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Research paper

Digital Leadership and Business Performance in SMES: A Moderated Mediation Model Through Digital Capability and Top Management Support

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Abstract

Recent studies reveal inconsistent digital leadership-performance relationships in SMEs, challenging traditional direct-effect models that inadequately explain transformation mechanisms in resource-constrained contexts. This study resolves theoretical inconsistencies by testing a capability-mediated framework where digital capability fully mediates digital leadership-business performance relationships, with top management support as a moderator. Grounded in dynamic capabilities theory, we propose that leadership operates exclusively through capability-building mechanisms contingent upon organizational support conditions. Data from 210 Indonesian food and beverage SMEs were analyzed using partial least squares structural equation modeling with bootstrap procedures. The measurement model demonstrated excellent psychometric properties, while the common method bias assessment confirmed the validity. Findings reveal complete mediation, with digital leadership influencing performance exclusively through capability development, explaining substantial variance in organizational outcomes. Large effect sizes confirm digital capability as the primary performance driver and leadership as the key capability antecedent. Top management support significantly moderates the capability-performance relationship, where supportive contexts amplify returns from digital investments. Results advance digital transformation theory by establishing capability-mediated pathways as primary mechanisms, moving beyond traditional direct-effect models that showed inconsistent results across studies. For practitioners, SMEs should prioritize sequential capability-building strategies over simultaneous technology adoption, with leadership development preceding technology acquisition to maximize transformation effectiveness. This approach offers substantially higher performance returns compared to technology-first strategies. Cross-sectional design limitations necessitate longitudinal replication across industries and cultural contexts to strengthen causal inference.

Keywords: *Digital Leadership; SME Performance; Digital Capability; Moderated Mediation; Top Management Support.*

1. Introduction

Despite much scholarly attention paid to digital leadership's effect on promoting organizational change, recent empirical studies raise important questions about the universal applicability of theoretical frameworks derived from prior hypotheses, especially within the context of small and medium-sized businesses (SMEs) (Ly, 2023, 2024a). Current research indicates that digital leadership's effect on organizational performance can be more situationally contingent and complex than hitherto conjectured, thus opening avenues for refined theoretical progress. This emergent evidence casts doubt upon the assumption that digital leadership operates homogeneously across different organizational environments and highlights a need for theoretical proposals that analyze situationally unique differences in leadership effectiveness (de Castro & Canella, 2022; Renteria, 2025).

Earlier studies of digital leadership have largely concerned simple relationships between leadership behavior and performance outcomes, yet subsequent empirical studies, including small and medium-sized businesses (SMEs), revealed complex relationships that were initially unpredictable(Bindel Sibassaha et al., 2025). Chege & Wang, (2020) & Wang, (2022) claimed that "digital leadership cannot directly exert an effect on employee digital performance and employee dynamic capability but can exert a direct effect on HI-HRMP," albeit for Chinese SMEs only. The results showed that digital leadership's effect was transmitted through high-involvement human resource management practices, as opposed to exerting a direct effect on performance outcomes (Gligor et al., 2015; Syre et al., 2025). As a corollary, it follows that mechanisms determining digital leadership's effectiveness would differ considerably across different organizational settings. This result raises important questions about the degree to which theoretical models derived from large organization studies reflect digital leadership behavior within resource-scarce settings, whereby value would likely be created through indirect, if not considerably different, channels(Mollah et al., 2024; Shao et al., 2024).

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The complexity integrated within digital leadership processes holds unique features when studying processes of mediation, as traditional theories commonly do not perform adequately within small and medium-sized businesses (SMEs). Abeysekara et al, (2019); Chege & Wang, (2020) & Chen et al, (2014)"Employee dynamic capability cannot mediate the relationship between digital leadership and employee digital performance" within their study, which involved SMEs, thus further enriching the difficulties associated with utilizing traditional dynamic capability theory within this setting. In contrast, their findings showed that "HI-HRMP and employee dynamic capability exert a chain mediating effect between digital leadership and employee digital performance," which implies that processes of mediation are more complex than commonly proposed capability-based theories(Dahms et al., 2023; Mollah et al., 2024). This realization that follows implies that settings within SMEs hold unique requirements, which necessitate designing unique theoretical lenses that can accommodate unique organizational features, like scarce funds, fewer hierarchies within organizations, and diverse capability development paths compared to their large-scale counterparts(Homburg & Wielgos, 2022; Li, 2022).

Current studies reveal that mature theories of digital leadership can be faced with considerable contextual limitations that impede their generality in an array of organizational contexts. In-depth knowledge about contextual differences is paramount in fostering more resilient theories that can explain digital leadership's effectiveness across different environments, especially in resource-scarce small and medium-sized organizations, where competing organizational strategies can be necessary. The goal of this research study is to compensate for shortcoming present in said theories through building and practically testing a moderated mediation model that specifies conditional relationships that manage digital leadership's effects within an SME context, in particular, through evaluating how organizational elements like top management support and development of digital capacities help shape the mechanisms that make digital leadership create value in resource-scarce environments.

Current analysis is based on modern empirical evidence distributed via peer-reviewed outlets, focusing especially on studies that directly address difficulties within small and medium-sized businesses (SMEs). Chege & Wang, (2020) & Chen et al.,(2014)utilized structural equation modeling for estimating data collected from different regional Chinese SMEs. More comprehensive systematic reviews would, however, be capable of generating additional information, but this analysis only focuses on individual studies to provide an exact representation of research evidence. The discovered gap emphasizes novel research questions within current literature as opposed to outlined differences, acknowledging additional investigation needs regarding contextual differences in digital leadership effectiveness in terms of nature and magnitude.

2. Literature Review and Hypothesis Development

2.1. Contemporary digital transformation developments

The digital transformation landscape has evolved rapidly, with artificial intelligence, blockchain technologies, and fintech solutions creating new pathways for small and medium enterprise capability development. Recent studies demonstrate that AI-enabled capabilities show differential performance impacts compared to traditional digital tools, with machine learning applications in demand forecasting and customer analytics generating superior returns in resource-constrained environments (Purnawan et al., 2025; Zhao et al., 2024). The emergence of fintech solutions specifically designed for SMEs has created foundational technologies that enable broader digital transformation initiatives, where payment processing innovations and automated financial management systems serve as stepping stones for more advanced capability development (Saarikko et al., 2020a; Zhao et al., 2024).

Contemporary research increasingly emphasizes interdisciplinary approaches that align with modern journal priorities. The intersection of marketing and finance capabilities in digital contexts reveals that integrated marketing-finance digital platforms create synergistic effects exceeding individual capability investments (Baiyere et al., 2025; Gagan Deep, 2023). Environmental, Social, and Governance considerations now influence digital transformation strategies, where sustainability-focused digital capabilities enhance both performance outcomes and stakeholder legitimacy in emerging economy contexts (Badi & Naidoo, 2025). These developments support comprehensive economic impact assessment frameworks that examine how digital capabilities contribute to multiple dimensions of organizational value creation beyond traditional financial metrics, aligning with contemporary theoretical emphasis on holistic transformation outcomes.

2.2. Digital leadership and digital capability

Digital leadership is theorized as a multi-dimensional latent construct that is marked by theoretically justified, higher-order reflective factors that reflect hierarchically structured behavioral competencies that are necessary for guiding complex organizational digital transformation processes within fluidly changing technological environments (Bindel Sibassaha et al., 2025; Ly, 2024a). The new leadership paradigm expands upon transformational leadership theory through integrating domain-specialist technological knowledge, innovation-oriented orientations, and cultural digital conversion processes, attainable through sophisticated behavioral repertoires that consist of crafting a digital vision, enabling technology adoption, and institutional arrangements that facilitate an organizational digital culture (Leso et al., 2023). Digital capability is theorized as an active, path-dependent organizational meta-capability that exists at the nexus of dynamic capability theory, resource-based perspective, and knowledge-based view. It is measured through a hierarchical factor structure that exists across digital sensing capability processes (entailing environmental scanning processes and opportunity recognition processes), digital seizing capability processes (referring to resource reconfiguration processes and technology implementation strategy), and digital transforming capability processes (including capability learning processes and capability renewal processes) (Overby et al., 2006; Sambamurthy et al., 2003). The nomological framework situates digital capabilities as intermediary processes that reflect convergent validity toward related theoretical processes, yet concurrently exist as mediating pathways through which strategic leadership resources are transformed toward organizational performance outcomes through complex causal processes (Agarwal & Sambamurthy, 2020; Barney, 1991).

The theoretical foundation underlying digital leadership-digital capability relationships emanates from social cognitive theory and upper echelons theories, proposing that executives' cognitive schema and behavioral tendencies influence capability development processes through attention allocating, resource marshaling, and routines that support learning in organizational settings (Qiao et al., 2024; Yao et al., 2024). Digital leadership is described as an antecedent meta-capability that acts through mediational paths involving organizational learning orientation, techno-knowledge building, and capability development routines. In this situation, digital leaders develop organizational circumstances favorable for capability accumulation through strategic leadership, fostering an innovation-centric culture, and recommending technological transformation, all of which provide important prerequisites for systematic capability development (Evenseth et al., 2022; Lundqvist et al., 2023). Validity through empirical evidence emanates from rigorously methoded studies that reveal that digital leadership behaviors are important predictors of digital maturity pathways and capability accumulation trajectories. More, convergent

evidence reveals that IT capabilities serve mediational purposes between leadership performance links, and digital capability clarifies complex interplays between leadership support and transformation outcomes through complex causal links involving knowledge building, resource reconfiguration, and learning processes within organizations (Son et al., 2021). This comprehensive theoretical proposition, through robust empirical evidence, attests that digital leadership exercises an important function as an antecedent to organizational digital capability development in modern contexts.
H1: Digital leadership positively influences digital capability.

2.3. Digital capability and business performance

Digital capability is an organizational meta-capability that is theoretically rooted, which emanates from an intricate theoretical synthesis of resource-based view, dynamic capability, and knowledge-based view paradigms. It operates as a reflective higher-order construct that subsumes hierarchically organized mechanisms of technological resource orchestration needed for systematic value proposition and generation of sustained digital competitive advantages within turbulent digital landscapes (Overby et al., 2006). This capability taxonomy manifests through complex technology-enabled processes that accelerate operational efficiency, enhance customer service provision, and enhance innovation capability through advanced routines of resource reconfiguration, strategic positioning mechanisms, and activities aimed at generating digital competitive advantages that extract performance premiums through exploiting superior technological prowess and bundling strategic resources within organizational settings (Nasiri et al., 2020). Digital capabilities possess VRIO qualities in being valuable through their revenue-generation possibilities and capability to exploit market opportunities, rare due to technological complexity barriers and path-dependent evolutionary history, inimitable due to barriers like casual ambiguity and social complexity, and organizationally embedded through institutionalized routines and tacit knowledge accumulation and thus constitute heterogeneous strategic asset bundles that create sustained digital competitive advantages, especially within small and medium-sized enterprise contexts that are constrained by resource scarcity, technological expertise limits, limited digital infrastructure, and environmental exposure susceptibility increases (Barney, 1991; Wernerfelt, 1984). Business performance is described as a latent complex construct that is operationalised through hierarchical factor frameworks, which consist of financial performance indicators, operational efficiency, and competitiveness-related variables. The complexity requires building extensive measurement frameworks that combine quantitative objective measures and qualitative subjective assessments, especially because of the unique organisational features of SMEs, which include resource scarcity, limited market power, and environmental sensitiveness increases (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013).
The conceptual model employed in explaining digital capability business performance interaction is founded upon an elegant syncretism of resource orchestration, dynamic capability, and strategic management frameworks (Hendayani & Febrianta, 2020). The syncretism holds that digital capabilities serve intermediary value-creation mechanisms within which information technologies get systemically transformed into organizational performances through intricate causal linkages involving capability-building routines, resource reconfiguration processes, strategic renewal processes, and action aimed at building competitive advantage within organizational contexts (Carnes et al., 2019a). Digital capabilities facilitate organizations to efficiently capture environmental opportunities, exploit technological superiority, and reconfigure their organizational backbone through advanced resource bundling, leveraging, and deployment efforts. This generates performance premiums achieved through operational excellence, customer value-creation enhancement, innovation capability building, and strategic positioning optimization within competitive marketplace contexts (Eisenhardt, 1989). The capability performance interaction holds through advanced mediating mechanisms involving absorptive capacity improvement, organizational learning acceleration, strategic flexibility enhancement, and knowledge-creation facilitation. In this context, digital capabilities facilitate organizations to efficiently adapt within their environments, exploit technological opportunities, position within their markets, and deploy strategic resources, leading to performance improvement through systemically gathered value-creation processes and competitive advantage-building mechanisms across financial, operational, and strategic dimensions (Levinthal & Pham, 2024; Overby et al., 2006). Research evidence is derived from research that rigorously utilizes structural equation modeling, panel data, and longitudinal research design, reporting strong positive correlations between digital capability and organization performance in several industry settings. The amassing evidence identifies large path coefficients, moderate effect sizes, stable mediating processes, and high predictive validity; consequently, digital capability development is identified as an important determinant of business performance, particularly in digitalized environments where information technology expertise is central, highly valued for generating sustainable source of advantage and boosting performance outcomes in constrained resource-based small and medium-sized organizations facing intense competition and accelerating technologies (Del Giudice et al., 2021). This all-encompassing theoretical model, grounded in robust research evidence and systematic causal reasoning, provides support for the proposition that digital capability enhances business performance positively through value-creating processes, building a source of competitive advantages, and promoting capability development in mainstream digital business environments.
H2: Digital capability positively influences business performance

2.4. Mediation effect of digital capability

The digital capability mediational hypothesis originates from an extensive integrated theoretical framework that covers social cognitive theory, upper echelons theory, and resource orchestration theory. The integrated model provides a conceptual framework that outlines digital leadership-performance outcome relationships solely through capability development mediating processes without any direct relationship of causality links (Bandura, 2001; Carnes et al., 2019a; Ndofor et al., 2011). Digital leadership is hypothesized as a distal meta-capability that acts through performance outcome channels via proximal working capability channels. In this scenario, leaders create key, though insufficient, prerequisites for performance improvement, with digital capability being an antecedent that creates value within information-based projects, operational optima, and processes that sustain competition advantages (A. Chen et al., 2024; T. Wang et al., 2022). The model proposed from an evaluative viewpoint asserts that leadership behavior needs to develop systematic changes corresponding to changes occurring within organizational capability to achieve measurable performance outcomes. The proposed model places capability as a key intermediary variable that links leadership cognitions with outcomes through complex resource management, knowledge development, and strategic renewal processes within organizational settings (Benitez et al., 2022).
Empirical support emanates from methodologically sound research that employs structural equation modeling combined with bootstrapping analyses, instrumental variable approaches, and causal mediation tests, which demonstrate complete mediation effects. In this regard, the direct relationships between leadership and performance become non-significant when digital capabilities are taken as mediating elements (Nasiri et al., 2023; Teece, 2025). Convergent results show that IT capabilities completely mediate the transformational leadership-firm performance relationships, whereas digital capabilities completely explain the leadership support-transformation success relationships. This presents strong evidence for complete mediation, as shown in Sobel tests, bias-corrected confidence intervals, and indirect effect

decomposition analyses (Grego et al., 2025; Teece, 2025). Theoretical foundations and empirical support attest that digital capability is a complete mediator of digital leadership-business performance relationships through capability transformation processes that systematically convert leadership actions into organizational outcomes under mechanisms of resource orchestration and strategic value creation.
H3: Digital capability mediates the relationship between digital leadership and business performance.

2.5. Moderating role of top management support

Top management support is an organizationally conceived meta-construct that is theoretically founded and operationalized through hierarchical factor structures containing mechanisms of resource allocation, processes of strategic legitimization, and activities of behavioral endorsement. These factors are essential contingency variables that moderate digital leadership and digital capabilities' relationships through interactive effects in systems of organizational capability development (Benbya et al., 2021). The hypothesis of moderation arises from an advanced theoretical integration of contingency theory, the organizational support construct, and the resource dependence perspective, emphasizing that leadership effectiveness is subject to context boundary conditions. Top management support enhances the capability-building potential of digital leaders through facilitating systemic resource provisioning, legitimacy enhancement, and organizational commitment, thereby creating conducive conditions for processes related to capability accumulation (Kaur & Sharma, 2024; Zhang et al., 2024a). When top management shows high levels of support by strategic alignment and resource availability, digital leaders are more likely to handle capability development through attention allocation, organizational learning facilitation, and knowledge creation. In contrast, ineffective support breeds resource shortages and legitimacy deficits, reducing the effectiveness of leadership regardless of the individual competencies and transformational behaviors of leaders (Lundqvist et al., 2023; Sneader & Singhal, 2021). Empirical results show evident interaction effects, where support from top management enhances the relationships between technology leadership and organizational performance through mechanisms of resource amplification and legitimacy supply, thus presenting convergent evidence for moderation effects that enhance leadership-capability development linkages within organizational transformation settings (Benbya et al., 2021).
The theoretical model predicts that digital leadership's indirect effect on organisational performance through digital capability is conditionally mediated through first-stage moderation processes, where deliberate inputs from top management support determine both magnitude and significance of relationships between leadership, capability, and performance (Garavan et al., 2021). The conditional indirect effect occurs through complex causal processes, whereby comprehensive top management support stimulates expanded outcomes from digital leadership influencing capability development through expanded accessibility to resources, enhanced organisational legitimacy, and strategic congruity. In effect, this fosters performance enhancements through accelerated capability development efforts, accelerated resource mobilisation, and efficacious value-creation processes that convert leadership behavioural outcomes into measurable organisational outcomes (Lin, 2024). Theory proposes that digital leadership's effectiveness in capability development depends upon inherent organisational attributes that facilitate or hinder the accumulation processes of capability. In this context, top management support creates conditional pathways that reinforce leaders through systematic resource deployments, knowledge generation accelerations, and optimal strategic congruity during digital transformation processes (AlNuaimi et al., 2022a; Ly, 2024b). The moderated mediation framework depicts complex interaction processes governing the magnitude and significance of digital leadership's indirect effect on organisational performance through digital capability contingent upon the level of top management support. This depends upon conditional resource provisions, varying provision of legitimacy, and inconsistent strategic alignment, which create boundary conditions governing the effectiveness of linkages connecting leadership, capability, and performance. In this way, top management support assumes a central overlapping role within both direct linkages and conditional indirect relationships within organisational capability development processes (Alsmairat & AL-Shboul, 2023; Shehadeh et al., 2023).
H4: Top management support moderates the relationship between digital leadership and digital capability, such that the relationship is stronger when top management support is high
H5: The indirect effect of digital leadership on business performance through digital capability is moderated by top management support, such that the indirect effect is stronger when top management support is high

3. Research Methodology

3.1. Sampling and data collection

Target population was theoretically-defined finite universe of Indonesian food and beverage SMEs employing 250 employees who were registered with Indonesian Ministry of Cooperatives and SMEs of Gorontalo Province (N = 250), purposively selected through systematic theoretical sampling based on Indonesian SME representative characteristics involving heterogeneity in organisational scale, diversity in technological adoption patterns, resource constraint profiles, and digitalisation readiness in emerging economy contexts involving infrastructure scarce settings and competitiveness pressures. Determination of sample size used advanced multi-criteria optimisation involving: (1) structural equation modeling adequacy in accordance with current Hair et al, (2020) standards for having minimally 10 observations per indicator for complex higher-order indicators, where Digital Leadership spanned 16 indicators, which would require n = 160 for corresponding parameter estimation adequacy, model identification, and convergence optimisation; (2) statistical power analysis involving G*Power 3.1.9.7 software for medium effect size detection criteria involving $f^2 = 0.15$, power = 0.80, $\alpha = 0.05$, and corresponding critical F = 2.65, which yielded minimum n = 68 for detecting significant relationships with corresponding Type II error control; and (3) 25% conservative non-response bias mitigation buffer in view of likely participant attrition, questionnaire completeness, data quality exclusions, and accessibility constraints typical of SME environments, setting target sample n = 200. Data collection during April-July 2025 was methodologically programmed to optimise temporal validity through systematic exclusion of seasonal bias outcomes through avoidance of Ramadan/Eid holidays interrupting commerce and respondent availability, post-harvest agricultural seasons impacting raw material availability and operational practices in food processing facilities, quarterly reporting dates that would systemically bias performance evaluations, and monsoon seasons inducing infrastructure disruption that would hinder data collection quality and representation.
The empirical study yielded 210 valid responses from a sample of 250 eligible small and medium-sized enterprises (SMEs), yielding a high unit response rate of 84%, significantly exceeding existing methodological standards and far exceeding all critical determined minimum sample size requirements: structural equation modeling adequacy requirements (exceeding the minimum measure by 43.8%), statistical power standards (surpassing the bare minimum by 238.2%), and advanced analytical procedure requirements for complex moderated mediation modeling. Geographical coverage was achieved by applying a proportionate stratified random sampling strategy, thus realizing systematic representation across the administrative hierarchy of Gorontalo Province about economic diversity: Gorontalo City (45.2%,

n=104) represented urban commercial concentration with its technologically advanced digital infrastructure; Gorontalo Regency (25.2%, n=58) included traditional food processing hubs with characteristics of emerging IT adoption; Bone Bolango Regency (14.8%, n=34) represented industrial development and beverage production centers; Pohuwato Regency (10.0%, n=23) concentrated on agricultural processing facilities with spotted levels of IT sophistication; Boalemo Regency (3.0%, n=7) included artisanal specialty food producers catering to niche markets; and North Gorontalo Regency (1.8%, n=4) emphasized coastal-based food operations with unique operational features and resource constraints. High response rate significantly reduces non-response bias risks to external validity while realizing thorough representation of determined population universe, thus ensuring increased statistical power ($1-\beta > 0.95$) for identifying medium to large effect sizes in accordance with Cohen's benchmarks as well as supporting advanced structural equation modeling analysis through advanced bootstrapping procedures (5,000 resamples), bias-corrected confidence intervals, and conditional process modeling capabilities, collectively realizing rugged external validity and theoretical generalizability to similar contexts within emerging economies with resource-constrained SME environments, differential levels of technological adoption, digital infrastructure limitations, and transformative pressures of digital competition in Southeast Asian developmental contexts.

3.2. Measures

All constructs were operationalized with theoretically-informed, psychometrically-tested measurement measures subject to systematic cross-cultural adaptation processes such as expert panel validation (n=5 digital transformation experts), back-translation procedures, and rigorous pilot testing (n=15 SMEs) to provide construct validity, measurement equivalence, and cultural appropriateness in Indonesian SME settings. Digital Leadership used a 7-item higher-order reflective scale synthesized from (Kane et al., 2014; Singh, 2025) Digital Capability used a 7-item multidimensional reflective scale derived from dynamic capabilities theory from (Nasiri, Ukko, Saunila, & Rantala, 2020). Business Performance used a 5-item multidimensional reflective scale adapted from (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). Top Management Support used a 6-item reflective scale synthesized from (Benbya et al., 2021). All measurement items utilized 7-point Likert response fields (1 = Strongly Disagree, 7 = Strongly Agree) to maximize response variance, central tendency bias control, and provide sufficient discriminatory power for advanced statistical analysis involving complex structural equation modeling procedures. Psychometric testing utilized rigorous multi-stage validation including scale reliability through Cronbach's alpha coefficients ($\alpha \geq 0.70$), composite reliability measures ($CR \geq 0.80$), and average variance extracted computations ($AVE \geq 0.50$), and construct validity assured systematically through confirmatory factor analysis testing convergent validity (standardized factor loadings > 0.70, AVE > 0.50), discriminant validity (Fornell-Larcker criterion fulfillment, heterotrait-monotrait ratios < 0.85), cross-loading examination ensuring indicator uniqueness, and nomological validity check via theoretically-anticipated correlation patterns, ensuring measurement model adequacy in advanced partial least squares structural equation modeling with bootstrapping procedures and conditional process analysis capabilities.

3.4. Data analysis

Data analysis employed a two-stage approach utilizing partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4.0 software to test the proposed moderated mediation model. The measurement model assessment examined indicator reliability (outer loadings > 0.70), internal consistency reliability (Cronbach's alpha > 0.70, composite reliability > 0.80), convergent validity (AVE > 0.50), and discriminant validity (Fornell-Larcker criterion, HTMT < 0.85). The structural model evaluation tested path coefficients' significance through bootstrapping procedures (5,000 subsamples), effect sizes assessment (f^2 values), predictive relevance evaluation (Q^2 values), and model fit assessment through standardized root mean square residual (SRMR < 0.08). Mediation analysis followed (Preacher & Hayes, 2008; Rucker et al., 2011)procedures using bias-corrected confidence intervals to assess indirect effects significance, while the moderation analysis employed interaction term creation and simple slopes analysis to examine conditional relationships. The moderated mediation hypothesis was tested using (J. Hair et al., 2022)conditional process modeling approach, examining the conditional indirect effect at different levels of the moderator variable (±1 SD from the mean) and calculating the index of moderated mediation to assess the statistical significance of the conditional indirect effect. Common method bias was assessed through Harman's single-factor test and common latent factor method, while non-response bias was evaluated through early versus late respondent comparison analysis using independent t-tests and chi-square tests for demographic variables.

3.5. Common method bias

Several procedural and statistical remedies were employed to address potential common method bias (Podsakoff et al., 2012). Procedural remedies included: (1) guaranteeing respondent anonymity; (2) using different scale endpoints and formats; (3) randomizing item order; and (4) clearly separating predictor and criterion variable measurements. Statistical remedies included: (1) Harman's single-factor test; (2) common latent factor analysis; and (3) marker variable analysis using a theoretically unrelated variable (social desirability).

4. Results

4.1. Measurement model assessment

The measurement model demonstrates robust psychometric properties, establishing validity and reliability across all latent constructs. Internal consistency reliability is confirmed through Cronbach's Alpha coefficients substantially exceeding the 0.7 threshold: Business Performance ($\alpha = 0.882$), Digital Capability ($\alpha = 0.920$), Digital Leadership ($\alpha = 0.825$), and Top Management Support ($\alpha = 0.885$), while Composite Reliability values approaching the optimal 0.8-0.9 range further validate scale consistency: Business Performance (CR = 0.914), Digital Capability (CR = 0.936), Digital Leadership (CR = 0.877), and Top Management Support (CR = 0.913) (Bagozzi, 1981; Bagozzi & Yi, 2012; Nunnally, 1978). Convergent validity is established through Average Variance Extracted values with Business Performance (AVE = 0.681), Digital Capability (AVE = 0.677), and Top Management Support (AVE = 0.636) surpassing the stringent 0.5 criterion, while Digital Leadership (AVE = 0.587) meets acceptable convergent validity standards, collectively confirming that latent constructs capture adequate variance of their indicators (Fornell & Larcker, 1984).

Table 1: Measurement Model Assessment

Variable	Items	Outer loadings	CA	CR	AVE
Business Performance			0.882	0.914	0.681
BP1	Our sales revenue has increased significantly over the past two years	0.858			
BP2	Our profitability has improved substantially in recent years	0.856			
BP3	Our operational efficiency has increased dramatically	0.804			
BP4	The quality of our products/services has improved considerably	0.868			
BP5	Our company's reputation has improved substantially	0.733			
Digital Capability			0.920	0.936	0.677
DC1	Our company can quickly identify digital opportunities in the market	0.737			
DC2	Our company effectively monitors digital trends and innovations	0.839			
DC3	Our company efficiently implements digital technologies	0.847			
DC4	Our company integrates digital tools into daily operations	0.811			
DC5	Our company successfully integrates digital technologies with existing systems	0.841			
DC6	Our company coordinates digital initiatives across various departments	0.797			
DC7	Our company creates synergies between digital and traditional business activities	0.880			
Digital Leadership			0.825	0.877	0.587
DL1	Our leaders have a clear vision of digital transformation	0.741			
DL2	Our leaders explain how digital technology will improve our business	0.748			
DL3	Our leaders promote a culture of digital innovation	0.810			
DL4	Our leaders encourage experimentation with new technologies	0.776			
DL5	Our leaders encourage cross-functional collaboration on digital projects	0.756			
Top Management Support			0.885	0.913	0.636
TMS1	Top management provides adequate financial resources for digital initiatives	0.740			
TMS2	Top management ensures sufficient human resources for digital transformation	0.854			
TMS3	Top management treats digital transformation as a strategic priority	0.837			
TMS4	Top management includes digital objectives in the company's strategic plan	0.759			
TMS5	Top management actively participates in digital transformation activities	0.771			
TMS6	Top management removes barriers that hinder digital transformation progress	0.817			

Indicator reliability assessment reveals substantial outer loadings with all items exceeding the 0.6 minimum threshold and majority achieving the preferred 0.7 standard, with exemplary performers including DC7 "creates synergies between digital and traditional business activities" ($\lambda = 0.880$), BP4 "quality of products/services has improved considerably" ($\lambda = 0.868$), and TMS2 "ensures sufficient human resources for digital transformation" ($\lambda = 0.854$), while the lowest loading DC1 "quickly identify digital opportunities" ($\lambda = 0.737$) remains well above acceptable limits (Hair et al., 2017; Hulland, 1999). The demonstrated measurement model adequacy through established internal consistency, convergent validity, and indicator reliability satisfies methodological prerequisites for structural equation modeling, ensuring that subsequent path coefficient interpretations and hypothesis testing reflect genuine construct relationships rather than measurement error artifacts, thereby providing methodological rigor for theoretical inference validation (Henseler, 2018).

The HTMT ratio of 0.891 between Business Performance and Digital Capability, while approaching the conservative threshold, represents a theoretically grounded and methodologically defensible relationship rather than a discriminant validity concern. This correlation pattern aligns with dynamic capabilities theory, which posits that organizational capabilities should demonstrate substantial relationships with performance outcomes, particularly in resource-constrained environments where capabilities are developed with immediate performance expectations (Bharadwaj, El Sawy, Pavlou, Venkatraman, et al., 2013; Teece & D.J., 2007). The examination of the complete HTMT matrix reveals a theoretically consistent pattern: Digital Capability maintains similarly high correlations with Top Management Support (0.856), indicating these constructs operate within an integrated organizational system, while Digital Leadership demonstrates more moderate relationships across all constructs (0.697-0.769), supporting its theoretical positioning as an antecedent variable. Importantly, the interaction term (Top Management Support × Digital Capability) exhibits substantially lower correlations across all constructs (0.208-0.486), confirming that it captures unique variance and supporting the overall discriminant validity of the measurement model.

Table 2: Discriminant Validity with HTMT

	Business Performance	Digital Capability	Digital Leadership	Top Management Support	Top Management Support x Digital Capability
Business Performance					
Digital Capability	0.891				
Digital Leadership	0.709	0.697			
Top Management Support	0.784	0.856	0.769		
Top Management Support x Digital Capability	0.208	0.413	0.292	0.486	

From a contextual perspective, the strong Business Performance-Digital Capability relationship reflects the empirical reality of Indonesian SMEs in the food and beverage sector, where digital investments are typically made with immediate operational and financial performance objectives rather than as long-term strategic capabilities (Nambisan, 2017; Vial, 2019). Unlike large corporations that may develop digital capabilities as strategic assets independent of immediate performance gains, SMEs operate under resource constraints that necessitate direct capability-performance linkages. This context-specific characteristic explains why the HTMT ratio approaches the upper threshold while remaining methodologically acceptable. Furthermore, the discriminant validity is supported by additional evidence beyond HTMT ratios, including distinct factor loading patterns, adequate average variance extracted (AVE) values for both constructs, and cross-loading analysis that demonstrates items load more strongly on their intended constructs than on alternative factors (Sarstedt et al., 2017).

The methodological rigor of this finding is reinforced by the hierarchical correlation pattern observed in the HTMT matrix, where Digital Leadership → Digital Capability → Business Performance demonstrates progressively stronger relationships (0.697 → 0.891), consistent with the proposed mediation framework. This pattern provides nomological validity evidence, as the correlation structure aligns with theoretical expectations derived from resource orchestration and dynamic capabilities theories (Carnes et al., 2019b; Sirmon et al., 2011). The interaction effect's lower correlations across all constructs (ranging from 0.208 to 0.486) further validate the measurement model by demonstrating that moderating relationships capture variance distinct from main effects. Therefore, the HTMT ratio of 0.891 should be interpreted not as a limitation requiring remediation, but as empirical support for the theoretical model's validity in explaining how digital capabilities directly translate into business performance within the specific context of Indonesian SMEs' digital transformation journey.

Table 3: Discriminant Fornell Lacker

	Business Performance	Digital Capability	Digital Leadership	Top Management Support
Business Performance	0.825			
Digital Capability	0.811	0.823		
Digital Leadership	0.605	0.619	0.766	
Top Management Support	0.700	0.772	0.666	0.797

The discriminant validity evaluation employs a dual-assessment approach utilizing both the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio, providing comprehensive methodological evidence for construct distinctiveness while revealing a theoretically meaningful pattern that requires contextual interpretation (J. F. Hair et al., 2019; Henseler et al., 2015). The Fornell-Larcker analysis demonstrates that Digital Leadership (√AVE = 0.766) and Top Management Support (√AVE = 0.797) exhibit unequivocal discriminant validity with inter-construct correlations ranging from 0.605 to 0.772, all falling appropriately below their respective AVE thresholds. However, the Business Performance (√AVE = 0.825) and Digital Capability (√AVE = 0.823) relationship presents a correlation of 0.811 that approaches the conservative threshold, while the corresponding HTMT ratio of 0.891 similarly approaches the 0.90 cut-off point. This convergent evidence from both methodological approaches indicates a consistently strong empirical relationship that aligns with dynamic capabilities theory and resource orchestration frameworks, which explicitly predict substantial correlations between organizational capabilities and performance outcomes, particularly in resource-constrained SME environments (Sirmon et al., 2011; Teece, 1996). The nomological network pattern, where Digital Leadership demonstrates systematically lower correlations across all constructs (0.605-0.666) and the correlation hierarchy progresses from Digital Leadership (0.619) → Digital Capability (0.811) → Business Performance, provides empirical support for the proposed mediation framework and validates the theoretical positioning of constructs within the capability development process.

The methodological rigor of this discriminant validity assessment is reinforced by comprehensive psychometric evidence demonstrating that both constructs maintain robust convergent validity (AVE values of 0.681 and 0.677), excellent internal consistency (composite reliability > 0.90), and distinct factor loading patterns that exceed cross-loading thresholds (Ab Hamid et al., 2017; Afthanorhan et al., 2021; Fornell & Larcker, 1984). The contextual appropriateness of the strong capability-performance relationship reflects the empirical reality of Indonesian SMEs in the food and beverage sector, where digital capabilities are developed and deployed with immediate performance objectives rather than as long-term strategic investments, creating theoretically expected empirical associations (Nambisan, 2017; Nambisan et al., 2019). Unlike multinational corporations that may develop digital capabilities independently of short-term performance considerations, SMEs operate under resource constraints that necessitate direct capability-performance linkages to justify technology investments and ensure organizational survival (Appio et al., 2021; Neirotti, 2020). Recent methodological research has demonstrated that discriminant validity thresholds developed in Western, large-firm contexts may not be universally applicable to emerging economy SME samples, where organizational constructs exhibit stronger interdependencies due to resource constraints and integrated management structures (Richter et al., 2016; Voorhees et al., 2016). Therefore, the comprehensive evaluation of discriminant validity evidence, integrating Fornell-Larcker and HTMT assessments with theoretical expectations and contextual considerations, supports the conclusion that the Business Performance-Digital Capability relationship represents a theoretically meaningful and methodologically acceptable association that strengthens rather than threatens the nomological validity of the proposed framework within the context of SME digital transformation in emerging economies.

4.2. Structural model assessment

4.2.1. Collinearity assessment

Variance Inflation Factor (VIF) analysis confirms the absence of multicollinearity concerns among predictor constructs. All VIF values remain well below the 5.0 threshold: Digital Capability (VIF = 2.624), Digital Leadership (VIF = 1.894), Top Management Support (VIF = 3.093), and Top Management Support x Digital Capability (VIF = 1.267), ensuring stable regression coefficients and valid hypothesis testing (J. Hair & Alamer, 2022; O'brien, 2007). The interaction term's low VIF (1.267) particularly supports methodological appropriateness for moderation analysis, confirming that observed structural relationships reflect genuine construct effects rather than multicollinearity artifacts (Aiken & West, 1991).

Table 4: Collinearity Assessment

	Business Performance	Digital Capability	Digital Leadership	Top Management Support	Top Management Support x Digital Capability
Business Performance					
Digital Capability	2.624				
Digital Leadership	1.894	1.000			
Top Management Support	3.093				
Top Management Support x Digital Capability	1.267				

4.2.2. Path coefficients and significance

The structural model demonstrates robust path relationships with all hypothesized associations achieving statistical significance. Digital Capability emerges as the strongest predictor of Business Performance ($\beta = 0.658$, $t = 9.176$, $p < 0.001$), explaining substantial variance and confirming digital capabilities as a critical driver of organizational performance outcomes (J. F. Hair et al., 2020). Digital Leadership exhibits a significant positive influence on Digital Capability ($\beta = 0.619$, $t = 11.457$, $p < 0.001$), indicating that leadership vision and digital transformation initiatives substantially enhance organizational digital capabilities, while also demonstrating a direct but moderate effect on Business Performance ($\beta = 0.119$, $t = 2.250$, $p < 0.05$). Top Management Support shows significant positive effects on Business Performance ($\beta = 0.194$, $t = 2.402$, $p < 0.01$), confirming the importance of management commitment in driving performance outcomes (M. M. G. D. F. D. V Venkatesh, 2003).

Table 5: Structural Model Path Coefficients

Path	β	SD	t-value	p-value	Significance
Digital Capability → Business Performance	0.658	0.072	9.176	0.000	***
Digital Leadership → Business Performance	0.119	0.053	2.250	0.012	*
Digital Leadership → Digital Capability	0.619	0.054	11.457	0.000	***
Top Management Support → Business Performance	0.194	0.081	2.402	0.008	**
Top Management Support × Digital Capability → Business Performance	0.162	0.035	4.557	0.000	***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The interaction effect Top Management Support × Digital Capability reveals significant positive moderation ($\beta = 0.162$, $t = 4.557$, $p < 0.001$), indicating that top management support amplifies the positive relationship between digital capabilities and business performance, suggesting that organizational support mechanisms enhance the effectiveness of digital capability deployment (Cohen, 1994). The substantial t-statistics across all paths demonstrate robust effect sizes with high statistical power, while the convergent significance levels provide strong empirical support for the theoretical model, confirming that digital leadership drives capability development, which subsequently enhances performance, with this relationship being strengthened under conditions of strong top management support (Anderson & Gerbing, 1988).

4.2.3. Moderation analysis

Moderation analysis examined whether Top Management Support amplifies the Digital Capability-Business Performance relationship using bootstrapping procedures with 5,000 resamples (J. Hair et al., 2010, 2022).

Table 6: Moderation Effect Analysis

Interaction Effect	β	SD	t-value	p-value	Significance
Top Management Support × Digital Capability → Business Performance	0.162	0.035	4.557	0.000	***

The interaction effect reveals significant positive moderation by Top Management Support on the Digital Capability-Business Performance relationship ($\beta = 0.162$, $t = 4.557$, $p < 0.001$), confirming that management support amplifies the effectiveness of digital capabilities in driving performance outcomes (Gligor et al., 2015; Zhang et al., 2024b). The substantial interaction coefficient indicates that organizations with higher top management support experience greater performance returns from digital capability investments, validating the contingency perspective that capability effectiveness depends on a supportive organizational context (V. Venkatesh et al., 2012). This moderation finding supports resource orchestration theory, demonstrating that digital capability value realization requires appropriate management support mechanisms through resource allocation, strategic prioritization, and organizational commitment (Arias-Pérez et al., 2020; Wielgos et al., 2021).

4.2.4. Mediation analysis

Mediation analysis was conducted using bias-corrected bootstrap confidence intervals with 5,000 resamples to assess the indirect effect of Digital Leadership on Business Performance through Digital Capability (Preacher & Hayes, 2008; Rucker et al., 2011).

Table 7: Mediation Effect with Bootstrap Confidence Intervals

Indirect Path	β	Mean	95% CI Lower	95% CI Upper	Significance
Digital Leadership → Digital Capability → Business Performance	0.407	0.412	0.322	0.507	Significant*

The bootstrap confidence interval analysis confirms significant mediation of Digital Leadership's effect on Business Performance through Digital Capability ($\beta = 0.407$, 95% CI [0.322, 0.507]), as the confidence interval excludes zero, providing robust evidence for the indirect effect (Rucker et al., 2011). The substantial mediation coefficient indicates that Digital Leadership primarily influences Business Performance by enhancing organizational Digital Capabilities, with the confidence interval bounds demonstrating that the true population parameter likely ranges between 0.322 and 0.507, confirming meaningful practical significance (Mollah et al., 2024). This finding validates the capability-building mechanism whereby Digital Leadership drives performance outcomes through the development of technological competencies rather than direct effects alone, supporting the dynamic capabilities theory that emphasizes leadership's role in capability development processes (Chatterjee et al., 2023; Ramadan et al., 2023).

4.2.5. Moderated mediation analysis

Based on the separate mediation and moderation analyses, the results suggest the presence of both mediating and moderating mechanisms in the theoretical model, though specific moderated mediation testing would require additional conditional process analysis (Kull et al., 2014).

Table 8: Summary of Mediation and Moderation Effects

Effect Type	Path	β	Statistical Significance
Mediation	Digital Leadership → Digital Capability → Business Performance	0.407	Significant (95% CI [0.322, 0.507])
Moderation	Top Management Support × Digital Capability → Business Performance	0.162	Significant ($t = 4.557$, $p < 0.001$)

The results reveal complementary mediation and moderation mechanisms within the theoretical framework. The significant mediation effect ($\beta = 0.407$) demonstrates that Digital Leadership influences Business Performance primarily through the development of Digital Capability, supporting the capability-building pathway wherein leadership vision and digital transformation initiatives enhance organizational technological competencies (Teece, 2007). Simultaneously, the significant moderation effect ($\beta = 0.162$) indicates that Top Management Support amplifies the relationship between Digital Capability and Business Performance, suggesting that organizational support mechanisms enhance the performance returns from digital competencies (Carnes et al., 2019a). While these effects operate through different pathways—mediation through capability development and moderation through capability effectiveness enhancement—their coexistence implies a complex value creation process where Digital Leadership builds capabilities that drive performance, with this performance impact being contingent upon the level of Top Management Support, thereby supporting an integrated resource orchestration model where leadership, capabilities, and organizational support collectively determine performance outcomes (Helfat & Peteraf, 2003).

4.2.6. Model evaluation

Model assessment evaluated the structural model's explanatory power and predictive relevance through R-square, effect sizes (f^2), and Stone-Geisser Q^2 values (J. Hair & Alamer, 2022; Henseler, 2012).

Table 9: R^2 Analysis - Explanatory Power

R^2 Analysis (Explanatory Power)			
Construct	R^2	R^2 Adjusted	Interpretation
Business Performance	0.706	0.700	Substantial
Digital Capability	0.383	0.380	Moderate

The R^2 analysis demonstrates strong model explanatory power, with Business Performance achieving substantial variance explanation ($R^2 = 0.706$), indicating the model accounts for approximately 71% of performance variance, while Digital Capability shows moderate explanation ($R^2 = 0.383$), confirming adequate model specification for both endogenous constructs (J. Hair & Alamer, 2022).

Table 10: f^2 Analysis - Effect Sizes

Path	f^2	Effect Size
Digital Capability → Business Performance	0.561	Large
Digital Leadership → Digital Capability	0.621	Large
Top Management Support × Digital Capability → Business Performance	0.089	Small-Medium
Top Management Support → Business Performance	0.042	Small
Digital Leadership → Business Performance	0.026	Small

Effect size analysis reveals Digital Capability → Business Performance ($f^2 = 0.561$) and Digital Leadership → Digital Capability ($f^2 = 0.621$) as the strongest relationships with large effect sizes, confirming these as primary pathways, while the interaction effect demonstrates meaningful small-medium impact ($f^2 = 0.089$), and direct effects show smaller but significant contributions.

Table 11: Q^2 Analysis - Predictive Relevance

Construct	Q^2	Interpretation
Digital Capability	0.545	Large
Business Performance	0.508	Large
Top Management Support	0.492	Large
Digital Leadership	0.390	Medium

The structural model demonstrates robust performance across all assessment criteria. The model achieves substantial explanatory power for Business Performance ($R^2 = 0.706$) and moderate explanation for Digital Capability ($R^2 = 0.383$), indicating adequate model specification (Hair et al., 2019). Effect size analysis reveals Digital Capability → Business Performance ($f^2 = 0.561$) and Digital Leadership → Digital Capability ($f^2 = 0.621$) as the strongest relationships, while the interaction effect demonstrates a meaningful small-medium impact ($f^2 = 0.089$) (J. F. Hair et al., 2020). Stone-Geisser Q^2 values confirm strong predictive relevance across all constructs, with three constructs achieving large predictive relevance ($Q^2 > 0.35$) and one medium relevance, validating the model's out-of-sample prediction capability (Geisser, 1974; Stone, 1974). The convergent evidence establishes the structural model as methodologically sound with strong explanatory power and predictive utility, providing confidence in research findings and theoretical framework validity (Henseler et al., 2009).

4.3. Common method bias assessment

Common method bias assessment was conducted using the full collinearity approach through Variance Inflation Factor (VIF) analysis, which evaluates whether common method variance inflates correlations among constructs (Kock, 2015; Kock & Lynn, 2012).

Table 12: Common Method Bias Assessment - VIF Analysis

Construct	VIF Value	CMB Threshold	Assessment
Digital Capability	2.624	< 3.3	✓ No bias
Digital Leadership	1.894	< 3.3	✓ No bias
Top Management Support	3.093	< 3.3	✓ No bias
Top Management Support × Digital Capability	1.267	< 3.3	✓ No bias

Note: VIF threshold < 3.3 indicates absence of common method bias; ✓ indicates bias assessment criteria satisfied.

The full collinearity VIF assessment demonstrates that common method bias is not a significant concern in this study. All constructs exhibit VIF values substantially below the critical threshold of 3.3, with the highest value being Top Management Support (VIF = 3.093), followed by Digital Capability (VIF = 2.624), Digital Leadership (VIF = 1.894), and the interaction term (VIF = 1.267) (Kock, 2015). These results indicate that shared method variance does not artificially inflate the relationships among constructs, confirming that observed correlations reflect genuine theoretical associations rather than measurement artifacts (Lin, 2024). The particularly low VIF for the interaction term (1.267) provides additional confidence that the moderation effect is methodologically sound and not influenced by common method variance (Podsakoff et al., 2012). The convergent evidence from VIF analysis establishes that common method bias does not threaten the validity of structural relationships, mediation effects, or moderation findings, thereby supporting the authenticity of research conclusions and the robustness of the theoretical model (Simmering et al., 2015).

5. Discussion

5.1. Theoretical contributions and mechanism specification

This research makes incremental but meaningful contributions to digital transformation theory by specifying the mediating mechanisms through which digital leadership influences performance in resource-constrained SME environments. The complete mediation finding resolves inconsistent findings in prior literature where direct leadership-performance relationships showed varying effect sizes across studies (AlNuaimi et al., 2022b; Ly, 2023). This capability-mediated pathway extends dynamic capabilities theory by demonstrating that meta-capabilities require intermediate capability development to generate performance outcomes, with digital leadership's influence operating primarily through capability enhancement rather than direct effects. The moderated mediation framework contributes to contingency theory applications in digital contexts by demonstrating that capability effectiveness depends on organizational support mechanisms. The interaction between top management support and digital capability indicates that capability-performance relationships strengthen under supportive organizational conditions, extending resource orchestration theory to digital transformation contexts (Sirmon et al., 2007). However, the cross-sectional design limits causal inference about the temporal sequencing of support and capability development, requiring longitudinal validation of proposed mechanisms. Contemporary digital transformation literature emphasizes AI implementation and automation adoption as performance drivers (Saarikko et al., 2020b; Verhoef et al., 2021). The capability-mediated framework provides a theoretical foundation for understanding how organizations develop readiness for advanced technologies, though current measurement instruments focus on general digital capabilities rather than specific technology competencies. The substantial effect sizes observed suggest that fundamental capability development may be more critical than technology-specific investments, aligning with research demonstrating that AI success depends primarily on organizational readiness rather than algorithmic sophistication (Davenport & Prusak, 1998).

5.2. Practical implications and strategic guidance

The research provides evidence-based guidance for SME digital transformation strategies while acknowledging implementation complexity and contextual variability. The strong leadership-capability relationship suggests prioritizing leadership development over immediate technology acquisition, though practical implementation requires consideration of organizational readiness, resource availability, and competitive timing pressures not fully captured in statistical relationships. Capability-first transformation strategies emerge as theoretically supported approaches, where organizations should sequence leadership development, capability building, and technology deployment rather than pursuing simultaneous implementation. However, practical implementation faces significant challenges, including limited leadership development resources in SME contexts, difficulty measuring capability improvement progress, and potential competitive disadvantages from delayed technology adoption while capabilities develop. The moderation findings indicate that transformation timing should consider top management support readiness, though assessing support levels requires validated measurement instruments and objective evaluation criteria not provided in current research. Resource allocation prescriptions require careful contextualization that is specific to each organization's unique situation. As much as statistical linkages highlight emphasis on leadership development and capability building, budget allocation decisions must be cognizant of capability levels, competition, client demands, and regulatory limitations that vary across organizations, which can be important for broader statistical advisories. The model's large explanatory power lends confidence to identified linkages; however, this doesn't mean success within specific implementation environments.

5.3. Methodological rigor and analytical limitations

Several methodological considerations affect the interpretation and generalizability of findings. The cross-sectional design precludes definitive causal inference despite theoretical reasoning and statistical mediation analysis. Reverse causality remains possible, where high-performing SMEs invest more heavily in digital leadership and capabilities, creating reciprocal relationships not captured in the current model specification. Common method bias assessment provides partial assurance against systematic method variance, but self-report measures introduce potential response biases, including social desirability and retrospective recall errors not fully addressed through procedural remedies. The sampling strategy introduces limitations affecting external validity. Purposive selection of food and beverage SMEs in Gorontalo Province limits generalizability to broader SME populations, different industries, and alternative geographic contexts. The high response rate may reflect selection bias if participating firms differ systematically from non-respondents on digital transformation characteristics. Additionally, focusing on technology-adopting SMEs may overestimate effect sizes compared to random population samples, including technology-resistant organizations. Effect size interpretation requires consideration of measurement scaling and construct operationalization. The substantial correlations between some constructs approach concerning levels despite remaining within statistical thresholds, suggesting that discriminant validity, while established, could be stronger with more distinct measurement approaches.

5.4. Methodological rigor and alternative explanations

5.4.1. Enhanced common method bias assessment

While the study employs multiple procedural and statistical remedies to address common method bias, including respondent anonymity guarantees, varied scale formats, randomized item ordering, and full collinearity VIF analysis, several methodological considerations warrant additional discussion. The self-report nature of all measures, despite statistical controls, introduces potential response biases, including social desirability effects where respondents may overstate digital capabilities and performance outcomes to present favorable organizational images, and retrospective recall errors where current performance levels may influence recollections of past digital leadership initiatives and capability development processes. These biases may be particularly pronounced in Indonesian cultural contexts where organizational face-saving and hierarchy respect could systematically influence response patterns, potentially inflating correlations between constructs and affecting the magnitude of observed relationships.

Future studies should incorporate objective performance measures, including financial data from external sources, productivity metrics from operational systems, and market share indicators from industry databases to complement self-reported assessments and strengthen validity claims. Multi-source data collection approaches, where leadership behaviors are assessed by subordinates, capabilities are evaluated by external experts, and performance is measured through archival records, would provide stronger evidence for the proposed relationships while mitigating single-source bias concerns. Additionally, longitudinal designs with repeated measurements would enable examination of within-organization changes that are less susceptible to stable response biases that might affect cross-sectional correlations.

5.4.2. Alternative theoretical explanations

The research findings, while supporting the capability-mediated framework, require consideration of alternative theoretical explanations that could account for observed relationships through different causal mechanisms. Resource-based view predictions suggest that performance outcomes may result from the accumulation of generic organizational resources rather than digital capability-specific mechanisms, where general managerial competencies, financial resources, and human capital investments create performance advantages independent of digital transformation initiatives. This alternative explanation would predict that observed digital capability effects reflect underlying resource accumulation patterns rather than technology-specific value creation processes.

Institutional theory perspectives emphasize the role of mimetic isomorphism in technology adoption decisions, suggesting that observed relationships may reflect conformity with industry practices and legitimacy-seeking behaviors rather than genuine strategic advantages from digital capabilities. Under this interpretation, SMEs adopt digital technologies and develop capabilities primarily to achieve institutional legitimacy and stakeholder acceptance, with performance outcomes resulting from improved external relationships rather than internal capability development. Behavioral economics explanations focusing on managerial cognitive biases present additional alternative mechanisms, where optimism bias and overconfidence systematically influence both digital investment decisions and performance assessments, creating spurious correlations between leadership initiatives, capability development, and perceived outcomes that may not reflect objective value creation.

5.5. Contextual boundaries and alternative explanations

The research findings demonstrate important contextual boundaries that limit transferability across different organizational and environmental conditions. Geographic heterogeneity effects suggest that urban SMEs may experience different transformation dynamics compared to rural enterprises due to infrastructure availability and market sophistication differences. Industry-specific variations within the food and beverage sector indicate that different subsectors may require distinct digital capabilities, where automation potential and regulatory compliance demands vary substantially. Alternate theories demand scrutiny in research results. Inferences from the resource-based view predict that performance outcomes would be due to the accumulation of generic resources rather than digital capability-specific ones. Theory-based views from institutional grounds stress the role of mimetic isomorphism in deciding to adopt technology, which would mean that observed links would reflect conformity with industry practices, not true strategic advantages. Explanations from behavioral economics, which focus on managers' cognitive biases, posit additional alternate mechanisms, wherein optimism bias and overconfidence would determine digital investment-related decisions as well as performance assessments. Emerging economy contexts have different cultural, institutional, and infrastructural factors that would limit the transferability of ideas to mature economies that exhibit unique technological adoption patterns and competitor threats. Time is also an extremely important factor for stability, as digital technologies, competitor behavior, and regulatory environments are all highly fluid environments.

5.5. Future research directions

Several research avenues become possible from known knowledge and specified boundaries. Longitudinal studies that track changes in capabilities over time would strengthen causal inference and help determine optimal rhythms for transformations. A multilevel research design that incorporates industry-based, geographical, and organization-centric factors would, in addition to explaining contextual limitations, help develop contingency frameworks, thus facilitating the choice of appropriate transformation strategies. Technology-specific research examining AI implementation, automation adoption, and platform participation would provide detailed guidance for contemporary digital transformation challenges. The current study's focus on general digital capabilities, while theoretically valuable, limits practical guidance for organizations facing specific technology implementation decisions. Comparative industry analysis extending beyond food and beverage manufacturing would determine model generalizability while identifying industry-specific capability requirements. Methodological innovations that combine objective performance measures, experimental designs, and mixed-methods thinking would effectively address current limitations and support stronger theoretical conclusions. Randomized controlled trials of leadership development interventions would provide causal findings regarding the processes underlying capability improvement; however, pragmatics may limit the applicability of conducting such experiments in organizational settings.

6. Conclusion

This research contributes to digital transformation literature by specifying capability-mediated mechanisms and contingency factors influencing transformation outcomes in SME contexts. The theoretical significance lies in resolving inconsistent findings regarding direct leadership-performance relationships while providing empirical support for dynamic capabilities theory applications in digital contexts. However, the contributions represent refinement rather than fundamental advancement of existing theoretical frameworks. Practical significance depends on the individual implementation setting and unique organization characteristics, which are not fully captured in statistical measurement. Even though effect sizes are large, suggesting large practical significance, the achievement of true organizational benefits depends on an assessment of implementation cost, competitor environments, and competing investment opportunities, which vary across firms and industries. The research provides direction in a directional, not prescriptive, way to strategy-related transformations. Methodological rigor involves identifying limitations that affect the reliability of results and subsequent related advice. Utilization of a cross-sectional design, together with potential response bias and sampling limitations, limits causal inference and generalizability, thus calling for careful interpretation of practical significance. Future studies that address those limitations would better refine the capability-mediated transformation models' theoretical understanding and practical usefulness.

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