

BUILDING OPERATIONAL INFRASTRUCTURE READINESS IN THE HOTEL SECTOR: A DYNAMIC CAPABILITIES APPROACH

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ABSTRACT: This study investigates dynamic capability as the mediating mechanism through which technology support for customer service and the supporting environment produce operational infrastructure readiness in hotel service organizations. It extends the dynamic capabilities–resource-based view integration into a domain with limited-empirical address. Employing partial least squares structural equation modeling, the study collects data from 328 hotel managers. Technology support for customer service constitutes the dominant antecedent of dynamic capability, exerting substantially greater influence than the supporting environment. Dynamic capability is the dominant structural determinant of operational infrastructure readiness. Both antecedent effects reach operational readiness exclusively through the dynamic capability pathway, confirming full mediation. Hotel organizations cannot produce infrastructure readiness through technology investment or environmental alignment alone; deliberate capability development is the non-eliminable mechanism through which digital assets are converted into operational readiness.

Keywords: Dynamic Capability; Operational Infrastructure Readiness; Technology Support; Hotel Service Operations; Digital Transformation

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INTRODUCTION

The hotel and hospitality industry confronts a defining operational challenge of the contemporary period. Digital transformation has repositioned technology as the primary infrastructure through which service delivery, guest experience, and operational efficiency are organized and sustained. Investment in digital systems — cloud-based property management platforms, artificial intelligence-enabled customer service tools, integrated revenue management infrastructure, and real-time guest engagement technologies — accelerated markedly across the global hospitality sector in the years following the COVID-19 crisis, as hotels were compelled to reconfigure their operational architecture under conditions of acute demand volatility and constrained human resources (Tussyadiah, 2020; Sigala, 2020). The pandemic compressed digital transformation timelines that industry analysts had projected across a decade into a period of fewer than three years, making operational infrastructure readiness — the organized capacity of hotel service organizations to deploy and sustain digital and physical systems in current service contexts — a strategic imperative rather than a competitive differentiator (Verhoef et al., 2021). Yet the empirical record reveals a persistent and theoretically significant anomaly: hotels with comparable levels of technology investment exhibit substantially unequal levels of operational infrastructure readiness. Some organizations translate digital investment into coherent, adaptive, and deployable operational systems; others accumulate technological assets that remain operationally inert. This heterogeneity — systematic, observable, and organizationally consequential — constitutes the research phenomenon. It argues that the relationship between technology investment and operational readiness in hotel service operations is neither direct nor automatic, and that an organizational mechanism intervenes between input and outcome. Identifying, theorizing, and empirically establishing that mechanism is the central task of this study.

The dominant framework in operations management and information systems research treats technology investment as the primary and largely sufficient driver of organizational performance — implying a direct causal relationship between technological endowment and operational capability. This direct-effect account has strong intuitive appeal and partial empirical support: organizations that invest more heavily in digital infrastructure tend, on average, to exhibit stronger operational performance profiles (Mithas & Rust, 2016). It fails, however, to resolve the heterogeneity puzzle that motivates the present study. If technology investment directly determined operational readiness, resource-equivalent organizations would exhibit equivalent readiness outcomes. The resource-based view supplies a foundational qualification: sustained performance advantage derives from resources that are simultaneously valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991). Hitt et al. (2016) extend this argument to operations management, reframing operational functions from cost-minimization activities into strategic capability-building processes in which resource configuration — not resource possession alone — determines the range of available organizational responses. The resource-based view, however, faces a parallel and analytically more consequential limitation: it identifies the attributes of advantage-generating resources without theorizing the organizational processes through which those resources are activated and converted into operational outcomes. This is the theoretical gap the present study addresses. Existing scholarship establishes that technology investment is a necessary condition for operational readiness but has not produced consensus on the sufficient organizational mechanism through which that investment produces readiness in hotel service contexts (Mikalef & Pateli, 2017; Schilke et al., 2018). The persistence of this gap in a practically consequential research domain justifies the present inquiry.

Dynamic capabilities theory provides the theoretical resolution to this gap by locating the source of performance heterogeneity in the higher-order organizational competences through which resources are integrated, deployed, and reconfigured. Teece et al. (1997) define dynamic capabilities as the organizational ability to sense opportunities and threats, seize them through timely decision-making and resource mobilization, and transform the asset base as operating demands evolve. This framework argues that technology investment produces operational readiness only when the organization possesses the sensing-seizing-transforming competences to activate its technological endowments. Two unresolved debates, however, complicate this theoretical picture. The first concerns the nature of dynamic capability itself. Eisenhardt and Martin (2000) challenge the hierarchical DCT account, arguing that dynamic capabilities are best

understood as specific, identifiable organizational processes — product development routines, alliance formation practices, strategic reconfiguration mechanisms — rather than as meta-level structures operating uniformly above operational routines. This debate is not merely definitional: it bears directly on whether dynamic capability can be empirically modeled as a reflective latent construct in the hotel operations context or whether it must be decomposed into its constituent processes. Helfat and Winter (2011) resolve this tension through a purpose-based distinction — dynamic capabilities alter the way the organization functions; operational capabilities enable it to function — a distinction that makes infrastructure readiness the downstream product of dynamic capability development and provides the theoretical spine of the present model. The second debate concerns the relative explanatory weight of technology support and environmental conditions as antecedents of dynamic capability. The IT capability literature argues that technology support builds organizational competence through the deployment and configuration of digital systems (Nambisan et al., 2017; Svahn et al., 2017). A parallel literature establishes that environmental conditions — regulatory frameworks, industry ecosystems, and competitive pressures — stimulate capability investment and shape its productivity (Zollo & Winter, 2002; Warner & Wäger, 2019). Neither stream has established which antecedent dominates in hotel service contexts, nor whether both operate exclusively through dynamic capability as a mediating mechanism. These two theoretical debates define the specific empirical questions the present study is designed to answer.

This study advances the theoretical literature in four specific and novel ways. First, it extends the integrated dynamic capabilities–resource-based view framework into the domain of operational infrastructure readiness in hotel service organizations — a domain that prior dynamic capabilities research has not empirically examined despite its centrality to digital transformation outcomes in the hospitality sector (Hanelt et al., 2021; Vial, 2019). By establishing that infrastructure readiness is a downstream product of dynamic capability development rather than a direct consequence of technology investment or environmental alignment, this study operationalizes the Helfat-Winter distinction between dynamic and operational capabilities in a hotel service context for the first time. Second, it resolves the antecedent competition debate by empirically establishing that technology support for customer service constitutes the dominant predictor of dynamic capability in hotel operations — exerting substantially greater influence than the supporting environment — thereby specifying the relative explanatory weights of technological and environmental antecedents within a unified structural model and advancing the IT capability debate beyond the commodity-versus-capability binary. Third, it demonstrates that dynamic capability fully mediates both the technology support → operational readiness and supporting environment → operational readiness pathways, establishing the capability-conversion mechanism as the necessary and sufficient organizational bridge between upstream inputs and downstream operational outcomes — a finding that argues against direct-effect accounts of technology-driven operational performance in service contexts (Verhoef et al., 2021; Warner & Wäger, 2019). Fourth, it provides the hotel service operations literature with a structurally validated partial least squares structural equation model that simultaneously estimates direct antecedent effects, mediated causal pathways, and predictive accuracy for both endogenous constructs — thereby establishing an empirically tractable, theoretically grounded, and practically actionable model for digital transformation research and capability development practice in the hotel industry.

THEORETICAL REVIEW

This study constructs its theoretical foundation on the integrated logic of dynamic capabilities theory and the resource-based view, applying that foundation within the applicative domain of hotel service operations research. These two traditions are not competing frameworks; they are hierarchically related. The resource-based view establishes the premise that organizational performance is rooted in the heterogeneous configuration of internal resources. Dynamic capabilities theory extends that premise by arguing that the differential value of resources is determined by the higher-order organizational competences through which resources are deployed, integrated, and reconfigured. Their integration provides the theoretical architecture necessary to explain how hotel organizations build operational infrastructure readiness from technological and environmental inputs.

Dynamic Capabilities Theory and the Resource-Based View: An Integrated Theoretical Anchor

The resource-based view establishes that sustained competitive advantage derives from resources that are simultaneously valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991). Applied to hotel service operations, this framework directs analytical attention toward the physical, technological, and relational assets that constitute a hotel's operational infrastructure. Property management systems, customer relationship platforms, revenue management tools, and the integrated digital architecture connecting them represent the resource base from which service delivery capacity is constructed. Hitt et al. (2016) extend this logic to operations management specifically, arguing that the resource-based view reframes operational functions from cost-minimization activities into strategic capability-building processes in which resource configuration determines the range of organizational responses available. Operational infrastructure readiness, on this account, is not a cost item but a strategic asset configuration whose value depends on how well it is assembled, maintained, and aligned with evolving service demands.

The resource-based view, however, generates a theoretical gap that dynamic capabilities theory is positioned to resolve. If resources alone determined organizational performance, organizations with equivalent technological endowments would exhibit equivalent operational readiness profiles. The persistence of performance heterogeneity among resource-equivalent hotels demonstrates that resource possession is necessary but insufficient; what differentiates organizations is the capacity to deploy and reconfigure those resources adaptively. This is the foundational claim of dynamic capabilities theory. Teece et al. (1997) define dynamic capabilities as the organizational ability to integrate, build, and reconfigure internal and external competences in response to rapidly changing environments. The framework disaggregates organizational adaptation into three interdependent sub-processes: sensing, which identifies and assesses opportunities and threats; seizing, which mobilizes resources to address identified opportunities; and transforming, which realigns the organization's asset base when operating circumstances demand structural change (Teece, 2018).

The integration of the resource-based view and dynamic capabilities theory generates a unified explanatory logic for the present model. The resource-based view establishes that organizational performance is resource-contingent; dynamic capabilities theory establishes that resource value is capability-contingent. Together, they argue that operational infrastructure readiness is the product of a two-stage process: first, the accumulation of technological and environmental resources that constitute the inputs to organizational capability; second, the exercise of dynamic capabilities — sensing, seizing, and transforming — through which those resources are converted into deployable operational infrastructure. Schilke et al. (2018) meta-analytically confirm that dynamic capabilities exert their strongest effects on operational performance in contexts of high reconfiguration demand — the defining condition of hotel operations under current digital transformation pressure. Warner and Wäger (2019) demonstrate that digital transformation in service organizations is driven by the continuous exercise of dynamic capabilities that integrate new technological competences into existing operational structures. The integrated RBV-DCT framework thus provides both the foundational premise and the explanatory mechanism for the present study.

Operations Research in Hotel Service Contexts: The Applicative Domain

Operations research in service contexts addresses the systematic design, management, and optimization of service delivery systems. Contemporary operations research in hospitality has shifted its theoretical center of gravity toward digital transformation, technology integration, and capability-driven service performance — a shift that reflects the fundamental restructuring of hotel operations around digital platforms, data-driven decision-making, and technology-mediated guest experiences. Vargo and Lusch (2016) argue through service-dominant logic that value in service contexts is co-created through the application of operant resources — knowledge, skills, and dynamic competences — in service exchange. This argument reframes operational infrastructure readiness as a capability question rather than a physical asset question: readiness is determined not by infrastructure configuration alone but by the dynamic competences that activate and reconfigure that infrastructure in service of value co-creation. Nieves and Segarra-Ciprés (2015)

demonstrate in the hotel industry specifically that management innovation — the development of new organizational practices and service processes — is driven by the same knowledge-intensive, capability-building activities that dynamic capabilities theory identifies as the sources of adaptive advantage.

The digital transformation of hotel service operations has intensified the demand for operational infrastructure readiness as a strategic construct. Verhoef et al. (2021) identify the hospitality sector as one of the most digitally disrupted industries, characterized by platform-based competitors, AI-mediated service personalization, and continuous evolution of guest expectations around digital quality. Vial (2019) establishes that digital transformation outcomes are uniformly capability-mediated: organizations that develop dynamic capabilities to sense digital opportunities and reconfigure operational processes achieve superior transformation outcomes relative to those investing in technology without corresponding organizational competences. Hanelt et al. (2021) identify operational readiness as a critical precondition for digital transformation success and dynamic capability as the mechanism through which readiness is built and sustained. These theoretical anchors position the hotel service sector as the empirically and theoretically appropriate context for testing the capability-conversion logic the present model proposes.

Hypothesis Development

Technology support for customer service provides hotel organizations with the functional affordances through which dynamic capability sub-processes are directly activated. Sensing is enabled by systems that aggregate guest feedback, monitor competitive activity, and track real-time operational performance. Seizing is supported by platforms that allow rapid reconfiguration of pricing, booking, and service-delivery parameters. Transforming is facilitated by modular and cloud-based systems that restructure operational workflows without the friction of legacy infrastructure replacement. Mikalef and Pateli (2017) establish that IT-enabled dynamic capabilities mediate the relationship between technological investment and competitive performance — identifying technology support as the input to a capability-building process rather than a direct performance driver. Svahn et al. (2017) demonstrate that digital innovation in incumbent organizations requires the continuous reconfiguration of technological platforms in organizationally mediated ways, confirming that technology support activates rather than substitutes for dynamic capability. Nambisan et al. (2017) argue that digital platforms expand organizational options for sensing and seizing, directly amplifying the dynamic capability stock of technology-supported organizations. In hotel operations, technology support for customer service conditions the full sensing-seizing-transforming cycle through which dynamic capability is produced and renewed.

H1: Technology support for customer service positively and significantly influences dynamic capability in hotel service operations.

The supporting environment shapes the informational, regulatory, and resource conditions under which hotel organizations exercise their dynamic capabilities. Dynamic capabilities theory argues that sensing is intrinsically environmental: it requires the continuous scanning of external signals — technological trends, competitive developments, regulatory changes, and guest preference shifts — to which the supporting environment provides differential access and clarity (Teece, 2018). A supportive environment enriches the sensing function by reducing signal ambiguity, increasing information availability, and lowering the organizational cost of environmental monitoring. It enables the seizing function by reducing regulatory and resource barriers to capability investment. And it facilitates the transforming function by providing the ecosystem conditions — infrastructure standards, technology partnerships, and industry-wide alignment — within which operational reconfiguration is tractable. Zollo and Winter (2002) argue that experience accumulation — a primary mechanism of dynamic capability development — is shaped by the richness and diversity of environmental stimuli to which an organization is exposed; a supportive environment amplifies this richness. Schilke et al. (2018) confirm meta-analytically that environmental conditions moderate the productivity of dynamic capability investment, with supportive environments amplifying the capability-building returns to organizational effort. Girod and Whittington (2017) demonstrate that organizational reconfiguration produces stronger

performance effects when environmental conditions are conducive — a finding that identifies the supporting environment as an enabling antecedent of the transforming sub-process that dynamic capability theory specifies. In hotel service operations, a supportive environment does not generate dynamic capabilities; it provides the external conditions under which capability development is more feasible, more productive, and more aligned with operational demands.

H2: The supporting environment positively and significantly influences dynamic capability in hotel service operations.

Dynamic capability is theorized as the dominant structural determinant of operational infrastructure readiness because it constitutes the organizational process through which infrastructure is assembled, configured, and sustained over time. Operational infrastructure readiness — the organized capacity of a hotel to deploy and maintain the systems required for current service delivery — does not self-generate through resource accumulation. It requires sensing competences that identify infrastructure requirements before they become operational deficits; seizing competences that direct organizational resources toward infrastructure development at the right time; and transforming competences that restructure existing systems to accommodate new operational demands as they emerge. The RBV establishes that infrastructure resources are valuable; dynamic capabilities theory establishes that their value is actualized only through the capability-building process that organizes those resources into deployable readiness. Helfat and Winter (2011) provide the theoretical grounding: dynamic capabilities build and renew operational capability substrates, of which infrastructure readiness is a constitutive element. Girod and Whittington (2017) confirm empirically that organizational reconfiguration predicts structural performance change; the present study operationalizes infrastructure readiness as the outcome of precisely that reconfiguration process. Schilke et al. (2018) establish meta-analytically that dynamic capabilities exert their strongest performance effects under high reconfiguration demand — the condition that defines contemporary hotel operations under digital transformation pressure. Dynamic capability is the organizational mechanism without which technology support and environmental enablement remain inert resource conditions.

H3: Dynamic capability positively and significantly influences operational infrastructure readiness in hotel service operations.

The integrated RBV-DCT framework implies a specific mediated causal structure: technology support provides the resource inputs to dynamic capability development; dynamic capability performs the conversion of those inputs into operational outcomes; and operational infrastructure readiness is the product of that conversion. This mediation structure is theoretically necessary, not merely empirically plausible. If technology support directly determined infrastructure readiness, organizations with equivalent technological endowments would exhibit equivalent readiness profiles. The persistent heterogeneity in hotel operational readiness among technology-equivalent organizations establishes that direct-effect accounts are theoretically insufficient. The capability-conversion mechanism is the non-eliminable explanatory bridge. Hanelt et al. (2021) systematically confirm that digital transformation outcomes are capability-mediated: it is not the technology that transforms but the organizational capability to deploy and reconfigure it. Li et al. (2018) demonstrate that digital transformation success depends on the capability to assemble and reconfigure resources rather than on resource availability per se — a finding that directly mirrors the mediated structure this hypothesis proposes. Warner and Wäger (2019) establish that technology support initiates but does not complete the capability-building process: sustained dynamic capability development requires the deliberate organizational investment that transforms technological endowments into adaptive competences. Technology support is the necessary input; dynamic capability is the sufficient organizational mechanism; operational infrastructure readiness is the produced outcome.

H4: Dynamic capability mediates the positive relationship between technology support for customer service and operational infrastructure readiness in hotel service operations.

The same capability-conversion logic that structures H4 applies, with appropriate modification, to the relationship between the supporting environment and operational infrastructure readiness. The supporting environment shapes the external conditions under which dynamic capabilities are developed and exercised; it does not independently produce the

readiness outcomes that those capabilities generate. Readiness is not diffused from the environment into the organization; it is built internally through the capability-building processes that environmental conditions enable. Zollo and Winter (2002) establish that dynamic capabilities develop through deliberate learning — experience accumulation, knowledge articulation, and codification — all of which are organizationally internal processes that environmental conditions stimulate but do not perform. Vial (2019) identifies dynamic capability as the organizational mechanism that consistently bridges external conditions and digital transformation outcomes across institutional contexts, confirming that the environment → readiness pathway is capability-mediated rather than direct. Verhoef et al. (2021) reach the same conclusion: digital transformation outcomes in the hospitality sector reflect the organizational capability to leverage environmental conditions, not the conditions themselves. The supporting environment provides the external enabling structure; dynamic capability performs the conversion into operational readiness. The mediation is theoretically entailed by the integrated RBV-DCT framework and is consistent with the full body of digital transformation evidence in hotel service contexts.

H5: Dynamic capability mediates the positive relationship between the supporting environment and operational infrastructure readiness in hotel service operations.

RESEARCH METHOD

Data Collection and Sample Profile

To empirically validate the conceptual framework, a cross-sectional field survey was deployed targeting mid-to-senior level hotel managers within the hospitality industry. Data collection was executed over a dedicated window anchored in the 2025 fiscal year, ensuring contemporary relevance during a period of rapid technological and operational restructuring in the sector. Hotel managers were selected as the primary key informants due to their comprehensive strategic oversight regarding technology procurement, organizational adaptability, and infrastructure readiness. Out of the distributed instruments, 328 valid and complete responses were retained for final analysis. This sample size comfortably satisfies the minimum power requirements for complex structural equations, well exceeding the widely accepted "ten-times rule" and inverse square root method recommendations for variance-based structural equation modeling.

Analytical Approach

The research model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) executed via the SmartPLS 4 software environment. PLS-SEM was chosen over covariance-based alternatives (CB-SEM) for several distinct reasons aligned with operations management research paradigms. First, the framework emphasizes a prediction-oriented objective, specifically aiming to maximize the explained variance (R^2) of the ultimate endogenous construct: *Operational Infrastructure Readiness*. Second, the model evaluates an intricate causal chain involving a complex mediation path where external and technological supports are transformed through internal *Dynamic Capabilities*. PLS-SEM provides robust parameter estimations without requiring strict multivariate normality assumptions, making it ideal for processing survey-based perceptual data from hospitality executives. The assessment followed a rigorous two-step statistical procedure comprising measurement model evaluation (outer model verification) followed by structural model analysis (inner model path verification).

Measurement Model Evaluation: Reliability and Convergent Validity

The reflective measurement model was systematically assessed for internal consistency reliability and convergent validity using indicator loadings, Cronbach's alpha, composite reliability, and the Average Variance Extracted (AVE). As detailed in the empirical output, the exogenous construct Technology Support demonstrated exceptional properties, with an alpha of 0.904, composite reliability of 0.940, and an AVE of 0.840. Similarly, Supporting Environment displayed robust reliability metrics.

For the constructs Dynamic Capability, and Operational Infrastructure Readiness, Cronbach's alpha fell marginally below the traditional 0.70 threshold. However, because Cronbach's alpha is widely recognized to underestimate internal consistency reliability in PLS-SEM by assuming unweighted indicator configurations, methodological authorities (e.g., Hair et al.) recommend prioritizing Composite Reliability. Because the values for both constructs comfortably exceed the 0.70 benchmark, internal consistency is fully established. Furthermore, convergent validity was confirmed across all latent variables, as every construct yielded an AVE well above the critical 0.50 threshold (ranging from 0.581 to 0.840), meaning that the constructs explain more than half of their indicators' variance on average.

Indicator Loadings and Collinearity Diagnostics

Individual item performance was evaluated using outer loadings to guarantee indicator reliability. The item loadings for Technology Support (TechCS1 to TechCS3) and Supporting Environment (SupEnv1 to SupEnv6) were remarkably strong, spanning from 0.741 to 0.948. Within the Dynamic Capability and Operational Infrastructure Readiness, minor indicator loadings fell slightly below the optimal 0.70 target (specifically *Infr1* at 0.683 and *DynCap3* at 0.698). These indicators were intentionally retained within the final model to preserve content validity and domain representation; their removal was statistically unwarranted since the overall construct AVEs and composite reliabilities already sat safely above their respective cut-off points.

To ensure the structural path assessments were not distorted by lateral collinearity among the indicators, the Variance Inflation Factors (VIF) were cross-examined. All item-level VIF values remained safely below the conservative threshold of 5.0, with values ranging from a low of 1.089 (*DynCap3*) to a maximum of 4.501 (*TechCS2*). These diagnostics confirm that multicollinearity does not pose a threat to the stability or interpretability of the structural model parameters.

RESULTS

The present study employs partial least squares structural equation modeling (PLS-SEM) as its primary analytical strategy, consistent with the variance-based estimation logic appropriate for predictive-explanatory research designs in which constructs are operationalized reflectively and theoretical parsimony is prioritized over model-implied covariance reproduction (Hair et al., 2019). The analysis proceeds in two sequential stages: first, an evaluation of the outer (measurement) model to establish indicator reliability, internal consistency, convergent validity, and discriminant validity; second, an assessment of the inner (structural) model to test hypothesized direct and mediated relationships, quantify predictive accuracy via the coefficient of determination (R^2), and estimate effect magnitudes via Cohen's (1988) f^2 statistic. All path coefficients and mediated effects are estimated by bootstrapping with 5,000 subsamples under a two-tailed significance test at $\alpha = 0.05$.

Assessment of the Measurement Model

Evaluation of the measurement model addresses four sequential criteria: (i) indicator (outer) loading as a test of item-level reliability; (ii) internal consistency reliability assessed through both Cronbach's alpha (α), the rho-alpha coefficient (ρ_a), and composite reliability (ρ_c); (iii) convergent validity via the average variance extracted (AVE); and (iv) multicollinearity among indicators via the variance inflation factor (VIF). The results are presented in Table 1.

Table 1. Measurement Model of Outer Model

Construct	Item	Loading	VIF	α	CR (ρ_a)	CR (ρ_c)	AVE
<i>Dynamic Capability</i>	DynCap1	0.819	1.628	0.639	0.636	0.805	0.581
	DynCap2	0.764	1.598				
	DynCap3	0.698	1.089				
	Infr1	0.683	1.396				
<i>Operational Infrastructure Readiness</i>	Infr2	0.888	1.775	0.676	0.707	0.822	0.609
	Infr3	0.758	1.336				

Construct	Item	Loading	VIF	α	CR (ρ_a)	CR (ρ_c)	AVE
<i>Supporting Environment</i>	SupEnv1	0.822	2.112	0.892	0.903	0.917	0.650
	SupEnv2	0.809	2.027				
	SupEnv3	0.822	2.270				
	SupEnv4	0.741	1.795				
	SupEnv5	0.754	1.800				
	SupEnv6	0.882	2.898				
<i>Technology Support–CS</i>	TechCS1	0.872	2.287	0.904	0.910	0.940	0.840
	TechCS2	0.948	4.501				
	TechCS3	0.928	3.705				

Source: Primary data, processed using SmartPLS 4 (bootstrapping: 5,000 subsamples).

Notes. Loading = outer (reflective) loading; VIF = variance inflation factor; α = Cronbach's alpha; CR (ρ_a) = reliability coefficient rho-alpha; CR (ρ_c) = composite reliability (Dillon–Goldstein's rho); AVE = average variance extracted. Thresholds: Loading $\geq$ 0.60 (Hair et al., 2022); VIF < 5.0 (Hair et al., 2019); $\alpha \geq$ 0.70 (conventional); $\rho_c \geq$ 0.70 (Hair et al., 2022); AVE $\geq$ 0.50 (Fornell & Larcker, 1981).

All indicator loadings satisfy the threshold of $\lambda \geq$ 0.60, ranging from 0.698 (DynCap3) to 0.948 (TechCS2), confirming adequate item-level reliability across all four reflective constructs. The Technology Support–CS construct exhibits the most concentrated measurement quality, with loadings of 0.872, 0.948, and 0.928 for TechCS1–3 respectively, while the Dynamic Capability construct displays a more heterogeneous loading profile (0.698–0.819), reflecting the inherently multidimensional nature of dynamic capability as a higher-order organizational competence (Hair et al., 2019).

Regarding internal consistency, the Cronbach's alpha values for Dynamic Capability (α = 0.639) and Operational Infrastructure Readiness (α = 0.676) fall below the conventional 0.70 threshold. This observation, however, does not invalidate the measurement model. Cronbach's alpha is sensitive to the number of indicators: three-item scales structurally compress the alpha coefficient irrespective of true reliability, and the statistic further assumes tau-equivalence—an assumption routinely violated in PLS-SEM reflective models (Hair et al., 2022). The composite reliability coefficient ρ_c , which relaxes the equal-loading assumption, is more appropriate for variance-based SEM. The ρ_c values of 0.805 (Dynamic Capability) and 0.822 (Operational Infrastructure Readiness) both exceed the 0.70 threshold (Hair et al., 2019), and the ρ_a values of 0.636 and 0.707 are interpretively consistent with those findings. Supporting Environment (ρ_c = 0.917) and Technology Support–CS (ρ_c = 0.940) demonstrate strong internal consistency. Convergent validity is established for all constructs: AVE values range from 0.581 to 0.840, each exceeding the 0.50 threshold, indicating that constructs account for more than half of the variance in their respective indicators on average (Fornell & Larcker, 1981). Finally, all VIF values remain below the critical threshold of 5.0 (range: 1.089–4.501), precluding multicollinearity concerns at the indicator level, though TechCS2 (VIF = 4.501) warrants monitoring given its proximity to the ceiling.

Discriminant Validity

Discriminant validity—the degree to which a construct is empirically distinct from theoretically related constructs—is assessed through two complementary criteria: the heterotrait–monotrait ratio of correlations (HTMT) and the Fornell–Larcker criterion. The results for both criteria appear in Table 2.

Table 2. Discriminant Validity: HTMT Ratios and Fornell–Larcker Criterion

Construct	DC	OPI	Sup.Env.	Tech.CS
Panel A: HTMT Ratios				
Dynamic Capability	—			
Operational Infrastructure Readiness	0.908*	—		
Supporting Environment	0.573	0.588	—	
Technology Support–CS	0.716	0.650	0.442	—
Panel B: Fornell–Larcker Criterion ($\sqrt{\text{Ave}}$ on Diagonal)				
Dynamic Capability	0.762			

Operational Infrastructure Readiness	0.618	0.781		
Supporting Environment	0.447	0.471	0.806	
Technology Support-CS	0.553	0.509	0.399	0.916

Source: Primary data, processed using SmartPLS 4.

Notes. Panel A: HTMT = heterotrait–monotrait ratio of correlations. Threshold: HTMT < 0.85 (conservative, Henseler et al., 2015) or < 0.90 (liberal, Gold et al., 2001). * DC–OPI HTMT = 0.908 marginally exceeds the liberal threshold; see interpretive discussion in text. Panel B: Diagonal entries (in bold, red) are the square roots of AVE ($\sqrt{\text{AVE}}$); off-diagonal entries are Pearson inter-construct correlations. Discriminant validity is supported where $\sqrt{\text{AVE}}$ exceeds all corresponding off-diagonal values in the same row and column (Fornell & Larcker, 1981).

HTMT analysis reveals that the DC–OPI dyad produces a ratio of 0.908, which marginally exceeds the liberal threshold of 0.90 proposed by Gold et al. (2001) and substantially exceeds the conservative benchmark of 0.85 recommended by Henseler et al. (2015). This finding warrants interpretive caution: a HTMT value near or above 0.90 suggests that respondents may perceive the two constructs as sharing a non-trivial domain overlap, consistent with the theoretical proposition that dynamic capability and operational infrastructure readiness are causally proximate constructs within the same organizational performance chain. All remaining HTMT ratios are well below the conservative 0.85 threshold (range: 0.442–0.716), confirming adequate discriminant validity for the remaining construct pairs. The Fornell–Larcker criterion offers a complementary perspective: the $\sqrt{\text{AVE}}$ diagonal values (DC = 0.762, OPI = 0.781, SupEnv = 0.806, TechCS = 0.916) each exceed all inter-construct correlations in the corresponding row and column, satisfying the criterion without exception (Fornell & Larcker, 1981). The convergent satisfaction of the Fornell–Larcker criterion alongside the borderline HTMT finding for DC–OPI suggests that construct distinctiveness is preserved at the variance-extraction level, even as perceptual overlap may be partially inflating the monotrait–heteromethod correlations; this interpretation is consistent with the structural finding that DC exerts a large causal effect on OPI (see Section 3.4), which would naturally elevate their shared variance.

Model Fit Assessment

Although PLS-SEM is primarily a predictive technique and global model fit is a secondary consideration relative to the variance-based criteria assessed above, the present study evaluates model fit through four indices reported across the saturated and estimated models. The estimated model imposes the theoretical structure specified in the conceptual framework, while the saturated model allows all constructs to correlate freely and serves as a baseline.

The saturated model achieves a SRMR of 0.074, which satisfies the good-fit threshold of 0.08 recommended by Henseler et al. (2014). The estimated model SRMR of 0.093 is slightly above this threshold yet remains within the broadly acceptable range of 0.10 used in exploratory structural research. The d_G indices—0.232 and 0.254 for the saturated and estimated models respectively—are closely comparable, suggesting that the imposed structural constraints introduce only modest misfit relative to the unconstrained baseline. The NFI values of 0.829 and 0.817 fall below the 0.90 conventionally associated with acceptable fit in covariance-based SEM (Hu & Bentler, 1999); however, NFI is known to be downwardly biased in PLS-SEM and is not regarded as a primary fit criterion in variance-based approaches (Hair et al., 2022). Taken together, the model fit evidence supports the conclusion that the estimated structural model adequately represents the data, with the SRMR of the saturated model providing the most defensible fit indicator.

Structural Model and Hypothesis Testing

The structural model specifies five hypotheses: two direct antecedent paths to Dynamic Capability (H1, H2), one direct effect of Dynamic Capability on Operational Infrastructure Readiness (H3), and two mediated paths through Dynamic Capability (H4, H5). All path coefficients are estimated from bias-corrected bootstrapping with 5,000 subsamples. The coefficient of determination (R^2) evaluates predictive accuracy; Cohen's (1988) f^2 effect size—calculated as $\Delta(R^2) / (1 - R^2)$ upon inclusion versus exclusion of the predictor—quantifies the substantive contribution of individual paths. Results are presented in Table 4.

Table 4. Structural Model Results

Hypothesis / Statistic	β / R^2 / f^2	t -value	p -value	Decision
H1 Technology Support–CS → Dynamic Capability	0.445	8.972	< 0.001	Supported
H2 Supporting Environment → Dynamic Capability	0.270	5.013	< 0.001	Supported
H3 Dynamic Capability → OPI	0.618	17.929	< 0.001	Supported
H4 Technology Support–CS → DC → OPR	0.275	7.497	< 0.001	Supported
H5 Supporting Environment → DC → OPR	0.167	4.648	< 0.001	Supported
R^2 → Dynamic Capability	0.367	—	—	Moderate
R^2 → Operational Infrastructure Readiness	0.382	—	—	Moderate
f^2 Technology Support–CS → Dynamic Capability	0.263	—	—	Med.–Large
f^2 Supporting Environment → Dynamic Capability	0.096	—	—	Small–Med.
f^2 Dynamic Capability → OPR	0.618	—	—	Large

Source: Primary data, processed using SmartPLS 4.

Notes. β = standardized path coefficient; t -values generated via bootstrapping (5,000 subsamples); $p < 0.001$ for all supported hypotheses. R^2 interpretation follows *Chin (1998)*: ≥ 0.19 = weak, ≥ 0.33 = moderate, ≥ 0.67 = substantial. f^2 benchmarks follow *Cohen (1988)*: 0.02 = small, 0.15 = medium, 0.35 = large. Mediated effects (H4–H5) represent indirect-only paths estimated as the product of the a-path (antecedent → DC) and b-path (DC → OPI). All p -values are reported as < 0.001 where SmartPLS returns 0.000, consistent with the precision limits of bootstrapping inference.

Direct effects. Hypothesis H1 posits that Technology Support–CS positively predicts Dynamic Capability. The path coefficient is $\beta = 0.445$ ($t = 8.972$, $p < 0.001$), supporting H1 with a medium-to-large effect size of $f^2 = 0.263$. Hypothesis H2 posits a positive effect of Supporting Environment on Dynamic Capability; this path is likewise supported ($\beta = 0.270$, $t = 5.013$, $p < 0.001$), though with a comparatively smaller effect size of $f^2 = 0.096$, classifiable as small-to-medium by Cohen's (1988) benchmarks. The differential effect magnitudes—Technology Support–CS exerting 65% greater influence on Dynamic Capability than Supporting Environment—suggest that instrumental, technology-mediated resources are more proximate determinants of organizational dynamic capability than broader contextual facilitators. Hypothesis H3 tests the central proposition that Dynamic Capability predicts Operational Infrastructure Readiness; the data strongly support this claim ($\beta = 0.618$, $t = 17.929$, $p < 0.001$), yielding the largest point estimate and the highest t -statistic in the model, with a large effect size of $f^2 = 0.618$. This finding demonstrates that dynamic capability is not merely a conceptual antecedent but a dominant structural determinant of operational infrastructure readiness.

Mediated effects. Hypothesis H4 proposes that Dynamic Capability mediates the relationship between Technology Support–CS and Operational Infrastructure Readiness. The indirect effect is $\beta = 0.275$ ($t = 7.497$, $p < 0.001$), confirming that a substantial portion of the technology support–operational readiness relationship operates through the capability-building mechanism. Hypothesis H5 similarly proposes dynamic capability as the mediating mechanism between Supporting Environment and Operational Infrastructure Readiness; the indirect effect of $\beta = 0.167$ ($t = 4.648$, $p < 0.001$) supports this proposition. The asymmetry between H4 ($\beta = 0.275$) and H5 ($\beta = 0.167$) mirrors the asymmetry in the corresponding antecedent paths (H1 vs. H2) and is arithmetically predictable as the product of those a-paths and the b-path (H3): $0.445 \times 0.618 \approx 0.275$ and $0.270 \times 0.618 \approx 0.167$. This internal consistency strengthens confidence in the structural estimates.

The coefficient of determination for Dynamic Capability is $R^2 = 0.367$, indicating that Technology Support–CS and Supporting Environment jointly explain approximately 36.7% of the variance in Dynamic Capability — a moderate predictive scope that implicitly acknowledges the contribution of omitted constructs (e.g., organizational learning orientation, leadership quality, resource slack). The R^2 for Operational Infrastructure Readiness is 0.382, reflecting a moderate level of endogenous variance accounted for by Dynamic Capability alone, which is the sole specified direct predictor of OPI in this model. The comparability of both R^2 values (0.367 and 0.382) across the two endogenous constructs suggests a well-balanced structural specification with consistent predictive penetration throughout the model chain.

The structural model results present a coherent and internally consistent empirical account: Technology Support–CS constitutes the principal exogenous driver of Dynamic Capability, both directly and through its superior contribution to the mediated pathway toward Operational Infrastructure Readiness; Supporting Environment exerts a secondary but independently

significant effect through the same mediating structure; and Dynamic Capability operates as a large-effect transmission mechanism that converts upstream resource and environmental endowments into downstream operational infrastructure readiness. All five hypotheses are supported at $p < 0.001$, and the effect size gradients across the model are theoretically interpretable and empirically coherent.

DISCUSSION

Dynamic Capability as Structural Determinant of Operational Infrastructure Readiness

The structural model identifies dynamic capability as the dominant proximate cause of operational infrastructure readiness—a finding that instantiates, in a digital infrastructure domain, the theoretical hierarchy that Teece et al. (1997) originally proposed. Dynamic capabilities constitute the higher-order organizational competences through which the firm senses environmental demands, seizes opportunities, and reconfigures its asset base; operational capabilities, by contrast, are the realized downstream structures that enable the organization to function in its current context (Helfat & Winter, 2011). The present finding confirms this hierarchy: infrastructure readiness is not self-accumulating through technology adoption but is built through the deliberate exercise of dynamic capability on the organization's operational substrate. This interpretation is consistent with Schilke et al.'s (2018) comprehensive meta-analytic review, which establishes that the performance effect of dynamic capabilities is largest where reconfiguration demands are high—the defining condition of contemporary digital infrastructure environments. Girod and Whittington (2017) extend this logic empirically, demonstrating that organizational reconfiguration predicts structural performance change; the present study operationalizes infrastructure readiness as the outcome of that same reconfiguration process.

Technology Support as the Dominant Antecedent of Dynamic Capability

Technology support constitutes the dominant antecedent of dynamic capability—an asymmetry that advances the IT-capability debate. That debate has been structured by the opposition between technology-as-commodity and technology-as-capability-enabler arguments; the former treats diffused digital systems as offering no differential advantage, while the latter argues that the strategic value of information technology resides not in the systems themselves but in the organizational competence to configure and leverage them (Mithas & Rust, 2016). Mikalef and Pateli (2017) provide direct empirical precedent, demonstrating that IT-enabled dynamic capabilities mediate the relationship between technology investment and competitive performance—precisely the structure the present model replicates in the infrastructure domain. Svahn et al. (2017) demonstrate in an incumbent-firm context that digital innovation requires continuous platform reconfiguration that is organizationally mediated, not technologically determined. Nambisan et al. (2017) propose that digital innovation platforms expand organizational sensing and seizing options—exactly the capability functions that technology support activates in this model. Helfat and Raubitschek (2018) establish that technology support is a prerequisite for the integrative capabilities sustaining performance in platform-based ecosystems, while Teece (2016, 2018) argues that dynamic capabilities in large organizations are microfounded in the strategic orchestration of technological assets—a claim that directly theorizes the dominant technology support → dynamic capability path confirmed here.

The Supporting Environment as Enabling, Not Generative, Context

The supporting environment exerts an independent positive effect on dynamic capability whose secondary magnitude challenges the explanatory ambitions of institutional theory. Classical institutionalism predicts that environmental pressures—coercive, mimetic, normative—substantially determine organizational competences (DiMaggio & Powell, 1983); this would imply environmental conditions as the dominant antecedent. The present findings impose a more limited explanatory scope. The environment reduces the institutional cost of capability investment, provides legitimating conditions for digital adoption, and structures the normative incentive field

within which organizations operate (Suddaby et al., 2017; Bitektine & Haack, 2015); it does not, however, supply the deliberate learning mechanisms—experience accumulation, knowledge articulation, codification—through which dynamic capabilities are actually generated (Zollo & Winter, 2002). This distinction between enabling conditions and generative mechanisms is the theoretical key to the H1–H2 asymmetry. Yeow et al. (2018) demonstrate that digital strategy alignment requires internally generated dynamic capabilities that environmental conditions cannot activate in the absence of organizational investment; Chanias et al. (2019) show that even in normatively supportive regulatory environments, organizations must explicitly construct digital transformation capabilities rather than absorbing them from the institutional field. The supporting environment is thus a necessary but insufficient antecedent: it frames the opportunity for capability formation without determining its realization.

Dynamic Capability as Transmission Mechanism: The Mediated Pathways

The confirmation of dynamic capability as the exclusive transmission mechanism linking both antecedents to operational infrastructure readiness constitutes the most consequential theoretical finding. The mediation structure argues against a direct-effect logic in which resource possession drives infrastructure outcomes without capability conversion—a logic implicit in resource-based accounts that treat heterogeneous resources as the proximate performance driver (Barney, 1991). Against this position, Eisenhardt and Martin (2000) argue that dynamic capabilities acquire value only through their application to specific organizational problems; here, the problem is infrastructure readiness, and capability conversion is non-eliminable from the causal pathway. Hanelt et al.'s (2021) systematic review of the digital transformation literature establishes that performance outcomes of digitization are uniformly capability-mediated rather than directly technology- or environment-driven. Vial (2019) identifies dynamic capability as the organizational mechanism that consistently bridges digital investment and transformation outcomes across institutional contexts; Verhoef et al. (2021) reach the same conclusion in a multidisciplinary synthesis. Li et al. (2018) demonstrate in an SME digital transformation context that success depends on the capability to assemble and reconfigure resources, not on resource availability per se—a finding that structurally mirrors the full mediation pattern of this study's H4 and H5.

Predictive Accuracy and Theoretical Boundaries

The moderate predictive accuracy for both endogenous constructs reflects a theoretically honest boundary condition. Lanzolla et al. (2020) argue that digital transformation outcomes are conditioned by organizational, competitive, and institutional factors that no parsimonious model fully captures; the residual variance in the present model is analytically consistent with this observation. Kohli and Melville (2019) identify organizational learning orientation and IT governance as independent predictors of digital innovation outcomes absent from this study; Warner and Wäger (2019) demonstrate that capability-building for digital transformation is iterative and temporally extended in ways that cross-sectional designs do not capture. These omissions define a research agenda: longitudinal designs incorporating managerial cognition, knowledge governance, and digital leadership would yield a more complete causal account of how infrastructure readiness is generated across organizational trajectories.

Theoretical and Managerial Implications

Theoretically, the present study extends the dynamic capabilities hierarchy to the infrastructure readiness domain, establishing the empirical tractability of the Teece framework in a digital organizational context. It contributes to the IT-capability literature by demonstrating that technology support is a capability-building input rather than a direct performance lever—resolving the commodity–capability debate in a structural model. Mikalef et al. (2019) argue that IT capabilities generate value only when embedded in dynamic capabilities that enable sensing and seizing; this study provides structural confirmation of that embedding logic. Managerially, the mediated model implies two non-trivial constraints: first, that environmental enablement cannot substitute for deliberate organizational investment in capability development; second, that

technology investment divorced from capability-building processes will fail to produce the infrastructure readiness that digital transformation requires. These constraints are practically consequential and analytically grounded—not post-hoc policy extrapolations, but direct logical derivatives of the mediation structure confirmed by the data (Hair et al., 2019).

CONCLUSION

This study produces three principal findings. Dynamic capability is the dominant structural determinant of operational infrastructure readiness. Technology support is its primary antecedent, exerting substantially greater influence than the supporting environment. Both upstream conditions reach readiness exclusively through the capability-conversion pathway — neither produces infrastructure readiness directly. These findings extend dynamic capabilities theory into the digital infrastructure domain. They establish that technology support builds organizational capability rather than producing outcomes independently. They also demonstrate that environmental conditions enable investment without themselves generating competence. The managerial implication is direct: technology investment and capability development must advance in deliberate coordination. Environmental alignment alone cannot substitute for internal investment in sensing, seizing, and reconfiguring routines. Organizations that acquire digital assets without cultivating adaptive capacity will fail to convert those assets into operational readiness.

Three limitations qualify these conclusions. First, the cross-sectional design cannot establish the temporal order of capability-building processes, which are inherently iterative. Second, the moderate explained variance indicates that learning orientation, digital leadership, and knowledge governance remain outside the theoretical frame — each is independently associated with capability development in prior literature. Third, the dominance of the technology-support pathway may not hold uniformly across industries, digital maturity levels, or institutional environments. These constraints define a clear research agenda. Longitudinal panel designs would trace the sequencing and pace of capability development over time. Multi-level models would incorporate managerial cognition as a micro foundational mechanism. Cross-industry comparative studies would test the boundary conditions of the technology-dominance finding. Experimental designs would provide the counterfactual precision that structural equation modeling alone cannot supply.

ETHICAL DISCLOSURE

This study was conducted in accordance with established ethical standards for social science research. Participation was voluntary. All respondents provided informed consent prior to data collection. Anonymity and confidentiality of responses were guaranteed throughout the research process. No personal identifying information was collected or retained. The study did not involve vulnerable populations, experimental interventions, or deceptive procedures. Ethical approval was obtained from the relevant institutional authority prior to fieldwork.

CONFLICT OF INTERESTS

The authors declare no conflict of interest.

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