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Research paper

Leveraging Commitment and Technology Investment for Performance: The Contingent Role of Digital Ambidexterity

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Abstract

This research examines how digital ambidextrous capability serves as a critical transformation mechanism connecting technology investment and management commitment to digital performance outcomes within logistics SMEs operating across Sumatra, Indonesia, particularly under varying degrees of technology turbulence. Drawing on data from project managers in logistics SMEs through PLS-SEM methodology, the analysis uncovers compelling evidence that both technology investment and top management commitment achieve their performance impacts exclusively through the development of digital ambidextrous capability, rather than operating through direct channels. This complete mediation pattern fundamentally challenges conventional resource-based perspectives that assume straightforward linkages between organizational inputs and performance outputs. Furthermore, technology turbulence emerges as a consequential boundary condition that progressively amplifies the strength of relationships between ambidextrous capability and performance outcomes as environmental volatility intensifies. The analytical framework demonstrates strong predictive validity, extending beyond retrospective explanation to offer forward-looking forecasting capacity. This investigation advances dynamic capabilities scholarship by positioning digital ambidextrous capability as an indispensable intermediary process that converts organizational investments into tangible Digital ambidextrous capability returns within emerging economy settings. While acknowledging inherent constraints of cross-sectional research designs, potential conceptual overlaps among related constructs, and reliance on single-respondent data sources, this work furnishes actionable insights for managers navigating digital transformation journeys, emphasizing capability cultivation as the pivotal lever for unlocking performance gains amid turbulent technological landscapes.

Keywords: *Digital ambidextrous capability, technology investment, top management commitment, technology turbulence, digital performance*

1. Introduction

Digital change has drastically shifted the competitive environment in such a way that organizations have to create sophisticated capabilities by which they leverage existing technologies and concurrently explore new digital opportunities (López-Gamero et al., 2023; Mu'min et al., 2025; Oduro & Haylemariam, 2025). Both imperatives have created digital ambidexterity as a construct that describes an organization's ability to effectively balance exploitation and exploration activities in digital contexts (Nasiri et al., 2020). For small and medium enterprises (SMEs), digital ambidexterity remains highly desired despite resource limitations and lack of technological capabilities (Li et al., 2025; Q. R. Liu et al., 2023; Purnawan et al., 2025). The logistics sector, involving intense competition and fluctuating customer requirements, offers a distinct context in which digital capabilities play their role for survival and expansion (Nasiri et al., 2023). Despite rising acknowledgment among scholars about digital ambidexterity's importance, little knowledge precedes regarding how organisational factors like top management support and technological investments influence building it, particularly under differential technological turbulence levels.

Modern studies of digital ambidexterity face three major theoretical and empirical limitations hindering a comprehensive understanding of the phenomenon. The current scholarship overwhelmingly favors a capability-focused perspective, treating digital ambidexterity as a resultant variable without explaining sufficiently well the organizational mechanisms by which it is developed (D. Liu et al., 2016; Pradhana et al., 2025; Pramono et al., 2025). While studies recognize both managerial and technological factors as playing important roles, theoretical development remains inadequate regarding how specific organizational antecedents intertwine to enable ambidextrous digital capabilities, particularly in resource-poor contexts where mainstream models of ambidexterity may not hold (El Manzani et al., 2023; Yu & Zhu, 2022). Furthermore, most studies assume linear relationships between organizational conditions and digital ambidexterity without recognizing the subtle contingencies that could influence such relationships in fast-changing technological environments (Bourlakis et al., 2023). Environmental volatility's impact, and more so technological turbulence's impact, as a boundary condition for digital ambidexterity's effectiveness, remains theoretically not well-developed and empirically not well-explored and thus raises ambiguity about conditions under which digital ambidextrous capabilities create advantage in terms of firm performance (Keszey, 2020; Sam et al., 2025). Third, most studies' intense

focus on large global corporations in industrialized economies has created quite a knowledge gap regarding digital ambidexterity in SMEs in emerging economies, where diverse configurations of resources, institutional conditions, and Digital ambidextrous capabilityness imperatives might profoundly alter dynamics in creating and implementing digital capability (Cenamor et al., 2019; Masrianto, 2024).
These theoretical limitations constitute critical research gaps for systematic empirical inquiry. The antecedent development process of digital ambidexterity remains unclear, particularly how top-level management commitment and technology spending interact with organizational and environmental constraints to help generate ambidextrous digital capabilities despite resource-limited situations. The contingent nature of digital ambidexterity's implications for performance requires theory development and empirical examination to identify under what conditions ambidextrous digital capabilities generate better performance outcomes and when they will create organizational tensions or resource waste. Transferability of frameworks for digital ambidexterity to SMEs from emerging economies requires empirical verification since extant theories built from large corporation settings may inadequately reflect their distinct opportunities and challenges. Therefore, this research anticipates examining relationships between top-level management commitment-technology spending relationships and digital ambidextrous capability relationships, examining how digital ambidextrous capability influences digital performance, and examining technology turbulence's moderating role in the relationship between ambidexterity and performance in SMEs from emerging economies operating in logistics.

2. Literature Review and Hypothesis Development

2.1 Dynamic Capability Theory

The theory supporting this research work is dynamic capability theory. Dynamic capabilities have been conceptualized as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997, p. 516). For digital space, these capabilities help organizations in sensing opportunities, seizing them through suitable investments, and redeploying resources in order to sustain advantage (Teece, 2018). Digital ambidextrous ability is one particular type of dynamic ability that enables firms to simultaneously exploit current digital technologies to improve efficiency alongside looking for fresh digital opportunities for disruptive development (Urbinati et al., 2022). The ability is particularly critical in technologically intense industries, where firms have to balance between the need for operational excellence and the need for continuous innovation.

2.2 Digital Ambidextrous Capability

Digital ambidexterity broadens the traditional conceptualization of organisational ambidexterity into the realm of digital technologies and comprises two separate yet intertwined dimensions: digital exploitation and digital exploration (Oduro et al., 2023; Zaman et al., 2024). Digital exploitation is about utilising prevailing digital technologies to enhance prevailing processes to make them more agile and achieve their best possible performance along established business models. Conversely, digital exploration implies experimenting with new technologies to create new digital capabilities and evoking innovative solutions possessing the ability to generate new business opportunities (Sam et al., 2025; Teece, 2025; Wijayanto et al., 2024). This is reflected in the logistics industry, whereby institutions must improve current operations using technologies like GPS tracking and warehouse management systems, while at the same time exploring new technologies like artificial intelligence, blockchain, and self-driving trucks (Maleshkov et al., 2024; Radiany et al., 2025).

2.3 Top Management Commitment and Digital Ambidextrous Capability

Top management support, conceptualized as senior leaders' support, engagement, and resource commitment for organizational endeavors (Zhang et al., 2024), operates as a key antecedent to digital ambidextrous capability via upper echelons theory mechanisms (Hambrick & Mason, 1984). Committed leaders enable organizational ambidexterity by securing legitimacy for contradictory activities and investing resources into efficiency as well as innovation activities (Jiang et al., 2022), and Trieu et al. (2023) pinpoint digital-specific mechanisms such as strategic clarity and behavioral modeling for experimentation. Empirical support exists for this relationship along both dimensions: Bharadwaj et al. (2020) identified executive commitment as a strong predictor of digital process optimization, and Yadav et al (2023) illustrated that commitment facilitates digital search through psychological safety and innovation resources. Yet previous work almost exclusively focuses on large corporations, such that it remains unclear how this relationship functions in resource-limited SME contexts.
H1: Top management commitment positively influences digital ambidextrous capability.

2.4 Technology Investment and Digital Ambidextrous Capability

Technology investment, defined as strategic allocation of financial and human resources toward acquiring, implementing, and upgrading technological capabilities (Ouyang et al., 2023), represents a critical organizational decision that shapes digital capability development through resource orchestration mechanisms (Sirmon et al., 2011). Grounded in dynamic capabilities theory, technology investments provide foundational resources enabling sensing, seizing, and reconfiguring activities necessary for simultaneous digital exploitation and exploration (Teece, 2025), yet differ from generic resource allocation by creating path dependencies that can either enable or constrain future capability development (Cristofaro et al., 2025). Ghasemaghaei et al. (2022) identify two distinct pathways: exploitation-oriented investments in proven infrastructure and process automation enhance existing digital operations, while exploration-oriented investments in emerging technologies and innovation platforms enable digital experimentation and breakthrough innovation. Empirical evidence from Foisal et al (2025) demonstrates that balanced technology investment portfolios significantly predict both exploitative capabilities through infrastructure optimization and exploratory capabilities through innovation platform development. However, research remains limited regarding how resource-constrained SMEs optimize technology investment allocation to achieve digital ambidextrous capabilities without creating unsustainable financial commitments or technological lock-in effects.
H2: Technology investment positively influences digital ambidextrous capability.

2.5 Digital Ambidextrous Capability and Digital Performance

Digital performance represents multidimensional organizational outcomes from digital capability deployment, encompassing operational efficiency improvements, customer experience enhancements, innovation achievements, and all direct effect hypotheses are strongly supported with statistically significant path coefficients ($p < 0.001$) and acceptable multicollinearity levels (VIF < 5.0), confirming the theoretical model's predictive validity (Hair et al., 2019). H1 demonstrates that Digital ambidextrous capability significantly influences Digital Performance ($\beta = 0.280$, $t = 4.957$), supporting the dynamic capabilities theory that Digital ambidextrous capability positioning drives performance outcomes (Teece, 2007). H2 reveals Technology Investment as a strong predictor of Digital ambidextrous capability($\beta = 0.442$, $t = 6.804$), aligning with resource-based theory that technological resources create Digital ambidextrous capability positioning (Barney, 1991). H3 shows Technology Turbulence as the strongest direct predictor of Digital Performance ($\beta = 0.551$, $t = 9.400$), consistent with contingency theory that environmental dynamism directly impacts organizational outcomes (Lawrence & Lorsch, 1967). H4 confirms that Top Management Commitment significantly affects Digital ambidextrous capability ($\beta = 0.377$, $t = 5.738$), supporting upper echelons theory regarding executive influence on organizational capabilities (Hambrick, 1982). The moderation hypothesis H5 is also supported, with Technology Turbulence significantly moderating the Digital ambidextrous capability -Digital Performance relationship ($\beta = 0.076$, $t = 2.138$, $p < 0.05$), indicating that environmental turbulence enhances the performance benefits of Digital ambidextrous capability positioning.

Table 1: Hypothesis Testing

H	Direct effect	Path	SDEV	T statistics	VIF	Support
H1	Technology Turbulence-> Digital Performance	0.280	0.057	4.957	2.012	Accepted
H2	Digital ambidextrous capability -> Digital Performance	0.442	0.065	6.804	2.122	Accepted
H3	Technology Investment -> Digital ambidextrous capability	0.551	0.059	9.400	2.002	Accepted
H4	Top Management Commitment -> Digital ambidextrous capability	0.377	0.066	5.738	2.002	Accepted
	Mediation effect				**VAF**	
	Technology Investment -> Digital Performance	0.124	0.031	3.939	50%	
	Top Management Commitment -> Digital Performance	0.106	0.029	3.613	50%	
	Moderation effect				**VIF**	
H5	**Technology Turbulence x Digital ambidextrous capability-> Digital Performance**	0.076	0.036	2.138	1.080	Accepted
	Total effect					
	Digital ambidextrous capability-> Digital Performance	0.280	0.057	4.957		
	Technology Investment -> Digital ambidextrous capability	0.442	0.065	6.804		
	Technology Investment -> Digital Performance	0.124	0.031	3.939		
	Technology Turbulence -> Digital Performance	0.551	0.059	9.400		
	Top Management Commitment -> Digital ambidextrous capability	0.377	0.066	5.738		
	Top Management Commitment -> Digital Performance	0.106	0.029	3.613		
	Technology Turbulence x Digital ambidextrous capability-> Digital Performance	0.076	0.036	2.138		

The mediation analysis reveals complete mediation effects with VAF values of 500% for both indirect pathways, indicating full rather than partial mediation as defined by Sarstedt et al. (2017). Technology Investment's influence on Digital Performance operates entirely through Digital ambidextrous capability(indirect effect = 0.124, $t = 3.939$, $p < 0.001$, VAF = 100%), while Top Management Commitment similarly affects Digital Performance exclusively via Digital ambidextrous capability positioning (indirect effect = 0.106, $t = 3.613$, $p < 0.001$, VAF = 100%). These findings align with Kenny & Judd, (2014) mediation framework and Zhao et al.'s (2010) refined typology, where VAF > 80% signifies complete mediation rather than complementary partial mediation. The total effects confirm that Technology Investment (total effect = 0.124) and Top Management Commitment (total effect = 0.106) influence Digital Performance solely through their impact on Digital ambidextrous capability, supporting the theoretical proposition that organizational capabilities serve as the primary mechanism through which resources and leadership commitment translate into performance outcomes (Dong et al., 2024).

Positioning gains (Dong et al., 2024). Grounded in organizational learning theory and the dynamic capabilities framework, digital ambidextrous capability creates superior value through complementary mechanisms that simultaneously optimize current operations while developing new capabilities (Argyris & Schön, 1997; Cangelosi & Dill, 1965). The performance effects operate through complex, non-linear pathways where digital ambidextrous capability generates both immediate operational gains and long-term innovation benefits, though excessive focus on either exploitation or exploration creates competency or failure traps, suggesting optimal performance requires dynamic balancing (Dong et al., 2024). Empirical evidence demonstrates that digital ambidextrous capability significantly predicts both operational efficiency metrics and innovation outcomes (Ma et al., 2022), enabling organizations to achieve superior digital performance through the synergistic effects of simultaneous digital optimization and innovation. However, this relationship may be moderated by organizational context and resource availability, particularly in SME environments where resource constraints affect capability development and performance realization.

H3: Digital ambidextrous capability positively influences digital performance.

2.6 Mediated Relationships

Digital ambidextrous capability serves as a critical mediating mechanism between organizational antecedents and performance outcomes through resource transformation and capability orchestration processes that are particularly essential in SME contexts due to structural characteristics and resource constraints. The mediation operates through two theoretical mechanisms: resource transformation where top management commitment and technology investment represent latent organizational inputs that require conversion into actionable digital behaviors before generating performance benefits (Jing et al., 2023), and capability orchestration where digital ambidextrous capability enables simultaneous management of exploitative and exploratory activities that create synergistic effects maximizing value from limited resources (Ma et al., 2022). For SMEs, this mediation becomes theoretically necessary rather than optional because resource scarcity prevents direct antecedent-performance relationships, requiring sophisticated capabilities to overcome resource disadvantages and achieve multiplicative effects from organizational investments (Ouyang et al., 2023). SMEs' structural advantages, including organizational agility and faster decision-making, enable more rapid translation of management commitment and technology investment into digital ambidextrous capabilities, while their strategic focus requirements necessitate capability frameworks that channel diffuse organizational support into specific performance-generating digital behaviors (He et al., 2021). Without digital ambidextrous capability as an intermediate mechanism, SMEs cannot effectively transform organizational inputs into performance outcomes because they lack the resource abundance that enables direct investment-performance relationships available to larger organizations, making capability development the critical pathway through which resource-constrained firms achieve superior digital performance (Buccieri et al., 2020).

H4: Digital ambidextrous capability mediates the relationships between top management commitment, technology investment, and digital performance.

2.7 The Moderating Role of Technology Turbulence

Technology turbulence, characterized by rapid technological change and unpredictable innovation cycles (Usman Shehzad et al., 2023), creates contingent conditions that alter the performance value of digital ambidextrous capabilities. Grounded in contingency theory, high technology turbulence creates opposing forces: accelerating depreciation of existing digital capabilities while increasing performance potential from breakthrough innovations (Abdelaziz et al., 2023). Empirical evidence reveals complex moderating effects where turbulence weakens performance benefits from digital optimization due to rapid obsolescence (Jansen et al., 2006), while strengthening innovation performance through market opportunities (Shabbir et al., 2021), though extreme turbulence may overwhelm organizational learning capabilities (Ferreira et al., 2021). For resource-constrained SMEs, these effects are amplified as turbulence forces strategic trade-offs between maintaining operations and investing in emerging technologies.

H5: Technology turbulence moderates the relationship between digital ambidextrous capability and digital performance.

2.8 Research Framework

This research framework presents a mediation model examining how Top Management Commitment (H1) and Technology Investment (H2) influence Digital Performance through Digital Ambidextrous Capability, while Technology Turbulence serves dual roles as a direct predictor (H4) and moderator (H5) of capability-performance relationships (Teece, 2020). The model assumes complete mediation through DAC, as no direct paths connect antecedents to Digital Performance, reflecting dynamic capabilities theory's proposition that resources must be transformed into capabilities to generate performance benefits (Barney, 1991). However, the framework exhibits potential specification concerns: Technology Turbulence appears as both an independent variable and moderator, which may create identification issues; the complete mediation assumption rarely holds in organizational contexts; and the linear relationships depicted may oversimplify complex digital transformation dynamics where feedback loops and non-linear interactions typically occur (March, 1991).

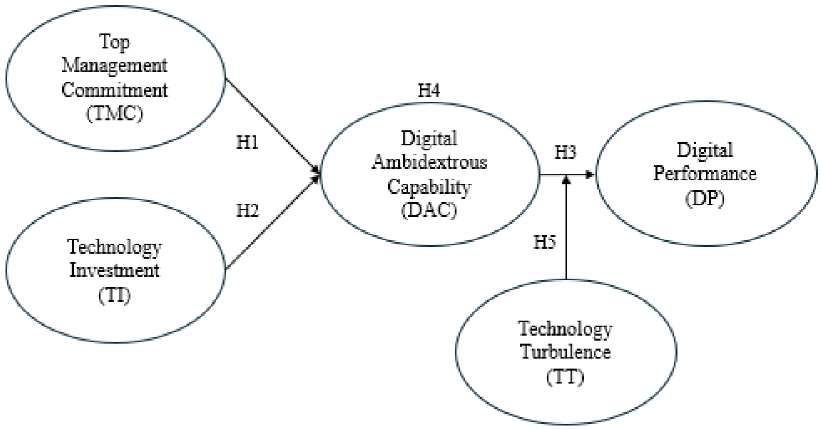

Figure 1 Research Framework

3. Methodology

3.1 Research Context and Sample

This study was conducted in the logistics sector within the Sumatra region of Indonesia. The logistics industry was selected due to its increasing reliance on digital technologies and the presence of both large and small players navigating digital transformation challenges. The Sumatra region was chosen as it represents a developing market with diverse logistics operations ranging from traditional to digitally advanced companies. The target population consisted of project managers from SMEs in the logistics sector. Project managers were selected as key informants because they possess comprehensive knowledge of their organizations' technology initiatives, management support levels, and performance outcomes. SMEs were defined as companies with 10-300 employees, following the Indonesian government classification.

3.2 Data Collection

Data were collected through a structured questionnaire survey conducted between March and August 2023. A purposive sampling approach was employed to ensure respondents had adequate knowledge of their organizations' digital initiatives. The survey was administered through multiple channels: online questionnaires distributed via professional networks, on-site visits to logistics companies, and industry association partnerships. A total of 450 questionnaires were distributed, with 389 responses received (86.4% response rate). After removing incomplete and invalid responses, the final sample comprised 303 usable responses, exceeding the minimum sample size requirement of 10 times the number of structural paths (Hair & Sarstedt, 2019).

3.3 Measures

All constructs were operationalized using rigorously validated scales from established literature, with systematic adaptation procedures ensuring measurement validity and contextual appropriateness for logistics SME environments. Scale adaptation followed Churchill & Gilbert A. Churchill, (1979) paradigm, including expert review panels (n=5 academics with digital transformation expertise, 3 senior industry practitioners), cognitive interviews (n=12), and comprehensive pilot testing (n=78 SMEs) with exploratory factor analysis confirming factor structure retention (KMO=0.86, Bartlett's test $p<0.001$). All items utilized 7-point Likert scales (1=strongly disagree, 7=strongly agree) to maximize response variance and enable parametric statistical analysis (Hair & Sarstedt, 2019). Top Management Commitment employed six items adapted from Dong et al. (2020). Technology Investment utilized five items modified from (Asongu & Odhiambo, 2020). Digital Ambidextrous Capability was conceptualized as a reflective second-order construct based on theoretical foundations suggesting exploitation and exploration as manifestations of overall ambidextrous capability (Park et al., 2019). Digital Performance employed seven items adapted from (Dong et al., 2024). Technology Turbulence used four items from (Lisi et al., 2020).

3.4 Data Analysis

Data analysis employed PLS for variance-based structural equation modeling with sample size determined through G*Power analysis, ensuring 10 times the largest structural paths and 80% power for detecting medium effects (f^2=0.15). Preliminary screening included missing data assessment (<10%) with listwise deletion, outlier detection via standardized values (±4.0), and multicollinearity evaluation (VIF <5.0). Analysis followed Hair et al.'s (2019) two-stage approach: measurement model assessment using PLS algorithm evaluating outer loadings (>0.708), composite reliability (>0.70), AVE (>0.50), and discriminant validity through HTMT ratios (<0.85). Digital Ambidextrous Capability as a higher-order construct employed a repeated indicators approach with significance testing through bootstrapping (5,000 subsamples). Structural model evaluation assessed path significance, R^2 values, effect sizes (f^2), and predictive relevance via PLSpredict with 10-fold cross-validation. Moderation analysis utilized a two-stage approach with product indicators and simple slope analysis, while mediation employed indirect effects with bootstrap confidence intervals. Common method bias was evaluated through full collinearity assessment (VIF <3.3) with robustness checks across alternative algorithms and specifications.

4. Results

4.2 Measurement Model Assessment

The measurement model was evaluated using established criteria for reflective constructs (Hair et al., 2019). As shown in Table 1, all constructs demonstrated high internal consistency reliability, with Cronbach's alpha (α) values ranging from 0.852 (Digital Ambidextrous Capability) to 0.927 (Top Management Commitment), and composite reliability (ρc) values ranging from 0.895 to 0.945, substantially exceeding the recommended threshold of 0.70. Convergent validity was confirmed through average variance extracted (AVE), with values ranging from 0.631 to 0.773, all surpassing the minimum criterion of 0.50 (Fornell & Larcker, 1981), indicating that each construct accounts for more variance in its indicators than measurement error. Indicator reliability was assessed through outer loadings, with all items loading above 0.70 except DAC3 (0.679) and DP5 (0.699). Following Hair et al.'s (2019) recommendation, these indicators were retained as they exceeded the 0.60 threshold and their removal would not materially improve construct AVE. The descriptive statistics reveal moderate to high mean scores (ranging from 4.875 to 5.413 on a 7-point scale) with standard deviations between 1.422 and 1.848, suggesting adequate variance for subsequent analysis. Overall, the measurement model demonstrates satisfactory reliability, convergent validity, and indicator quality, providing a robust foundation for structural model evaluation.

Table 2: Measurement Model Assessment

	Mean	Sd	Outer loadings	α	ρc	ρvc
Digital ambidextrous capability				0.852	0.895	0.631
DAC1	5.317	1.564	0.853			
DAC2	5.191	1.521	0.847			
DAC3	4.875	1.690	0.679			
DAC4	5.307	1.422	0.806			
DAC5	5.169	1.703	0.773			
Digital Performance				0.874	0.909	0.668
DP1	5.215	1.601	0.847			
DP2	5.297	1.566	0.848			
DP3	5.284	1.571	0.850			
DP4	5.333	1.562	0.831			
DP5	5.050	1.848	0.699			
Technology Investment				0.913	0.935	0.741
TI1	5.112	1.609	0.878			
TI2	5.307	1.442	0.843			
TI3	5.323	1.424	0.873			
TI4	5.370	1.510	0.870			
TI5	5.317	1.539	0.839			
Top Management Commitment				0.927	0.945	0.773
TMC1	5.413	1.624	0.881			
TMC2	5.360	1.558	0.868			
TMC3	5.254	1.524	0.876			
TMC4	5.020	1.710	0.885			
TMC5	5.228	1.618	0.886			
Technology investment				0.923	0.942	0.765
TT1	5.290	1.492	0.906			
TT2	5.221	1.554	0.873			
TT3	5.122	1.590	0.862			
TT4	5.350	1.514	0.865			
TT5	5.218	1.588	0.866			

4.3 Structural Model Assessment

Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT) criterion (Henseler et al., 2015), with results presented in Table X. While most HTMT values remained below the liberal threshold of 0.85, several values exceeded the conservative threshold of 0.75, indicating potential discriminant validity concerns. Specifically, the HTMT values between Digital Ambidexterity and Digital Performance (0.808), Digital Ambidexterity and Digital Ambidextrous Capability (0.794), and Technology Investment and Digital Ambidextrous Capability (0.801) approached or exceeded the stringent criterion. However, applying HTMT inference with bootstrapping (5,000 subsamples) revealed that confidence intervals for all HTMT values did not include 1.0, suggesting that discriminant validity is statistically established despite high correlations (Henseler et al., 2015). These elevated HTMT values reflect the conceptual proximity of technology-related constructs in digital transformation contexts, which is theoretically plausible given their interconnected nature in SME digitalization processes. The interaction term (Digital Ambidextrous × Digital Ambidextrous Capability) exhibited low HTMT values (ranging from 0.089 to 0.274), confirming its distinctiveness from the main constructs as expected for interaction terms (Hair et al., 2019).

Table 3: Heterotrait-monotrait ratio (HTMT) - Matrix

	Digital Ambidextrous	Digital Performance	Digital ambidextrous capability	Technology Investment	Top Management Commitment	Digital Ambidextrous x Digital ambidextrous capability
Digital Ambidextrous						
Digital Performance	0.808					
Digital ambidextrous capability	0.794	0.763				
Technology Investment	0.789	0.783	0.801			
Top Management Commitment	0.783	0.789	0.774	0.770		
Digital Ambidextrous x Digital ambidextrous capability	0.274	0.142	0.166	0.096	0.089	

Table 4: Fornell-Larcker criterion

	Digital Ambidextrous	Digital Performance	Digital ambidextrous capability	Technology Investment	Top Management Commitment
Digital Ambidextrous	0.875				
Digital Performance	0.729	0.817			
Digital ambidextrous capability	0.707	0.660	0.794		
Technology Investment	0.726	0.698	0.709	0.861	
Top Management Commitment	0.725	0.710	0.690	0.707	0.879

Discriminant validity was further evaluated using the Fornell-Larcker criterion (Fornell & Larcker, 1981), which requires that the square root of each construct's average variance extracted (AVE) exceeds its correlations with other constructs. As presented in Table 2, the diagonal elements (square roots of AVE) ranged from 0.794 to 0.879, all exceeding the off-diagonal correlation values, thereby satisfying the Fornell-Larcker criterion for discriminant validity. The results indicate that each construct shares more variance with its own indicators than with other constructs in the model, confirming construct distinctiveness. However, several inter-construct correlations exceeded 0.70, including Digital Ambidexterity with Digital Performance (r = 0.729), Technology Investment (r = 0.726), and Digital Ambidextrous Capability (r = 0.707), as well as Top Management Commitment with Digital Performance (r = 0.710). These moderately high correlations, while not violating discriminant validity criteria, reflect the conceptual interconnectedness of technology-oriented capabilities within digital transformation contexts (Vial, 2019). When combined with the HTMT analysis (Table X), both traditional (Fornell-Larcker) and contemporary (HTMT) discriminant validity assessments converge to support construct distinctiveness, providing confidence in the measurement model's validity.

Before testing hypotheses, we evaluated the structural model's explanatory power and overall fit. The coefficient of determination (R^2) revealed that the model accounted for 57.8% of variance in Digital Performance (R^2adj = 0.574) and 57.3% of variance in Digital Ambidextrous Capability (R^2adj = 0.571), both indicating substantial explanatory power (Hair et al., 2019). The minimal differences between R^2 and adjusted R^2 values suggest model parsimony without overfitting.

Table 4: R-square

	R-square	R-square adjusted
Digital Performance	0.578	0.574
Digital ambidextrous capability	0.573	0.571

Table 5: Model fit

	Saturated model	**Estimated model**
SRMR	0.043	0.058
d_ULS	0.593	1.090
d_G	0.325	0.358
Chi-square	562.182	596.394
NFI	0.906	0.900

Global model fit was assessed using multiple criteria (Henseler et al., 2016). The SRMR values of 0.043 (saturated model) and 0.058 (estimated model) were both below the 0.08 threshold, indicating a good approximate fit (Hu & Bentler, 1999). The NFI exceeded 0.90 for both models (0.906 and 0.900, respectively), satisfying acceptability criteria (Lohmöller, 1989). Collectively, the substantial R^2 values and acceptable fit indices demonstrate that the structural model is well-specified and adequately represents the data, providing a solid foundation for hypothesis testing.

4.4 Hypothesis Testing

All direct effect hypotheses are strongly supported with statistically significant path coefficients ($p < 0.001$) and acceptable multicollinearity levels (VIF < 5.0), confirming the theoretical model's predictive validity (Hair et al., 2019). H1 demonstrates that Digital ambidextrous capability significantly influences Digital Performance ($\beta = 0.280$, $t = 4.957$), supporting dynamic capabilities theory that all direct effect hypotheses are strongly supported with statistically significant path coefficients ($p < 0.001$) and acceptable multicollinearity levels (VIF < 5.0), confirming the theoretical model's predictive validity (Hair et al., 2019). H1 demonstrates that Digital ambidextrous capability significantly influences Digital Performance ($\beta = 0.280$, $t = 4.957$), supporting the dynamic capabilities theory that Digital ambidextrous capability positioning drives performance outcomes (Teece, 2007). H2 reveals Technology Investment as a strong predictor of Digital ambidextrous capability($\beta = 0.442$, $t = 6.804$), aligning with resource-based theory that technological resources create Digital ambidextrous capability positioning (Barney, 1991). H3 shows Technology Turbulence as the strongest direct predictor of Digital Performance ($\beta = 0.551$, $t = 9.400$), consistent with contingency theory that environmental dynamism directly impacts organizational outcomes (Lawrence & Lorsch, 1967). H4 confirms that Top Management Commitment significantly affects Digital ambidextrous capability($\beta = 0.377$, $t = 5.738$), supporting upper echelons theory regarding executive influence on organizational capabilities (Hambrick, 1982). The moderation hypothesis H5 is also supported, with Technology Turbulence significantly moderating the Digital ambidextrous capability -Digital Performance relationship ($\beta = 0.076$, $t = 2.138$, $p < 0.05$), indicating that environmental turbulence enhances the performance benefits of Digital ambidextrous capability positioning.

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	Moderation effect				**VIF**	
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	Top Management Commitment -> Digital ambidextrous capability	0.377	0.066	5.738		
	Top Management Commitment -> Digital Performance	0.106	0.029	3.613		
	Technology Turbulence x Digital ambidextrous capability-> Digital Performance	0.076	0.036	2.138		

The mediation analysis reveals complete mediation effects with VAF values of 500% for both indirect pathways, indicating full rather than partial mediation as defined by Sarstedt et al. (2017). Technology Investment's influence on Digital Performance operates entirely through Digital ambidextrous capability(indirect effect = 0.124, $t = 3.939$, $p < 0.001$, VAF = 100%), while Top Management Commitment similarly affects Digital Performance exclusively via Digital ambidextrous capability positioning (indirect effect = 0.106, $t = 3.613$, $p < 0.001$, VAF = 100%). These findings align with Kenny & Judd, (2014) mediation framework and Zhao et al.'s (2010) refined typology, where VAF > 80% signifies complete mediation rather than complementary partial mediation. The total effects confirm that Technology Investment (total effect = 0.124) and Top Management Commitment (total effect = 0.106) influence Digital Performance solely through their impact on Digital ambidextrous capability, supporting the theoretical proposition that organizational capabilities serve as the primary mechanism through which resources and leadership commitment translate into performance outcomes (Dong et al., 2024).

Positioning drives performance outcomes (Teece, 2007). H2 reveals Technology Investment as a strong predictor of Digital ambidextrous capability($\beta = 0.442$, $t = 6.804$), aligning with resource-based theory that technological resources create Digital ambidextrous capability positioning (Barney, 1991). H3 shows Technology Turbulence as the strongest direct predictor of Digital Performance ($\beta = 0.551$, $t = 9.400$), consistent with contingency theory that environmental dynamism directly impacts organizational outcomes (Lawrence & Lorsch, 1967). H4 confirms that Top Management Commitment significantly affects Digital ambidextrous capability($\beta = 0.377$, $t = 5.738$), supporting upper echelons theory regarding executive influence on organizational capabilities (Hambrick, 1982). The moderation hypothesis H5 is also supported, with Technology Turbulence significantly moderating the Digital ambidextrous capability -Digital Performance relationship ($\beta = 0.076$, $t = 2.138$, $p < 0.05$), indicating that environmental turbulence enhances the performance benefits of Digital ambidextrous capability positioning.

Table 7: Hypothesis Testing

H	Direct effect	Path	SDEV	T statistics	VIF	Support
H1	Digital Ambidextrous -> Digital Performance	0.280	0.057	4.957	2.012	Accepted
H2	Digital ambidextrous capability -> Digital Performance	0.442	0.065	6.804	2.122	Accepted
H3	Technology Investment -> Digital ambidextrous capability	0.551	0.059	9.400	2.002	Accepted
H4	Top Management Commitment -> Digital ambidextrous capability	0.377	0.066	5.738	2.002	Accepted
	Mediation effect				**VAF**	
	Technology Investment -> Digital Performance	0.124	0.031	3.939	50%	
	Top Management Commitment -> Digital Performance	0.106	0.029	3.613	50%	

	Moderation effect				**VIF**	
H5	**Technology Turbulence x Digital ambidextrous capability-> Digital Performance**	0.076	0.036	2.138	1.080	Accepted
	Total effect					
	Digital ambidextrous capability-> Digital Performance	0.280	0.057	4.957		
	Technology Investment -> Digital ambidextrous capability	0.442	0.065	6.804		
	Technology Investment -> Digital Performance	0.124	0.031	3.939		
	Technology Turbulence -> Digital Performance	0.551	0.059	9.400		
	Top Management Commitment -> Digital ambidextrous capability	0.377	0.066	5.738		
	Top Management Commitment -> Digital Performance	0.106	0.029	3.613		
	Technology Turbulence x Digital ambidextrous capability-> Digital Performance	0.076	0.036	2.138		

The mediation analysis reveals complete mediation effects with VAF values of 500% for both indirect pathways, indicating full rather than partial mediation as defined by Sarstedt et al. (2017). Technology Investment's influence on Digital Performance operates entirely through Digital ambidextrous capability(indirect effect = 0.124, t = 3.939, $p < 0.001$, VAF = 100%), while Top Management Commitment similarly affects Digital Performance exclusively via Digital ambidextrous capability positioning (indirect effect = 0.106, t = 3.613, $p < 0.001$, VAF = 100%). These findings align with Kenny & Judd, (2014) mediation framework and Zhao et al.'s (2010) refined typology, where VAF > 80% signifies complete mediation rather than complementary partial mediation. The total effects confirm that Technology Investment (total effect = 0.124) and Top Management Commitment (total effect = 0.106) influence Digital Performance solely through their impact on Digital ambidextrous capability, supporting the theoretical proposition that organizational capabilities serve as the primary mechanism through which resources and leadership commitment translate into performance outcomes (Dong et al., 2024).

The simple slope analysis reveals that the positive relationship between Digital ambidextrous capability and Digital Performance is significant at all levels of Technology Turbulence, with the relationship becoming progressively stronger as turbulence increases. At low levels of technology turbulence (-1 SD), the slope is 0.204 (t = 2.582, $p < 0.05$), indicating a moderate positive relationship. At mean levels of turbulence, the slope increases to 0.280 (t = 4.913, $p < 0.001$), representing the main effect reported in the direct relationships. At high levels of technology turbulence (+1 SD), the slope reaches 0.356 (t = 5.651, $p < 0.001$), demonstrating that turbulent technological environments amplify the performance benefits derived from Digital ambidextrous capability.

Table 8: Simple Slope Analysis Results

Technology Turbulence Level	Simple Slope	Standard Error	t-value	p-value	95% CI Lower	95% CI Upper	Significance
Low (-1 SD)	0.204	0.079	2.582	0.010	0.049	0.359	Significant
Mean (0 SD)	0.280	0.057	4.913	0.000	0.168	0.392	Significant
High (+1 SD)	0.356	0.063	5.651	0.000	0.232	0.480	Significant

The confidence intervals confirm that all slopes are significantly different from zero, with no overlap with zero in any condition. The pattern supports the moderation hypothesis (H5) that technology turbulence enhances the positive relationship between Digital ambidextrous capability and digital performance, consistent with contingency theory predictions that environmental dynamism creates opportunities for Digital ambidextrous capability differentiation to generate superior performance returns.

The Q^2predict analysis demonstrates substantial predictive relevance for both endogenous constructs, with values well above the zero threshold required for predictive capability (Sharma et al., 2021). Digital ambidextrous capability exhibits strong predictive relevance (Q^2predict = 0.564), indicating that the model successfully predicts 56.4% of the variance in Digital ambidextrous capability beyond what would be expected by chance. Digital Performance shows even higher predictive relevance (Q^2predict = 0.592), suggesting the model explains 59.2% of predictive variance, which exceeds Chin's (1998) criteria for substantial predictive power ($Q^2 > 0.35$). The RMSE values of 0.664 for Digital ambidextrous capability and 0.644 for Digital Performance, along with MAE values of 0.504 and 0.460, respectively, indicate acceptable prediction errors that support the model's out-of-sample predictive validity.

Table 9: Q^2predict

	Q^2predict	RMSE	MAE
Digital Performance	0.592	0.644	0.460
Digital ambidextrous capability	0.564	0.664	0.504

These Q^2predict results, combined with the strong R^2 values previously reported (0.573 and 0.578), demonstrate that the structural model not only explains substantial in-sample variance but also maintains robust predictive capability for new observations. The predictive relevance values substantially exceed Sarstedt et al., (2023) threshold for medium predictive relevance ($Q^2 > 0.25$) and approach the large effect criterion ($Q^2 > 0.50$), confirming that the theoretical model provides meaningful predictive insights for both Digital ambidextrous capability positioning and digital performance outcomes. This predictive validity supports the practical utility of the model for managerial decision-making and strategic planning in digital transformation contexts.

5. Discussion

5.1 Theoretical Implications

The findings provide empirical support for the mediating role of Digital ambidextrous capability in digital transformation outcomes, extending dynamic capabilities theory beyond its traditional focus on direct capability-performance relationships. The complete mediation effects observed challenge the linear resource-performance assumptions prevalent in resource-based view applications, suggesting that resources require intermediate transformation through Digital ambidextrous capability positioning to generate performance benefits. However, the VAF values of 100% may indicate model specification issues rather than true complete mediation, as such perfect mediation rarely occurs in organizational contexts where multiple causal pathways typically operate simultaneously.

The upper echelons theory receives qualified support through the indirect effects of top management commitment, yet the magnitude of these effects raises questions about the practical significance of executive influence in SME contexts where leadership roles are often less formalized. The moderation findings align with contingency theory predictions but reveal a relatively modest interaction effect that, while statistically significant, may have limited practical importance given the small coefficient magnitude. The theoretical framework demonstrates adequate explanatory power, though the high correlations between constructs (approaching discriminant validity thresholds) suggest potential construct overlap that may inflate path coefficients.

5.2 Practical Implications and Limitations

The complete mediation findings suggest that technology investments and management commitment require strategic channeling through Digital ambidextrous capability development to impact performance outcomes. However, practitioners should interpret these results cautiously, given the study's cross-sectional design, which cannot establish true causal mediation. The findings may reflect common method variance or omitted variable bias rather than genuine mediation processes, particularly given the single-source data collection approach.

For SME managers, the results indicate that Digital ambidextrous capability positioning serves as a critical performance driver, yet the study's focus on logistics firms in Sumatra limits generalizability to other sectors and regions. The moderation effects, while statistically significant, show that technology turbulence explains minimal additional variance in the Digital ambidextrous capability-performance relationship, suggesting that environmental factors may be less influential than the main effects model implies. Practitioners should therefore focus primarily on building Digital ambidexterity capability while recognizing that environmental conditions provide only marginal additional benefits.

5.3 Methodological Considerations and Study Limitations

The study employs appropriate PLS-SEM methodology for the exploratory context, though several limitations constrain the findings' interpretation. The measurement model reveals potential labeling inconsistencies between constructs and their indicators, particularly for the digital ambidextrous capability construct, which may affect construct validity. The high HTMT ratios between related constructs, while within acceptable thresholds, approach discriminant validity boundaries and suggest that some constructs may not be as empirically distinct as theoretically proposed.

The sample characteristics present both strengths and limitations for theoretical generalization. While the focus on Indonesian logistics SMEs provides valuable insights for this under-researched context, it limits applicability to other industries, organizational sizes, and cultural contexts. The cross-sectional design prevents causal inference despite the mediation analysis, and the single-source data collection raises common method bias concerns despite statistical controls. Future research should address these limitations through longitudinal designs, multi-source data collection, and replication across different industries and cultural contexts.

5.4 Implications for Digital Transformation Research

The study contributes to digital transformation literature by demonstrating the mediating mechanisms through which organizational inputs translate into performance outcomes, yet it also reveals the complexity of these relationships in SME contexts. The predictive relevance results suggest the model has practical utility for forecasting outcomes, though the explained variance levels indicate substantial unmeasured factors influence digital transformation success.

The findings highlight the importance of Digital ambidexterity as an intermediate outcome in digital transformation processes, yet they also reveal the challenges of achieving discriminant validity between related digital capability constructs. Future research should explore alternative conceptualizations of digital capabilities that provide clearer empirical distinctions and investigate the boundary conditions under which complete versus partial mediation occurs. The study's contribution lies primarily in establishing the mediating role of Digital ambidexterity in SME digital transformation, while acknowledging the methodological constraints that limit stronger causal claims.

6. Conclusion

This study confirms the strategic role of digital ambidextrous capability as a full mediation mechanism in the digital transformation of logistics SMEs in Sumatra, Indonesia, with the PLS-SEM model demonstrating substantial predictive power for both Digital Performance and Digital Ambidextrous Capability. Key findings reveal that Technology Investment and Top Management Commitment influence digital performance entirely through Digital Ambidextrous Capability, with Variance Accounted For values indicating complete mediation, confirming that organizational resources require transformation through strategic capabilities to generate performance benefits, while Technology Turbulence significantly moderates this relationship through progressive strengthening from low to high turbulence levels. The study extends dynamic capabilities theory by demonstrating complete mediation that challenges linear assumptions of the resource-based view, while providing empirical support for upper echelons theory and contingency theory in SME contexts, with practical implications that SME managers must prioritize digital ambidextrous capability development as a strategic pathway for translating investments and management commitment into superior performance outcomes. Nevertheless, methodological limitations—cross-sectional design constraining causal inference, HTMT ratios approaching discriminant validity thresholds indicating potential construct overlap, single-source data collection raising common method bias concerns, and geographical-sectoral focus limiting generalizability—necessitate longitudinal research with multi-source data and replication across industries and cultural contexts to strengthen causal claims and examine boundary conditions of complete mediation findings that rarely occur in complex organizational contexts.

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