knowing where a consignment is, and being able to say when it will arrive, are largely questions of information, and information is what digital infrastructure is built to carry (Ryuichi YOSHIMOTO, Toshinori NEMOTO,, 2005). Silicon Mountain, the technology cluster centred on Buea in Fako Division, is the clearest Cameroonian example of an environment in which such infrastructure could be put to work (Godlove Suila Kuaban, Valery Nkemeni, Onyeka J. Nwobodo, Piotr Czekalski, 2024). A recent survey indicated that there exist startups in the ecosystem, supported by technology hubs, developer communities, and a university base (Kuaban et al., 2024). The same survey records that members regard financing, skills, and policy as their main constraints, and that only about a third identified logistics as a promising application area for new technology (Kuaban et al., 2024). The ecosystem has the capability to build digital logistics, but it is not obvious that investment in digital infrastructure pays off for the logistics firms, startups and established small and medium-sized enterprises (SMEs) alike, that operate within it. The evidence from Cameroon is not encouraging. The most directly relevant study surveyed logistics-related firms and found that technology adoption and digital skills were significantly associated with logistics performance, whereas digital infrastructure was not (Ntule et al., 2024). The result matches a long-standing observation in information systems research that technology investment does not translate automatically into measured performance (Brynjolfsson, 1993). If infrastructure matters only through something else, the something else needs to be identified and this study is out to ascertain.

This paper proposes organisational culture as that mechanism. Culture governs how people develop skills, share information, coordinate work, and learn from problems, and these are the processes through which a technology base becomes better service. Research the impact of digitalization on firm performance: examining the role of digital culture and the effect of supply chain capability (Hautala-Kankaanpää, 2022) and the study treated culture as a prerequisite or moderator. Also, Martínez-Caro et al. (2020) argue that firms realise value from digital technologies only when

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they develop a supporting digital culture, and Hautala-Kankaanpää (2022) finds that digital culture helps explain how digital platforms affect operational performance. Less attention has gone to the possibility that infrastructure itself shapes culture, which would make culture a channel through which infrastructure acts. Shared systems make information visible across the organisation and create occasions for review, and these are the conditions under which coordination and learning practices form.

The study asks whether digital infrastructure is related to the performance of logistics startups and SMEs in Silicon Mountain and whether organisational culture carries part of that relationship. It tests four hypotheses on data from 308 startups and SMEs in Fako Division Cameroon using partial least squares structural equation modelling (PLS-SEM). It contributes by isolating one technology layer instead of using an aggregate adoption score, by testing culture as a mechanism and not only as a moderator, and by providing evidence from a Central African ecosystem that is largely absent from the logistics literature. Section 2 describes the context, Section 3 develops the theory and hypotheses, Section 4 describes the method, Section 5 reports the results, and Section 6 discusses them. Section 7 states limitations and Section 8 concludes.

2. RESEARCH CONTEXT

2.1 Silicon Mountain

Silicon Mountain is the technology ecosystem of Fako Division, centred on Buea in Cameroon's South West Region. Kuaban et al. (2024) trace its origin to 2006, when young web developers in the town began building a community, and date its rise in prominence to the years after the first cohort of engineering and technology graduates left the University of Buea in December 2014 and the first Silicon Mountain Conference was held in June 2015. By their count the ecosystem comprises more than fifty registered and active startups, seven technology hubs, five developer communities, and seven technology-oriented higher education institutions. Cameroon's other main clusters, Silicon Wouri and Silicon River, are in Douala and Yaoundé.

Two features matter here. The first is institutional density: universities, hubs, and developer communities sit close together, which shortens the paths along which practices and knowledge travel between firms. That density is a reason to expect that organisational routines can be shaped by shared infrastructure and shared learning. The second is the infrastructure profile. About half of the respondents in the Kuaban et al. (2024) survey rated poor connectivity and unreliable power as not serious problems, although the authors caution that this probably reflects the relatively better infrastructure ecosystem members enjoy compared with other parts of Cameroon and Central Africa. Infrastructure quality in the cluster is therefore likely to vary across firms, which gives the independent variable the spread it needs.

2.2 Logistics in Cameroon

The LPI positions Cameroon extremely far from the leading economies, with weak tracking and timeliness (World Bank, 2023) as indicated earlier. However, this index describes trade logistics as observed by international freight professionals and does not describe how domestic courier, delivery, or warehousing firms perform, yet the LPI is also indicating of the operational environment those firms inherit. Research on Sub-Saharan Africa has begun to treat digitalisation as a possible shortcut. Kuteyi and Winkler (2022) combined a structured literature review with interviews to identify the region's logistics challenges and the opportunities to leapfrog conventional practices, and they point to human capital training and to infrastructure and institutional improvement as important drivers.

3. THEORY AND HYPOTHESES

3.1 Digital infrastructure

Vial (2019) describes digital transformation as a process in which digital technologies trigger strategic responses and structural change that alter how a firm creates value, and Verhoef et al. (2021) describe a progression from digitisation through digitalisation to transformation. Digital infrastructure is the foundation of that progression: the underlying technology base on which applications and routines are built. In this study it refers to the firm's power resilience for digital systems, integrated software, secure and retrievable data, links with customers, partners, and platforms, and field devices and tools. It is shared and enabling instead of task-specific. A firm can own it without exploiting it, which is why its effect on performance is an empirical question.

3.2 Logistics performance

Mentzer and Konrad (1991) separated logistics performance into efficiency, the economical use of resources, and effectiveness, the achievement of goals, and Chow et al. (1994) review how logistics performance has been defined and measured. This study measures logistics performance (LP) as a single construct: the firm's operational performance relative to its main competitors over the previous twelve months, indicated by order-handling productivity, order-processing speed, and the avoidance of wasted resources through failed or repeated deliveries. Relative, perceived performance is used because objective indicators are rarely recorded consistently in young and small firms.

3.3 Resources, capabilities, and culture

The resource-based view holds that sustained advantage comes from resources that are valuable, rare, inimitable, and not readily substituted (Barney, 1991). Infrastructure is, taken alone, a weak candidate, since most of its components can be bought. Dynamic capabilities theory supplies the connection. Teece et al. (1997) define dynamic capabilities as a firm's ability to integrate, build, and reconfigure competences in changing environments, and Eisenhardt and Martin (2000) argue that advantage lies in how resources are configured and not in the capabilities themselves. On this view, the performance value of infrastructure depends on what the organisation builds on it.

Culture is a natural candidate for what is built. Schein (2010) describes culture as the shared assumptions that guide how members perceive and respond to problems, and notes that founders and leaders play a central part in embedding it. Barney (1986) argued that culture can itself be a source of sustained advantage when it is valuable, rare, and difficult to imitate. In this study organisational culture (OC) refers to the shared practices through which a firm develops its people, coordinates its work, and keeps its members informed (Appendix A).

3.4 Hypotheses

Direct effect. Dependable infrastructure should reduce duplicated effort and errors, support reliable order handling, and improve information flow, all of which bear on operational performance. Regional work identifies infrastructure investment as a driver of logistics growth (Kuteyi & Winkler,

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2022). The Cameroonian evidence is less encouraging, since infrastructure was not significantly related to performance (Ntule et al., 2024), and the productivity paradox literature supports caution (Brynjolfsson, 1993). The expectation is nonetheless positive.

H1. Digital infrastructure is positively related to logistics performance (direct effect, c′).

Infrastructure and culture. The direction of influence between technology and culture is contested. Martínez-Caro et al. (2020) treat digital culture as a prerequisite for realising technology's value. Pradana et al. (2022) note that adopting new technologies can influence culture, even though their own results suggest that digitalisation did not strongly affect digital organisational values. Three considerations favour an effect of infrastructure on culture in logistics startups and SMEs. Shared systems make operational information visible across the organisation, which changes how teams coordinate. Data from those systems create occasions for review, which supports learning. And the cultures of young and small firms are still malleable, so the practices that infrastructure makes possible can settle into routine more quickly than in older, larger organisations. A positive relationship is therefore proposed.

H2. Digital infrastructure is positively related to organisational culture (path a).

Culture and performance. A culture of skill development, coordination, and information sharing should improve operational performance, because these are the processes by which resources are used well and problems are caught early (Barney, 1986; Schein, 2010). A caution comes from Leonard-Barton (1992), who showed that strongly held routines can harden into rigidities, but in firms whose routines are young the beneficial reading is more plausible.

H3. Organisational culture is positively related to logistics performance (path b).

Mediation. If infrastructure shapes culture and culture drives performance, part of the effect of infrastructure on performance should travel through culture. Because infrastructure can also help directly, as in resilience of digital systems during power outages, partial mediation is expected. Hautala-Kankaanpää (2022) provides a related precedent in a different form: supply chain capability mediated the effect of digital platforms on operational performance, and culture shaped the strength of that effect.

H4. Organisational culture mediates the relationship between digital infrastructure and logistics performance (indirect effect a × b).

Figure 1 summarises the model.

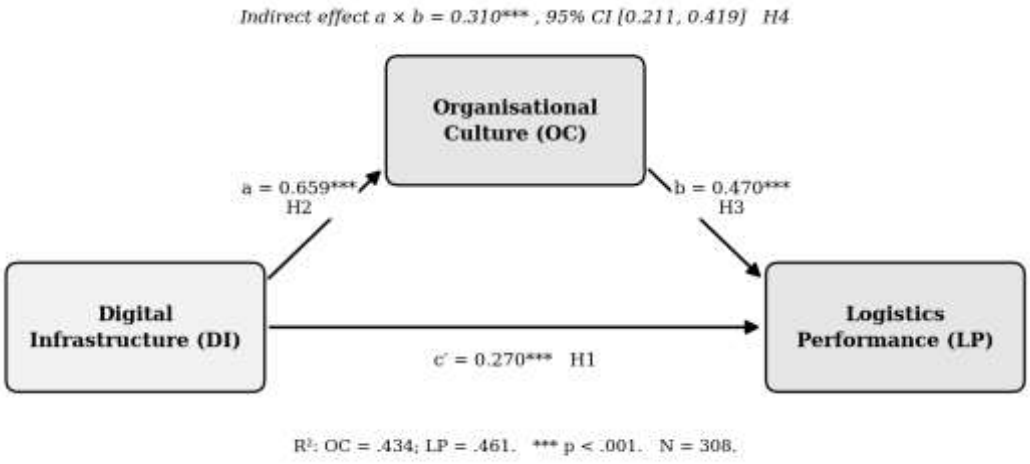

Figure 1. Research model with standardised path coefficients (N = 308).

4. METHOD

4.1 Design, sample, and procedure

The study used a cross-sectional survey of owners and managers of independent logistics firms, including startups and SMEs, operating in Silicon Mountain (Fako Division). Eligible firms were those whose main activity lies in the logistics chain: freight and haulage, courier and last-mile delivery, warehousing and fulfilment, or logistics technology and platforms. The study was widened from startups alone to include SMEs in order to obtain a sample large enough for structural modelling. The size criteria used to define SMEs, the sampling procedure, the data collection period and mode, the response rate, and the number of questionnaires removed during data cleaning and the criteria applied were 12 due to respondents' misconduct. Also, participants who did not respondent to 70% of the questions. After cleaning, 308 complete responses were retained, with no missing values on any retained indicator. Participation was voluntary and anonymous, informed consent was obtained, and results are reported in aggregate only.

4.2 Measures

All items were measured on five-point agreement scales (1 = strongly disagree, 5 = strongly agree). After measurement purification, five indicators of digital infrastructure (DI2 to DI6), three of organisational culture (OC1 to OC3), and three of logistics performance (LP3 to LP5) were retained; the remaining items (DI1, LP1, LP2,) were removed poor loadings, poor AVE and discriminant validity. Digital infrastructure items focused on the resilience of digital systems to power outages, integration of core operations on software, secure and retrievable data, connection with customers, partners or platforms, and field devices. Logistics performance items asked respondents to compare their firm with main competitors over the previous twelve months on orders handled per person, speed of order processing, and waste from failed or repeated deliveries. These items after purifications were ready for analysis.

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4.3 Analysis

The model was estimated by PLS-SEM in SmartPLS 4.1.1.9 (Ringle et al., 2024), which suits prediction-oriented models and do not have the stringent and better still makes few distributional assumptions, and evaluates paths by bootstrapping (Hair et al., 2019, 2021). The model adopted for this study was modelled as reflective. The factor weighting scheme was used with a maximum of 3,000 iterations and a stop criterion of 10^{-7}. For the results, significance was assessed with 5,000 bootstrap samples, a fixed seed, two-tailed tests, and percentile confidence intervals; bias-corrected intervals are also reported for the indirect effect. The mediation pattern was classified with the typology of Zhao et al. (2010), following Nitzl et al. (2016), and the four hypotheses were evaluated with the Holm (1979) sequential procedure at a level of .05.

The output for this study included the path coefficients, loadings, weights, confidence intervals, and descriptive statistics. These were computed independently from the indicator data by re-implementing the PLS algorithm, which reproduced every path coefficient, loading, weight, and bootstrap standard error in the report to the reported precision. They are: composite reliability, Cronbach's alpha, ρA, average variance extracted, heterotrait-monotrait ratios (HTMT) with bootstrapped intervals, cross-loadings, variance inflation factors, R^2, f^2, predictive power (10-fold cross-validation repeated ten times, following Shmueli et al., 2019), the model-implied SRMR, and the robustness analyses. Common method variance was assessed with the full collinearity test (Kock, 2015) and Harman's single-factor test, and careless responding was examined by counting respondents who gave identical answers to all eleven indicators (Meade & Craig, 2012). The assessment criteria follow Hair et al. (2019) and Henseler et al. (2015): outer loadings of at least 0.708, composite reliability between 0.70 and 0.95, AVE of at least 0.50, HTMT below 0.90, and variance inflation factors below 3.

5. RESULTS

5.1 Data screening

There were no missing values. Table 1 reports descriptive statistics. Means ranged from 4.00 to 4.23 on the five-point scale, and between 36% and 44% of respondents chose the highest category on each indicator. All indicators were negatively skewed (skewness −0.88 to −1.35), and the Cramér–von Mises tests rejected normality for every indicator ($p < .001$), which supports the use of a distribution-free estimator such as PLS-SEM. This was also expected especially for likert item constructs. Thirty-one respondents (10.1%) gave identical answers to all eleven indicators (22 answered 5 throughout, seven 4, and two 3). Because uniformly high agreement is plausible among well-performing firms, they were retained in the main analysis, and the model was re-estimated without them

Table 2. Descriptive statistics of retained indicators (N = 308)

Indicator	Mean	SD	Skewness	Excess kurtosis	% answering 5
DI2	4.10	0.95	−1.24	1.64	38.6
DI3	4.11	0.92	−1.19	1.63	37.7
DI4	4.12	0.89	−1.32	2.27	36.0
DI5	4.15	0.90	−1.20	1.64	39.9
DI6	4.21	0.83	−1.21	2.08	40.6
LP3	4.18	0.89	−0.97	0.55	42.9
LP4	4.19	0.86	−1.35	2.60	40.3
LP5	4.23	0.85	−1.21	1.73	43.8
OC1	4.07	0.95	−1.05	0.95	37.7
OC2	4.00	0.99	−0.98	0.65	35.7
OC3	4.10	0.88	−0.88	0.59	37.3

5.2 Measurement model

All outer loadings exceeded 0.708 and were significant ($p < .001$; Table 3). Composite reliability was 0.865 for digital infrastructure, 0.853 for organisational culture, and 0.812 for logistics performance, all within the 0.70 to 0.95 range, and AVE ranged from 0.563 to 0.660, above the 0.50 threshold. Cronbach's alpha was 0.807 for DI and 0.742 for OC. For LP, alpha (0.653) and ρA (0.656) fell just below 0.70 while composite reliability was satisfactory, and alpha, which assumes equal indicator weights, is conservative for a three-item scale; the scale is adequate but the least reliable of the three. Indicator variance inflation factors were low (1.26 to 1.67). However this was maintained given the reliability from the other constructs.

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Table 3. Indicator loadings, reliability, and convergent validity

Construct	Loadings (t)	α	ρA	CR	AVE	Indicator VIF
DI	0.720–0.776 (15.1–30.5)	0.807	0.819	0.865	0.563	1.49–1.67
OC	0.777–0.855 (21.7–45.0)	0.742	0.755	0.853	0.660	1.42–1.57
LP	0.751–0.794 (17.4–23.4)	0.653	0.656	0.812	0.590	1.26–1.30

Note. DI = digital infrastructure (5 indicators); OC = organisational culture (3); LP = logistics performance (3). CR = composite reliability (ρc); AVE = average variance extracted. Loadings are significant at $p < .001$.

Discriminant validity gave a mixed result (Table 4). The Fornell–Larcker criterion was met: the square root of each construct's AVE (0.750, 0.813, and 0.768) exceeded its correlations with the other constructs (at most 0.659), and every indicator loaded highest on its own construct, with the largest cross-loading at 0.610. HTMT was 0.828 for DI and OC and 0.779 for DI and LP, both below 0.85 in point estimate, but 0.924 for OC and LP, above the 0.90 threshold, and its bootstrapped 95% interval [0.806, 1.041] included 1. Discriminant validity between culture and performance was therefore not fully established by the stricter criterion. This matters for the interpretation of H3 and H4 and is taken up in Section 7.

Table 4. Discriminant validity

Construct	DI	OC	LP	HTMT with 95% CI
DI	0.750			
OC	0.659	0.813		DI–OC: 0.828 [0.731, 0.921]
LP	0.580	0.648	0.768	DI–LP: 0.779 [0.624, 0.927]
				OC–LP: 0.924 [0.806, 1.041]

Note. Diagonal entries are the square roots of AVE; off-diagonal entries are latent variable correlations (Fornell–Larcker criterion). HTMT intervals are percentile intervals from 5,000 bootstrap samples.

Common method variance did not appear to threaten the results. The first unrotated factor accounted for 45.0% of the variance in the eleven indicators, below the 50% level, and full collinearity variance inflation factors were 1.90 (DI), 2.18 (OC), and 1.86 (LP), below the 3.3 threshold (Kock, 2015). These tests are limited, since all data are self-reported from one respondent per firm. The model-implied SRMR, computed independently, was 0.09 (0.08 when diagonal elements are included), marginally above the 0.08 guideline; because the structural model is saturated, the value reflects the measurement part only, and global fit is given limited weight in prediction-oriented PLS-SEM (Hair et al., 2019).

5.3 Structural Model and Hypothesis Tests

Table 5 reports the structural estimates and Table 6 the decisions. All four hypotheses were supported. Digital infrastructure had a positive direct and significant effect on logistics performance (H1: $\beta = 0.270$, SE = 0.079, $t = 3.44$, 95% CI [0.119, 0.426]). Also, this study uncovered that there is a strong positive and significant effect on organisational culture (H2: $\beta = 0.659$, SE = 0.039, $t = 16.77$, 95% CI [0.581, 0.734]). Culture was positively related to performance (H3: $\beta = 0.470$, SE = 0.071, $t = 6.63$, 95% CI [0.326, 0.606]). The indirect effect of infrastructure on performance through culture was positive and significant (H4: $\beta = 0.310$, SE = 0.054, $t = 5.78$, 95% CI [0.211, 0.419]; bias-corrected 95% CI [0.214, 0.423]).

Table 5. Structural model estimates (5,000 bootstrap samples)

Path	β	SE	t	p	95% CI (percentile)
DI → OC (a)	0.659	0.039	16.77	< .001	[0.581, 0.734]
OC → LP (b)	0.470	0.071	6.63	< .001	[0.326, 0.606]
DI → LP (c′, direct)	0.270	0.079	3.44	< .001	[0.119, 0.426]
DI → OC → LP (a × b)	0.310	0.054	5.78	< .001	[0.211, 0.419]
DI → LP (total)	0.580	0.053	10.87	< .001	[0.473, 0.682]

Note. β = standardised path coefficient. SE = bootstrap standard deviation. Two-tailed p values; exact values below .001 are not reported.

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The findings revealed that both were positive. Because the direct and indirect effects were both positive and significant, the mediation is complementary (partial) in the typology of Zhao et al. (2010). About 53% of the total effect (0.310 of 0.580) operated through culture, and the remainder was direct. This proportion is descriptive and should be read with caution, given the cross-sectional design. Table 6 applies the Holm procedure; all four hypotheses remained significant after adjustment.

Table 6. Hypothesis decisions

ID	Path	Raw p	Holm-adjusted p	Decision
H1	DI → LP (direct)	< .001	< .001	Supported
H2	DI → OC	< .001	< .001	Supported
H3	OC → LP	< .001	< .001	Supported
H4	DI → OC → LP (indirect)	< .001	< .001	Supported (complementary partial mediation)

5.4 Explained variance and effect sizes

The model explained 43.4% of the variance in organisational culture (adjusted R^2 = .432) and 46.1% in logistics performance (adjusted R^2 = .458). By the conventions of Hair et al. (2019), these values are weak to moderate, approaching the 0.50 level labelled moderate. Effect sizes (Cohen, 1988) showed a large effect of infrastructure on culture (f^2 = 0.77), a medium-to-large effect of culture on performance (f^2 = 0.23), and a small effect of infrastructure on performance once culture was included (f^2 = 0.08). Inner variance inflation factors were 1.77 for both predictors of performance, indicating no collinearity concern.

5.5 Predictive relevance

Cross-validated predictions had positive Q^2predict values for all six endogenous indicators (0.157 to 0.347; see Table 7), so the model predicts better than simply using the training mean. Compared with a linear regression benchmark that uses the infrastructure indicators directly, the PLS model gave lower prediction error for five of the six indicators and slightly higher for one (OC2), which indicates medium predictive power (Shmueli et al., 2019).

Table 7. Predictive power of endogenous indicators

Indicator	Q^2predict	RMSE (PLS)	RMSE (LM)	PLS lower?
OC1	0.347	0.766	0.768	Yes
OC2	0.266	0.853	0.850	No
OC3	0.214	0.783	0.787	Yes
LP3	0.157	0.815	0.827	Yes
LP4	0.156	0.794	0.795	Yes
LP5	0.242	0.745	0.751	Yes

Note. RMSE = root mean squared error; LM = linear regression benchmark. Ten-fold cross-validation repeated ten times.

5.6 Robustness checks

Two checks were run. First, the 31 respondents who gave identical answers to all indicators were removed (n = 277) and the model re-estimated. All paths remained positive and significant, with smaller magnitudes: DI → OC β = 0.611 (95% CI [0.525, 0.700]), OC → LP β = 0.449 ([0.300, 0.587]), the direct effect β = 0.243 ([0.084, 0.404]), and the indirect effect β = 0.275 ([0.177, 0.386]); R^2 fell to .373 for culture and .394 for performance, and HTMT for OC and LP was 0.910 (interval [0.760, 1.053]). The conclusions were unchanged, and the larger estimates in the full sample are partly attributable to uniformly high respondents.

Second, because the three constructs are connected by all three possible paths, the model is just identified, and alternative causal orderings fit the data identically. In the reversed ordering, in which culture precedes infrastructure, culture's effect on performance operates partly through infrastructure (indirect effect = 0.178, 95% CI [0.082, 0.285]), with the same R^2 for performance.

6. DISCUSSION

6.1 Principal findings

Digital infrastructure was positively related to the performance of logistics startups and SMEs in Silicon Mountain, and about half of that relationship was associated with organisational culture. The finding is consistent with the view that technology investment pays off through what the organisation builds on it (Eisenhardt & Martin, 2000), and it extends work that treats culture as a precondition for value from digital technologies (Hautala-Kankaanpää, 2022; Martínez-Caro et al., 2020) by showing that, in this sample, culture is also strongly associated with infrastructure. The size of that association (β = 0.659, f^2 = 0.77) is the largest in the model.

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The result for the direct effect differs from the earlier Cameroonian finding that digital infrastructure was not significantly related to logistics performance (Ntule et al., 2024). The studies differ in sample, infrastructure measure, and performance measure, so the difference cannot be attributed to any one of them. Two features of the present study may be relevant: the infrastructure measure emphasises resilience, integration, data security, partner links, and field tools and not connectivity itself, and the sample comes from an ecosystem where infrastructure is relatively better than elsewhere in Cameroon (Kuaban et al., 2024). Whether the effect would appear in firms outside such clusters is an open question.

The direct effect remained after culture was included, although its effect size was small ($f^2 = 0.08$). Infrastructure therefore appears to help in two ways: directly, through the reliability and integration of systems, and indirectly, through the organisational practices that shared systems support. The indirect route was the larger of the two.

6.2 Theoretical implications

The study contributes to the dynamic capabilities literature by treating organisational culture as a channel through which a technology base affects performance and not only as a condition that moderates it. The competing evidence that technology can shape culture (Pradana et al., 2022) and that culture can precede technology value (Martínez-Caro et al., 2020) suggests that the two are probably mutually reinforcing, and the just-identified structure of the present model cannot separate them. A longitudinal design is needed to determine the order.

6.3 Practical implications

For founders and managers, the results suggest that infrastructure spending is unlikely to deliver its full benefit unless it is accompanied by attention to the practices of skill development, coordination, and information sharing that the infrastructure makes possible. Systems that connect functions, store data securely, and link the firm with customers and partners create the conditions for those practices, but the practices must still be built. For technology hubs and ecosystem organisers, the findings favour shared training and peer learning alongside access to equipment. For policymakers, financing, skills, and policy were the main constraints reported by Silicon Mountain members (Kuaban et al., 2024); the present results suggest that infrastructure support for logistics firms should be paired with support for skills.

These implications are associational. The effects are statistically clear, but explained variance was moderate, and the direct effect of infrastructure was small once culture was included.

7. LIMITATIONS AND FUTURE RESEARCH

Several limitations qualify the findings. The design is cross-sectional, so the results show association and not causation, and, as Section 5.6 shows, the ordering of infrastructure and culture cannot be determined from the data. All constructs were reported by one respondent per firm; the common method checks were reassuring but are limited tests. Responses were strongly skewed toward agreement, with 36% to 44% choosing the top category on each indicator, which restricts variance and may reflect optimism or social desirability. Ten percent of respondents gave identical answers to every item; the results held when they were removed, but careless responding cannot be ruled out entirely.

Measurement limitations are also important. Logistics performance has three indicators, with alpha and ρA just under 0.70, and its content is limited to productivity, speed, and waste; the cost and equipment-use items were removed during purification, so the construct does not capture cost outcomes or service quality. The infrastructure measure retains no item on connectivity itself. Organisational culture is measured by three indicators and reflects only part of the broader construct. Most importantly, discriminant validity between culture and performance was not fully established (HTMT = 0.924, interval including 1), which means that the two constructs may not be empirically distinct in this sample, and the culture-to-performance path and the mediation result should be interpreted with that in mind. Future work should add culture items that are conceptually remote from performance outcomes, or measure performance with objective indicators.

Finally, the sample combines startups and SMEs, and the data set contains no firm-type variable, so differences between the two groups could not be examined. The model-implied SRMR was marginally above the conventional guideline. The findings apply to logistics firms in Silicon Mountain and should not be assumed to extend to other Cameroonian clusters or to rural operators. Replication across firm types, longitudinal designs, and objective performance indicators would strengthen the evidence.

8. CONCLUSION

Using survey data from 308 logistics startups and SMEs in Silicon Mountain, this study finds that digital infrastructure is positively related to logistics performance both directly and indirectly through organisational culture, with culture accounting for about half of the total effect. The result supports an argument that infrastructure investment works partly through the practices it supports, and it suggests that investment in infrastructure and in organisational practices should proceed together. The conclusions are limited by the cross-sectional, self-reported design, by the narrow content of the performance measure, and by incomplete discriminant validity between culture and performance. Within those limits, the evidence offers founders, ecosystem organisers, and policymakers a practical lesson: infrastructure is necessary, but its benefit depends on the organisation that uses it.

REFERENCES

1) Barney, J. (1986). Organizational culture: Can it be a source of sustained competitive advantage? *Academy of Management Review, 11*(3), 656–665. https://doi.org/10.5465/amr.1986.4306261
2) Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108
3) Brynjolfsson, E. (1993). The productivity paradox of information technology. *Communications of the ACM, 36*(12), 66–77. https://doi.org/10.1145/163298.163309
4) Chow, G., Heaver, T. D., & Henriksson, L. E. (1994). Logistics performance: Definition and measurement. *International Journal of Physical Distribution & Logistics Management, 24*(1), 17–28.
5) Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

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6) Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal, 21*(10–11), 1105–1121.
7) Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
8) Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
9) Hautala-Kankaanpää, T. (2022). The impact of digitalization on firm performance: Examining the role of digital culture and the effect of supply chain capability. *Business Process Management Journal, 28*(8). https://doi.org/10.1108/BPMJ-03-2022-0122
10) Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
11) Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics, 6*(2), 65–70.
12) Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101
13) Kuaban, G. S., Nkemeni, V., Nwobodo, O. J., Czekalski, P., & Mieyeville, F. (2024). Internet of Things adoption in technology ecosystems within the Central African region: The case of Silicon Mountain. *Future Internet, 16*(10), Article 376. https://doi.org/10.3390/fi16100376
14) Kuteyi, D., & Winkler, H. (2022). Logistics challenges in Sub-Saharan Africa and opportunities for digitalization. *Sustainability, 14*(4), Article 2399. https://doi.org/10.3390/su14042399
15) Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal, 13*(S1), 111–125. https://doi.org/10.1002/smj.4250131009
16) Martínez-Caro, E., Cegarra-Navarro, J. G., & Alfonso-Ruiz, F. J. (2020). Digital technologies and firm performance: The role of digital organisational culture. *Technological Forecasting and Social Change, 154*, Article 119962. https://doi.org/10.1016/j.techfore.2020.119962
17) Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods, 17*(3), 437–455. https://doi.org/10.1037/a0028085
18) Mentzer, J. T., & Konrad, B. P. (1991). An efficiency/effectiveness approach to logistics performance analysis. *Journal of Business Logistics, 12*(1), 33–62.
19) Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems, 116*(9), 1849–1864. https://doi.org/10.1108/IMDS-07-2015-0302
20) Ntule, N. D., Ongo Nkoa, B. E., & Fuein, V. (2024). Effect of digitalization on logistics performance among logistics related companies in Cameroon. *American Journal of Supply Chain Management, 9*(3), 1–16. https://doi.org/10.47672/ajscm.2099
21) Pradana, M., Silvianita, A., Syarifuddin, S., & Renaldi, R. (2022). The implication of digital organisational culture on firm performance. *Frontiers in Psychology, 13*, Article 840699. https://doi.org/10.3389/fpsyg.2022.840699
22) Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4* [Computer software]. SmartPLS. https://www.smartpls.com
23) Schein, E. H. (2010). *Organizational culture and leadership* (4th ed.). Jossey-Bass.
24) Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189
25) Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533.
26) Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022
27) Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems, 28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003
28) World Bank. (2023). *Logistics Performance Index 2023* [Data set]. https://lpi.worldbank.org/international/global
29) Zhao, X., Lynch, J. G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197–206. https://doi.org/10.1086/651257

Appendix A. Retained Indicators

Five-point agreement scale: 1 = strongly disagree, 5 = strongly agree. Performance items are relative to main competitors over the last 12 months.

Code	Statement	Construct
DI2	Our digital systems keep running during power outages.	DI
DI3	Our core operations run on integrated software systems rather than separate manual records.	DI
DI4	Our operational data are stored securely and can be retrieved whenever needed.	DI
DI5	Our systems connect with those of our customers, partners, or platforms.	DI

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Code	Statement	Construct
DI6	Our staff in the field have the devices and tools needed to use our digital systems.	DI
OC1	Our firm invests in developing the skills of its staff.	OC
OC2	Staff receive the training they need to do their work well.	OC
OC3	Our firm builds the capabilities it will need for future growth.	OC
LP3	Our staff handle more orders per person than our competitors' staff.	LP
LP4	We process orders faster than our competitors.	LP
LP5	We waste fewer resources through failed or repeated deliveries than our competitors.	LP

Items removed during purification: DI1 ("Our firm has reliable internet connectivity at every location where we operate."); LP1 ("Our cost per delivery is lower than that of our competitors."); LP2 ("We use our vehicles and equipment more fully than our competitors."); and the culture items not listed above [list].

Appendix B. Indicator Loadings and Cross-Loadings

Indicator	DI	OC	LP	Own-construct t (bootstrap)	Highest on own?
DI2	0.773	0.480	0.438	22.46	Yes
DI3	0.759	0.519	0.379	19.71	Yes
DI4	0.720	0.416	0.368	16.09	Yes
DI5	0.776	0.610	0.554	30.49	Yes
DI6	0.721	0.400	0.394	15.07	Yes
LP3	0.411	0.512	0.760	17.45	Yes
LP4	0.411	0.482	0.751	19.24	Yes
LP5	0.509	0.499	0.794	23.43	Yes
OC1	0.597	0.855	0.597	44.98	Yes
OC2	0.525	0.803	0.491	27.11	Yes
OC3	0.475	0.777	0.482	21.73	Yes

Note. In each row, the value under the indicator's own construct is its outer loading; the other two values are cross-loadings. All loadings are significant at $p < .001$.

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