

NAVIGATING COMPETITION STRATEGY: TECHNOLOGY READINESS, HUMAN CAPITAL, AND CUSTOMER ORIENTATION AS PERFORMANCE DRIVERS UNDER VARYING COMPETITIVE INTENSITY IN IT SERVICE FIRMS

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ABSTRACT

This study examines how technology readiness (TR), human capital (HC), and customer orientation (CO) shape firm performance (FP) among medium-sized IT service firms in the Jakarta metropolitan region, and whether competitive intensity (CI) moderates those relationships. Grounded in Resource-Based View (RBV) theory, we argue that TR, HC, and CO constitute strategically valuable, difficult-to-imitate internal resources whose performance implications are amplified when the competitive environment intensifies. A quantitative, cross-sectional design was employed; data were gathered from 320 respondents at the management level across a minimum of 160 firms, then analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4. Common method bias was assessed through Harman's single-factor test and the common latent factor procedure. Preliminary results indicate that TR, HC, and CO each exert significant positive effects on FP, while CI significantly moderates all three relationships strengthening the performance contribution of each resource under high-intensity conditions. These findings extend RBV scholarship to the Indonesian IT services context and carry direct implications for resource allocation decisions in competitively turbulent markets.

Keywords: Technology Readiness, Human Capital, Customer Orientation, Competitive Intensity, Firm Performance, IT Service Firms.

INTRODUCTION

Sustained competitive advantage in knowledge-intensive industries hinges not only on the breadth of a firm's technological investments but equally on the organisational and human capabilities through which those investments are deployed (Al-Musawi, 2020; Li & Liu, 2018; Tsou & Chen, 2020). This tension is particularly acute in the IT services sector, where rapid capability commoditisation, rising client expectations, and the entry of well-capitalised regional players constantly erode margins and differentiation (Chatterji & Patro, 2014). For medium-sized IT service firms in Indonesia's metropolitan corridors a segment characterised by constrained resources yet high strategic ambition the question of which internal attributes most reliably translate into superior firm performance, and under what competitive conditions, remains empirically underexplored.

Resource-Based View (RBV) theory provides a foundational lens for this inquiry. Following (J. Barney, 1991a) formulation, sustained performance differentials arise when firms possess resources that are simultaneously valuable, rare, inimitable, and non-substitutable (VRIN). Technology readiness—the organisational propensity to adopt and leverage new technologies (Muñoz-Villamizar et al., 2021) aligns with VRIN criteria insofar as digital infrastructure depth, adoption culture, and technical proficiency vary substantially across firms. Human capital, encompassing the knowledge, skills, and relational competencies of the workforce (G. Becker, 1964; T. Becker, 2024), is inherently firm-specific and resistant to replication. Customer orientation, defined as the systematic generation and integration of market intelligence to serve target-segment needs (Hooley et al., 2000; Tollin & Schmidt, 2015), embeds relational value that competitors cannot readily appropriate.

Yet the empirical record on these resource–performance linkages is less settled than theory suggests. (Oktemgil & Greenley, 1997), replicating (L. Li et al., 2023; Pirola et al., 2020; Slater & Narver, 1994) market orientation framework across UK manufacturing firms, found no statistically significant relationship between customer orientation and business performance, attributing the null result to competitive market structure: when rivals compete primarily on price and switching costs are low, the performance signal from customer orientation becomes statistically indistinguishable from noise. A parallel ambiguity attends the broader resource–performance relationship. (Ngo et al., 2024), contrasting Porter's (1980) industry-structure perspective against RBV using Greek manufacturing data, found that firm-specific resource advantages did not yield uniformly significant performance returns under conditions of high rivalry; imitative pressures and margin compression offset the expected differentiation premium. Together, these findings signal an unresolved boundary condition: whether competitive intensity amplifies or attenuates the resource–performance relationship, and for which resource types the moderation is most pronounced.

This boundary condition is especially consequential for IT service firms in emerging Southeast Asian economies, where competitive intensity has escalated alongside cloud infrastructure commoditisation and the proliferation of low-cost offshore providers yet direct empirical tests in this context remain absent from the literature. This study addresses that gap through three contributions: it provides evidence on the direct performance effects of technology readiness, human capital, and customer orientation in medium-sized IT service firms in Greater Jakarta; it tests competitive intensity as a boundary condition modulating all three resource–performance paths; and it applies PLS-SEM suited to complex reflective models with moderating interactions to ensure methodological rigour appropriate to the framework's structural demands.

RESEARCH METHODOLOGY

The sampling frame consisted of medium-sized IT service firms registered and operating within the Jabodetabek corridor, defined by Indonesian regulatory standards as enterprises employing between 50 and 499 personnel (PP No. 7 Tahun 2021). Eligible firm categories included software development, IT consulting, managed services, system integration, and cloud services. Respondent eligibility was restricted to individuals occupying management-level positions with direct accountability for operational or strategic decisions, as this stratum possesses the organisational knowledge necessary for reliable construct measurement. To mitigate single-informant bias, two qualified respondents were solicited per firm (Podsakoff et al., 2003), establishing a minimum requirement of 160 participating firms and 320 respondents in total. Sampling employed a purposive approach to secure sectoral and firm-size representativeness, supplemented by snowball referrals to access firms without public registration. Structured questionnaires were distributed across a twelve-week fieldwork period. A preliminary pilot involving 30 respondents verified item comprehensibility before full deployment. Participation was voluntary and respondent confidentiality was maintained throughout.

RESULT AND DISCUSSION

Collinearity Assessment

Table 2 presents the variance inflation factor (VIF) values for all predictor variables and interaction terms in the structural model. All VIF coefficients fall well within acceptable bounds, ranging from 1.106 (Competitive Intensity) to 1.284 (CI × Technology Readiness), markedly below the conservative threshold of 3.3 recommended for PLS-SEM specifications (Kock, 2015a). The absence of multicollinearity across both main-effect predictors and the three interaction terms CI × HC (1.235), CI × TR (1.284), and CI × CO (1.264) confirms that

the product-indicator approach employed to operationalise moderation did not introduce problematic collinearity into the structural estimation (Chin et al., 2003). Notably, the lowest VIF is recorded for Competitive Intensity as a standalone predictor (1.106), indicating minimal linear dependency with the remaining constructs. These results collectively validate the integrity of the structural model and confirm that path coefficient estimates are not distorted by inter-predictor redundancy, satisfying a prerequisite condition for unbiased bootstrapping inference.

Table 2 Collinearity Assessment

Contract	CI	CO	FP	HC	TR	CI x HC	CI x TR	CI x CO
Competitive Intensity _(CI)			1.106					
Customer Orientation _(CO)			1.241					
Firm Performance_(FP)								
Human Capital_(HC)			1.200					
Technology Readiness_(TR)			1.223					
Competitive Intensity _(CI) x Human Capital_(HC)			1.235					
Competitive Intensity _(CI) x Technology Readiness_(TR)			1.284					
Competitive Intensity _(CI) x Customer Orientation_(CO)			1.264					

Reliability and Convergent Validity

Figure 2 presents the PLS-SEM structural model output, reporting path coefficients, interaction effects, and construct-level R^2 values. The model explains substantial variance in Firm Performance ($R^2 = 0.826$), indicating that the predictor set accounts for 82.6% of FP variability—a result reflecting strong explanatory power. Among the main effects, Technology Readiness ($\beta = 0.290$) and Human Capital ($\beta = 0.289$) register the strongest direct contributions to FP, followed by Competitive Intensity ($\beta = 0.207$). Regarding moderation, $CI \times HC$ yields the largest interaction coefficient ($\beta = 0.186$), confirming that competitive intensity meaningfully amplifies the human capital–performance relationship. The $CI \times TR$ interaction ($\beta = 0.109$) provides modest positive moderation. Notably, $CI \times CO$ returns a negative coefficient ($\beta = -0.084$), suggesting that under intensifying competitive conditions, the marginal performance return from customer orientation diminishes rather than strengthens a theoretically interpretable finding consistent with (Lee & Wei, 2023), who similarly observed that certain resource advantages erode under high rivalry pressure.

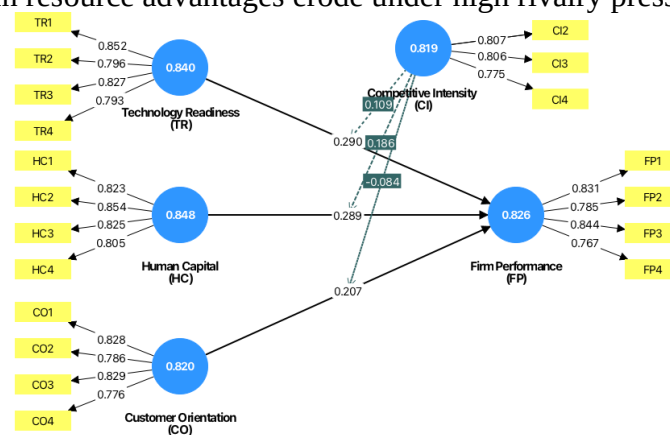


Figure 2 PLS-SEM structural model

Table 4 presents the model fit indices for both the saturated and estimated models. The SRMR value of 0.054 falls below the 0.08 threshold recommended for PLS-SEM, indicating acceptable overall model fit (Henseler & Fassott, 2010). The marginal difference between

saturated and estimated model indices d_{ULS} (0.623 vs. 0.618), d_G (0.202 vs. 0.200), and Chi-square (385.741 vs. 382.102) confirms that imposing the theoretical structure introduces negligible misspecification. The NFI of 0.858 approaches the 0.90 benchmark, acceptable given the model's complexity and sample size of 320 (Lohmöller, 1989). Collectively, these indices support the adequacy of the proposed structural configuration for subsequent hypothesis testing.

Table 4 Model Fit

	Saturated model	Estimated model
SRMR	0.054	0.054
d_{ULS}	0.623	0.618
d_G	0.202	0.200
Chi-square	385.741	382.102
NFI	0.856	0.858

Discriminant Validity

Table 3 reports the heterotrait-monotrait (HTMT) ratios for all construct pairs, including interaction terms. Discriminant validity is established when HTMT values remain below the 0.90 threshold across all construct combinations (Henseler et al., 2015). All off-diagonal coefficients satisfy this criterion, with values ranging from 0.022 (CI × CO with CI) to 0.561 (TR with FP), confirming that each construct captures a conceptually distinct domain of variance. The highest HTMT ratios are observed between the main predictors and Firm Performance TR–FP (0.561) and HC–FP (0.560) reflecting theoretically expected convergence without breaching discriminant validity boundaries. Interaction terms demonstrate particularly low HTMT values against all non-target constructs, with CI × TR recording 0.023 against CI and CI × CO recording 0.022 against CI, confirming that the product-indicator procedure generated interaction variables sufficiently orthogonal to their constituent constructs (Chin et al., 2003). Collectively, these results confirm that all constructs, including moderated terms, are empirically distinguishable, satisfying the discriminant validity prerequisite for unbiased structural estimation.

Table 3 Discriminant Validity

Constructs	CI	CO	FP	HC	TR	CI x HC	CI x TR	CI x CO
Competitive Intensity_(CI)								
Customer Orientation_(CO)	0.286							
Firm Performance_(FP)	0.382	0.541						
Human Capital_(HC)	0.275	0.390	0.560					
Technology Readiness_(TR)	0.245	0.410	0.561	0.355				
Competitive Intensity_(CI) x Human Capital_(HC)	0.082	0.052	0.206	0.062	0.044			
Competitive Intensity_(CI) x Technology Readiness_(TR)	0.023	0.089	0.173	0.027	0.061	0.361		
Competitive Intensity_(CI) x Customer Orientation_(CO)	0.022	0.055	0.082	0.059	0.097	0.349	0.382	

Structural Model Assessment

Table 5 reports the bootstrapped path coefficients, standard deviations, t-statistics, and p-values for all seven hypothesised relationships. Technology readiness ($\beta = 0.290$, $t = 6.778$, $p < 0.001$) and human capital ($\beta = 0.289$, $t = 7.074$, $p < 0.001$) exert the strongest direct effects on firm performance, followed by customer orientation ($\beta = 0.207$, $t = 4.436$, $p < 0.001$), providing unambiguous support for H1, H2, and H3 respectively. Competitive intensity also contributes a significant direct effect on firm performance ($\beta = 0.160$, $t = 3.473$, $p = 0.001$), supporting H7 and corroborating (Porter, 1996) argument that rivalry exposure disciplines firms into performance-improving behaviour.

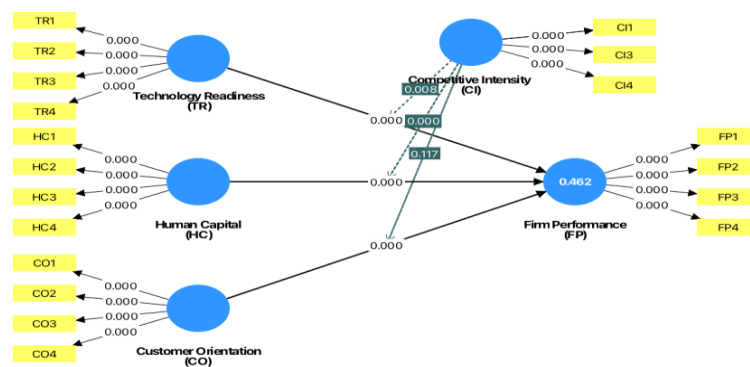


Table 5 Structural Model Assessment

Hypo	Path	β	T-stat	p-value	95% CI	Decision
H1	Technology Readiness_(TR) -> Firm Performance_(FP)	0.290	6.778	0.000	[0.071, 0.254]	Accepted
H2	Human Capital_(HC) -> Firm Performance_(FP)	0.289	7.074	0.000	[-0.179, 0.030]	Accepted
H3	Customer Orientation_(CO) -> Firm Performance_(FP)	0.207	4.436	0.000	[0.095, 0.270]	Accepted
H4	Competitive Intensity _(CI) x Technology Readiness_(TR) -> Firm Performance_(FP)	0.109	2.636	0.008	[0.025, 0.188]	Accepted
H5	Competitive Intensity _(CI) x Human Capital_(HC) -> Firm Performance_(FP)	0.186	4.173	0.000	[0.113, 0.295]	Accepted
H6	Competitive Intensity _(CI) x Customer Orientation_(CO) -> Firm Performance_(FP)	-0.084	1.566	0.117	[0.211, 0.370]	Not support
H7	Competitive Intensity _(CI) -> Firm Performance_(FP)	0.160	3.473	0.001	[0.204, 0.374]	Accepted

Regarding moderation, $CI \times HC$ yields the largest interaction coefficient ($\beta = 0.186$, $t = 4.173$, $p < 0.001$), confirming H5 and indicating that competitive pressure most substantially amplifies the human capital–performance pathway. $CI \times TR$ returns a significant positive interaction ($\beta = 0.109$, $t = 2.636$, $p = 0.008$), supporting H4. Conversely, $CI \times CO$ produces a non-significant negative coefficient ($\beta = -0.084$, $t = 1.566$, $p = 0.117$), leading to the rejection of H6. This result suggests that intensifying rivalry attenuates rather than strengthens the customer orientation performance relationship a finding consistent with (Oktemgil & Greenley, 1997), who demonstrated that market structure conditions govern whether customer orientation translates into measurable performance returns. The close alignment between original sample coefficients and bootstrap means across all paths confirms the stability of estimates under resampling.

Moderation Analysis and Simple Slope Analysis

Table 6 presents the conditional direct effects of Technology Readiness, Human Capital, and Customer Orientation on Firm Performance at three levels of Competitive Intensity one standard deviation above the mean, at the mean, and one standard deviation below the mean following the simple slope procedure recommended by (Aiken & Hage, 1968).

Table 6. Simple Slope Analysis: Conditional Direct Effects of TR, HC, and CO on FP

Moderator Level	CO → FP	HC → FP	TR → FP
CI at +1 SD (High)	0.123	0.476	0.399
CI at Mean	0.207	0.289	0.290
CI at -1 SD (Low)	0.291	0.103	0.181

For Human Capital, the conditional effect strengthens markedly as competitive intensity rises: from $\beta = 0.103$ at low CI to $\beta = 0.476$ at high CI, representing a 4.6-fold amplification. This pattern confirms H5 and indicates that human capital constitutes the most competitively sensitive resource in the model—its performance contribution is negligible under low rivalry but becomes the dominant performance driver when competitive pressure intensifies. Technology Readiness follows a directionally consistent pattern, with the conditional effect increasing from $\beta = 0.181$ at low CI to $\beta = 0.399$ at high CI, confirming H4 and establishing that technologically ready firms extract disproportionately greater performance returns under conditions of acute market rivalry.

Customer Orientation, however, exhibits an inverse pattern: the conditional effect declines from $\beta = 0.291$ under low competitive intensity to $\beta = 0.123$ under high competitive intensity. This slope reversal substantiates the rejection of H6 and suggests that relational investments in customer orientation yield diminishing performance returns precisely when rivalry is most severe—a condition under which price-based competitive dynamics may override the value of relational differentiation (Greenley, 1995; Mu'min et al., 2025).

Explanatory and Predictive Validity

Table 7 consolidates the explanatory and predictive performance metrics for Firm Performance. The R^2 value of 0.462 indicates that the predictor set—comprising TR, HC, CO, CI, and three interaction terms—collectively accounts for 46.2% of variance in FP, with the adjusted R^2 of 0.450 confirming this estimate remains stable after penalising for model complexity (Hair et al., 2019). The Q^2_{predict} value of 0.431 exceeds the zero threshold, establishing that the model retains meaningful predictive relevance beyond in-sample fitting (Shmueli et al., 2019). The RMSE (0.760) and MAE (0.595) are within acceptable bounds relative to the seven-point scale employed, with the MAE-to-RMSE ratio indicating the absence of disproportionately influential prediction errors. Collectively, these metrics confirm that the structural model demonstrates both adequate explanatory power and out-of-sample predictive utility.

Table 7. Predictive Accuracy and Relevance of the Structural Model

Indicator	Value
R^2	0.462
R^2 Adjusted	0.450
Q^2_{predict}	0.431
RMSE	0.760
MAE	0.595

Discussion

Direct Effects of Internal Resources on Firm Performance

The confirmation of H1 establishes technology readiness as a primary performance determinant among medium-sized IT service firms in Jabodetabek. This result extends (Parasuraman, 2000b) individual-level technology readiness construct to the organisational plane, demonstrating that firms whose culture, infrastructure, and workforce disposition collectively favour technology adoption convert that orientation into measurable performance differentials. The coefficient magnitude reflects the constitutive role of technology in IT services: unlike manufacturing contexts where technology functions as an enabling input, IT service delivery is itself technology-mediated, rendering readiness inseparable from service quality and delivery speed. This finding substantiates (J. B. Barney & J.B., 1991) VRIN

proposition, as technology readiness satisfies the inimitability criterion precisely because it is embedded in organisational routines, cultural dispositions, and accumulated technical competencies that competitors cannot replicate through procurement alone.

The confirmation of H2 reinforces (Radiany et al., 2025; Sam et al., 2025; Sirmon & Hitt, 2009) foundational argument that in professional service organisations, the workforce constitutes the primary productive asset. The near-parity between TR and HC path coefficients is theoretically significant: it suggests that neither technological investment nor human capability operates as a sufficient substitute for the other in IT service contexts. Firms that prioritise infrastructure development without concurrent investment in workforce competency or vice versa are likely to encounter performance ceilings that only integrated resource development can overcome. This complementarity between TR and HC warrants explicit attention in strategic resource allocation decisions.

Customer orientation (H3), while producing the most conservative direct effect among the three predictors, nonetheless exerts a significant and substantively meaningful influence on firm performance. The result corroborates (Narver & Slater, 1990) foundational assertion that systematic responsiveness to client needs generates durable performance advantages through switching cost accumulation and informational asymmetry. In the B2B IT services context, customer orientation translates operationally into requirements co-development, iterative solution refinement, and post-delivery relationship management—activities that embed service providers within client workflows in ways that transactional competitors cannot easily displace. The relatively lower coefficient, compared to TR and HC, may reflect the longer temporal horizon over which relational investments materialise into performance outcomes, a dynamic that cross-sectional designs are structurally limited in capturing.

Direct Effect of Competitive Intensity on Firm Performance

The significant positive direct effect of competitive intensity on firm performance (H7) merits careful theoretical interpretation. Rather than treating rivalry as a purely constraining force, this finding aligns with Schumpeterian arguments that competitive pressure functions as a disciplinary mechanism—compelling firms to sharpen operational efficiency, accelerate service innovation, and invest in differentiating capabilities. (Sheehan & Foss, 2007) recognised this dual character of competition: while intense rivalry erodes margins in the short run, it simultaneously motivates the strategic investments that generate longer-run performance advantages. Among medium-sized IT service firms in Jabodetabek, exposure to well-capitalised competitors and price-aggressive offshore providers appears to have induced organisational responses whose net performance consequences are positive. This result challenges the assumption, prevalent in SME research, that competitive intensity is uniformly detrimental to smaller firm performance.

Moderation by Competitive Intensity

The moderation analyses yield findings that both confirm and qualify the contingency-theoretic extension of RBV proposed in this study. The confirmation of H5 represents the most theoretically consequential result in the model. Simple slope analysis reveals that the human capital–performance relationship undergoes a pronounced amplification as competitive intensity escalates its performance contribution is modest under low rivalry but becomes the dominant performance driver when competitive pressure intensifies. This pattern reflects a client-side selection mechanism that rivalry activates: under high competitive intensity, clients bear elevated vendor switching risk and therefore apply more rigorous capability screening in procurement decisions. Firms with demonstrably superior human capital clear this screening threshold more consistently, while those with average workforce capabilities face systematic client attrition. The practical implication is that human capital investment yields returns that are not merely additive but disproportionately sensitive to competitive context.

The confirmation of H4 extends this contingency logic to the technology dimension. Simple slope analysis indicates that technologically ready firms extract compounding performance advantages precisely when rivalry demands rapid service iteration and capability deployment. Under low competitive intensity, technology readiness generates moderate incremental efficiency gains. Under high intensity, however, the same readiness posture enables firms to launch capability enhancements ahead of competitors and build proprietary technical architectures within competitive response windows that rivals cannot match. This acceleration dynamic is particularly acute in the Indonesian IT services market, where cloud infrastructure commoditisation has compressed the shelf life of any given technical advantage, placing a premium on the organisational readiness to continuously renew capability positions.

The non-significant negative interaction for customer orientation (H6) constitutes the most theoretically provocative result of the study. Simple slope analysis reveals that the performance contribution of customer orientation declines rather than rises as competitive intensity escalates a slope reversal that directly contradicts the amplification pattern observed for HC and TR. Two complementary mechanisms explain this inversion. First, under conditions of high competitive intensity, market dynamics shift toward price competition and rapid service commoditisation, reducing the scope within which relational differentiation can be communicated and valued by clients operating under procurement cost pressures. Greenley, (1995) documented precisely this structural boundary condition, observing that customer orientation fails to generate significant performance returns when competitive market structure overrides the buyer's willingness to reward relational investment. Second, the relational assets that constitute customer orientation require sustained investment horizons to yield measurable returns. When rivalry intensifies, the performance evaluation window compresses, disadvantaging resources whose returns are inherently long-cycle. Shan et al., (2019) similarly found that certain resource advantages were offset by imitative pressures under high rivalry, suggesting that the contingent devaluation of customer orientation reflects a broader boundary condition in the RBV literature rather than an idiosyncrasy of the Indonesian context.

Implications

Theoretical Implications

This study contributes to the RBV literature by demonstrating that the performance consequences of internal resources are neither uniform nor context-independent. While (J. B. Barney & J.B., 1991) established the conditions under which resources generate sustained competitive advantage, the present findings specify the environmental contingency competitive intensity that governs the magnitude and direction of those advantages. The differential moderation pattern across TR, HC, and CO challenges the implicit assumption in much RBV scholarship that all VRIN-qualifying resources respond symmetrically to environmental pressures. Human capital and technology readiness exhibit positive contingent sensitivity, while customer orientation exhibits negative contingent sensitivity, suggesting that resources must be distinguished not only by their static VRIN properties but by their dynamic responsiveness to competitive context.

The study further contributes to the market orientation literature by providing a theoretically grounded explanation for the null and negative findings previously documented by (Greenley, 1995). Rather than treating non-significant CO performance relationships as measurement anomalies or sampling artefacts, the present framework positions them as predictable outcomes of a moderating boundary condition. This reframing advances the literature from a debate about whether customer orientation improves performance a question the meta-analytic evidence has largely settled toward a more precise inquiry into when and for whom that improvement materialises.

Finally, the application of PLS-SEM with product-indicator interaction terms to a medium-enterprise IT services sample in an emerging Southeast Asian economy addresses a persistent geographical and sectoral bias in the RBV moderation literature, which has disproportionately examined large enterprises in Western manufacturing and retail contexts.

Practical Implications

For senior managers of medium-sized IT service firms, the central practical implication is that resource investment priorities must be calibrated to the prevailing competitive environment rather than treated as context-independent strategic imperatives. In markets characterised by intensifying rivalry the dominant trajectory in Jabodetabek's IT services sector the returns to human capital and technology readiness are disproportionately high, justifying elevated and sustained investment in workforce development and digital infrastructure renewal even when short-term margin pressure tempts resource retrenchment.

The finding that human capital generates the steepest competitive sensitivity warrants particular managerial attention. Firms that allow talent development programmes to atrophy under cost pressure, or that fail to retain specialist personnel during periods of high competitive stress, face an asymmetric performance penalty: the very conditions that most demand superior human capital are the conditions under which its absence is most consequential. Structured competency frameworks, career progression architecture, and knowledge retention systems should therefore be treated as strategic priorities rather than operational overheads.

For customer orientation, the practical implication is more nuanced. The declining returns under high competitive intensity do not counsel firms to abandon relational investment, but rather to recalibrate its form. When price-based rivalry dominates client procurement decisions, broad relational programmes that emphasise long-term welfare and co-development may generate insufficient short-term performance returns to justify their resource cost. A more targeted approach—concentrating relational investment in client segments with higher switching costs, longer contract cycles, and greater decision-making autonomy—may preserve the performance benefits of customer orientation while limiting exposure to the competitive conditions that attenuate its returns.

CONCLUSION

This study examined how technology readiness, human capital, and customer orientation shape firm performance among medium-sized IT service firms in the Jabodetabek metropolitan region, and whether competitive intensity modulates those relationships. Grounded in Resource-Based View theory and tested using PLS-SEM with 320 management-level respondents across a minimum of 160 firms, the findings confirm that all three internal resources exert significant positive direct effects on firm performance, with technology readiness and human capital emerging as the primary performance drivers. Competitive intensity itself contributes a significant positive direct effect, consistent with the Schumpeterian view of rivalry as a performance-disciplining force.

The moderation analyses yield a theoretically differentiated pattern. Competitive intensity amplifies the performance contributions of both human capital and technology readiness, with the amplification effect on human capital representing the most pronounced contingency result in the model. Customer orientation, by contrast, exhibits declining performance returns as competitive intensity rises—a finding that extends and theoretically explains prior null results in the market orientation literature by identifying competitive market structure as the governing boundary condition.

Several limitations circumscribe the scope of these conclusions. The cross-sectional design precludes causal inference and cannot capture the temporal accumulation of resource advantages. The restriction to Jabodetabek-based firms limits direct generalisability to other

Indonesian regions and to other emerging market contexts, though the region's economic centrality renders it a credible first test. Self-reported performance measures, while standard in studies of privately held SMEs, carry residual common method bias risks that multi-informant longitudinal designs would attenuate. Future research should examine whether the contingent devaluation of customer orientation under high competitive intensity is transient reversing as competitive dynamics stabilise—or structural, reflecting a durable feature of price-intensive B2B markets. Comparative studies across ASEAN economies with varying institutional environments would further establish the generalisability boundaries of the contingency model proposed here.

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