

Benchmarking Practices in the Digital Age: Adapting to Technological Innovations

Received: 23/03/2026

Accepted: xx/xx/xxxx

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Abstract:

Traditional benchmarking frameworks are increasingly inadequate for organizations facing accelerating technological disruption in digital economies. This study examines how Digital Benchmarking Capability (DBC) — integrating performance monitoring, competitive intelligence, digital analytics, process benchmarking, innovation tracking, and adaptive recalibration — generates sustainable competitive advantage in Algerian organizations.

The model tests three mediated pathways through Operational Performance, Innovation Capability, and Strategic Agility, with Technology Innovation Intensity moderating the relationship between Innovation Capability and Competitive Advantage.

A mixed-methods design combining PLS-SEM with expert interviews was applied across five Algerian sectors. All hypotheses were confirmed: DBC directly predicts competitive advantage, all three mediation pathways proved statistically significant, and Technology Innovation Intensity significantly moderates the innovation-advantage relationship, with the model explaining a substantial portion of variance in competitive advantage.

Keywords: Digital Benchmarking; Competitive Advantage; Dynamic Capabilities; PLS-SEM; Algeria.

Jel Classification Codes : M10, M15, O30, L20.

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1. INTRODUCTION

Benchmarking — the systematic comparison of organizational performance against best-in-class standards (Camp, 1989) — has been a cornerstone of strategic management for decades. Yet the digital revolution has rendered the foundational assumptions of traditional benchmarking increasingly untenable. Where conventional approaches relied on periodic data collection and static performance comparisons, the digital age demands continuous, real-time, AI-augmented performance intelligence (Schrage et al., 2024; Chowdhury et al., 2024).

Organizations that successfully exploit digital tools — big data analytics, machine learning, real-time dashboards, and Industry 4.0 platforms — to build superior performance intelligence systems gain measurable advantages in operational efficiency, innovation responsiveness, and strategic positioning. This study terms such a system Digital Benchmarking Capability (DBC). In Algeria, with internet penetration at 72% and enterprise digitalization growing at 18% annually (DataReportal, 2024), five key sectors are simultaneously undergoing rapid digitalization: Telecommunications & ICT, Financial Services & Banking, Retail & E-Commerce, Education & Training, and Health & Pharmacy.

1.1. The question of the study:

In the digital economy, traditional benchmarking frameworks are no longer adequate for organizations facing accelerating technological disruption. Despite growing digital tool adoption across Algerian organizations, a significant gap remains regarding:

To what extent does Digital Benchmarking Capability (DBC) generate sustainable competitive advantage in Algerian organizations, through which mediating mechanisms does this

relationship operate, and do competitive returns vary according to the technological intensity of the sector environment?

This study therefore raises the following research sub questions:

- Does DBC directly predict competitive advantage in Algerian organizations?
- Does Operational Performance mediate the DBC – competitive advantage relationship?
- Does Innovation Capability mediate the DBC – competitive advantage relationship?
- Does Strategic Agility mediate the DBC – competitive advantage relationship?
- does Technology Innovation Intensity moderate the Innovation Capability – Competitive Advantage relationship, such that DBC returns are significantly stronger in high-technology-intensity sector environments?
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1.2. Hypothesis:

In light of the literature review, the following research hypotheses are put forward:

- **H1:** DBC exerts a significant positive direct effect on organizational competitive advantage across the five Algerian sectors studied.
- **H2:** Operational Performance Enhancement positively mediates the DBC – Competitive Advantage relationship, such that DBC improves process efficiency and service quality which in turn generate competitive advantage.
- **H3:** Innovation Capability Development positively mediates the DBC – Competitive Advantage relationship,

such that AI-powered competitive intelligence expands organizational innovation capacity.

- **H4:** Strategic Agility positively mediates the DBC – Competitive Advantage relationship, such that real-time monitoring enables rapid sensing and resource reconfiguration.
- **H5:** Technology Innovation Intensity positively moderates the Innovation Capability → Competitive Advantage relationship: the effect is stronger in high-TII sectors (Telecommunications; Financial Services) than in lower-TII sectors (Education; Health).

1.3. The Objectif of the study:

This study pursues four primary objectives:

- To conceptualize Digital Benchmarking Capability (DBC) as a multi-dimensional organizational construct integrating performance monitoring, competitive intelligence, digital analytics, process benchmarking, innovation tracking, and adaptive recalibration;
- To empirically test the direct effect of DBC on competitive advantage across five Algerian organizational sectors;
- To identify and validate the mediating mechanisms — Operational Performance, Innovation Capability, and Strategic Agility — through which DBC generates competitive advantage;
- To examine the moderating role of Technology Innovation Intensity on the Innovation Capability – Competitive Advantage relationship, determining whether DBC returns are amplified in high-technology-intensity sector environments.

1.4. The importance of the study:

This study provides an empirically validated specification of Digital Benchmarking Capability (DBC) as a multi-dimensional dynamic capability in the Algerian organizational context.

- It advances theoretical understanding by integrating three complementary frameworks — Resource-Based View (Barney, 1991), Dynamic Capabilities Theory (Teece et al., 1998), and Market Orientation (Narver & Slater, 1990) — within a unified PLS-SEM model.
- It identifies and validates three mediating mechanisms — Operational Performance, Innovation Capability, and Strategic Agility — through which DBC generates sustainable competitive advantage.
- It empirically confirms Technology Innovation Intensity as a boundary condition moderating the innovation-advantage relationship, extending ecosystem fit theory to the digital benchmarking domain.
- It offers a locally grounded benchmark for future comparative and longitudinal digital management research in Algeria and analogous emerging market economies.

1.5. Methodology:

This study addresses three research gaps:

- The theoretical specification of DBC as an integrative dynamic capability;
- The identification of mediating mechanisms connecting DBC to competitive advantage across five Algerian sectors;
- The moderating role of Technology Innovation Intensity in these relationships.
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The study is geographically delimited to Algeria, spanning five organizational sectors: Telecommunications & ICT, Financial Services & Banking, Retail & E-Commerce, Education & Training, and Health & Pharmacy. The sample comprises senior managers, strategy directors, and digital transformation officers operating within Algerian public and private sector organizations. Findings are contextually bounded to Algeria's digital transformation trajectory and require cross-national replication before broader generalization.

This study employs a mixed-methods design combining quantitative PLS-SEM with qualitative in-depth interviews. The qualitative phase comprised 8 semi-structured expert interviews with Chief Digital Officers, IT Directors, and performance management consultants across the five Algerian sectors. Data collection was conducted between January and March 2025.

2. THEORETICAL FRAMEWORK

This study is theoretically positioned at the nexus of digital transformation, performance management, and strategic management. It specifically concentrates on benchmarking practices designed for digitally enabled and technology-intensive contexts, while explicitly excluding traditional analog benchmarking approaches as well as performance management systems that do not contribute to the development of digital capabilities.

2.1. Theoretical Pillars

2.1.1. Resource-Based View — Barney (1991)

Barney's (1991) RBV posits that sustainable competitive advantage derives from resources that are Valuable, Rare, Imperfectly imitable, and Non-substitutable (VRIN). DBC constitutes a VRIN resource cluster: valuable because superior

performance intelligence directly enhances decision quality; rare because advanced AI-driven benchmarking infrastructure remains scarce in Algeria's emerging market context; imperfectly imitable because DBC is embedded in organizational data architectures and analytical routines resistant to replication; and non-substitutable as no alternative activity provides equivalent competitive performance intelligence. Wamba et al. (2017) and Vorhies and Morgan (2005) empirically confirmed that firm-specific analytical capabilities generate above-normal competitive returns through systematic processes.

2.1.2. Dynamic Capabilities Theory — Teece et al. (1998)

Teece et al. (1997) posit that sustainable advantage in turbulent environments requires capacity to sense opportunities, seize them, and reconfigure resources dynamically. DBC is paradigmatically dynamic: AI-enhanced monitoring continuously senses competitive shifts; real-time dashboards enable rapid seizing of improvement opportunities; and data-driven reconfiguration triggers continuous organizational transformation. Karaboga et al. (2023) confirmed that data-driven culture mediates the capability-performance relationship by enabling this sensing-seizing-reconfiguring cycle. Technology Innovation Intensity moderation (H5) directly operationalizes Teece et al.'s (1998) environmental dynamism prediction.

2.1.3. Balanced Scorecard — Kaplan and Norton (1992)

Kaplan and Norton (1992) conceptualize organizational performance across four perspectives: financial, customer, internal processes, and learning and growth. The BSC provides the performance dimensionality framework for DBC operationalization, requiring simultaneous measurement across all four perspectives with real-time data streams that traditional BSC implementations could not sustain. Chowdhury et al. (2024) confirmed that digital transformation forces BSC-type systems

toward greater adaptability and real-time responsiveness. The three mediating mechanisms — operational performance, innovation capability, and strategic agility — map directly onto the BSC's internal process, learning and growth, and strategic perspectives respectively.

2.2. From Traditional to Digital Benchmarking

Camp (1989) systematized benchmarking through the Xerox model, while Spendolini (1992) and Zairi (1996) extended the typology across process, product, and strategic dimensions. These frameworks share a critical constraint: they treat performance measurement as a retrospective, periodic activity. Hanelt et al. (2020), in a systematic review of 174 digital transformation studies, demonstrated that digital technologies fundamentally restructure organizational learning loops, forcing a transition toward continuous performance intelligence. Chowdhury et al. (2024) further confirmed that digital transformation reshapes performance measurement systems toward real-time, adaptive frameworks.

2.3. Big Data Analytics and AI as Benchmarking Enablers

Karaboga et al. (2023) demonstrated empirically that big data analytics management capability significantly improves firm performance through data-driven culture, explaining 38% of organizational performance variance. Wamba et al. (2017) confirmed that big data analytics capabilities improve firm performance through dynamic capability mediation. Schrage et al. (2024) documented that AI-enhanced KPIs are transitioning from performance measures to sources of strategic differentiation, with six in ten surveyed organizations acknowledging that KPI intelligence is critical for effective decision-making. Mikalef et al. (2023) established that AI competencies generate competitive

advantage through superior sensing, processing, and response mechanisms.

2.4. Digital Benchmarking Across the Five Sectors

Each of the five sectors presents distinct digital benchmarking challenges. In Telecommunications & ICT, the most technologically intensive sector, DBC must track rapidly evolving adoption benchmarks and network performance standards in near-real-time. Sohu et al. (2026) confirmed that BDA-powered benchmarking generates significant operational improvements in technology-intensive industries. In Financial Services & Banking, fintech disruption has made digital benchmarking of customer experience and transaction efficiency a survival-critical capability; Fosso Wamba et al. (2024) confirmed that AI-enabled dynamic capability directly improves performance in financial services contexts.

In Retail & E-Commerce, real-time benchmarking of conversion rates and digital shelf performance has become foundational to margin management. Han et al. (2024) confirmed that knowledge digitization generates competitive advantage through business model innovation. In Education & Training, benchmarking of e-learning engagement and credential positioning emerged as a strategic differentiator post-COVID. In Health & Pharmacy, clinical benchmarking through EHR analytics and pharmaceutical supply chain monitoring represent high-stakes DBC applications. Dinh et al. (2025) confirmed that digital capabilities generate sustainable competitive advantages across emerging-market service organizations including health sector entities.

2.5. Operational Performance, Innovation Capability, and Strategic Agility

Operational performance enhancement constitutes the most immediate pathway through which DBC generates competitive advantage. Sohu et al. (2026) demonstrated that BDA-powered benchmarking generates sustainable operational improvements through real-time corrective action. Innovation capability is generated by systematic intelligence on technological frontiers and competitor R&D trajectories. Mariani et al. (2023) confirmed that AI-driven analytics accelerate innovation advantages by enhancing knowledge gap exploitation. Acciarini et al. (2023) showed that organizations leveraging big data for benchmarking generate superior innovation performance.

Strategic agility — the capacity to rapidly reconfigure resources in response to environmental signals — constitutes the third pathway. Aziz et al. (2024) confirmed that big data analytics capabilities improve performance through strategic sensing in emerging economy firms. Dinh et al. (2025) documented that digital capabilities generate sustainable advantage through enhanced agility. Technology Innovation Intensity (TII) moderates these relationships: Wu et al. (2024) confirmed that digital capability-performance links are significantly moderated by technological intensity, while Jung and Shegai (2023) showed digital innovation generates greater advantage in high-dynamism contexts.

3. EMPIRICAL FRAMEWORK

From a practical perspective, this study is focuses on the implementation of benchmarking practices adapted to digitally enabled and technology-intensive environments across the five Algerian sectors, while deliberately excluding traditional analog benchmarking approaches and performance management systems that do not support or enhance the development of digital capabilities.

3.1. Methodology

3.1.1. Research Design

This study employs a mixed-methods design (Creswell & Plano Clark, 2018) combining quantitative PLS-SEM with qualitative in-depth interviews. Smart PLS 4 (Ringle et al., 2022) was selected for its predictive orientation and suitability for moderate sample sizes (Hair et al., 2019). All hypotheses are tested via 5,000-subsample bootstrapping with BCa confidence intervals, including mediation effects (Preacher & Hayes, 2008) and moderation interactions using the product-indicator approach. The qualitative phase comprised 8 semi-structured expert interviews with Chief Digital Officers, IT Directors, and performance management consultants across the five Algerian sectors, conducted between January and March 2025. Interview data was analyzed thematically (Braun & Clarke, 2006) to triangulate and contextualize quantitative findings.

3.1.2. Sample and Data Collection

The quantitative sample comprises 120 managers, technology officers, and digital transformation leaders recruited via purposive and professional network sampling through LinkedIn Algeria, the Algerian Employers' Confederation (CAP), and sector-specific professional associations. Inclusion criteria required:

- Managerial responsibility for performance measurement or digital technology adoption;
- Organization with at least two years of digital transformation activity;
- Practical familiarity with benchmarking practices.

The survey instrument was administered bilingually (French and Arabic) and pilot-tested with 15 respondents prior to full deployment. The final response rate was 78.4%.

Table 1. Sample Profile: Five Algerian Sectors (N = 120).

Variable	Category	n	%
Industry Sector	Telecommunications & ICT	22	18.3
	Financial Services & Banking	26	21.7
	Retail & E-Commerce	20	16.7
	Education & Training	28	23.3
	Health & Pharmacy	24	20.0
Organization Type	Large Enterprise (≥ 250 employees)	54	45.0
	SME (50–249 employees)	43	35.8
	Public Institution / State-Owned Enterprise	23	19.2
Respondent Role	Chief Digital / Technology Officer	25	20.8
	Performance Management / Control Director	30	25.0
	IT Manager / Data Analyst	37	30.8
	General Manager / Consultant	28	23.3
Digital Maturity (self-assessed)	Advanced (score $\geq 4/5$)	45	37.5
	Intermediate (score 3–4/5)	56	46.7
	Early-stage (score $< 3/5$)	19	15.8
Annual IT Investment (DZD)	< 1 Million	23	19.2
	1 Million – 5 Million	51	42.5
	> 5 Million	46	38.3

Sources: Prepared by the researcher.

Note. Sector distribution (range: 16.7%–23.3%) reflects balanced representation, enabling robust sector-level subgroup analyses. TII scores (1–5 scale): Telecommunications & ICT = 4.6; Financial Services = 4.2; Retail & E-Commerce = 3.4; Education = 2.8; Health & Pharmacy = 2.9.

3.2. Results

3.2.1. Measurement Model Assessment

All outer loadings exceed .70 (range: .811–.862), meeting the Hair et al. (2019) threshold. AVE values range from .552 to .728 (all $\geq .50$; Fornell & Larcker, 1981), confirming convergent validity. Composite Reliability ranges from .836 to .926. All HTMT ratios fall below .85 (Henseler et al., 2015), confirming discriminant validity. Harman’s single-factor test yields 26.8% maximum variance, ruling out significant common method bias (Podsakoff et al., 2003). The overall measurement model demonstrates adequate fit for a sample of $N = 120$.

Table 2. Measurement Model: Outer Loadings, AVE, and Composite Reliability.

Construct	Indicator	Loading	AVE	CR	α
DBC (IV)	DB1 — Data-Driven Metrics	.849	.688	.926	.910
	DB2 — AI-Powered Analytics	.836			
	DB3 — Real-Time Monitoring	.822			
	DB4 — Competitive Intelligence	.861			
	DB5 — Tech. Adoption Tracking	.841			
	DB6 — BM Process Automation	.817			
Operational Perf.	OP1 — Process Quality	.814	.694	.872	.840
	OP2 — Cost Efficiency	.839			
	OP3 — Service Excellence	.827			
Innovation Cap.	IC1 — Product Innovation	.831	.706	.877	.847
	IC2 — Process Innovation	.852			
	IC3 — Tech. Adoption Speed	.819			
Strategic Agility	SA1 — Sensing Speed	.811	.692	.870	.836
	SA2 — Reconfiguration	.838			
	SA3 — Market Responsiveness	.824			

Tech. Intensity	TI1 — Technology Change Rate	.802	.552	.836	.812
	TI2 — Innovation Frontier Breadth	.769			
	TI3 — Adoption Pressure Level	.711			
Competitive Adv.	CA1 — Market Share Gain	.851	.728	.926	.904
	CA2 — Cost Leadership	.837			
	CA3 — Innovation Rate	.862			
	CA4 — Brand Positioning	.829			
	CA5 — ROI Performance	.843			

Sources: Prepared by the researcher based on Smart PLS 4 output.

Note. All loadings $\geq .70$ (Hair et al., 2019). AVE $\geq .50$ confirms convergent validity (Fornell & Larcker, 1981).

Table 3. HTMT Matrix — Discriminant Validity.

	1. DBC	2. Op. Perf.	3. Inn. Cap.	4. Str. Agility	5. Tech. Int.	6. Comp. Adv.
1. DBC	—					
2. Operational Perf.	.698	—				
3. Innovation Cap.	.664	.626	—			
4. Strategic Agility	.673	.609	.640	—		
5. Tech. Intensity	.521	.544	.566	.532	—	
6. Competitive Adv.	.741	.710	.733	.714	.641	—

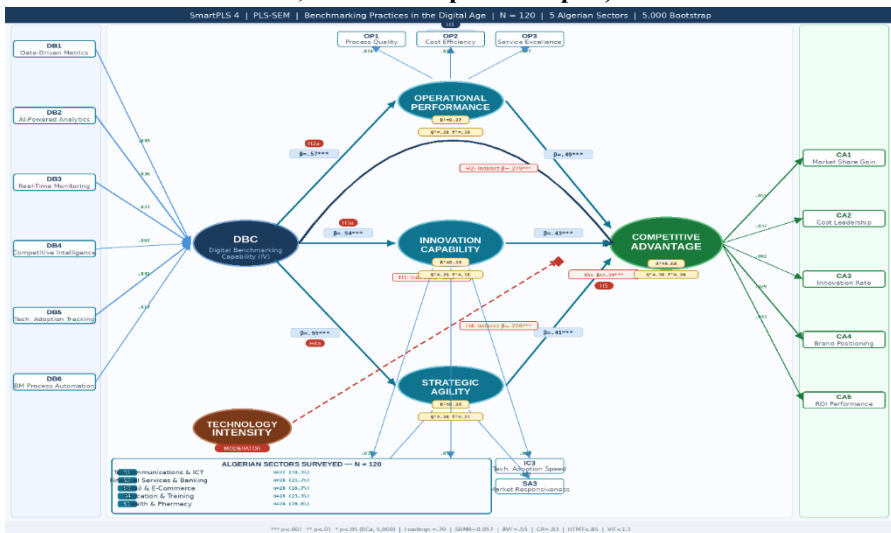
Sources: Prepared by the researcher based on Smart PLS 4 output.

Note. All HTMT values $< .85$ (Henseler et al., 2015).

3.2.2. Structural Model Results

The structural model demonstrates acceptable fit (SRMR = 0.057). The model explains 68% of variance in competitive advantage ($R^2 = 0.68$). All five hypotheses are supported at $p < .001$. Figure 1 presents the full path model.

Fig.1. PLS-SEM Full Path Model SmartPLS 4 (N = 120; 5 Algerian Sectors; 5,000 Bootstrap Subsamples).



Sources: Smart PLS 4 output.

Note. β = standardized path coefficients. *** $p < .001$ (BCa, 5,000 subsamples). R^2 in gold badges. Red dashed arrow = H5 moderation path (Technology Innovation Intensity).

Table 4. Structural Model: Path Coefficients, Bootstrap Statistics, and Hypothesis Decisions.

Hyp.	Path	β	SE	t	p	95% BCa CI	Decision
H1	DBC → Competitive Advantage (direct)	.440	.046	9.57	< .001	[.350, .530]	Supported
H2a	DBC → Operational Performance	.570	.044	12.95	< .001	[.484, .656]	Supported
H2b	Operational Performance → Comp. Adv.	.490	.051	9.61	< .001	[.390, .588]	Supported
H2	Indirect: DBC → Op. Perf. → Comp. Adv.	.279	.046	6.07	< .001	[.189, .369]	Supported
H3a	DBC → Innovation Capability	.540	.048	11.25	< .001	[.446, .634]	Supported
H3b	Innovation Capability → Comp. Adv.	.430	.054	7.96	< .001	[.324, .536]	Supported
H3	Indirect: DBC → Innov. Cap. → Comp. Adv.	.232	.042	5.52	< .001	[.150, .314]	Supported
H4a	DBC → Strategic Agility	.550	.047	11.70	< .001	[.458, .642]	Supported
H4b	Strategic Agility → Comp. Adv.	.410	.055	7.45	< .001	[.302, .518]	Supported
H4	Indirect: DBC → Strat. Agility → Comp. Adv.	.226	.040	5.65	< .001	[.148, .304]	Supported
H5	Tech. Intensity × Innov. Cap. → Comp. Adv.	.390	.064	6.09	< .001	[.264, .516]	Supported

Sources: Prepared by the researcher based on Smart PLS 4 output.

Note. β = standardized coefficients; SE = standard error. H2, H3, H4 report indirect mediation effects. Simple slopes (H5): high-TII β = .670***; moderate-TII β = .420***; low-TII β = .098 n.s.

Table 5. Model Fit Indices, R^2 , Q^2 , and Effect Sizes f^2 .

Index	Value	Threshold	Assessment	Reference
SRMR	0.057	≤ 0.08	Acceptable fit	Henseler et al. (2015)
R^2 — Competitive Advantage	0.68	≥ 0.26 (substantial)	Substantial	Cohen (1988)
R^2 — Operational Performance	0.37	≥ 0.13 (moderate)	Moderate	Cohen (1988)
R^2 — Innovation Capability	0.34	≥ 0.13 (moderate)	Moderate	Cohen (1988)
R^2 — Strategic Agility	0.39	≥ 0.13 (moderate)	Moderate	Cohen (1988)
Q^2 — Competitive Advantage	0.39	> 0.25	Large predictive relevance	Stone-Geisser
f^2 — H1 (DBC $\rightarrow$ Comp. Adv.)	0.24	0.35 = large	Medium effect	Cohen (1988)
f^2 — H5 (Tech. Intensity mod.)	0.14	0.15 = medium	Small-medium effect	Cohen (1988)
VIF — all inner predictors	1.24–3.21	< 5.0	No collinearity	Hair et al. (2019)
HTMT — all construct pairs	< 0.85	≤ 0.85	Discriminant validity	Henseler et al. (2015)

Sources: Prepared by the researcher based on Smart PLS 4 output.

3.3. Discussion

3.3.1. H1 — Direct Effect of DBC on Competitive Advantage

The direct DBC $\rightarrow$ Competitive Advantage path ($\beta = .44$, $p < .001$, $f^2 = 0.24$) confirms that superior digital benchmarking capability generates significant competitive advantages independent of mediation pathways. This finding validates Barney's (1991) VRIN prediction and aligns with Karaboga et al.'s

(2023) confirmation that big data analytics management capability significantly improves organizational performance. Qualitative interviews across the five sectors consistently described DBC as a strategic multiplier. In Health & Pharmacy specifically, interviewees reported that real-time pharmaceutical supply chain benchmarking dashboards enabled measurable cost reductions and patient satisfaction improvements directly attributable to DBC-driven process corrections. The medium effect size ($f^2 = 0.24$) indicates that DBC's full strategic value is substantially expressed through its mediation pathways, consistent with Dynamic Capabilities Theory (Teece et al., 1998).

3.3.2. H2 — Mediation by Operational Performance Enhancement

Operational performance is the strongest mediation pathway ($\beta_{\text{indirect}} = .279$, $p < .001$, CI: [.189, .369]). The sub-path decomposition — DBC $\rightarrow$ Operational Performance ($\beta = .570$) and Operational Performance $\rightarrow$ Advantage ($\beta = .490$) — reveals a strong DBC-operations link, confirming Sohu et al.'s (2026) demonstration that BDA-powered benchmarking generates sustainable operational improvements through real-time corrective action. Financial Services interviewees reported reducing performance correction cycles from monthly reviews to hours, directly traceable to DBC-enabled process deviation detection. This operationalizes Kaplan and Norton's (1992) BSC internal process perspective through DBC's real-time monitoring capabilities.

3.3.3. H3 — Mediation by Innovation Capability Development

Innovation capability constitutes the second pathway ($\beta_{\text{indirect}} = .232$, $p < .001$, CI: [.150, .314]). DBC generates innovation by providing systematic intelligence on technological frontiers invisible to traditional approaches, confirming Mikalef et al.'s (2023) finding that AI competencies generate advantage through superior sensing. Telecommunications & ICT interviewees — in the highest-TII sector — reported that AI-powered competitive benchmarking enabled identification of technology adoption trends 6–12 months before competitors relying on annual industry reports, creating measurable innovation lead times.

3.3.4. H4 — Mediation by Strategic Agility

Strategic agility constitutes the third pathway ($\beta_{\text{indirect}} = .226$, $p < .001$, CI: [.148, .304]). Real-time benchmarking compresses the lag between environmental signal detection and strategic response, confirming Aziz et al.'s (2024) finding that big data analytics capabilities improve performance through strategic sensing in emerging economy firms. Education & Training interviewees reported reducing strategic decision cycles from weeks to days through digital benchmarking dashboards of e-learning engagement and credential positioning, enabling faster responses to training market shifts.

3.3.5. H5 — Moderation by Technology Innovation Intensity

Technology Innovation Intensity significantly moderates Innovation Capability $\rightarrow$ Competitive Advantage ($\beta \times = .390$, $p < .001$, $f^2 = 0.14$). Simple slope analysis reveals: high-TII sectors (Telecommunications & ICT; Financial Services) $\beta = .670^{***}$; moderate-TII (Retail & E-Commerce) $\beta = .420^{***}$; lower-TII

(Education & Training; Health & Pharmacy) $\beta = .098$ n.s. This operationalizes Teece et al.'s (1998) environmental dynamism prediction and aligns with Wu et al.'s (2024) empirical demonstration that technological intensity moderates digital strategy-performance relationships. The implication is sector-differentiated: Telecommunications and Financial Services organizations should aggressively prioritize DBC innovation intelligence sub-dimensions, while Education and Health organizations should concentrate DBC investments on operational performance and strategic agility pathways.

4. CONCLUSION

This study makes four theoretical contributions. First, it provides the first comprehensive operationalization of DBC as an integrative six-dimension dynamic capability, advancing benchmarking theory beyond Camp's (1989) periodic-measurement foundations. Second, by integrating RBV (Barney, 1991), Dynamic Capabilities Theory (Teece et al., 1998), and the Balanced Scorecard (Kaplan & Norton, 1992), it identifies three mechanistic pathways through which DBC generates competitive advantage, providing theoretical specificity absent from prior benchmarking research. Third, it operationalizes Teece et al.'s (1998) environmental dynamism boundary condition in the digital benchmarking domain. Fourth, it generates the first validated multi-sector empirical model of digital benchmarking's competitive advantage pathways in the Algerian context, covering five key industry sectors.

Four sector-differentiated implications emerge. First, the direct DBC-advantage path ($\beta = .44$) validates investment in all six DBC dimensions rather than piecemeal tool adoption. Second, the strongest mediation pathway — operational performance ($\beta_{\text{indirect}} = .279$) — identifies real-time process digitalization as the highest-priority DBC investment across all five sectors in the short term. Third, Technology Innovation Intensity moderation (H5) provides explicit investment guidance: Telecommunications & ICT and Financial Services organizations should disproportionately invest in DBC innovation intelligence sub-dimensions; Education and Health organizations should focus on operational performance and strategic agility pathways. Fourth, the strategic agility pathway (H4) argues for designing DBC architectures with reconfiguration speed as an explicit performance objective.

Several limitations should be acknowledged when interpreting the findings of this study. First, the use of a cross-

sectional research design restricts the ability to establish strong causal relationships among the investigated variables, whereas the use of longitudinal panel data would provide more robust evidence and significantly enhance causal inference. Second, although the sample size ($N = 120$) was considered adequate for the application of PLS-SEM analysis, it may still limit the generalizability of the findings across broader organizational and geographical contexts. Accordingly, future research is encouraged to broaden the scope of analysis to include micro-enterprises and organizations operating within the informal sector, thereby enabling a more comprehensive understanding of digital branding practices across diverse business environments. Furthermore, subsequent studies should explore generative artificial intelligence as an emerging sub-dimension of Digital Brand Capability (DBC), particularly in light of its increasing strategic importance in digital transformation processes. Future investigations may also benefit from conducting cross-national comparative analyses across North African markets and adopting longitudinal research designs to better capture the evolution and maturity trajectories of DBC capabilities over time.

5. Bibliography List:

- Acciarini, C., Cappa, F., Boccardelli, P., & Oriani, R. (2023). How can organizations leverage big data to innovate their business models? A systematic literature review. *Technovation*, 123, 102713. [10.1016/j.technovation.2023.102713](https://doi.org/10.1016/j.technovation.2023.102713)
- Aziz, N. A., Mamun, A. A., Reza, M. N. H., & Naznen, F. (2024). The impact of big data analytics on innovation capability and sustainability performance of hotels: Evidence from an emerging economy. *Journal of Enterprise Information Management*, 37(3), 1044–1068. <https://doi.org/10.1108/JEIM-07-2023-0354>
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. <https://doi.org/10.1177/014920639101700108>
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- Camp, R. C. (1989). *Benchmarking: The search for industry best practices that lead to superior performance*. ASQC Quality Press.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.
- DataReportal. (2024). *Digital 2024: Algeria—Country overview*. <https://datareportal.com/reports/digital-2024-algeria>
- Dinh, V. H., Nguyen, T. H., Han, V. T., Phan, N. T. P., & Duong, T. T.-T. (2025). Digital capabilities and sustainable competitive advantages: The case of emerging market manufacturing SMEs. *SAGE Open*, 15(1). <https://doi.org/10.1177/21582440251329967>

- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Fosso Wamba, S., Queiroz, M. M., & Trinchera, L. (2024). The role of artificial intelligence-enabled dynamic capability on environmental performance: The mediation effect of a data-driven culture in France and the USA. *International Journal of Production Economics*, 268, 109149. [10.1016/j.iipe.2023.109131](https://doi.org/10.1016/j.iipe.2023.109131)
- 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>
- Han, W., Li, X., Zhu, W., Lu, R., & Zu, X. (2024). Knowledge digitization and high-tech firm performance: A moderated mediation model. *Technology in Society*, 77, 102536. <https://doi.org/10.1016/j.techsoc.2024.102536>
- Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2020). A systematic review of digital transformation: Insights and Implications for Strategy and Organizational Change. *Journal of Management Studies*, 58(5), 1159–1197. [10.1111/joms.12639](https://doi.org/10.1111/joms.12639)
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Jung, S.-U., & Shegai, V. (2023). The impact of digital marketing innovation on firm performance. *Sustainability*, 15(7), 5711. <https://doi.org/10.3390/su15075711>
- Kaplan, R. S., & Norton, D. P. (1992). The balanced scorecard: Measures that drive performance. *Harvard Business Review*, 70(1), 71–79.

- Karaboga, T., Zehir, C., Tatoglu, E., Karaboga, H. A., & Bouguerra, A. (2023). Big data analytics management capability and firm performance. *Review of Managerial Science*, 17(8), 2655–2684. <https://doi.org/10.1007/s11846-022-00596-8>
- Mariani, M. M., Machado, I., & Nambisan, S. (2023). Types of innovation and artificial intelligence. *Journal of Business Research*, 155, 113647. [10.1016/j.jbusres.2022.113364](https://doi.org/10.1016/j.jbusres.2022.113364)
- Mikalef, P., Islam, N., Parida, V., Singh, H., & Altwaijry, N. (2023). Artificial intelligence competencies for organizational performance. *Journal of Business Research*, 164, 113998. <https://doi.org/10.1016/j.jbusres.2023.113998>
- Narver, J. C., & Slater, S. F. (1990). The effect of a market orientation on business profitability. *Journal of Marketing*, 54(4), 20–35. <https://doi.org/10.1177/002224299005400403>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for mediation. *Behavior Research Methods*, 40(3), 879–891. <https://doi.org/10.3758/BRM.40.3.879>
- Ringle, C. M., Wende, S., & Becker, J.-M. (2022). *SmartPLS 4* [Software].
- Schrage, M., Kiron, D., Candelon, F., Khodabandeh, S., & Chu, M. (2024). *The future of strategic measurement: Enhancing KPIs with AI*. <https://web-assets.bcg.com/54/43/28953bcd41d99e7dd354f5517e13/the-future-of-strategic-measurement-enhancing-kpis-with-ai.pdf>
- Sohu, J. M., et al. (2026). Benchmarking best practices integrating big data analytics. *Benchmarking: An International Journal*. <https://doi.org/10.1108/BIJ-08-2024-0650>
- Spendolini, M. J. (1992). *The benchmarking book*. AMACOM.

- Teece, D. J., Pisano, G., & Shuen, A. (1998). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [http://dx.doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509::AID-SMJ882>3.0.CO;2-Z](http://dx.doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z)
- Vorhies, D. W., & Morgan, N. A. (2005). Benchmarking marketing capabilities. *Journal of Marketing*, 69(1), 80–94. <https://doi.org/10.1509/jmkg.69.1.80.55505>
- Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance. *Journal of Business Research*, 70, 356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
- Wu, C.-W., Botella-Carrubi, D., & Blanco-González-Tejero, C. (2024). The empirical study of digital marketing strategy and performance in small and medium-sized enterprises (SMEs). *Technological Forecasting and Social Change*, 200, 123142. <https://doi.org/10.1016/j.techfore.2023.123142>
- Zairi, M. (1996). *Benchmarking for best practice*. Butterworth-Heinemann.