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Digital Technology and Firm Performance in IT Services: The Mediating Role of Technology Value Customization

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ABSTRACT

Purpose – This study examines whether Technology Value Customization (TVC) mediates the effects of Digital Technology (DT), Dynamic Capability (DC), and Customer Orientation (CO) on Firm Performance (FP) in Indonesia's IT services industry, drawing on Dynamic Capability Theory and Service-Dominant Logic.
Design/Methodology/Approach – Data from 240 IT service firms in Jakarta, Surabaya, and Bandung were collected via a seven-point Likert questionnaire and analyzed using PLS-SEM (5,000-subsample bootstrapping), Necessary Condition Analysis (NCA), and Confirmatory Tetrad Analysis.
Findings/Results – DT and DC had no significant direct effect on FP, while CO's direct effect and all paths to and from TVC were significant. The DT-FP and DC-FP relationships showed statistically significant indirect-only associations via TVC (consistent with, though not definitive proof of, full mediation per Zhao et al., 2010), while CO-FP showed a complementary partial-mediation pattern; NCA identified CO, DT, and TVC as necessary conditions for FP, while DC was not.
Originality/Value – TVC offers a plausible mechanism reconciling prior inconsistent findings on technology's direct effect on performance, integrating Service-Dominant Logic with Dynamic Capability Theory. The key implication is that technological resources drive performance only when customized into customer-relevant value.

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1. Introduction

Indonesia's information and communication sector grew by 9.65 percent year-on-year in the third quarter of 2025, far outpacing the 5.04 percent national economic growth rate recorded over the same period (BPS, 2025). IT service firms function as the infrastructure providers underpinning this digital acceleration, making the pressure to continuously upgrade technological capability a strategic imperative. The prevailing assumption holds that digital technology investment is directly proportional to firm performance. Recent empirical evidence, however, points in the opposite direction: this relationship is inconsistent across studies.

Two recent studies illustrate this inconsistency directly. Barba-Sánchez et al., (2024), surveying 246 cross-sector firms using PLS-SEM, found that IT capability has a significant positive effect on firm performance through digital orientation and digital transformation. In contrast, Hoang et al., (2024), surveying 297 manufacturing SMEs in Vietnam using PLS-SEM combined with an artificial neural network, found that digital capability has no significant direct effect on firm performance, even though it significantly affects product and process innovation capability. Both studies apply the same analytical approach and draw on the same dynamic-capability perspective, yet arrive at contradictory conclusions regarding the direct effect of digital technology on performance.

This inconsistency suggests the presence of an intervening variable that neither model measures explicitly. Dynamic Capability Theory explains how firms reconfigure resources to respond to environmental change (Teece, 1996), but does not explain why such reconfiguration sometimes fails to translate directly into performance. Service-Dominant Logic offers a complementary explanation: technological value is realized only when it is customized to the context of the value recipient, rather than being automatically embedded in the product (Vargo & Lusch, 2004). This value-in-context principle indicates that the effect of technology on performance requires an intervening process, namely value customization, which neither Barba-Sánchez et al., (2024) & Hoang et al., (2024) tested explicitly as a mediator.

Building on this reasoning, this study proposes Technology Value Customization (TVC) as a mediating variable that explains the inconsistency between the two studies' findings. The argument is that the effect of technology on performance depends on the extent to which technology is customized to customer needs: when customization is high, the direct effect of technology on performance is more likely to be significant, and vice versa. Based on this argument, the study formulates four research questions: first, whether Digital Technology, Dynamic Capability, and Customer Orientation have a significant positive effect on Firm Performance among IT service firms in Indonesia; second, whether these same three constructs have a significant positive effect on Technology Value Customization; third, whether Technology Value Customization itself has a significant positive effect on Firm Performance; and fourth, whether Technology Value Customization positively mediates the relationships among Digital Technology, Dynamic Capability, and Customer Orientation on Firm Performance.

TVC is positioned here as conceptually narrower than the customization-related constructs it most closely resembles. Solution customization and mass customization describe the operational adaptation of a product or service offering itself; digital service adaptation describes the technical reconfiguration of a platform or interface; technology-market alignment and service personalization describe fit at the level of a market segment or a single service encounter. TVC, by contrast, is defined at the level of the value proposition a firm's technological and organizational resources are translated into for a specific client relationship, encompassing but not reducible to any single one of these adjacent processes. Customer value co-creation is the closest conceptual neighbor, since both draw on Service-Dominant Logic; the two differ in that co-creation describes a joint, interactive process between firm and customer, whereas TVC, as operationalized in this study, describes the firm-side capability to convert internal resources, digital technology, dynamic capability, and customer-need information, into a customized value proposition prior to or independent of the customer's own participation in that process. This boundary matters theoretically because it is what allows TVC to be positioned as a mediator between resource-side constructs (DT, DC, CO) and a performance outcome (FP), a role co-creation, being interactional rather than resource-transformational, is not specified to play. The gap this study addresses is accordingly narrower than "prior studies report inconsistent direct effects of technology on performance": inconsistent coefficients alone do not establish that a mediator is missing, since they are equally consistent with sampling variation, unmeasured moderators, or model misspecification unrelated to customization. The more specific gap is that existing technology-performance models, including the two motivating studies discussed above, model digital technology and dynamic capability as resources with a hypothesized direct effect on performance, without a construct representing the translation of those resources into client-specific value; competing candidate mediators such as innovation capability, digital transformation, and service quality each capture part of this translation process but not the customer-specific customization component this study argues is the operative mechanism in IT services, where offerings are frequently configured per client rather than standardized. This positioning is developed further in the Method section, where TVC is compared systematically against five adjacent constructs.

This study aims to empirically test these ten paths through PLS-SEM among 240 medium- to large-scale IT service firms. It offers three novel contributions. Conceptually, TVC is positioned as an explicit mediator that explains the source of the inconsistent effect of technology on performance, differing from both reference studies, which tested direct effects without a comparable mediator. Methodologically, the study tests a ten-path mediation model with an explicit sample-size justification. Contextually, the study targets the IT services industry in three major Indonesian cities, in contrast to the cross-sector sample used by (Barba-Sánchez et al., 2024) and the manufacturing sample used by (Van Hoang & Hien, 2024).

2. Literature Review & Hypothesis Development

2.1 Digital Technology and Firm Performance (H1)

Dynamic Capability Theory explains a firm's ability to integrate, build, and reconfigure internal and external competencies in response to rapid environmental change, operationalized through sensing, seizing, and reconfiguring (Teece, 1996; Teece, 2007). Digital Technology (DT) represents the extent to which digital infrastructure, platforms, and tools are adopted and embedded within a firm's business processes. Applying the resource-based view together with the dynamic capability perspective, digital transformation research has generally proposed that digital technology functions as a strategic resource capable of reconfiguring a firm's resource base, such that higher adoption is expected to yield superior performance. This expectation is not, however, uniformly supported empirically: (Barba-Sánchez et al., 2024) found IT capability to significantly predict firm performance, whereas Hoang et al., (2024) found no significant direct effect of digital capability on performance among manufacturing SMEs. In the IT services context, where digital technology is simultaneously the firm's core offering and its operational infrastructure, its direct translation into measurable performance gains cannot be assumed a priori and instead warrants direct empirical testing.

H1: Digital Technology has a significant positive effect on Firm Performance.

2.2 Dynamic Capability and Firm Performance (H2)

Dynamic Capability Theory holds that sensing, seizing, and reconfiguring routines allow firms to adapt continuously to environmental turbulence and thereby sustain competitive advantage (Teece, 1996; Teece, 2007). Firms with well-developed dynamic capabilities are theorized to detect market and technological shifts earlier, mobilize resources more decisively, and reconfigure internal structures more effectively than competitors, translating adaptive capacity directly into superior performance (Hoque et al., 2022). Empirical support for this translation exists in adjacent technology-intensive contexts: dynamic capabilities encompassing digital orientation, digital capability, and organizational willingness to change have been shown to strengthen the competitiveness of technology firms through responsible innovation practices (de la Torre & De la Vega, 2025), suggesting that capability-driven adaptiveness can manifest as a measurable performance advantage. IT service firms, which compete in a market characterized by continual technological and client-requirement change, plausibly depend on comparable sensing, seizing, and reconfiguring routines to remain competitive; firms exhibiting stronger dynamic capability are therefore expected to convert that adaptive capacity into superior firm performance rather than leaving it latent or unrealized (Abidin et al., 2022). Based on this reasoning, it is proposed:

H2: Dynamic Capability has a significant positive effect on Firm Performance.

2.3 Customer Orientation and Firm Performance (H3)

Service-Dominant Logic (SDL) reframes value as something always co-created between the service provider and the customer, rather than a property automatically embedded in a product or technology (Vargo & Lusch, 2016). Under this view, Customer Orientation, an organization-level capability reflecting the extent to which a firm systematically gathers, disseminates, and acts upon customer-need information, functions as a foundational co-creation capability rather than a peripheral marketing activity. Firms with a strong customer orientation are theorized to understand the specific needs of value recipients more accurately than less customer-oriented competitors, which in turn should improve the effectiveness of the value-creation process itself. Consistent with this reasoning, customer orientation, operationalized as a service-dominant, co-creation-based capability, has been empirically linked to improvements in both customer-related and financial performance outcomes (Karpen et al., 2015), indicating that its effects extend beyond customer-facing metrics into overall firm performance. In the IT services context, where solutions are typically delivered through direct, ongoing client engagement, customer orientation is plausibly a particularly consequential driver of performance relative to more arm's-length industries.

H3: Customer Orientation has a significant positive effect on Firm Performance.

2.4 Digital Technology and Technology Value Customization (H4)

Digital Technology provides the data infrastructure, platforms, and technical capabilities that firms draw upon to tailor solutions to customer needs (Holst et al., 2024). Beyond its operational role, digital technology can function as a connective mechanism that coordinates and accelerates value co-creation practices across organizational levels and client interfaces, enabling firms to capture and act upon client-specific information more rapidly than otherwise possible. Firms with higher digital technology adoption therefore possess a stronger technical foundation from which to customize technological value: richer data on client usage patterns, more flexible platforms for configuring solutions, and faster feedback loops between client needs and service delivery (Ramdani et al., 2013). Because Technology Value Customization (TVC) is conceptualized as the process of adapting technological capability into solutions relevant to specific customer contexts, consistent with Service-Dominant Logic's value-in-context principle (Vargo & Lusch, 2016), digital technology is theorized to function as a necessary technical antecedent of this process rather than as a determinant of performance in its own right. In the IT services context, where digital infrastructure is the primary medium through which customization is delivered, this antecedent role is expected to be especially pronounced.

H4: Digital Technology has a significant positive effect on Technology Value Customization.

2.5 Dynamic Capability and Technology Value Customization (H5)

Dynamic Capability Theory explains how firms reconfigure internal resources responsively as market needs shift, through the coordinated processes of sensing, seizing, and reconfiguring (Teece, 1996; Teece, 2007). Applied to the customization process specifically, dynamic capability supplies the organizational mechanism through which a firm translates sensed customer requirements into reconfigured service offerings: sensing routines detect emerging or heterogeneous client needs, seizing routines mobilize the resources required to address them, and reconfiguring routines adjust the firm's technological and operational base accordingly (Lavie et al., 2012; M Popper, 2000). Applied to the customization process, this sensing-seizing-reconfiguring sequence implies that firms with stronger dynamic capability are better positioned to detect heterogeneous client requirements and reallocate technological resources to address them, providing a theoretical, resource-reconfiguration basis for expecting dynamic capability to drive customization-related outcomes, independent of any single supporting empirical citation. Within the IT services context, firms with stronger sensing, seizing, and reconfiguring routines are theorized to be better equipped to convert generic technological capability into client-specific, customized value than firms with weaker dynamic capability.

H5: Dynamic Capability has a significant positive effect on Technology Value Customization.

2.6 Customer Orientation and Technology Value Customization (H6)

Customer Orientation functions as a primary informational input to the technology value customization process, since firms must first understand the specific, often heterogeneous needs of individual clients before technological capability can be meaningfully tailored to them (Adusei et al., 2020; Frambach et al., 2016). Service-Dominant Logic's value-in-context principle holds that value is realized only within the particular context of the recipient's needs and use situation, rather than as an inherent property of a product or technology (Vargo & Lusch, 2016); under this principle, accurate knowledge of that context, the substantive content of customer orientation, is a logical prerequisite for effective customization rather than a parallel or independent contributor to it. Firms with a stronger customer orientation are therefore theorized to possess more accurate and more current knowledge of client-specific requirements, enabling them to configure technological solutions more precisely to individual client contexts than firms with weaker customer orientation (Konopik et al., 2022). In IT services specifically, where client requirements are often idiosyncratic and evolve over the course of an engagement, this informational role is expected to be a particularly strong driver of the extent to which technology is successfully customized to client value.

H6: Customer Orientation has a significant positive effect on Technology Value Customization.

2.7 Technology Value Customization and Firm Performance (H7)

Technology Value Customization (TVC) is theorized to enable firms to translate internal technological and organizational capabilities into solutions relevant to individual customers, thereby closing the gap between resource possession and realized performance. In this study, TVC operationalizes Service-Dominant Logic's value-in-context principle (Konopik et al., 2022): the process of adapting general technological capability into a form relevant to specific customer needs and use contexts. As such, TVC functions as the conceptual bridge between the internal-capability perspective of Dynamic Capability Theory (Teece, Pisano, & Shuen, 1997; Teece, 2007) and the customer-facing, value-co-creation perspective of SDL, positioning it as the mechanism through which internally held resources are ultimately converted into externally recognized, performance-relevant value. Firms that more effectively customize their technological offerings to client-specific contexts are therefore expected to be more successful at capturing the performance benefits of their capabilities than firms that possess comparable capabilities but customize them less effectively. This path is central to the mediation logic developed in Section 2.8, where TVC is proposed as the mechanism reconciling prior studies' inconsistent findings on the direct effect of technology on performance.

H7: Technology Value Customization has a significant positive effect on Firm Performance.

2.8 Mediation: Technology Value Customization (H8, H9, H10)

Dynamic Capability Theory and Service-Dominant Logic are integrated here as sequential, not parallel, explanations. DCT's sensing-seizing-reconfiguring logic explains how a firm builds and rearranges internal resources in response to a changing environment, but on its own describes a change in what the firm possesses, not a change any client recognizes as valuable. SDL supplies that missing step: value is co-created in context, becoming value only through use and application to a specific customer's circumstances. TVC operationalizes this transition, the point at which a reconfigured resource is actively shaped around an identified client need, so DCT explains the resource-side input and SDL explains why that input must pass through customization before it is recognized as value and reflected in performance. This sequencing motivates the asymmetric mediation proposed below: DT and DC are internally generated, not inherently client-oriented, so their path to performance is theorized to run through TVC, whereas CO is inherently customer-facing by definition, already embedding the interactional element DT and DC lack, and is theorized to retain a direct path to performance while also feeding TVC with client-need information.

Sections 2.1–2.6 jointly imply that DT, DC, and CO may each influence FP through both a direct path and an indirect path via TVC. Mediation theory holds that decomposing a predictor's total effect into direct and indirect components carries substantive theoretical meaning about the underlying mechanism, not merely statistical formality (Zhao et al., 2010). This study proposes TVC as the mechanism reconciling technology's and capability's inconsistent direct effects on performance reported in prior studies (Barba-Sánchez et al., 2024; Hoang et al., 2024): generic, uncustomized resources confer little direct advantage since competitors can replicate them, whereas resources customized to client contexts generate harder-to-replicate, performance-linked value. For DT and DC, largely internal and resource-oriented, this implies their effects should operate substantially or entirely through TVC, since Dynamic Capability Theory explains how such resources are sensed, seized, and reconfigured (Teece, 1996; Teece, 2007) but not why reconfiguration doesn't reliably translate into performance, a gap TVC is proposed to fill. CO, by contrast, is inherently customer-facing, already engaged in routine collection and use of client-need information (Karpen et al., 2015) independent of any customization step, so its direct path is theorized to remain meaningful alongside its indirect contribution through TVC. Based on this reasoning, it is proposed:

H8: Technology Value Customization positively mediates the relationship between Digital Technology and Firm Performance.

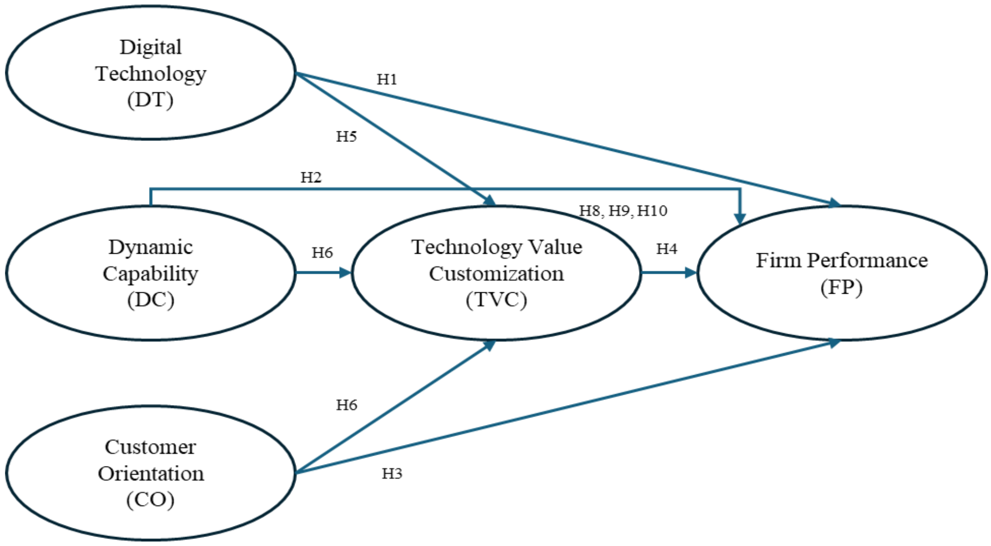
H9: Technology Value Customization positively mediates the relationship between Dynamic Capability and Firm Performance.

H10: Technology Value Customization positively mediates the relationship between Customer Orientation and Firm Performance.

2.9 Research framework

This framework specifies Technology Value Customization (TVC) as the central mediating construct linking three exogenous resources, Digital Technology (DT), Dynamic Capability (DC), and Customer Orientation (CO), to Firm Performance (FP). Three direct paths (H1, H2, H3) test whether each antecedent independently predicts FP without mediation, grounded in the assumption that resource possession alone may be sufficient for performance. Three further paths (H4, H5, H6) test whether these same antecedents predict TVC, positioning value customization as the mechanism through which internal technological, capability-based, and customer-facing resources are converted into client-relevant value, consistent with Service-Dominant Logic's value-in-context principle. H7 tests TVC's own effect on FP, the final link in the mediating chain. H8, H9, and H10 formally test the indirect (mediated) effects of DT, DC, and CO on FP through TVC. Structurally, the model treats TVC as a single mediator absorbing three parallel antecedents, allowing the direct and indirect paths to be compared to determine whether each antecedent's influence on performance is direct, statistically indirect-only (consistent with full mediation), or complementarily/partially mediated by customization.

Figure 1. Research Framework



3. Research Method

3.1 Sample and Data Collection

This study adopted a positivist, quantitative explanatory, cross-sectional design to test theory-based causal hypotheses at a single point in time; a limitation is its inability to establish causal direction with certainty, so interpretation remains grounded in the theory established prior to data collection. The population comprises medium- to large-scale IT service firms in Jakarta, Surabaya, and Bandung, Indonesia's largest ICT growth centers, which grew 9.65% year-on-year in Q3 2025 (BPS, 2025). The sample comprises 240 firms, one respondent per firm at director or senior-manager level, given their strategic understanding of the firm's capability and performance.

Sample size is justified by two approaches: the 10-times rule (minimum = ten times the largest number of paths to a single construct; TVC's three paths yield a minimum of 30) (Hair et al., 2011), and the more statistically accurate inverse square root method, typically requiring 75–160 respondents (Kock & Hadaya, 2018). At 240, the sample exceeds both thresholds. Purposive sampling required firms to have operated at least three years with an active technology-based unit. Primary data were collected via online and offline questionnaires administered to directors/senior managers recruited through IT industry associations and professional networks.

Common method bias was addressed procedurally (respondent anonymity, randomized item ordering, varied response-scale formats across blocks) and checked statistically in two ways. A full-collinearity VIF test (all values < 3.3) gives an indirect check on inflated shared variance but does not directly estimate method-variance magnitude (Kock, 2015; Podsakoff et al., 2003). Harman's single-factor test on all 30 indicators (unrotated PCA) showed a significant Bartlett's test ($\chi^2 = 4528.99$, $p < .001$) and KMO = .914; five components had eigenvalues greater than 1.0, matching the five theorized constructs, and the first unrotated component explained 29.2% of variance, well below the 50% threshold conventionally used to flag pervasive common method variance (Podsakoff et al., 2003). Together these results provide converging, though not conclusive, evidence that a single latent method factor does not account for the bulk of covariance among indicators. More direct techniques for single-source designs, a marker-variable test or an unmeasured latent method-factor (ULMC) model (Podsakoff et al., 2003; Williams et al., 2010), were not implemented, since no marker variable was included in the instrument and no post hoc method factor was estimated in SmartPLS.

3.2 Measures

This study involves five latent variables: Digital Technology (DT), Dynamic Capability (DC), and Customer Orientation (CO) as exogenous variables; Technology Value Customization (TVC) as the mediating variable; and Firm Performance (FP) as the endogenous variable. All variables are operationalized as first-order reflective constructs measured directly through their indicators. Table 2 presents the operational definitions and example indicators; all indicators used a seven-point Likert scale adapted from prior instruments relevant to Dynamic Capability Theory and SDL, adjusted to Indonesia's IT services context.

Because TVC is introduced here as a relatively new construct, its item pool was developed rather than borrowed from a single validated scale. Item development began deductively from Dynamic Capability Theory's sensing-seizing-reconfiguring logic (Teece, 1996; Teece, 2007), applied specifically to customizing technological and organizational resources around client-specific value, rather than from an existing solution-customization or service-personalization scale. Item wording then drew on phrasing conventions from related empirical sources, including da Silva and Cardoso (2024), Faems et al. (2010), Sam, Mu'min, Wahyudono et al. (2025), and Weinreich et al. (2022), adapted to the IT services context; this wording step is distinct from, and does not substitute for, the conceptual anchoring in Dynamic Capability Theory. This grounding distinguishes TVC from adjacent constructs such as solution customization or service personalization: those describe the adapted offering itself, whereas TVC's items capture the dynamic-capability process, sensing client needs, seizing the opportunity to reconfigure resources, and reconfiguring assets, through which that offering is produced. The item pool's content-validity review and pilot test followed the same procedure applied to all five constructs jointly, not as a separate TVC-only exercise; this content-level evidence is distinct from statistical discriminant validity, which shows TVC's indicators empirically separate from DT, DC, and CO in this sample but does not by itself establish that the construct's content domain was conceptually distinguished from these related constructs at the design stage.

Table 1. Conceptual Comparison of Technology Value Customization with Adjacent Constructs

Construct	**Definition**	**Theoretical Foundation**	**Unit of Analysis**	**Dimensionality**	**Typical Antecedents**	**Typical Outcomes**	**Empirical Measures**
Technology Value Customization (TVC, this study)	Firm-side capability that converts internal technological and organizati	Dynamic Capability Theory (sensing-seizing-reconfiguring) integrate	Firm-client dyad; value proposition level.	Unidimensional, first-order reflective (empirically tested via	Digital Technology, Dynamic Capability, Customer	Firm Performance (financial and non-financial).	6-item reflective scale developed for this study (Table 2);

Construct	Definition	Theoretical Foundation	Unit of Analysis	Dimensionality	Typical Antecedents	Typical Outcomes	Empirical Measures
	onal resources into a value proposition tailored to a specific client's needs and use context.	d with SDL's value-in-context principle.		CTA-PLS, Section 4.9).	Orientation.		7-point Likert.
Solution customization / mass customization	Operational adaptation of the product or service offering itself to individual customer specifications.	Operations management; modularity theory.	Product/service configuration level.	Typically formative (module/option combinations).	Modular product architecture, manufacturing flexibility.	Order fulfillment accuracy, customer satisfaction.	Configuration-count or option-fit indices; rarely a Likert perceptual scale.
Service personalization	Tailoring of a single service encounter or interaction to an individual customer's preferences.	Services marketing; relationship marketing.	Single service encounter/episode.	Usually unidimensional, encounter-specific.	Frontline employee discretion, CRM data use.	Encounter satisfaction, repurchase intention.	Encounter-level perceptual scales, often dyadic (customer-rated).
Technology-market alignment	Degree of fit between a firm's technological capability and the requirements of a	Strategic fit / contingency theory.	Market-segment level.	Typically formative composite of fit indicators.	Market sensing, R&D-marketing integration.	Market share, product-market success.	Fit indices or difference scores between capability and market-requirem

Construct	Definition	Theoretical Foundation	Unit of Analysis	Dimensionality	Typical Antecedents	Typical Outcomes	Empirical Measures
	target market segment.						ent profiles.
Customer value co-creation	Joint, interactive process through which firm and customer collaboratively generate value.	Service-Dominant Logic (co-creation axiom).	Firm-customer interaction/dyad.	Multidimensional (e.g., dialogue, access, risk assessment, transparency).	Customer participation, platform interactivity.	Customer engagement, co-created value.	Multi-item scales capturing customer-perceived participation, often customer-sampled.
Digital service adaptation	Technical reconfiguration of a digital platform or interface to changing user or environmental requirements.	Information systems / dynamic capability.	Platform/interface level.	Often formative (feature-level adaptations).	IT infrastructure flexibility, agile development capability.	System usability, adoption/continuance.	Feature-adaptation counts or IS-usability perceptual scales.

As Table 1 shows, TVC's closest neighbor is customer value co-creation, since both draw on Service-Dominant Logic, but the two diverge on unit of analysis and interactivity: co-creation is customer-participatory by definition, whereas TVC, as operationalized here, is a firm-side conversion capability that can, in principle, be exercised prior to or independent of the client's own participation. The remaining constructs differ from TVC on dimensionality or unit of analysis, or both, supporting the claim that TVC is not a relabeling of an existing construct but occupies a distinct position defined jointly by its dyadic, value-proposition-level unit of analysis and its dual theoretical grounding in Dynamic Capability Theory and Service-Dominant Logic.

Table 2. Operationalization of Research Variables

Variable	Definition	Example Indicator	Key Sources
Digital Technology (DT)	Firm's level of digital technology adoption	Adopts current cloud/AI technology in service operations.	Alford & Jones (2024); Sung et al. (2022)

Variable	Definition	Example Indicator	Key Sources
	and integration in business processes.		
Dynamic Capability (DC)	Firm's ability to sense, seize, and reconfigure resources for market change.	Quickly detects new technology opportunities in the market.	Teece et al. (1997); Teece (2007)
Customer Orientation (CO)	Firm's strategic orientation toward understanding and meeting customer needs.	Routinely involves customers in service design.	Frambach et al. (2016); Smith & Jambulingam (2018)
Technology Value Customization (TVC)	Adapting technological value to specific customer needs and context of use.	Tailors technology features to each client's unique needs.	da Silva & Cardoso (2024); Weinreich et al. (2022)
Firm Performance (FP)	Firm's financial and non-financial performance relative to targets or competitors.	Revenue growth has increased over the past three years.	Adomako et al. (2018); Mu'min et al. (2025)

The research instrument is a closed-ended questionnaire using a seven-point Likert scale ranging from (1) strongly disagree to (7) strongly agree. Instrument development followed a single, chronologically ordered procedure applied uniformly across all five constructs, including the newly developed TVC scale. First, a content-validity review was conducted through expert judgment by three academics in strategic management and marketing, who independently rated each item for relevance and clarity; items on which raters disagreed were revised for wording, and none were dropped at this stage since all were judged conceptually relevant. Formal indices such as the Content Validity Index or Content Validity Ratio were not computed from these ratings, a limitation noted for future refinement of the scale. Second, the revised instrument was pilot-tested with 50 respondents drawn from the target population of IT service firm directors and senior managers, sampled outside the main data-collection frame, to confirm item clarity and initial internal consistency. All items were retained following the pilot test, none fell below the loading or reliability thresholds applied in the main analysis, so no items were dropped or reworded before the main survey.

TVC was specified a priori as a first-order reflective construct, a choice justified explicitly here given its process-based definition. Reflective specification requires indicators to be interchangeable manifestations of a common factor that covary highly and remain individually replaceable (Jarvis et al., 2003); formative specification instead treats indicators as jointly defining the construct, so they need not correlate or be interchangeable (Coltman et al., 2008). TVC's item pool spans four conceptually distinct sub-processes, sensing client-specific needs, seizing the opportunity to reconfigure resources, reconfiguring technological assets, and converting those assets into client-recognized value (Table 2), which under a strict process-based reading could argue for a formative or second-order specification, since a firm could plausibly excel at one sub-process while lagging on another. Three considerations support the reflective specification instead. First, the items were written to capture a single underlying disposition, a firm's general propensity to convert technological capability into client-specific value, rather than to measure each sub-process as a separate dimension with its own indicator block, so the item pool lacks the multi-item-per-dimension structure a formative or higher-order model requires. Second, convergent- and discriminant-validity results (loadings .734-.856, AVE = .620) are consistent with, though not proof of, a reflective interpretation, since indicators load consistently on one factor. Third, Confirmatory Tetrad Analysis found no significant tetrad violations for TVC, the strongest empirical evidence available in this dataset against a formative alternative for this construct specifically. An alternative formative or second-order TVC specification was not estimated for direct model comparison, since the sub-process items were not collected with formative indicator weights or a redundancy-analysis validation item in mind; this is acknowledged as a limitation, and future refinements of the TVC scale should collect indicators explicitly designed to support such a comparison, following Hair et al.'s (2017) guidance on higher-order construct specification.

3.3 Data Analysis

This study used Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, selected for its ability to test complex multi-path structural models, including mediation, without strict normality assumptions, and its suitability for predictive-exploratory models with relatively new constructs such as TVC. Because PLS-SEM tests sufficiency (average effects), it is complemented by Necessary Condition Analysis (NCA), which tests necessity, whether a minimum predictor level is a precondition for an outcome level regardless of other predictors (Dul, 2016; R. Richter et al., 2023); the two logics are distinct, and PLS-SEM path coefficients alone cannot detect necessity conditions. Analysis proceeded in three stages. The outer model was evaluated via convergent validity (outer loadings ≥ 0.70; AVE ≥ 0.50), discriminant validity (Fornell-Larcker criterion, Fornell & Larcker, 1981; HTMT ≤ 0.90), and reliability (composite reliability and Cronbach's alpha ≥ 0.70). The inner model was evaluated via multicollinearity (VIF), path significance (bootstrapping, 5,000 subsamples, 5 percent level), R^2, f^2, and Q^2 (blindfolding); mediation for H8–H10 was tested via Variance Accounted For (VAF), complemented by bootstrapped significance of indirect effects to classify mediation as full, partial, or absent.

The third stage applied NCA to DT, DC, CO, and TVC as potential necessary conditions for FP, using PLS-SEM construct scores, following (N. F. Richter & Tudoran, 2024). A ceiling line was plotted for each predictor-outcome pair using Ceiling Envelopment-Free Disposal Hull (CE-FDH) as the primary technique, appropriate for discrete Likert-based scores, with Ceiling Regression-Free Disposal Hull (CR-FDH) as a robustness check. Necessity was quantified via effect size d, benchmarked as small ($0 < d < 0.10$), medium (0.10–0.30), large (0.30–0.50), or very large (≥ 0.50) (Cohen, 1988; Dul et al., 2023), with significance assessed by permutation test. Bottleneck tables translated ceiling lines into minimum predictor levels required for given

Firm Performance levels (0–100%), yielding "must-have" thresholds that complement PLS-SEM's average-effect results.

4. Results and Discussion

4.1 Inner Model: Collinearity Assessment

Before path coefficients are interpreted, the structural model was checked for collinearity among predictor constructs using the variance inflation factor (VIF), since high collinearity can inflate standard errors and distort path estimates (Hair & Sarstedt, 2019). VIF was computed for each exogenous predictor against both endogenous constructs it predicts: Firm Performance (FP) and Technology Value Customization (TVC).

Table 3. Inner Model Collinearity Statistics (VIF)

Predictor	VIF (→ FP)	VIF (→ TVC)
Customer Orientation	1.206	1.042
Digital Technology	1.178	1.047
Dynamic Capability	1.135	1.007
Technology Value Customization	1.514	—

All VIF values for Customer Orientation, Digital Technology, and Dynamic Capability, both as predictors of FP (1.135–1.206) and as predictors of TVC (1.007–1.047), fall well below the conservative threshold of 3.0 and the more lenient threshold of 5.0 (Hair & Sarstedt, 2019), indicating no problematic collinearity among the exogenous predictors. The VIF for Technology Value Customization as a predictor of FP is 1.514, the highest value in the model, consistent with TVC sharing variance with DT, DC, and CO as its own antecedents, but still well within the acceptable range. Overall, with all VIF values below 2.0, the structural model shows no evidence of significant multicollinearity, indicating that the subsequent path coefficient estimates can be interpreted without bias arising from predictor redundancy.

4.2 Outer Model: Measurement Model Evaluation

Table 4 showed that the outer loading and construct reliability results demonstrate strong convergent validity across all five constructs. All 30 items exhibited loadings above the 0.70 threshold (Hair et al., 2019), ranging from 0.734 (TVC4) to 0.904 (FP3), indicating that each indicator adequately represents its intended latent construct. Internal consistency reliability was uniformly high across constructs, with Cronbach's alpha ranging from 0.877 to 0.948 and composite reliability (rho_c) ranging from 0.907 to 0.958, both well above the 0.70 threshold. Average Variance Extracted (AVE) for all constructs ranged from 0.619 to 0.792, exceeding the 0.50 threshold, confirming that each construct explains more than half of its indicators' variance relative to measurement error. Firm Performance displayed the strongest convergent validity (AVE = 0.792; rho_c = 0.958), while Technology Value Customization showed the lowest, though still acceptable, value (AVE = 0.620). Collectively, these findings provide adequate empirical support for the convergent validity and reliability of the measurement instrument prior to proceeding with structural model testing. Full item wording for all 30 indicators, including Firm Performance's six items (FP1-FP6), is reported in Appendix A to allow direct evaluation of face and content validity alongside the loadings reported here; this disclosure is particularly relevant for Firm Performance given the CTA-PLS finding reported in Section 4.9 and discussed further in Sections 5.6 and 6.3.

Table 4. Outer Loadings and Construct Reliability and Convergent Validity

Construct	Item	Outer Loading	Mean	SD	Cronbach's α	rho_c (CR)	AVE
Customer Orientation					.877	.907	.619
	CO1	.791	5.129	1.105			
	CO2	.788	5.112	1.129			
	CO3	.800	5.188	1.112			
	CO4	.740	5.192	0.994			
	CO5	.811	5.179	1.150			
	CO6	.789	5.158	1.068			
Digital Technology					.909	.929	.685
	DT1	.873	5.000	1.169			
	DT2	.869	5.042	1.172			
	DT3	.790	5.033	1.186			
	DT4	.863	4.987	1.160			
	DT5	.791	4.992	1.180			
	DT6	.773	5.121	1.087			
Dynamic Capability					.886	.913	.637
	DC1	.718	4.879	1.098			
	DC2	.870	4.963	1.184			
	DC3	.831	4.867	1.169			
	DC4	.840	4.912	1.094			
	DC5	.777	4.967	1.125			
	DC6	.743	4.987	1.135			
Firm Performance					.948	.958	.792
	FP1	.870	5.117	1.174			
	FP2	.893	5.142	1.178			
	FP3	.904	5.138	1.163			
	FP4	.893	5.138	1.195			
	FP5	.888	5.183	1.228			
	FP6	.892	5.096	1.174			
Technology Value Customization					.877	.907	.620
	TVC1	.856	5.146	1.125			
	TVC2	.786	5.150	1.195			
	TVC3	.803	5.050	1.098			
	TVC4	.734	5.083	1.111			
	TVC5	.778	5.162	1.104			
	TVC6	.762	5.146	1.114			

4.3 Discriminant Validity

Discriminant validity was assessed through the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the heterotrait-monotrait ratio (HTMT). Under the Fornell-Larcker criterion, the square root of each construct's AVE (diagonal, Table 5) exceeded its correlations with every other construct, satisfying the criterion for all five constructs. Under HTMT (Table 6), all construct pairs fell well below the conservative .85 threshold and the more lenient .90 threshold (Dijkstra & Henseler, 2015), with the highest value observed between TVC and FP (HTMT = .543). Item-level cross-loadings (in the underlying SmartPLS output) further confirmed that every item loaded highest on its intended construct. Together, these results support discriminant validity across the measurement model.

Table 5. Fornell-Larcker Criterion (diagonal = √AVE)

	Customer Orientation	Digital Technology	Dynamic Capability	Firm Performance	Technology Value Customization
Customer Orientation	.787				
Digital Technology	.199	.828			
Dynamic Capability	.039	.082	.798		
Firm Performance	.423	.226	.128	.890	
Technology Value Customization	.399	.384	.327	.499	.788

Table 6. Heterotrait-Monotrait Ratio (HTMT)

	Customer Orientation	Digital Technology	Dynamic Capability	Firm Performance	Technology Value Customization
Customer Orientation					
Digital Technology	.214				
Dynamic Capability	.081	.095			
Firm Performance	.457	.230	.129		
Technology Value Customization	.455	.418	.358	.543	

4.4 Structural Model: Explanatory and Predictive Power

The model explains 33.9% of the variance in TVC ($R^2 = .339$, adjusted $R^2 = .331$) and 30.9% of the variance in FP ($R^2 = .309$, adjusted $R^2 = .297$) (Table 7), both representing moderate explanatory power for a cross-sectional organizational model (Hair & Sarstedt, 2019). Effect sizes (f^2, Table 8) indicate that CO is the strongest individual predictor of TVC ($f^2 = .158$, medium effect per Cohen, 1988 benchmarks), followed by DC ($f^2 = .127$) and DT ($f^2 = .125$), both small-to-medium. For FP, TVC is the strongest predictor ($f^2 = .144$, small-to-medium effect), followed by CO ($f^2 = .083$, small effect); DT and DC contribute negligible unique effect size to FP ($f^2 = .001$ and .000, respectively) once their indirect paths through TVC are accounted for.

Table 7. R^2 and R^2 Adjusted

Endogenous Construct	R^2	R^2 adjusted
Technology Value Customization	.339	.331
Firm Performance	.309	.297

Table 8. f^2 Effect Sizes

Path	f^2	Effect Size
Customer Orientation -> Firm Performance	.083	Small
Customer Orientation -> Technology Value Customization	.158	Medium
Digital Technology -> Firm Performance	.001	None
Digital Technology -> Technology Value Customization	.125	Small
Dynamic Capability -> Firm Performance	.000	None
Dynamic Capability -> Technology Value Customization	.127	Small
Technology Value Customization -> Firm Performance	.144	Small

4.5 Structural Model: Path Coefficients and Hypothesis Testing (H1–H7)

Direct-path hypotheses were tested using bootstrapping with 5,000 subsamples, as specified in Section 3.3, based on the two-tailed t-statistics and p-values reported in the supplied bootstrapping output. A path was considered statistically significant at $p < .05$ ($|t| > 1.96$).

Table 9. Path Coefficients and Bootstrapped Significance

Hyp.	Path	β	t	p	Decision
H1	Digital Technology → Firm Performance	.026	.417	.676	Not supported
H2	Dynamic Capability → Firm Performance	-.011	.201	.841	Not supported
H3	Customer Orientation → Firm Performance	.263	4.041	<.001	Supported
H4	Digital Technology → Technology Value Customization	.294	5.867	<.001	Supported
H5	Dynamic Capability → Technology Value Customization	.290	6.373	<.001	Supported
H6	Customer Orientation → Technology Value Customization	.329	6.194	<.001	Supported
H7	Technology Value Customization → Firm Performance	.388	5.883	<.001	Supported

Five of the seven hypothesized direct paths were statistically significant and in the hypothesized positive direction: H3 (CO → FP: $\beta = .263$, $t = 4.041$, $p < .001$), H4 (DT → TVC: $\beta = .294$, $t = 5.867$, $p < .001$), H5 (DC → TVC: $\beta = .290$, $t = 6.373$, $p < .001$), H6 (CO → TVC: $\beta = .329$, $t = 6.194$, $p < .001$), and H7 (TVC → FP: $\beta = .388$, $t = 5.883$, $p < .001$) were all supported. H1 (DT → FP: $\beta = .026$, $t = 0.417$, $p = .676$) and H2 (DC → FP: $\beta = -.011$, $t = 0.201$, $p = .841$) were not supported: neither Digital Technology nor Dynamic Capability had a statistically significant direct effect on Firm Performance. Notably, the two paths that were not supported (H1, H2) are precisely the direct technology/capability-to-performance paths that (Barba-Sánchez et al., 2024; Hoang et al., 2024) reported inconsistently across their respective samples, while all paths involving TVC (H3–H7) were significant a pattern directly consistent with this study's central proposition that TVC, not DT or DC directly, is what reliably links technological and capability resources to firm performance.

4.6 Mediation Analysis and Hypothesis Testing (H8–H10)

Mediation hypotheses (H8–H10) were tested using the bootstrapped significance of the specific indirect effects (DT/DC/CO → TVC → FP), classified using the typology of (Zhao et al., 2010): complementary mediation (direct and indirect effects both significant and samesigned), competitive mediation (both significant, opposite-signed), or indirect-only/full mediation (indirect significant, direct effect not significant).

Table 10. Specific Indirect Effects and Mediation Type

Hyp.	Indirect Path	Indirect β	t	p	Direct	Type (Zhao et al., 2010)
H8	DT → TVC → FP	.114	4.093	<.001	n.s.	Indirect-only (full)
H9	DC → TVC → FP	.113	4.431	<.001	n.s.	Indirect-only (full)
H10	CO → TVC → FP	.128	3.981	<.001	Sig. (+)	Complementary (partial)

All three indirect effects were statistically significant, supporting H8, H9, and H10. For H8 (DT → TVC → FP: indirect $\beta = .114$, $t = 4.093$, $p < .001$) and H9 (DC → TVC → FP: indirect $\beta = .113$, $t = 4.431$, $p < .001$), the corresponding direct effects (H1, H2) were not statistically significant, so both qualify as indirect-only (full) mediation: DT's and DC's effects on FP operate entirely through TVC, with no statistically detectable direct effect. For H10 (CO → TVC → FP: indirect $\beta = .128$, $t = 3.981$, $p < .001$), the direct effect (H3) was itself significant and positive, H10 qualifies as complementary (partial) mediation: TVC accounts for part, but not all, of CO's effect on FP. Together, these results are consistent with Technology Value Customization operating as the statistically detectable pathway through which digital technology and dynamic capability relate to firm performance in this sample, while customer orientation retains an additional, TVC-independent path to performance. This pattern is consistent with, rather than proof of, TVC as one mechanism that may help account for prior studies' inconsistent findings on the direct effect of technology on performance; given the cross-sectional design, alternative or additional mechanisms cannot be ruled out.

4.7 Model Fit

Model fit was assessed using the standardized root mean square residual (SRMR), the unweighted (d_ULS) and geodesic (d_G) discrepancy measures, chi-square, and the normed fit index (NFI) (Table 11). The estimated model's SRMR of .050 is well below the conventional .08 cutoff for acceptable fit (Henseler, 2017) and identical to the saturated model's SRMR, indicating the specified structural model does not meaningfully misfit relative to a fully saturated model. NFI = .885 falls just below the traditional .90 benchmark, a common occurrence in PLS-SEM models of this size and complexity; consistent with current PLS-SEM guidance, SRMR is treated as the primary fit indicator here, with d_ULS, d_G, and chi-square reported for completeness rather than interpreted against fixed cutoffs, since their distributional properties in PLS-SEM remain debated (Henseler, 2017). The chi-square degrees of freedom, which depend on the specific model's indicator and construct count, should be reported alongside the statistic in Table 11 rather than left implicit.

Table 11. Model Fit Indices

Fit Index	Saturated Model	Estimated Model
SRMR	.050	.050
d_ULS	1.185	1.185
d_G	.400	.400
Chi-square(df)	545.555([Author: add df])	545.555([Author: add df])
NFI	.885	.885

4.8 Necessary Condition Analysis (NCA)

Before presenting the necessity results, it is useful to state explicitly why each of the four predictors is theoretically plausible as a necessary, rather than merely sufficient, condition for

Firm Performance, since PLS-SEM sufficiency logic and NCA necessity logic ask conceptually different questions and a predictor's inclusion in the necessity test should be motivated on its own terms rather than by default because it appears in the structural model (Dul, 2016). Digital Technology is a plausible necessary condition because IT service delivery in this industry is technically infeasible below some minimum level of digital infrastructure, independent of how well a firm scores on other resources; a firm cannot compensate for a complete absence of digital tooling with customer orientation alone. Technology Value Customization is plausible as a necessary condition under the value-in-context principle itself (Vargo & Lusch, 2016): if value is realized only through customization, then some non-zero level of customization may be a precondition for any performance gain, not merely a factor that raises average performance. Customer Orientation is plausible as a necessary condition because, without some baseline understanding of client needs, a firm's technological and capability resources have no target to be directed toward. Dynamic Capability is the least obviously necessary of the four on theoretical grounds, since sensing-seizing-reconfiguring routines are, in principle, substitutable by other adaptive mechanisms such as customer feedback loops mediated through Customer Orientation; its non-significant necessity result (below) is accordingly consistent with, rather than a contradiction of, this weaker theoretical expectation. These predictions are tested, not assumed, in the results that follow.

As specified in Section 3.3, NCA was applied to test whether CO, DT, DC, and TVC are necessary (though not necessarily sufficient) conditions for FP, complementing the sufficiency-based PLS-SEM results above. Ceiling lines were estimated using both the Ceiling Envelopment-Free Disposal Hull (CE-FDH) and Ceiling Regression-Free Disposal Hull (CR-FDH) techniques, with the effect size d benchmarked per (Dul, 2016) and statistical significance assessed via a permutation test (5,000 samples, α = .05), consistent with Section 3.3.

Table 12. NCA Effect Sizes and Permutation Significance

Predictor of FP	d (CE-FDH)	p (CE-FDH)	d (CR-FDH)	p (CR-FDH)
Customer Orientation	.177	.000*	.167	.000*
Digital Technology	.153	.001*	.138	.002*
Dynamic Capability	.062	.133	.045	.293
Technology Value Customization	.211	.000*	.198	.000*

Three of the four predictors were statistically significant necessary conditions for FP under both ceiling techniques: Customer Orientation (d = .177 CE-FDH / .167 CR-FDH, both $p < .001$), Digital Technology (d = .153 / .138, p = .001 / .002), and Technology Value Customization (d = .211 / .198, both $p < .001$), all in the small-to-medium range per Dul's (2016) benchmarks, with TVC showing the largest necessity effect of the four. Dynamic Capability was not a statistically significant necessary condition (d = .062 CE-FDH, p = .133; d = .045 CR-FDH, p = .293), consistent with DC's non-significant sufficiency-based direct effect on FP (H2, Section 4.5). Digital Technology's result is the more theoretically interesting of the two: DT was NOT a significant sufficiency-based predictor of FP (H1 not supported, β = .026, p = .676) but IS a significant necessary condition for FP, illustrating a central methodological point of combining PLS-SEM with NCA (Richter et al., 2020): a predictor can be necessary for an outcome, imposing a bottleneck below which the outcome cannot be achieved regardless of other predictors, without being sufficient to move the outcome on average. In practical terms, some minimum level of digital technology adoption appears to be a precondition for high firm performance in this sample, even though higher DT alone does not reliably produce higher FP on average.

Table 13 (CE-FDH bottleneck table) illustrates these necessity thresholds in practical terms: to reach 90% of the observed range of Firm Performance, Technology Value Customization must reach at least 21.7% of its own range and Customer Orientation at least 30.0%, with Digital Technology requiring a comparatively modest 5.8%, whereas Dynamic Capability shows essentially no binding constraint until the very top of the FP range (only becoming non-zero, at 3.75%, from the 90% FP level onward), reflecting its non-significant necessity effect. These percentages are derived from a single cross-sectional sample of 240 firms and from perceptual, Likert-based construct scores rather than objective operational metrics; they should be read as sample-specific illustrations of a necessity pattern rather than as fixed managerial minimums, and their external validity to other samples, industries, or measurement approaches has not been established. Percentages in Table 13 are scaled 0-100% of each construct's own observed range in this sample (not of the seven-point Likert range itself), following standard NCA bottleneck-table reporting (Dul, 2016); permutation tests for both CE-FDH and CR-FDH ceiling lines used 5,000 permutations and a two-tailed 5% significance level, applied identically across all four predictors and reported jointly in Table 12, so that the significance and effect-size columns are directly comparable across predictors and across techniques.

Table 13. CE-FDH Bottleneck Table

Firm Performance	Customer Orientation	Digital Technology	Dynamic Capability	Technology Value Customization
0%	0.00	0.00	0.00	0.00
10%	0.00	0.42	0.00	0.00
30%	0.42	0.83	0.00	0.00
50%	2.08	0.83	0.00	1.67
70%	2.92	5.83	0.00	12.92
90%	30.00	5.83	3.75	21.67
100%	30.00	21.25	37.08	21.67

4.9 Confirmatory Tetrad Analysis (CTA-PLS)

Because all five constructs were specified a priori as first-order reflective (Section 3.2), Confirmatory Tetrad Analysis in PLS-SEM (CTA-PLS) was used to test this specification empirically, following (Ringle & Sarstedt, 2016), who adapted Bollen and Ting's (2000) vanishing-tetrad logic to a bootstrapped PLS-SEM test. Under a reflective specification, all non-redundant tetrads implied by a four-indicator block should not differ statistically from zero; a construct with one or more tetrads significantly different from zero provides evidence against a purely reflective specification for that construct. Bootstrapping used 10,000 subsamples, a two-tailed test, and a .10 significance level, consistent with Gudergan et al., (2008) recommendation to use a more liberal significance level for CTA-PLS than for path-coefficient testing, given the test's comparatively low power.

Table 14. Summary of Confirmatory Tetrad Analysis

Construct	Non-redundant tetrads tested	Significant at p < .10	Min. p-value	Conclusion
Customer Orientation	8	0 of 8	.205	Reflective

Construct	Non-redundant tetrads tested	Significant at p < .10	Min. p-value	Conclusion
Digital Technology	8	0 of 8	.135	Reflective
Dynamic Capability	8	1 of 8	.079	Reflective[1]
Firm Performance	8	4 of 8	.042	Reflective[2]
Technology Value Customization	8	0 of 8	.170	Reflective

For Customer Orientation, Digital Technology, and Technology Value Customization, none of the eight non-redundant tetrads were statistically significant (all $p > .13$), providing clear support for the a priori reflective specification of these three constructs. Dynamic Capability showed one borderline tetrad ($p = .079$, significant only at the more liberal .10 level), which, taken alone, does not provide strong grounds to reject its reflective specification. Firm Performance is the clear exception: four of its eight tetrads were significant at $p < .10$, including one significant even at the conventional .05 level ($p = .042$), a substantially higher rate of tetrad violations than any other construct in the model. This does not necessarily mean FP is better modeled as formative, since CTA-PLS is known to have inflated Type I error rates when several tetrads are tested per construct (Gudergan et al., 2008), and FP's six items retained uniformly high outer loadings (.870–.904, Section 4.2) and the highest composite reliability and AVE of any construct (Table 5), both of which are more consistent with a reflective than a formative specification. Nonetheless, the concentration of tetrad violations in FP specifically, rather than distributed evenly across constructs, is a finding that should be reported transparently and flagged for attention in any subsequent revision of the FP measurement instrument or in the paper's limitations.

4.10 Discussion

This study tested whether Technology Value Customization (TVC) mediates the relationships among Digital Technology (DT), Dynamic Capability (DC), and Customer Orientation (CO) on Firm Performance (FP), as a candidate explanation for the inconsistent direct effects of technology and capability on performance reported by (Barba-Sánchez et al., 2024; Hoang et al., 2024). Across 240 IT service firms in Jakarta, Surabaya, and Bandung, the results (Section 4) provide strong support for this proposition. Most of the hypothesized paths were statistically supported; the two exceptions were precisely the two direct technology/capability-to-performance paths whose inconsistency across prior studies motivated this research (Section 1), while every path involving TVC, and every mediation hypothesis, was supported. These patterns were corroborated, and substantially enriched, by two complementary analyses: Necessary Condition Analysis (NCA), which showed that digital technology is a necessary though not sufficient condition for performance, and Confirmatory Tetrad Analysis (CTA-PLS), which supported the reflective specification of most constructs while flagging a measurement concern for Firm Performance.

4.11 Why Digital Technology and Dynamic Capability Did Not Directly Predict Performance

Consistent with (Hoang et al., 2024) finding that digital capability had no significant direct effect on firm performance among Vietnamese manufacturing SMEs, this study found no meaningful direct effect of either Digital Technology or Dynamic Capability on Firm Performance among Indonesian IT service firms (Section 4.5). This contrasts with Barba-

Sánchez et al.'s (2024) finding of a significant positive effect of IT capability on performance, though critically, their model tested this effect through digital orientation and digital transformation as intervening mechanisms rather than as an unmediated direct path. Read together, the three studies are not actually contradictory once mediating mechanisms are made explicit: technology and capability resources appear to require translation, whether through digital orientation and transformation (Barba-Sánchez et al., 2024), product/process innovation capability (Hoang et al., 2024), or value customization (this study), before they manifest as measurable performance gains. Dynamic Capability Theory's sensing-seizing-transforming logic (Teece, 1996; Teece, 2007) explains how firms build and reconfigure resources, but, as anticipated in Section 1, it does not by itself explain why that reconfiguration does not translate directly and reliably into performance; the present findings supply an empirical answer specific to the IT services context studied here: the translation mechanism, TVC, is the operative pathway, not the underlying resources themselves.

4.12 The Central Role of Technology Value Customization

All three exogenous constructs, Customer Orientation, Digital Technology, and Dynamic Capability, emerged as meaningful positive drivers of Technology Value Customization, which was in turn the strongest single predictor of Firm Performance in the entire model (Section 4.5). Substantively, this pattern is consistent with the value-in-context principle of Service-Dominant Logic (Vargo & Lusch, 2004): digital infrastructure, dynamic capability, and customer orientation each function as antecedent resources, but the value these resources create is realized only once it is adapted to the specific context and needs of the client, the process this study operationalizes as TVC. Customer Orientation stood out as the most influential of the three antecedents, which is intuitive given that customer orientation reflects an organization-level co-creation capability(Karpen et al., 2015) already oriented toward understanding the recipient's context, whereas DT and DC represent more general-purpose resources that still require translation into customer-specific solutions.

4.13 Mediation Patterns and Their Bearing on Prior Inconsistent Findings

The mediation results (Section 4.6) provide the most direct test of this study's central proposition. For DT and DC, the results are statistically consistent with indirect-only mediation by TVC: neither construct retained a statistically significant direct effect once TVC was included, using the typology of (Zhao et al., 2010). For CO, TVC partially, complementarily, mediates the path, with CO retaining its own direct, same-directional effect alongside the indirect one. This asymmetry, statistically indirect-only association for DT and DC, complementary partial mediation for CO, is theoretically informative rather than incidental: it suggests customer orientation contributes to performance through both an already customer-facing direct channel and an indirect channel via technology value customization, whereas digital technology and dynamic capability contribute to performance only once customized, having no reliable performance effect on their own. This indirect-only pattern is consistent with, rather than proof of, TVC as the exclusive mechanism linking DT and DC to FP: the non-significant direct paths (H1, H2) could also reflect omitted variables not modeled here (Section 6.3), measurement overlap between TVC and its antecedents given their shared conceptual grounding in Dynamic Capability Theory, or structural model misspecification, so the mediation classification should be read as a statistical description of this model given these variables, not as a definitive causal claim. This is precisely the mechanism proposed in Section 1 to reconcile Barba-Sánchez et al., (2024) & Hoang et al., (2024) divergent findings. In the IT services context studied here, the direct effect of technology on performance was not statistically detectable once TVC was included in the model, a pattern consistent with technological resources requiring customization before they relate to customer value. This finding is offered as one plausible pathway rather than as evidence that customization is the sole explanation for the inconsistent effects reported across the prior studies, which differed from the present study in industry, country, and model specification.

4.14 Necessity Versus Sufficiency: Insights from NCA

The NCA results (Section 4.9) add a dimension to this interpretation that the sufficiency-based PLS-SEM results alone cannot provide. While DT showed no meaningful sufficiency-based direct effect on FP (H1), it nonetheless emerged as a statistically significant necessary condition for FP, meaning some minimum level of digital technology adoption functions as a bottleneck below which high firm performance cannot be achieved, regardless of how favorable a firm's other resources are. This is not a contradiction of the H1 result but a complementary finding under a different causal logic (Dul et al., 2021; R. Richter et al., 2023): DT is apparently a must-have, but not sufficient, resource, consistent with a floor-level infrastructural role for digital technology in IT service delivery, while the question of whether additional DT predicts additional FP on average is better answered by TVC's mediating role than by DT directly. Dynamic Capability, by contrast, was neither a meaningful sufficiency-based predictor nor a significant necessity-based precondition for FP, the most consistent null result in the study, whereas CO and TVC were both significant under both logics, reinforcing their centrality to the performance-generation process.

4.15 Measurement Model Robustness: Insights from CTA-PLS

The CTA-PLS results (Section 4.9) provide an additional layer of validation for, and one caveat to, the measurement model. Customer Orientation, Digital Technology, and Technology Value Customization showed no evidence of tetrad violations, strongly supporting their a priori first-order reflective specification (Gudergan et al., 2008, building on Bollen & Ting, 2000) and, by extension, the validity of the outer-model results on which the structural results in Sections 4.4-4.9 depend. Dynamic Capability's single borderline tetrad does not materially alter this conclusion. Firm Performance is the clear exception, showing a materially higher rate of tetrad violations than any other construct: while FP's outer-model indicators remained strong and consistent with a reflective specification (Section 4.2, the strongest reliability and convergent validity of any construct in the model), the elevated tetrad-violation rate suggests FP's six items may not be perfectly interchangeable indicators of a single underlying reflective factor, an issue that does not undermine the substantive conclusions above but that should be investigated further, for example through exploratory examination of whether FP's financial and non-financial items load on a common factor as cleanly as assumed, before FP is used as an outcome construct in future extensions of this model. An exploratory factor analysis of FP's six items was conducted directly on the raw indicator data to test this possibility empirically. FP's inter-item correlations were uniformly high ($r = .708–.777$, with no evidence of a block pattern that would separate a financial subset from a non-financial subset), and an unrotated principal-component extraction yielded a first eigenvalue of 4.75, accounting for 79.2% of item variance, with a second eigenvalue of only 0.33, far below the Kaiser criterion of 1.0. A forced two-factor varimax rotation did not recover a clean simple structure: every item retained a substantial loading (> .37) on both rotated factors, with no item loading uniquely on one factor and near-zero on the other, which is inconsistent with FP decomposing cleanly into separate financial and non-financial dimensions in this sample. Taken together with the strong convergent-validity evidence in Section 4.2, this EFA result argues against respecifying FP as two separate first-order constructs or as a second-order formative composite for this dataset specifically, even though the CTA-PLS tetrad violations (Section 4.9) remain a legitimate reason for caution. The single first-order reflective specification is therefore retained on converging evidence, unidimensional EFA structure alongside strong loadings and reliability, rather than on the outer-loading evidence alone; a fully formative or second-order respecification was not estimated within the structural model itself, since doing so requires re-running the full PLS-SEM algorithm in SmartPLS under an alternative measurement model, which was outside the scope of this text-based revision. Future studies collecting new data, or re-analyzing this dataset directly in SmartPLS, should still test a second-order or dimension-specific FP specification as a robustness check, particularly if theory-driven financial/non-financial item groupings are specified a priori rather than inferred post hoc as done here.

6. Conclusion and Limitiations

6.1 Theoretical Contributions

This study offers three main theoretical contributions. First, it identifies Technology Value Customization as an empirically supported mediating mechanism that offers a plausible explanation for previously inconsistent findings on the direct effect of digital technology and dynamic capability on firm performance (Barba-Sánchez et al., 2024; Hoang et al., 2024), consistent with the possibility that the inconsistency itself is explained by whether a customization mechanism is included and tested, a possibility that should be tested directly in other industries and national contexts before being generalized. Second, it operationalizes Service-Dominant Logic's value-in-context principle (Vargo & Lusch, 2016) as a measurable mediating construct bridging Dynamic Capability Theory's internal resource-configuration logic (Teece et al., 1997; Teece, 2007) with SDL's customer-facing value co-creation logic, integrating two theoretical traditions typically applied separately in the technology-performance literature. Third, by combining PLS-SEM with NCA (Richter et al., 2020), the study demonstrates empirically that sufficiency and necessity are genuinely distinct causal logics in this context: Digital Technology's non-significant sufficiency effect alongside its significant necessity effect would have been invisible under a PLS-SEM-only design, illustrating the value of combining the two techniques rather than treating PLS-SEM path coefficients as a complete account of a predictor's role.

6.2 Managerial Implications

For IT service firm managers, the central practical implication is that investment in digital technology or dynamic capability alone is unlikely to translate into measurable performance gains unless paired with an explicit capacity to customize that technology to individual client value. Firms should treat technology value customization as a distinct organizational capability requiring its own investment and management attention, for example dedicated client-solution design roles or processes, rather than assuming that superior underlying technology or general adaptive capability will automatically be recognized and rewarded by clients or reflected in performance metrics. The NCA results add a further, more specific implication: digital technology functions as a necessary baseline, firms below a certain threshold of digital adoption appear unable to reach high performance regardless of their other strengths, so managers should treat a minimum level of digital technology investment as a precondition to be secured before relying on other capabilities or on customization efforts to differentiate performance. Taken together, these results point to three distinct, ordered priorities rather than a single generic recommendation: first, securing a baseline level of digital technology infrastructure, since the NCA results indicate this functions as a floor below which high performance is not observed in this sample; second, building technology value customization as its own organizational capability, for example through dedicated client-solution design roles, since it was the strongest single predictor of performance; and third, sustaining customer-oriented practices that keep the firm informed of client-specific needs, since these feed both the customization process and, independently, performance directly. These priorities are estimated from perceptual data collected from 240 IT service firms in three Indonesian cities at a single point in time, so managers in other industries, firm sizes, or national contexts should treat them as a starting hypothesis to test against their own performance data rather than as a validated prescription.

Several limitations qualify these conclusions. First, the cross-sectional design (Section 3.1) cannot establish the temporal or causal order implied by the hypothesized model; the mediation and necessity results are consistent with, but do not definitively prove, the proposed causal sequence from resources through customization to performance. Second, all constructs were measured through a single respondent per firm at one point in time, so common method bias, though addressed procedurally (Section 3.1) and checked statistically via VIF (Section 4.1), cannot be fully excluded. A full-collinearity VIF test detects one signature of common method variance but is not a substitute for a multi-source design, and it cannot rule out perceptual-consistency effects that arise from one respondent rating predictors, mediator, and outcome together; as discussed in Section 3.1, a marker-variable or confirmatory common-method-factor test would provide stronger evidence than VIF alone and was not implemented in this study. Reverse causality is also plausible: better-performing firms may have more slack resources to invest in digital technology, dynamic capability, and customization, so the hypothesized direction, from resources through TVC to performance, cannot be established from a single cross-sectional wave. Firm-level factors not modeled here, including firm size, firm age, service specialization, market turbulence, competitive intensity, digital maturity, and ownership structure, are a substantive, not merely nominal, source of potential bias: several plausibly affect both TVC and FP jointly, for example larger or older firms may have more slack resources to invest in both customization routines and performance-enhancing activities independent of DT, DC, or CO, which would inflate the estimated TVC-FP path if omitted, while higher market turbulence could simultaneously depress FP and increase the perceived need for customization, which would bias the DT/DC/CO-TVC paths in an undetermined direction. Because none of these variables were entered as controls or tested in a robustness specification, the path coefficients reported in

Section 4.5 should be interpreted as associations net of the constructs modeled in this study, not net of all plausible confounders, and the magnitude and even the sign of the affected paths could shift once these controls are introduced in future replications. Third, the CTA-PLS results (Section 4.9) raise a specific, unresolved question about the homogeneity of Firm Performance's six-item measurement, which future research should investigate directly rather than treat as fully resolved by this study's outer-loading and reliability evidence alone. Fourth, the sample is restricted to IT service firms in three Indonesian cities; the mediating role of TVC, and particularly the asymmetric pattern of indirect-only association for DT/DC versus complementary partial mediation for CO, should be tested in other industries and national contexts before being treated as a general property of the technology-performance relationship. Fifth, content validation of the TVC item pool (Section 3.2) combined expert judgment by three academics with a 50-respondent pilot test, but did not compute formal indices such as the Content Validity Index or Content Validity Ratio from the expert ratings; future refinements of the TVC scale should compute these indices from retained rating sheets, or use cognitive interviews or an independent validation sample, as a complementary, more quantifiable source of content-validity evidence.

6.3 Future Research

Future research should, first, replicate this model using longitudinal or experimental designs capable of establishing causal order between technology/capability resources, value customization, and performance. Second, given the CTA-PLS finding for Firm Performance, future studies should examine whether its financial and non-financial dimensions warrant separate first-order constructs, or a second-order formative specification, rather than a single first-order reflective factor. Such work should also consider supplementing the perceptual managerial assessments used here with objective performance indicators, for example revenue growth, profitability, client retention, project success rates, or market growth, since single-respondent perceptual measures cannot rule out the possibility that some of the tetrad violations reported in Section 4.9 reflect respondents evaluating financial and non-financial outcomes through a shared response tendency rather than through six equally interchangeable facets of one construct. Third, the necessity/sufficiency distinction uncovered for Digital Technology (Section 5.5) merits extension to Dynamic Capability and Customer Orientation across other samples, to establish whether a necessary-baseline, mediated-additional-effect pattern is a general feature of technology-performance relationships or specific to this study's context. Finally, researchers extending this model to other industries should consider whether the specific pattern observed here, statistically indirect-only association for DT and DC alongside complementary partial mediation for CO, replicates, since this pattern carries the substantive implication that customer-facing resources retain a direct path to performance that purely internal/technological resources do not. Finally, addressing the common-source concern raised in Section 6.3 will likely require a multi-source design in which operational or technology managers report Digital Technology and Dynamic Capability, commercial or client-facing managers report Customer Orientation and Technology Value Customization, and Firm Performance is drawn from archival records or an independent respondent, together with controls for firm size, age, service specialization, and market turbulence.

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Appendix A. Research Questions and Full Item Wording for All Constructs

Code	Item Statement	1 SD	2	3	4 N	5	6	7 SA
	Customer Orientation (CO)							
CO1	The firm routinely involves customers in the service design process.							
CO2	The firm regularly collects and analyzes customer feedback to improve its services.							
CO3	The firm's employees are trained to prioritize customer needs in daily operations.							
CO4	The firm anticipates shifts in customer needs before they become widely apparent in the market.							
CO5	The firm's strategic decisions are guided by a deep understanding of customer needs.							
CO6	The firm rewards employees or teams whose work directly improves customer satisfaction.							
	Digital Technology (DT)							
DT1	The firm adopts current cloud/AI technology in its service operations.							
DT2	The firm's digital systems are reliable and scalable enough to support business growth.							
DT3	The firm integrates digital tools across departments to support daily operations.							
DT4	The firm invests consistently in upgrading its digital technology capabilities.							
DT5	The firm's employees have adequate access to the digital tools needed for their work.							
DT6	The firm uses digital technology to monitor and improve service delivery.							
	Dynamic Capability (DC)							
DC1	The firm quickly detects new technology opportunities in the market.							
DC2	The firm is able to reconfigure its internal resources in response to market changes.							
DC3	The firm can rapidly adapt its business processes when the competitive environment shifts.							
DC4	The firm's management actively seeks new opportunities to improve organizational capability.							
DC5	The firm integrates new knowledge and skills quickly when circumstances require it.							
DC6	The firm regularly reviews and updates its internal capabilities to stay ahead of competitors.							
	Firm Performance (FP)							
FP1	The firm's revenue growth has increased compared with the past three years.							
FP2	The firm's profitability has improved compared with the past three years.							
FP3	The firm's market share has grown compared with its main competitors.							
FP4	The firm has retained a high proportion of its clients over the past three years.							
FP5	The firm's service quality has improved compared with the past three years.							
FP6	The firm's employees are satisfied with the organization's overall performance achievements.							
	Technology Value Customization (TVC)							
TVC1	The firm identifies each client's specific technology-related needs before designing a solution.							
TVC2	The firm is able to tailor technology features to each client's unique needs.							
TVC3	The firm reconfigures its technological resources to fit individual client requirements.							
TVC4	The firm adapts its service offerings so that clients recognize clear, customized value.							
TVC5	The firm adjusts its service delivery approach differently for each client based on their specific context.							
TVC6	The firm's client relationships benefit measurably from technology customized to their context.							