QUBAHAN ACADEMIC JOURNAL
VOL. 6, NO. 2, June 2026
https://doi.org/10.48161/qaj.v6n2a2512

Capability Configurations and Marketing Performance in MSMEs: The Conditional Role of Digital Capability

Sudarwati [1*], Septiana Novita Dewi [2], Aris Tri Haryanto [2], Muhammad Kholid Arif Rozaq [3], Agus Dwianto [4], Mukdad Ibrahim [5] and Gehad Mohammed Sultan Saif [6]

[1] Department of Management, Faculty of Economics, Universitas Islam Batik Surakarta, Surakarta 57145, Indonesia;
[2] Faculty of Economics and Business, Universitas Dharma AUB Surakarta, Surakarta 57126, Indonesia;
[3] Department of Art Management, Faculty of Fine Arts and Design, Institute Seni Indonesia Yogyakarta, Yogyakarta 55188, Indonesia;
[4] Department of Accounting, Faculty of Economics and Business, Universitas Sebelas Maret, Surakarta 57126, Indonesia;
[5] Department of Accounting and Finance, Business School, American University of Ras Al Khaimah, Ras Al Khaimah 72603, United Arab Emirates;
[6] Department of Accounting, MBA Finance, Bachelor of Science (Hons) in Accounting, University of Aden, Aden 89100, Yemen.

* **Corresponding author:** sudarwati@uibs.ac.id

ABSTRACT: This study examines how multiple strategic capabilities jointly influence marketing performance in Micro, Small, and Medium Enterprises (MSMEs) operating in emerging markets, with particular attention to the contingent role of digital capability. While prior studies have predominantly focused on isolated capabilities, limited research has systematically examined how diverse capabilities interact and whether digital capability consistently strengthens these relationships. Drawing on the integration of the resource-based view (RBV) and the Dynamic Capability's View (DCV), this study develops and tests a comprehensive model that incorporates innovation, market, technological, and relational capabilities. A sequential explanatory mixed-methods design was employed, combining qualitative insights from 18 MSME interviews with quantitative data from 700 MSMEs, analyzed using PLS-SEM. The findings reveal that not all capabilities contribute equally to marketing performance. Product exploration capability ($\beta = 0.205$), digital capability ($\beta = 0.165$), and future adaptation capability ($\beta = 0.155$) demonstrate significant positive effects, whereas product innovation capability shows a negative and non-significant relationship. Moreover, the moderating role of digital capability is limited and selective, with only one significant interaction effect (FAC × DC), which unexpectedly weakens the relationship with performance. These results suggest that marketing performance in MSMEs is shaped by a selective configuration of capabilities rather than uniformly positive effects across all capability types. Furthermore, digital capability functions as a conditional mechanism rather than a universally enabling factor. This study contributes to the literature by providing an integrated, empirically grounded framework that refines understanding of capability orchestration in emerging-market contexts. It also offers practical insights for MSMEs and policymakers by emphasizing the importance of aligning digital initiatives with specific organizational capabilities rather than assuming universal performance gains.

Keywords: Strategic Capabilities, Digital Capability, Marketing Performance, MSMEs, Emerging Markets.

I. INTRODUCTION

The process of digital transformation has been accelerated, irreversibly changing the world of commerce. This is particularly evident in emerging markets, where Micro, Small, and Medium-Sized Enterprises (MSMEs) are establishing new paradigms for competitiveness and economic resilience [1]. Shifting consumer expectations, intense competition, and digital technology mean that firms must continuously adapt their strategies and capabilities to maintain performance. Marketing performance, typically measured by sales growth, market share, profitability, and customer expansion, is a key indicator of a firm's competitiveness and sustainability within an industry [2, 3]. Previous studies have suggested that marketing performance is driven not by a single capability but by a combination of organizational capabilities that enable firms to sense market changes, respond to them, and create superior value propositions [3]. In terms of innovation, capabilities such as product development and exploration facilitate the generation of new outputs for firms [4, 5]. Market-oriented capabilities, such as market intelligence, support strategic decision-making by enabling businesses to gain better insights into customer needs and prevailing competitive dynamics [2, 6, 7]. Furthermore, technological and relational capabilities, such as access to technology and robust collaboration networks, promote operational efficiency, knowledge transfer, and innovation capabilities [8-11]. Similarly, strategic positioning and adaptive capabilities, such as consumer-preference orientation, niche-market mastery, and the ability to adapt to future changes, help firms to align their offerings with market demand while anticipating environmental changes [12-16].

Although there is a wealth of literature on this topic, prior work has been conducted in isolation. Existing studies tend to explore organizational capabilities individually or in limited combinations, and even fewer consider that firm performance results from the interaction and alignment of multiple capabilities rather than from their independent effects. This is particularly relevant in MSME contexts, where resource scarcity requires firms to deploy their capabilities more selectively and strategically. MSMEs must not only possess valuable capabilities, but also match these to changing market and technological conditions [17-19]. To overcome this limitation, the current study primarily draws on the Resource-Based View (RBV) and the dynamic capabilities view as its theoretical framework. The RBV suggests that firms gain a competitive advantage through valuable, rare, and imperfectly imitable resources and capabilities. However, resources alone may not suffice in rapidly changing environments. The Dynamic Capability's View (DCV) goes further, arguing that sustainable competitive advantage is determined not only by a firm's resource base but also by its ability to integrate, reconfigure, and renew that base in response to environmental change [20, 21]. In this context, organizational capabilities are not static resources, but rather dynamic processes that can be leveraged across the firm to address threats arising from market volatility and technological discontinuities.

The latest research considers digital capability to be a second-order dynamic capability that facilitates the use of digital technologies for opportunity sensing and data-driven decision-making [22]. Digital capabilities refer to a firm's ability to integrate digital platforms, analytics, and digital skills into strategic and operational processes. Previous studies have generally argued that better digital capabilities are a universal factor that supports all types of firm performance. This is evidenced by empirical studies in which researchers have found that the same types of capabilities have similar impacts across different contexts [23, 25]. This implies that digital capability is not inherently favorable, but rather a mechanism involving contingent relationships around performance. In light of this, this research paper aims to address two significant gaps in the literature. First, it develops a comprehensive framework that tests the direct influence of nine strategic capabilities across innovation, market, and technological dimensions, and considers relational, positioning, and adaptive perspectives on marketing performance. Secondly, it explores the moderating effect of digital capability on the strength and direction of these relationships. Thus, the study moves beyond fragmented, capability-based perspectives to provide a more nuanced view of how MSMEs can utilize strategic and digital capabilities in emerging markets. The study's methodological foundation is a sequential explanatory mixed-methods framework that integrates qualitative inputs from interviews with MSME practitioners and quantitative analyses of data from 700 survey firms using Partial Least Squares Structural Equation Modeling (PLS-SEM) [26, 27]. This gives us a good idea of how these things are connected and how well they work, which helps us to understand them better [26, 28, 29].

This study makes three main contributions. First, it provides a theoretical framework that integrates the RBV and the DCV, explaining how multiple strategic capabilities affect marketing performance and how digital capability moderates these relationships. Empirically, it draws on data from MSMEs in an emerging-market setting, where capability constraints and the imperative for digital transformation are most pronounced. In theory, it helps marketing performance in a multi-level setting, as it's one of the first studies to examine how mixed digital capabilities influence marketing performance in practice. It does this by showing which capabilities are more closely linked to marketing performance and by underscoring that only certain organizational capabilities should be changed digitally, rather than treating it as a magic solution.

The rest of this paper is structured as follows. Section II presents the hypothesis development and relevant literature review. Section III explains the research methodology. Section IV presents the empirical results and discussion. Finally, Section V concludes the study by outlining the implications, limitations, and future research.

II. LITERATURE REVIEW

1. THEORETICAL FOUNDATION

This study combines the RBV with the DCV to build a theoretical basis for understanding how firms attain competitive advantage in dynamic, technology-oriented environments characterized by digital media. RBV contends that resources and capabilities are the basis for firm performance, particularly in innovation, market orientation, and organizational processes [3, 30]. Firm capabilities in product innovation, market intelligence, and relational resources help firms deliver customer value, cope with competitive forces, and achieve long-term sustainable advantage [6, 7]. But RBV, while useful for elucidating the sources of competitive advantage, is inherently static. It fails to capture how firms reconfigure their resource portfolios in response to strategic change amid techno-economic discontinuities.

In the face of this limitation, DCV advances RBV by focusing on a firm's ability to adapt (i.e., integrate, reconfigure, and renew its resource base) in response to a changing environment [20, 21]. Dynamic capabilities help firms sense opportunities, seize them through strategic actions, and transform their operations to sustain a competitive advantage [31-33]. In this perspective, digital capability is theorized as a higher-order dynamic capability that underpins the higher relative effectiveness of existing organizational capabilities by enabling data-driven decision-making and technological assimilation to respond to market demands [22, 33-37]. This combination of RBV and DCV offers a strong theoretical foundation since it recognizes that marketing performance derives not from the capabilities per se, but their effective coordination and dynamic reconfiguration especially in the context of resource-scarce MSMEs facing uncertain environments [13, 19, 24].

2. STRATEGIC CAPABILITIES AND MARKETING PERFORMANCE

In the context of MSMEs, companies employ multiple strategic capabilities to create value, respond to changing market conditions, manage sources of sustainable competitive advantage, and ultimately achieve the desired marketing outcomes. According to the existing literature, marketing performance is defined as a multidimensional outcome of a combination of innovation, market, technology, and relational capabilities [2, 3]. This outcome includes positive outcomes, sales growth, market share, profitability, and the number of customers. Businesses that can innovate, either by offering new products or entering new markets, hold the competitive edge in a fast-changing market. Conversely, market-related capabilities such as market intelligence and literacy enable firms to interpret customer needs and anticipate competitors' actions, allowing them to make strategic decisions and leverage their presence in the marketplace to improve competitiveness [6, 7, 38].

While innovation and market orientation are crucial for identifying strategic goals, transforming these plans into tangible performance requires technological and relational capabilities. Technology enhances operational capacity, speeds up innovation, and enables entry into new markets through digital tools and systems [8, 11]. Partnerships and collaborative networks help manage key resources, including knowledge pools, resource sharing, and joint innovation. SMEs leverage these capabilities to realize their potential [9, 10]. Additionally, strategic positioning that aligns with customer preferences and manages niche markets allows firms to develop tailored value propositions and secure a sustainable market position [12, 14]. Organizational future-orientedness boosts resilience by anticipating environmental shifts and fostering adaptive responses, supporting long-term sustainability [13, 16]. Successful marketing depends on collective efforts; interdependent capabilities must work harmoniously to navigate market complexities.

3. DIGITAL CAPABILITY AS A MODERATING MECHANISM

Digital capabilities are an absolute necessity for most organizations today, especially MSMEs operating in the fast-evolving technology-driven market. These capabilities capture the extent to which firms can adopt, assimilate, and exploit digital assets through data analytics, digital platforms, and e-commerce systems in strategic and operational decision-making processes [22, 34, 36]. From a dynamic capability standpoint, however, digital capability has a much wider scope than merely technical infrastructure. It comprises an informal dataset that enhances a firm's capacity to swiftly and accurately detect, interpret, and respond to market opportunities [33, 37]. For example, digital capabilities can improve corporate performance by promoting data-driven strategic decisions and enabling greater customer engagement and organizational agility [39, 40].

Currently, it is widely recognized that digital capabilities directly affect performance and shape how other organizational capabilities translate into successful outcomes. These capabilities facilitate faster data processing, allow more adaptable resource reconfiguration, and enable broader market access. Consequently, they significantly affect the value generated by market and relational innovation capabilities [19, 24]. Nevertheless, research also indicates that the effects of digital capabilities can depend on context, suggesting their impact isn't uniformly positive across scenarios [41, 42]. In this context, digital capabilities can either augment or replace traditional capabilities, depending on how well they align with the company's strategy and resource setup. This perspective aligns with the idea that digital capabilities serve as a moderator, influencing the strength and direction of the relationship between strategic capabilities and marketing performance.

4. *CAPABILITY ORCHESTRATION: CONCEPTUAL CLARIFICATION*

The term "capability orchestration" describes how companies organize, combine, and utilize their resources and skills to improve outcomes. From a dynamic capability's perspective, competitive advantage comes not only from having valuable resources but, more importantly, from a firm's ability to coordinate and deploy those resources in response to environmental needs [20, 21]. As market environments become more complex and dynamic, firms must continuously reinvent their bundles of innovation, marketing, technology, and relationships to support entrepreneurial decision-making [31, 32, 43]. The conditions faced by MSMEs further emphasize this orchestration, requiring more focused, streamlined, and flexible integration of capabilities to achieve performance outcomes under resource constraints [13, 44].

This study uses the concept of capability orchestration to explain how strategic capabilities work together within a system, rather than in isolation, to affect marketing performance. This viewpoint challenges the idea of uniform or independent effects, instead emphasizing that interactivity (i.e., alignment and prioritization) and flexibility (i.e., reconfiguration in response to environmental change over time) are crucial for capability effectiveness. Building on the resource orchestration perspective, a small number of early studies emphasize that the successful relationship between digital transformation and organizational agility is jointly mediated by technological and structural capabilities [34, 45]. Similarly, digital capability serves as a higher-order enabling mechanism that creates coordination, improves information processing, and accelerates the recombination of resources across organizational functions [24, 33].

In an emerging market context, where uncertainty and institutional constraints are more prevalent, digital capability is the backbone of firms' sensing, seizing, and transforming capabilities. Empirically, the flexibility gained from digital capability has been found to facilitate dynamic capabilities; thus, it is a key condition of organizational resilience, making it valuable for business model innovation in volatile environments that threaten the viability of existing businesses [46, 47]. Therefore, digital capability cannot be considered merely an operational fact; rather, it is a moderating and enabling mechanism critical to the effective implementation of internal strategic capabilities. This orchestration process enables MSMEs to transform their diverse range of capabilities, such as product innovation, market intelligence, and collaborative networks, into enhanced marketing performance and sustained competitive advantage [48].

5. *HYPOTHESIS DEVELOPMENT*

In the context of integrating RBV and DCV, this study conceptualizes marketing performance in MSMEs as a consequence of the consistent deployment of resources to develop dynamic capabilities that are aligned with strategy rather than with resources alone. Firms with strategic capabilities such as innovation, market sensing, access to technology, relational networking, and the ability to adapt can discover opportunities, add value for customers, and remain competitive in a turbulent environment [3, 20]. Past research consistently indicates that capabilities such as innovation, market orientation, and the adoption of new technologies increase firm performance through value creation and responsiveness to market dynamics [2, 4, 6, 34]. From the perspective of MSMEs, these capabilities are limited by resource availability and will only be effective when used together to understand how they can influence customer alignment, differentiation, and agility [19, 35]. This study posits a number of direct and moderating relationships that explain how strategic capabilities, both individually and in combination, influence marketing performance. It also explains how digital capability strengthens these relationships within an integrated capability orchestration framework.

5.1 Strategic Capabilities and Marketing Performance

Strategic capability is the competence of a firm that helps MSMEs to create value, adapt to change and survive with limited resources. From the RBV and DCV perspectives, marketing performance is considered to be a systematic development–deployment–renewal process rather than the result of isolated resources, since firms continuously develop, deploy, and renew capabilities in order to fulfill customer needs in the face of competitive pressure or technological change [3, 20, 21]. Due to their limited financial, technological, and managerial resources, this capability development can be particularly important for MSMEs, encouraging numerous smaller firms to focus on these capabilities in order to achieve sales growth, increase the number of customers or clients served, and enhance their market competitiveness and profitability [2, 6, 19].

In the case of MSME competitiveness, innovation-related capabilities represent a fundamental building block. Product innovation capability enables firms to deliver unique, profitable products that align with market trends, enhancing differentiation and customer value [5, 30]. This is complemented by product exploration capability, which enables firms to search for new products, test ideas, and adapt offerings before competitors react to shifts in market trends [13, 30]. Such capabilities are particularly important in developing markets, where firms must routinely renew their offerings to meet changing consumer preferences and dynamic competitive conditions.

Expectations of marketing performance are strengthened by market-related capabilities, particularly a firm's ability to understand, interpret, and respond positively to market signals. Market intelligence, therefore, equips MSMEs to gather and utilize information about competitors, customers, and market dynamics, thereby aiding better strategic decision-making [7, 38]. Results suggest that market literacy enables firms to understand consumer behavior, identify ongoing or impending market movements, and adapt their strategies, thus avoiding strategic misalignment [2, 6]. Similarly, a focus on consumer preferences guides the development of products and services that meet customer expectations. Niche market mastery enables MSMEs to specialize in specific market segments, strengthening their position within their respective markets [12, 15].

Technological capabilities significantly influence MSME marketing performance [49]. So do relational capabilities. Adaptive capabilities also have a significant influence. Access to technology enables firms to utilize relevant technologies for production, service delivery, and customer reach [8, 11, 15]. Strong collaboration networks enable MSMEs to leverage external knowledge, resources, and market channels through partnerships and networks [9, 10]. The ability to adapt in the future enables firms to scan the environment and actively prepare for environmental shifts. It also gives them the flexibility to react more elastically to market and technological uncertainty, which is vital for resilience and long-term competitiveness [19, 35]. Recent studies on MSMEs suggest that strategic flexibility, technology adoption, and adaptive value creation are becoming increasingly important for firm performance in highly digitized economies and fragile market conditions [17, 18, 50]. Accordingly, this study proposes that each strategic capability contributes to marketing performance through a distinct yet complementary value-creation mechanism. Therefore, the following hypotheses are proposed:

- H1: Product Innovation Capability positively influences Marketing Performance.
- H2: Market Intelligence positively influences Marketing Performance.
- H3: Product Exploration Capability positively influences Marketing Performance.
- H4: Technology Accessibility positively influences Marketing Performance.
- H5: Collaboration Network Strength positively influences Marketing Performance.
- H6: Market Literacy positively influences Marketing Performance.
- H7: Consumer Preference Orientation positively influences Marketing Performance.
- H8: Niche Market Mastery positively influences Marketing Performance.
- H9: Future Adaptation Capability positively influences Marketing Performance.

5.2 The Contingent Role of Digital Capability in Capability–Performance Relationships

Digital capabilities are an increasingly important driver. They help shape how companies select and utilize their existing strategic capabilities. This helps them to deliver good performance outcomes. According to the dynamic capability's perspective, digital capability goes beyond technological infrastructure. It corresponds to higher-order organizational competencies. These detect, integrate, and reconfigure internal and externally acquired created relative resource bases. They do so in a sustainable, individual-impact manner in evolving environments [21, 31, 32]. SMEs have resource limitations and therefore have limited leverage over strategic adaptability. In this sense, digital capabilities become essential for utilizing existing capabilities more efficiently, improving coordination, and enabling faster decision-making [24, 33]. The impact of this strategy on companies' digital capabilities varies across performance dimensions.

The final dimension is better coordination across capabilities, or 'capability orchestration'. This involves aligning and orchestrating interactions across capability categories to improve overall marketing performance. Digital technologies are a key driver of the continuous evolution of the product innovation process, enabling companies to digitally and rapidly explore products. This is in sharp contrast to the traditional approach of physically testing experiments. Immediate analytics insights offer a broader understanding of market trends and customer behaviors [22, 34]. Similarly, digital capabilities can enrich collaborative networks by facilitating inter-organizational communication and knowledge transfer. Such capabilities can also help firms identify consumer preferences and quickly adapt to niche market trends [24]. Several empirical studies reveal that the impact of organizational capabilities on firm performance is arguably magnified by digital transformation processes [22, 36, 37], contributing to fundamental enterprise outcomes such as agility, responsiveness, and innovation.

In the context of disruption and digitalization, we argue that digital capabilities serve as a dynamic capability, moderating the speed at which strategic competencies translate into results. This challenges companies to dynamically reconfigure their resources, mitigate structural inertia, and respond quickly to emerging opportunities and threats [34, 49]. Indeed, recent findings demonstrate that the distinctive digital capabilities of a company long considered a defining characteristic of knowledge-based firms are more effective in converting innovation, market knowledge, and adaptive capabilities into improved performance for SMEs with high levels of digital maturity than for those with low levels [19, 25, 51, 52]. Therefore, digital capabilities act as a moderator between strategic capabilities and marketing performance. Therefore, this study proposes that the positive effect of strategic capabilities on marketing performance depends on digital capabilities. The moderation hypothesis is as follows:

- H10: Digital capabilities strengthen the relationship between product innovation capabilities and marketing performance.
- H11: Digital capabilities strengthen the relationship between market intelligence and marketing performance.
- H12: Digital capabilities strengthen the relationship between product exploration capabilities and marketing performance.
- H13: Digital capabilities strengthen the relationship between technology accessibility and marketing performance.
- H14: Digital capabilities strengthen the relationship between the strength of collaborative networks and marketing performance.
- H15: Digital capabilities strengthen the relationship between market literacy and marketing performance.
- H16: Digital capabilities strengthen the relationship between consumer preference orientation and marketing performance.
- H17: Digital capabilities strengthen the relationship between niche market mastery and marketing performance.
- H18: Digital capabilities strengthen the relationship between future adaptability and marketing performance.

6. CONCEPTUAL FRAMEWORK

We created a conceptual framework see Figure 1 that combines the RBV and the DCV to explain how SMEs coordinate their strategic marketing capabilities to achieve better results. While the RBV highlights the importance of unique, valuable resources for a firm's success, the DCV underscores the need to adapt and reconfigure these resources in a constantly changing business environment [32, 53]. Building on previous research in innovation and marketing capabilities, nine key strategic capabilities have been identified as critical to marketing performance [5, 6, 30]. These include product innovation, market intelligence, product exploration, access to technology, collaborative network strength, market literacy, consumer-preference focus, niche-market mastery, and future adaptability. Capabilities-based orchestration ensures these functions operate as an integrated system [21, 33]. Digital capabilities support these relationships by enabling agility and resource reconfiguration [22, 34, 54].

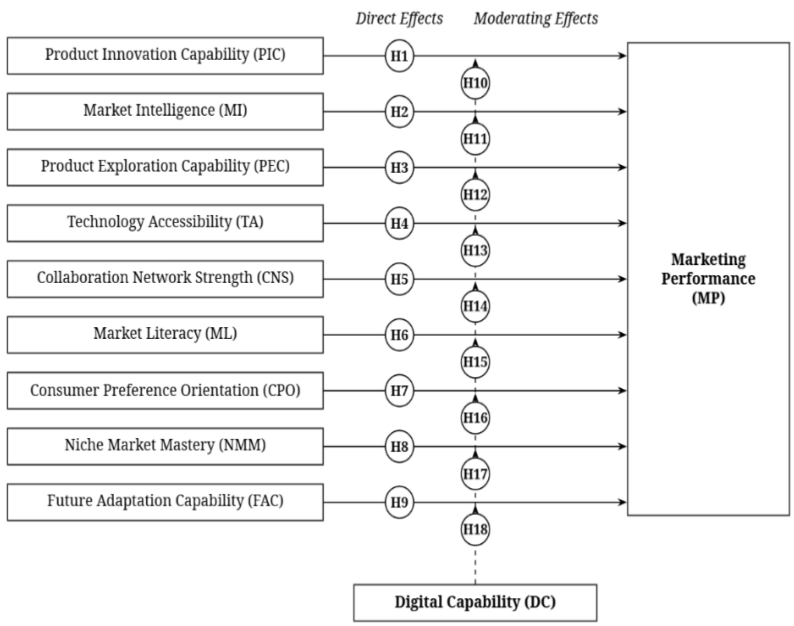

FIGURE 1. Conceptual framework.

III. RESEARCH METHODOLOGY

1. RESEARCH DESIGN AND MIXED-METHODS JUSTIFICATION

Our study employs a mixed-methods research design, combining qualitative and quantitative perspectives, to examine the relationships among strategic capabilities, digital capabilities, and marketing performance in MSMEs. An integrative approach enriches the contextual depth and empirical generalizability of the findings, contributing to methodological pragmatism and increasing external validity and reliability [26, 55]. The qualitative phase is examined through in-depth interviews, which enable further refinement and contextualization of key constructs. The quantitative phase is executed with a structured questionnaire to test hypotheses and analyze causal relationships. The approach taken here is akin to established mixed-methods frameworks, with an exploratory first phase [29, 54], followed by a confirmatory second phase [26]. Several recent studies have emphasized that combining survey-based analysis with qualitative methods strengthens explanations [56, 57]. Such an approach may minimize the methodological bias of the emerging body of research, particularly when developing the concept of digital transformation in relation to complex phenomena. Furthermore, innovation studies have highlighted that, given the significant variability in performance among SMEs, the approach must consider both statistical relationships and contextual dynamics [56]. Digital transformation involves converting corporate resources into digital transactions, thereby enhancing organizational capabilities through technology. This transformation offers a multilateral perspective that encourages the implementation of a multi-method approach [51]. Moreover, qualitative interviews revealed that interviewers exhibit both adaptive and disruptive innovative behavior [58].

2. QUALITATIVE AND QUANTITATIVE RESEARCH PHASES

This study uses a sequential mixed-methods approach (qualitative first, then quantitative). This design aims to make data materialization more context-aware and exploratory. The next step is an empirical analysis of MSMEs' strategic and digital capabilities. In Phase 2, you will conduct a series of in-depth, semi-structured interviews with a small number of SME practitioners. These interviews are designed to further explore capability configurations, validate the measures, and explain decisions that are difficult to capture quantitatively. This improves construct validity and ensures that the context reflects real-world corporate activity. The quantitative phase will consist of distributing a survey instrument based on the qualitative findings to a larger sample for statistical hypothesis testing and analyzing the strength of associations between variables. The combination of qualitative exploration and quantitative confirmation is a well-established method for capturing complex organizational phenomena and reducing single-method bias [26, 55, 57]. Recent research shows that qualitative interviews complement survey-based analysis, enhancing explanatory power [56, 58]. This method is effective in identifying behavioral patterns and generalizability across firms of different sizes when researching SMEs.

3. *SAMPLING STRATEGY AND DATA COLLECTION*

This study used a purposive sampling method. Indicating that the respondents selected for this study were chosen based on their expertise and experience in managing MSMEs in the food industry. Participants were limited to individuals currently in strategic decision-making roles as owners or managers of long-established businesses, to ensure the validity and relevance of their responses. Study Design and Target Population: Data were collected using a standardized questionnaire between October 2013 and March 2014 in five major geographic regions of Indonesia: Jakarta, West Java, Central Java, Special Region of Yogyakarta (DIY), and East Java. These areas were deliberately selected to enhance the representativeness and generalizability of our data. The restructuring of the data collection setup led us to gather richer data over a longer observation period (between early 2024 and January 2026), thereby facilitating a better-informed view of SME dynamics and improving data quality. Of the 1,000 distributed questionnaires, only 700 were screened (completeness checks) and validated for data quality (validity and consistency of responses with sampling method). This led to the exclusion of 300 responses for providing incomplete or contradictory answers. In the questionnaire we administered, perceptions of strategic, digital, and marketing capabilities were measured using a five-point Likert scale. Lastly, the qualitative phase of the study involved a series of follow-up interviews with a subset of informants to localize and contextualize the findings [27, 55, 59]. This hybrid data collection methodology allows the user to discern broader correlations while simultaneously providing detailed contextual information. These traits align with the aforementioned SME oeuvre [26, 55, 58]. Demographic details of respondents are reported in Table 1. For a more detailed description of the data collection process, please see Appendix 1.

Table 1. Demographic profile of respondents.

Variable	Category	Percentage (%)
Gender	Male / Female	55.1 / 44.9
Age	20–29 / 30–39 / 40–49 / ≥50	20.7 / 33.6 / 33.6 / 12.1
Business Location	Jakarta / West Java / Central Java / Yogyakarta / East Java	20.0 / 23.6 / 18.6 / 17.9 / 20.0
Business Experience	<2 years / 2–5 years / >5 years	11.4 / 30.0 / 58.6
Sector Type	Food / Beverage	58.6 / 41.4

Source: Author’s computation (2026)

4. *MEASUREMENT AND OPERATIONALIZATION*

We therefore endorse the adoption of an academic note-based measuring system for strategic capability, digital capability, and any type of marketing performance measures. This is for the following monetary and personal causes. With this system, we can establish common construct validity (convergent validity), reliability (CR), and theoretical consistency. Items for each construct were directly adopted from validated scales and operationalized as multiple items. These scales range from 'strongly disagree' to 'strongly agree' on a five-point Likert scale. Based on construct operationalizations established in strategic management and marketing literature [30, 32, 60], these performance indicators were developed. According to the RBV, a firm's capabilities are its competence base and quantifiable dimensional characteristics. To achieve content validity and contextual appropriateness for SMEs, constructs of innovation and marketing capabilities were adopted from previous empirical studies [5, 6, 61]. We also define 'digital capability' at a higher level as a corporate readiness to adopt, assimilate, and transform information and communication technology for decision-making and operational agility. This definition is consistent with the most recent literature on digital transformation [34, 37, 54]. It is widely accepted that outcome-driven indicators are one of the main factors determining whether a corporation will succeed. Indicators used to measure marketing performance include sales and customer growth in current markets, as well as relative growth compared to other firms [2, 30]. The reliability of these measurement scales is improved through validation and repeated measures. Adding more dimensions provides a more holistic view of how capabilities are orchestrated. When working as a team, multiple strategic competencies can deliver superior corporate performance compared to simply possessing individual strategic assets. This idea has been detailed [21, 33]. The measurement instruments for the variables are presented in Table 2, and the detailed operational indicators are presented in Appendix 2.

Table 2. Measurement instrument and operationalization

Construct	Definition	Key Dimensions	Type	Source(s)
Product Innovation Capability (PIC)	Ability to develop new and unique products	Innovation, design, product variation	Independent	[4, 5, 61]
Market Intelligence (MI)	Ability to gather and analyze market information	Competitor monitoring, feedback analysis	Independent	[5, 7]
Product Exploration Capability (PEC)	Capability to explore new product opportunities	Experimentation, opportunity identification	Independent	[5, 13, 30]
Technology Accessibility (TA)	Ability to access and utilize technology	Technology access, operational efficiency	Independent	[8, 10, 11]
Collaboration Network Strength (CNS)	Strength of strategic partnerships	Cooperation, long-term partnerships	Independent	[9, 10, 11]
Market Literacy (ML)	Understanding of market trends and behavior	Customer insight, demand analysis	Independent	[2, 6]
Consumer Preference Orientation (CPO)	Alignment with customer preferences	Loyalty, attraction, adaptation	Independent	[12, 14, 15]
Niche Market Mastery (NMM)	Ability to dominate specific market segments	Specialization, segmentation strategy	Independent	[12, 14, 15]
Future Adaptation Capability (FAC)	Ability to anticipate and adapt to change	Flexibility, foresight	Independent	[13, 16, 34]
Digital Capability (DC)	Ability to leverage digital technologies	Digital adoption, data usage, agility	Moderating	[22, 33, 34, 37]
Marketing Performance (MP)	Firm performance outcomes in the market	Growth, profitability, competitiveness	Dependent	[2, 3]

Source: Author's computation (2026)

5. DATA ANALYSIS TECHNIQUE

This study employed PLS-SEM in SmartPLS to examine the relationships among various constructs. PLS-SEM is especially useful for analyzing complex models involving multiple constructs, latent variables, and moderating effects. It is also effective in handling non-normally distributed data and larger sample sizes [62, 63]. In exploratory research, particularly in emerging fields such as SMEs and digital transformation, where theory is still developing, PLS-SEM is widely considered the preferred method for gaining deeper insights [27, 64]. The analysis proceeded in two stages. First, the measurement model was tested for validity and reliability. Next, the structural model was assessed using path coefficients, t-values, significance levels, and predictive relevance. Construct reliability was checked with composite reliability and Cronbach's alpha, while the AVE and HTMT criteria were used to evaluate convergent and discriminant validity [65]. This approach allows for comprehensive statistical analysis of the proposed relationships and offers valuable understanding of how strategic and digital competencies influence marketing performance.

6. COMMON METHOD BIAS AND ENDOGENEITY ASSESSMENT

This research productively implemented procedural and statistical measures to restrict Common Method Bias (CMB). To minimize bias arising from respondent evaluation, data were collected anonymously, items were clearly formulated, and measurement constructs were systematically separated in the questionnaire design (Podsakoff et al., 2003). Furthermore, qualitative interviews were employed in a mixed-methods design to reduce potential single-source bias by strengthening triangulation and contextual interpretation [26, 28]. The presence of a single factor was examined using Harman's one-factor test, as well as a full collinearity diagnostic using the VIF. This indicates whether multicollinearity is indeed a serious problem. If VIF values are below the recommended threshold, critical collinearity problems can be considered absent. Finally, to ensure that endogeneity issues do not materially bias the results, robustness checks were conducted. These included model specification tests and collinearity diagnostics [63]. These steps are reported to reduce the potential impact of omitted variables and reverse causation. Additionally, PLS-SEM was employed to estimate latent constructs jointly while controlling for structural relationships among them simultaneously [27]. This ultimately strengthens the robustness of the empirical evidence by providing an outcome variable and a multi-method, psychologically controlled perspective.

7. ETHICAL CONSIDERATIONS

The study adhered to established principles of ethical research involving human subjects. Participants volunteered and gave written informed consent before data collection, with the consent form outlining the study's purpose, participation details, the absence of harm, and confidentiality, while allowing withdrawal at any time without penalty. No identifiable personal data were gathered, and participants remained anonymous to safeguard their privacy. The research complied with the ethical standards of the Declaration of Helsinki, including informed consent, participant welfare, confidentiality, and research integrity [66]. Data were solely for academic use and stored securely in anonymized formats to prevent linking responses to individuals. Additionally, qualitative interviews were conducted ethically, ensuring voluntary participation, making necessary adjustments, and communicating respectfully, which supports the integrity, transparency, and credibility of the research findings.

IV. RESULTS AND DISCUSSION

1. DESCRIPTIVE STATISTICS

As illustrated in Table 3, the dataset shows a robust distribution across all measurement indicators, indicating its suitability for further analysis. The standardized data show that all indicators have means close to 0,000 and standard deviations range from 0.5490 to 0.7140 (consistent across constructs, as expected). The skewness values fall within a typical range (from -0.3420 to 0.2240), indicating balanced predictors without significant bias in the data distribution. Similarly, the moderate kurtosis values, ranging from −0.423 to 1.102, indicate no significant deviation from normality. A review of the indicators reveals that the data are mostly mesokurtic to platykurtic, indicating a normal distribution. These findings fall below the recommended thresholds for univariate normality (skewness < 2; kurtosis| < 7; [67]. The overall results confirm the suitability of the data distribution and the absence of major issues, thereby validating the effectiveness of PLS-SEM for additional measurement and structural model analyses in cases with minor deviations from normality.

Table 3. Descriptive statistics.

Indicator	Mean	Median	Min	Max	Std. Dev.	Kurtosis	Skewness
CNS.1	0.0000	0.0330	-2.0720	2.4030	0.6920	0.1380	-0.0560
CNS.2	0.0000	-0.0020	-2.1260	2.3520	0.7020	0.1280	-0.0500
CNS.3	0.0000	-0.0040	-1.8960	1.8880	0.6990	-0.0680	-0.0760
CNS.4	0.0000	-0.0130	-1.9170	2.8350	0.7010	0.2330	-0.0160

Indicator	Mean	Median	Min	Max	Std. Dev.	Kurtosis	Skewness
CNS.5	0.0000	-0.0150	-1.9540	1.8920	0.7080	-0.1460	-0.1570
CPO.1	0.0000	0.0160	-3.5740	1.8220	0.6910	1.1020	-0.2480
CPO.2	0.0000	0.0370	-1.8260	1.8990	0.6870	0.0220	0.0030
CPO.3	0.0000	-0.0220	-1.6890	1.8600	0.6890	-0.2060	-0.0120
CPO.4	0.0000	0.0120	-1.9320	1.9690	0.6950	0.0380	-0.0620
CPO.5	0.0000	-0.0450	-3.7330	2.2710	0.7030	1.0130	-0.2510
DC.1	0.0000	-0.0220	-1.5040	1.4430	0.5910	-0.4230	0.0550
DC.2	0.0000	0.0400	-1.8200	1.5700	0.6010	-0.0620	-0.0330
DC.3	0.0000	-0.0080	-2.3290	2.8710	0.6090	0.4060	0.0740
DC.4	0.0000	-0.0270	-1.3110	1.3990	0.5550	-0.2610	-0.0100
DC.5	0.0000	0.0190	-1.8000	1.4440	0.5490	0.0410	-0.1510
FAC.1	0.0000	0.0290	-1.6460	1.7000	0.6790	-0.2140	0.0030
FAC.2	0.0000	-0.0220	-2.2420	1.6750	0.6930	-0.0780	0.0100
FAC.3	0.0000	0.0100	-1.7310	1.7520	0.6660	0.0960	-0.2240
FAC.4	0.0000	0.0140	-1.8010	1.7960	0.6850	-0.0480	-0.0360
MI.1	0.0000	-0.0310	-2.9790	1.8460	0.7130	0.1100	-0.1650
MI.2	0.0000	0.0180	-1.8760	1.6970	0.6960	-0.2890	-0.1360
MI.3	0.0000	-0.0080	-2.0010	1.6870	0.7140	-0.3420	-0.1280
MI.4	0.0000	0.0550	-1.7990	1.9090	0.7010	-0.3020	-0.1170
MI.5	0.0000	0.0180	-1.9010	1.7220	0.6940	-0.2080	0.0220
ML.1	0.0000	0.0410	-1.8450	2.4000	0.6930	-0.0520	0.0500
ML.2	0.0000	0.0080	-1.9250	1.9230	0.7120	-0.2310	0.0590
ML.3	0.0000	0.0340	-1.7680	2.6240	0.6550	0.1390	-0.0080
ML.4	0.0000	-0.0220	-2.3020	1.8420	0.7110	0.0280	-0.0430
ML.5	0.0000	-0.0580	-1.9350	1.8080	0.7030	-0.1470	0.0600
MP.1	0.0000	-0.0130	-2.7660	1.8280	0.7100	0.1640	-0.1750
MP.2	0.0000	0.0120	-1.9470	2.1400	0.7040	-0.1320	0.0220
MP.3	0.0000	0.0000	-2.5500	2.3200	0.7070	0.0040	-0.1610
MP.4	0.0000	0.0120	-2.2750	1.8660	0.6950	-0.0710	-0.0600
MP.5	0.0000	-0.0090	-2.0680	1.8430	0.6980	-0.1320	-0.0190
NMM.1	0.0000	-0.0260	-1.8160	1.7640	0.6500	0.0800	-0.0840
NMM.2	0.0000	-0.0420	-1.8850	1.5500	0.6860	0.0070	-0.0960
NMM.3	0.0000	0.0410	-1.7490	1.8490	0.6610	0.0110	0.0040
NMM.4	0.0000	-0.0010	-1.7960	1.7950	0.6480	0.1800	-0.0710
NMM.5	0.0000	0.0350	-1.8510	2.7630	0.7010	0.4670	0.2240
PEC.1	0.0000	0.0160	-1.6430	1.6750	0.6640	-0.1440	-0.0540
PEC.2	0.0000	-0.0170	-2.0120	1.6970	0.6570	-0.0160	-0.1420
PEC.3	0.0000	-0.0020	-1.7560	1.6870	0.6800	-0.2410	-0.0710
PEC.4	0.0000	0.0190	-1.7180	1.7560	0.6830	-0.1900	-0.0110
PIC.1	0.0000	0.0330	-1.8110	1.9080	0.6840	-0.1700	-0.0220
PIC.2	0.0000	-0.0520	-1.7430	1.8820	0.6660	-0.1450	0.0020
PIC.3	0.0000	-0.0050	-1.7530	1.8690	0.7070	-0.2060	-0.2090
PIC.4	0.0000	0.0370	-1.6620	1.9660	0.7020	-0.3320	0.0200
PIC.5	0.0000	0.0170	-1.6950	2.6550	0.7040	-0.1390	-0.0130
TA.1	0.0000	0.0120	-1.9070	1.9300	0.6970	-0.1300	-0.0620
TA.2	0.0000	-0.0030	-1.9370	1.8800	0.7130	-0.1330	0.0080
TA.3	0.0000	-0.0020	-1.9320	1.9290	0.6840	-0.0590	0.0670

https://doi.org/10.48161/qaj.v6n2a2512

Indicator	Mean	Median	Min	Max	Std. Dev.	Kurtosis	Skewness
TA.4	0.0000	-0.0040	-1.8730	1.8650	0.6680	0.2010	-0.1010
TA.5	0.0000	-0.0020	-2.3830	1.7380	0.6610	0.2820	-0.1860

Note: N = 700. Data were standardized (Mean = 0; Variance = 1).
Source: Author's computation (2026)

2. *MEASUREMENT MODEL EVALUATION*

The measurement model exhibits robust psychometric properties, as shown in Tables 4–9. All indicator loadings exceed the recommended threshold of 0.70, confirming adequate convergent validity and indicating that each indicator accurately represents its respective construct. Digital Competence (DC) exhibits the highest loadings, notably DC.5 (0.836) and DC.4 (0.832), reflecting a robust measure of digital preparedness. The reliability of other constructs, such as Product Exploration Capability (PEC) and Niche Market Mastery (NMM), is also reinforced by the stability and consistency of their loadings. While some indicators (for example, MI.3 and TA.2) approach the lower threshold, they remain acceptable and meaningfully contribute to their respective constructs. Furthermore, external factor analysis confirms that all indicators are statistically significant ($p < 0.05$). This supports their relevance. Variations in loadings reflect the multidimensional nature of strategic capabilities. They do not reflect measurement weaknesses.

Table 4. Outer loadings.

Construct	Indicator	Loading	Construct	Indicator	Loading
CNS	CNS.1	0.7220	MI	MI.1	0.7010
	CNS.2	0.7130		MI.2	0.7180
	CNS.3	0.7150		MI.3	0.7000
	CNS.4	0.7130		MI.4	0.7130
	CNS.5	0.7060		MI.5	0.7200
CPO	CPO.1	0.7230	ML	ML.1	0.7210
	CPO.2	0.7260		ML.2	0.7020
	CPO.3	0.7250		ML.3	0.7560
	CPO.4	0.7190		ML.4	0.7030
	CPO.5	0.7110		ML.5	0.7120
DC	DC.1	0.8060	MP	MP.1	0.7040
	DC.2	0.7990		MP.2	0.7100
	DC.3	0.7930		MP.3	0.7070
	DC.4	0.8320		MP.4	0.7190
	DC.5	0.8360		MP.5	0.7160
FAC	FAC.1	0.7340	NMM	NMM.1	0.7600
	FAC.2	0.7200		NMM.2	0.7280
	FAC.3	0.7460		NMM.3	0.7510
	FAC.4	0.7290		NMM.4	0.7620
				NMM.5	0.7130
PEC	PEC.1	0.7470	PIC	PIC.1	0.7300
	PEC.2	0.7540		PIC.2	0.7460
	PEC.3	0.7330		PIC.3	0.7070
	PEC.4	0.7300		PIC.4	0.7120
TA	TA.1	0.7170		PIC.5	0.7100
	TA.2	0.7010			
	TA.3	0.7300			

Construct	Indicator	Loading	Construct	Indicator	Loading
	TA.4	0.7450			
	TA.5	0.7500			

Note: All outer loadings exceed the recommended threshold of 0.70 and are significant at $p < 0.001$ based on bootstrapping (5,000 subsamples). Source: Author's computation (2026)

These assessments further confirm the measurement model's reliability and validity. All constructs exceeded the thresholds for internal consistency (Cronbach's alpha and composite reliability >0.70) and convergent validity (AVE >0.50), with discriminant validity also demonstrated. This was evidenced by the Fornell–Larcker criteria and HTMT ratios, which showed distinct separation among constructs. Additionally, cross-loading analysis reveals that each indicator loads highest on its own construct, with minimal overlap between constructs. Overall, the measurement model is statistically sound, theoretically aligned, and appropriate for further structural equation modeling.

Table 5. Indicator weights.

Construct	Indicator	Weight	Construct	Indicator	Weight
CNS	CNS.1	0.2850	MI	MI.1	0.2810
	CNS.2	0.2830		MI.2	0.2930
	CNS.3	0.2830		MI.3	0.2480
	CNS.4	0.2760		MI.4	0.3080
	CNS.5	0.2730		MI.5	0.2770
CPO	CPO.1	0.3060	ML	ML.1	0.2980
	CPO.2	0.2850		ML.2	0.2450
	CPO.3	0.2690		ML.3	0.3020
	CPO.4	0.2490		ML.4	0.2710
	CPO.5	0.2790		ML.5	0.2730
DC	DC.1	0.2420	MP	MP.1	0.2830
	DC.2	0.1940		MP.2	0.2720
	DC.3	0.2460		MP.3	0.2810
	DC.4	0.2780		MP.4	0.2870
	DC.5	0.2670		MP.5	0.2840
FAC	FAC.1	0.3740	NMM	NMM.1	0.2940
	FAC.2	0.3420		NMM.2	0.2660
	FAC.3	0.3330		NMM.3	0.2660
	FAC.4	0.3160		NMM.4	0.2880
PEC	PEC.1	0.3530		NMM.5	0.2290
	PEC.2	0.3430	PIC	PIC.1	0.3000
	PEC.3	0.3380		PIC.2	0.2870
	PEC.4	0.3160		PIC.3	0.2740
TA	TA.1	0.2610		PIC.4	0.2570
	TA.2	0.2750		PIC.5	0.2680
	TA.3	0.2670			
	TA.4	0.2960			
	TA.5	0.2720			

Note: Outer weights indicate the relative contribution of each indicator to its construct. All weights are statistically significant at $p < 0.05$. Source: Author's computation (2026)

Table 6. Reliability and convergent validity.

Construct	Cronbach's Alpha	rho_A	Composite Reliability (CR)	AVE
CNS	0.7590	0.7590	0.8390	0.5090
CNS*DC	1.0000	1.0000	1.0000	1.0000
CPO	0.7690	0.7700	0.8440	0.5190
CPO*DC	1.0000	1.0000	1.0000	1.0000
DC	0.8730	0.8790	0.9070	0.6620
FAC	0.7130	0.7130	0.8220	0.5360
FAC*DC	1.0000	1.0000	1.0000	1.0000
MI	0.7550	0.7560	0.8360	0.5050
MI*DC	1.0000	1.0000	1.0000	1.0000
ML	0.7670	0.7690	0.8420	0.5170
ML*DC	1.0000	1.0000	1.0000	1.0000
MP	0.7560	0.7560	0.8360	0.5060
NMM	0.7970	0.8010	0.8600	0.5520
NMM*DC	1.0000	1.0000	1.0000	1.0000
PEC	0.7270	0.7270	0.8300	0.5490
PEC*DC	1.0000	1.0000	1.0000	1.0000
PIC	0.7690	0.7710	0.8440	0.5200
PIC*DC	1.0000	1.0000	1.0000	1.0000
TA	0.7790	0.7800	0.8500	0.5310
TA*DC	1.0000	1.0000	1.0000	1.0000

Note: All constructs exceed recommended thresholds (Cronbach's $\alpha > 0.70$; CR > 0.70; AVE > 0.50). Interaction terms (*DC) are modeled as single-item constructs, yielding perfect reliability.
Source: Author's computation (2026)

Table 7. Fornell–Larcker criterion.

Construct	CNS	CPO	DC	FAC	MI	ML	MP	NMM	PEC	PIC	TA
CNS	0.7140	0.6200	0.2780	0.5080	0.4870	0.6180	0.5650	0.5630	0.5350	0.5190	0.5910
CPO	0.6200	0.7210	0.2540	0.5570	0.5040	0.6210	0.5690	0.6160	0.5670	0.5080	0.6120
DC	0.2780	0.2540	0.8130	0.2070	0.2480	0.2030	0.3240	0.2350	0.2110	0.2730	0.2680
FAC	0.5080	0.5570	0.2070	0.7320	0.4750	0.5420	0.5460	0.6140	0.4790	0.4240	0.5710
MI	0.4870	0.5040	0.2480	0.4750	0.7110	0.4770	0.4630	0.4980	0.4650	0.4780	0.5280
ML	0.6180	0.6210	0.2030	0.5420	0.4770	0.7190	0.5650	0.5860	0.6170	0.5320	0.6310
MP	0.5650	0.5690	0.3240	0.5460	0.4630	0.5650	0.7110	0.5380	0.5780	0.4190	0.5530
NMM	0.5630	0.6160	0.2350	0.6140	0.4980	0.5860	0.5380	0.7430	0.4830	0.4780	0.5890
PEC	0.5350	0.5670	0.2110	0.4790	0.4650	0.6170	0.5780	0.4830	0.7410	0.5120	0.5360
PIC	0.5190	0.5080	0.2730	0.4240	0.4780	0.5320	0.4190	0.4780	0.5120	0.7210	0.5160
TA	0.5910	0.6120	0.2680	0.5710	0.5280	0.6310	0.5530	0.5890	0.5360	0.5160	0.7290

Note: Diagonal values (bold) represent the square root of AVE. Discriminant validity is established when diagonal values exceed inter-construct correlations.
Source: Author's computation (2026)

Table 8. Heterotrait–Monotrait ratio (HTMT).

Construct Pair	HTMT	Construct Pair	HTMT
CNS ↔ CPO	0.8090	MI ↔ ML	0.6290
CNS ↔ DC	0.3400	MI ↔ MP	0.6100
CNS ↔ FAC	0.6920	ML ↔ MP	0.7390
CNS ↔ MI	0.6440	NMM ↔ PEC	0.6330
CNS ↔ ML	0.8090	NMM ↔ PIC	0.6090
CNS ↔ MP	0.7450	NMM ↔ TA	0.7460
CNS ↔ NMM	0.7230	PEC ↔ PIC	0.6830
CNS ↔ PEC	0.7210	PEC ↔ TA	0.7130
CNS ↔ PIC	0.6780	PIC ↔ TA	0.6660
CNS ↔ TA	0.7690	CNSDC ↔ CPODC	0.8210
CPO ↔ DC	0.3100	CPODC ↔ MLDC	0.8850
CPO ↔ FAC	0.7500	FACDC ↔ NMMDC	0.8590
CPO ↔ MI	0.6630	MIDC ↔ TADC	0.7820
CPO ↔ ML	0.8060	NMMDC ↔ PECDC	0.8030
CPO ↔ MP	0.7430	PECDC ↔ PICDC	0.8140
CPO ↔ NMM	0.7870	All other pairs	< 0.850
CPO ↔ PEC	0.7570		
CPO ↔ PIC	0.6610		
CPO ↔ TA	0.7900		
DC ↔ FAC	0.2610		
DC ↔ MI	0.3060		
DC ↔ ML	0.2480		
DC ↔ MP	0.3940		
DC ↔ NMM	0.2790		
DC ↔ PEC	0.2650		
DC ↔ PIC	0.3330		
DC ↔ TA	0.3250		
FAC ↔ MI	0.6460		
FAC ↔ ML	0.7330		
FAC ↔ MP	0.7400		
FAC ↔ NMM	0.8120		
FAC ↔ PEC	0.6650		
FAC ↔ PIC	0.5690		
FAC ↔ TA	0.7660		

Note: HTMT values below the conservative threshold of 0.85 (and liberal threshold of 0.90) indicate satisfactory discriminant validity. Higher values involving interaction terms are expected due to shared components with their parent constructs.
Source: Author's computation (2026)

Table 9. Cross-loadings.

Indicator	CNS	CPO	DC	FAC	MI	ML	MP	NMM	PEC	PIC	TA
CNS.1	0.7220	0.4350	0.2380	0.3910	0.3580	0.3900	0.4110	0.3960	0.3350	0.4000	0.4310
CNS.2	0.7130	0.4380	0.1910	0.3460	0.3290	0.4290	0.4070	0.4000	0.3850	0.3370	0.4110
CNS.3	0.7150	0.4360	0.2270	0.3750	0.3600	0.4700	0.4080	0.4110	0.4220	0.3660	0.4250
CNS.4	0.7130	0.4260	0.1710	0.3300	0.3320	0.4330	0.3970	0.3530	0.3740	0.3710	0.4250
CNS.5	0.7060	0.4780	0.1640	0.3730	0.3590	0.4840	0.3930	0.4490	0.3940	0.3790	0.4170
CPO.1	0.4720	0.7230	0.2300	0.3800	0.3130	0.4750	0.4500	0.4050	0.4280	0.3520	0.4170
CPO.2	0.4380	0.7260	0.1470	0.3880	0.3710	0.4590	0.4190	0.4260	0.4260	0.3530	0.4570
CPO.3	0.4430	0.7250	0.1520	0.4170	0.4220	0.4580	0.3960	0.4370	0.4270	0.3990	0.4350
CPO.4	0.4250	0.7190	0.2290	0.3910	0.3820	0.4040	0.3660	0.4440	0.3910	0.3870	0.4380
CPO.5	0.4520	0.7110	0.1570	0.4340	0.3370	0.4340	0.4100	0.5120	0.3670	0.3420	0.4580

Indicator	CNS	CPO	DC	FAC	MI	ML	MP	NMM	PEC	PIC	TA
DC.1	0.2510	0.2350	0.8060	0.2070	0.2170	0.2070	0.2560	0.2150	0.1940	0.2330	0.2410
DC.2	0.2060	0.2010	0.7990	0.1240	0.2120	0.1560	0.2050	0.1630	0.1530	0.1980	0.2090
DC.3	0.2120	0.1940	0.7930	0.1980	0.2000	0.1490	0.2610	0.1670	0.1710	0.2170	0.2220
DC.4	0.2160	0.2160	0.8320	0.1740	0.1960	0.1800	0.2950	0.2290	0.1910	0.2340	0.2150
DC.5	0.2450	0.1890	0.8360	0.1350	0.1910	0.1320	0.2830	0.1760	0.1480	0.2220	0.2040
FAC.1	0.3680	0.4270	0.1560	0.7340	0.3520	0.4170	0.4370	0.4810	0.3550	0.3230	0.4090
FAC.2	0.3600	0.4220	0.1390	0.7200	0.3570	0.3720	0.4000	0.4640	0.3680	0.3330	0.4380
FAC.3	0.3670	0.3910	0.1710	0.7460	0.3450	0.3890	0.3890	0.4090	0.3120	0.3070	0.4320
FAC.4	0.3970	0.3870	0.1410	0.7290	0.3370	0.4090	0.3680	0.4410	0.3690	0.2740	0.3930
MI.1	0.3670	0.3780	0.2070	0.3250	0.7010	0.3240	0.3270	0.3480	0.3600	0.3430	0.3500
MI.2	0.3530	0.3310	0.2160	0.3360	0.7180	0.3310	0.3420	0.3350	0.2890	0.3550	0.3600
MI.3	0.3320	0.3280	0.1290	0.3390	0.7000	0.3420	0.2900	0.3270	0.3060	0.3340	0.3930
MI.4	0.2990	0.3590	0.1390	0.3540	0.7130	0.3460	0.3580	0.3850	0.3580	0.3090	0.3920
MI.5	0.3840	0.3940	0.1890	0.3340	0.7200	0.3530	0.3220	0.3700	0.3360	0.3590	0.3830
ML.1	0.4540	0.4670	0.1680	0.3810	0.3280	0.7210	0.4340	0.4330	0.4350	0.3960	0.4300
ML.2	0.4040	0.4550	0.1540	0.3740	0.3320	0.7020	0.3560	0.4470	0.4010	0.4030	0.4590
ML.3	0.4440	0.4350	0.1290	0.3960	0.3300	0.7560	0.4410	0.4360	0.4850	0.3710	0.4650
ML.4	0.4390	0.4550	0.1540	0.4060	0.3580	0.7030	0.3950	0.3980	0.4390	0.3970	0.4610
ML.5	0.4770	0.4230	0.1250	0.3930	0.3730	0.7120	0.3980	0.3940	0.4530	0.3490	0.4580
MP.1	0.4290	0.4170	0.2340	0.4050	0.3210	0.3850	0.7040	0.3670	0.3970	0.2720	0.3800
MP.2	0.3910	0.4030	0.2210	0.3520	0.3220	0.3820	0.7100	0.3630	0.4050	0.3050	0.4110
MP.3	0.3750	0.3910	0.2470	0.3890	0.3130	0.4060	0.7070	0.3390	0.4260	0.2810	0.4070
MP.4	0.3860	0.4200	0.2320	0.3950	0.3420	0.4440	0.7190	0.4570	0.4070	0.3160	0.3830
MP.5	0.4270	0.3940	0.2170	0.3990	0.3480	0.3920	0.7160	0.3840	0.4210	0.3180	0.3880
NMM.1	0.4190	0.4850	0.1960	0.4580	0.3780	0.4640	0.4350	0.7600	0.3860	0.3960	0.4570
NMM.2	0.3940	0.4490	0.1830	0.4440	0.3580	0.4330	0.3930	0.7280	0.3180	0.3230	0.4310
NMM.3	0.3980	0.4580	0.1760	0.4780	0.3490	0.4060	0.3940	0.7510	0.3220	0.3340	0.4350
NMM.4	0.4620	0.4510	0.1590	0.4700	0.3880	0.4600	0.4260	0.7620	0.3930	0.3800	0.4570
NMM.5	0.4180	0.4460	0.1570	0.4300	0.3770	0.4070	0.3380	0.7130	0.3750	0.3380	0.4050
PEC.1	0.3950	0.3740	0.1370	0.3610	0.3310	0.4610	0.4470	0.3470	0.7470	0.3520	0.3650
PEC.2	0.4150	0.4510	0.1430	0.3680	0.3080	0.4760	0.4350	0.3790	0.7540	0.3770	0.4210
PEC.3	0.3860	0.4280	0.1670	0.3660	0.3540	0.4540	0.4290	0.3850	0.7330	0.4050	0.4170
PEC.4	0.3900	0.4300	0.1830	0.3250	0.3890	0.4360	0.4010	0.3180	0.7300	0.3870	0.3870
PIC.1	0.4110	0.3810	0.1950	0.2890	0.3480	0.3810	0.3260	0.3160	0.3980	0.7300	0.3660
PIC.2	0.3860	0.3910	0.1710	0.3440	0.3520	0.4140	0.3130	0.3830	0.4010	0.7460	0.3910
PIC.3	0.3520	0.3220	0.1530	0.3390	0.3490	0.3990	0.2980	0.3620	0.3730	0.7070	0.3880
PIC.4	0.3780	0.3790	0.2490	0.2650	0.3600	0.3770	0.2800	0.3390	0.3150	0.7120	0.3830
PIC.5	0.3410	0.3560	0.2210	0.2880	0.3140	0.3460	0.2920	0.3260	0.3510	0.7100	0.3330
TA.1	0.4430	0.4610	0.2110	0.4320	0.3790	0.4850	0.3830	0.4420	0.4040	0.3900	0.7170
TA.2	0.3940	0.4400	0.1690	0.3830	0.3870	0.4180	0.4030	0.4080	0.3780	0.3590	0.7010
TA.3	0.4280	0.4120	0.1890	0.4220	0.3700	0.4390	0.3920	0.4300	0.3800	0.3880	0.7300
TA.4	0.4350	0.4580	0.2050	0.4130	0.4070	0.4570	0.4350	0.4500	0.3880	0.4020	0.7450
TA.5	0.4540	0.4580	0.2020	0.4330	0.3800	0.5020	0.3990	0.4160	0.4040	0.3400	0.7500

Note: Values in bold indicate the factor loadings of each indicator on its respective construct. Each indicator has the highest factor loading on its designated construct, confirming discriminant validity.
Source: Author 2026

As shown in Figure 2, the external loadings in the measurement model exceed the threshold, thereby confirming convergent validity (all $\lambda > 0.70$) and indicating adequate reliability. The DC has some of the highest and most consistent loadings, indicating that this variable is well measured. The structural model explains 53.8% of the variance in marketing performance ($R^2 = 0.538$), indicating moderate predictive capability. PEC exhibits the most significant direct positive effect on MP ($\beta = 0.205$, $p < 0.001$), followed by DC: $\beta = 0.165$, $p < 0.001$, and FAC ($\beta = 0.155$, $p < 0.01$). Specifically, the latter demonstrated an insignificant negative effect ($\beta = -0.049$, n.s.), indicating a negligible short-term market reaction to SME innovation activities consistent with the PIC. The FAC Cap (Diversity at-Firm Cap) is an integral component of the FACDC framework. The majority of the significant moderating effects of DC were evident for FAC.

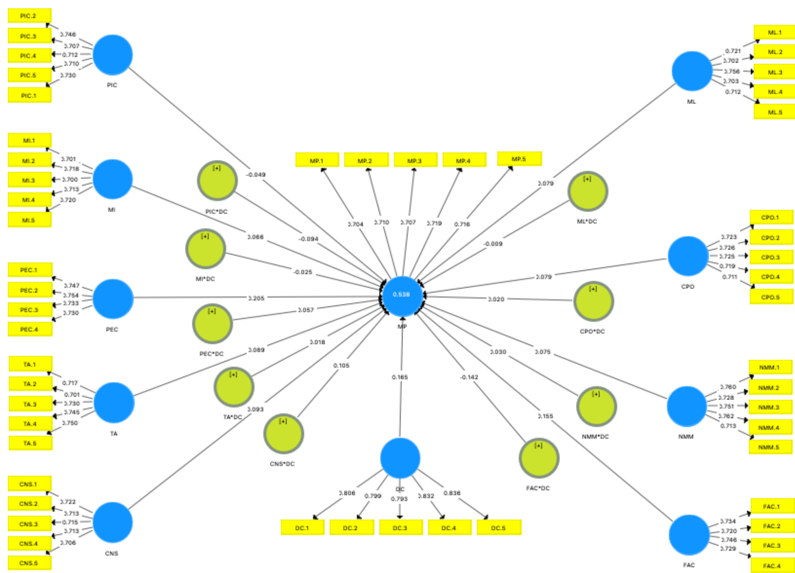

FIGURE 2. Measurement model with indicator loadings and construct relationships.

3. STRUCTURAL MODEL EVALUATION

Tables 10–14 present the results of the structural model, providing comprehensive evidence on the relationships among strategic capabilities, digital capabilities, and marketing performance. The study found support for five of the hypotheses (H1, H3, H4, H8, and H10), suggesting that the strength of collaborative networks, digital capabilities, future adaptability, product exploration, and technology accessibility has a direct and significant impact on marketing performance (see Table 10 for details). The findings reveal that Product Exploration Capability (β=0.205, $p<0.001$) and Digital Capability (β=0.165, $p<0.001$) have the strongest effects in this regard. This suggests that exploratory innovation and digital integration, in turn, are primary drivers of SME performance. In contrast, we found that several constructs, namely CPO, MI, ML, NMM, and PIC, were not significant. This means that performance also improves due to these factors, but not in all cases, aligning with the contingent nature (capability–performance relationship) of performance enhancement.

Regarding the moderation analysis (see Table 11), only the interaction term (H13) between Future Adaptive Capability and Digital Capability was significant, with a negative moderating effect ($\beta = -0.142$, $p = 0.010$). This suggests a substitution/diversity mechanism with diminishing returns or a limiting cross-level effect, where high digital ability tends to reduce the marginal effect on adaptive ability performance, an important boundary condition.

As demonstrated in Table 12, the effect size analysis indicates that all predictors exhibited small effects ($f^2 < 0.15$). This finding suggests that multiple capabilities contribute equally to performance, rather than a single capability dominating the others, as observed in MGT. The model demonstrates weak explanatory power ($R^2 = 0.538$) and strong predictive relevance ($Q^2 = 0.512$), indicating its robustness. Finally, the overall model fit indices (Table 4), including SRMR (0.048), show that the results from our structural model are adequate for hypothesis testing.

Table 10. Direct effects (Path Coefficients).

Hypothesis	Path	β (O)	Mean (M)	STDEV	t-value	p-value	95% CI (BC)
H1.	CNS > MP	0.0930	0.0880	0.0440	2.1190	0.0350	0.014, 0.184
H2.	CPO > MP	0.0790	0.0750	0.0470	1.6920	0.0910	-0.008, 0.175
H3.	DC > MP	0.1650	0.1760	0.0400	4.0990	0.0000	0.096, 0.238
H4.	FAC > MP	0.1550	0.1480	0.0480	3.1960	0.0010	0.068, 0.249
H5.	MI > MP	0.0660	0.0720	0.0400	1.6620	0.0970	-0.024, 0.133
H6.	ML > MP	0.0790	0.0830	0.0470	1.6840	0.0930	-0.011, 0.160
H7.	NMM > MP	0.0750	0.0710	0.0430	1.7400	0.0820	-0.003, 0.167
H8.	PEC > MP	0.2050	0.2060	0.0450	4.5770	0.0000	0.122, 0.295
H9.	PIC > MP	-0.0490	-0.0420	0.0410	1.2040	0.2290	-0.138, 0.023
H10.	TA > MP	0.0890	0.0860	0.0440	2.0160	0.0440	0.002, 0.178

Note: β = standardized path coefficient; BC = Bias-Corrected confidence interval; significance level $p < 0.05$.
Source: Author's computation using SmartPLS 4 (2026)

Table 11. Moderating effects.

Hypothesis	Interaction Path	β (O)	Mean (M)	STDEV	t-value	p-value	95% CI (BC)
H11.	CNS×DC > MP	0.1050	0.1070	0.0580	1.7990	0.0730	[-0.022, 0.207]
H12.	CPO×DC > MP	0.0200	0.0190	0.0690	0.2950	0.7680	[-0.116, 0.149]
H13.	FAC×DC > MP	-0.1420	-0.1560	0.0550	2.5840	0.0100	[-0.239, -0.035]
H14.	MI×DC > MP	-0.0250	-0.0230	0.0420	0.5950	0.5520	[-0.109, 0.053]
H15.	ML×DC > MP	-0.0090	-0.0100	0.0690	0.1270	0.8990	[-0.163, 0.116]
H16.	NMM×DC > MP	0.0300	0.0350	0.0620	0.4790	0.6320	[-0.106, 0.145]
H17.	PEC×DC > MP	0.0570	0.0470	0.0660	0.8760	0.3810	[-0.076, 0.167]
H18.	PIC×DC > MP	-0.0940	-0.0860	0.0490	1.9170	0.0560	[-0.207, -0.012]
H19.	TA×DC > MP	0.0180	0.0260	0.0600	0.3040	0.7610	[-0.104, 0.128]

Source: Author's computation using SmartPLS 4 (2026)

Table 12. Effect Size (f^2) of exogenous constructs on MP.

Construct	f^2	Effect Size Interpretation
DC	0.046	Small
PEC	0.045	Small
FAC	0.025	Small
CNS	0.008	Small
TA	0.007	Small
Others	< 0.02	Negligible

Note: $f^2 \geq 0.02$ (small), ≥ 0.35 (large).

Table 13. Predictive relevance (Q^2) and model fit indices.

Construct	R^2	Adjusted R^2	Q^2	Interpretation
MP	0.5380	0.5250	0.5120	Moderate–Strong

QUBAHAN ACADEMIC JOURNAL
VOL. 6, NO. 2, June 2026
https://doi.org/10.48161/qaj.v6n2a2512

Table 14. Model fit indices.

Fit Index	Value	Threshold	Interpretation
SRMR	0.0480	< 0.080	Good Fit
NFI	0.6930	> 0.900	Acceptable (PLS context)
rms Theta	0.1280	< 0.120	Marginal
d_ULS / d_G	—	—	Within acceptable range

Digital Capability (DC) in the model is a selective moderator, as shown in Figure 3. As is apparent, nearly all interaction effects are weak and non-significant, indicating limited moderating influence. Conversely, the interaction between Future Adaptation Capability (FAC) and DC is substantial and negative ($\beta = -0.142$), indicating a diminishing effect at higher levels of digital capability. This suggests that some capabilities are likely to be replaced rather than augmented by digital capabilities. Across all four constructs considered, the overall conclusion is that DC moderate's relationships contingently rather than consistently.

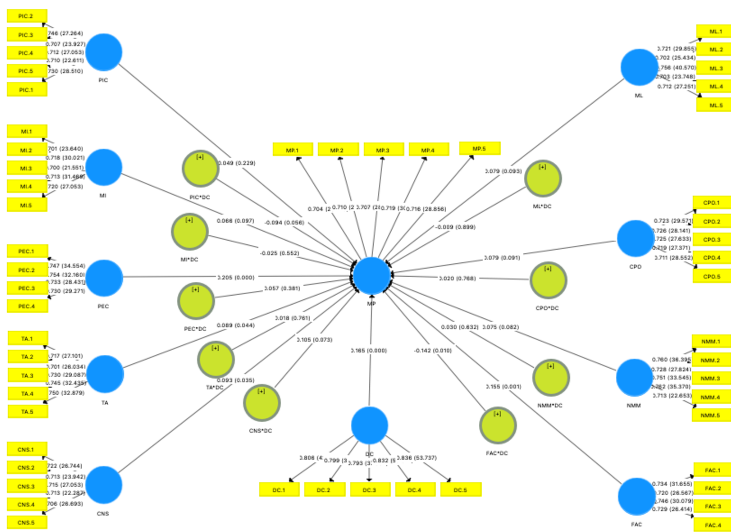

FIGURE 3. Moderating effects of digital capability.

4. DISCUSSION

These findings shed light on how strategic capabilities can affect the marketing performance of SMEs in emerging markets. In line with the RBV and the DCV, the findings show that performance is influenced by particular capabilities related to exploration, digital readiness, and adaptive responsiveness [21, 32]. Product exploration capability was the strongest predictor of marketing performance; therefore, firms should focus their efforts on market opportunities and base cost effectiveness on dynamic, innovative activities through experimentation rather than fortification. This aligns with previous literature highlighting the importance of organizational innovation capability, product-market renewal, and adaptive capability in dynamic environments [5, 13].

Additionally, digital capability exhibited significant direct effects on marketing performance, emphasizing its role as a higher-order dynamic capability in decision-making, customer engagement, operational agility, and resource reconfiguration [34, 37]. Similarly, organizations that can predict environmental changes and take strategic action are more likely to maintain performance advantages in uncertain markets [16, 35]. Collaboration network strength and technology accessibility were also positively related to marketing performance, implying that SMEs can overcome resource constraints to drive operational efficiency, knowledge exchange, and innovation support with technological resources and networks [8, 9, 10]. Conversely, market intelligence, market literacy, consumer preference orientation, and niche market mastery had no direct effect. As the results show, these capabilities are not expected to lead directly to performance outputs [20, 32], and may require complementary mechanisms, such as digital integration, strategic ambiguity and capability coordination.

It may be advisable to exercise caution regarding the negative and insignificant impact of product innovation capability. Although innovation is associated with higher performance, commercializing innovations can be challenging for SMEs due to resource constraints, weak market validation mechanisms, ineffective operationalization capabilities, and mismatches with customer needs. This suggests that innovation alone does not lead to performance unless it is supported by market learning, implementation capability, and a correctly aligned, supportive strategy [4, 30, 61]. However, moderation by digital capability did not always improve all capability–performance relationships. The only meaningful interaction indicator was between Future Adaptation Capability and Digital Capability, and the effect was negative. This suggests a potential substitution effect or diminishing returns, whereby higher levels of digital capability reduce the marginal benefit of adaptive capability to marketers' performance. These findings are consistent with the capability orchestration perspective, in that digital capability does not behave as a general performance enhancer, but rather as a selective, context-dependent mechanism [19, 24, 33, 69, 70]. In conclusion, our findings reveal that the marketing performance of SMEs is better explained by selective capability synergies than by acquiring many capability bundles. Digital capability, on the other hand, has a moderating effect, emphasizing the need for the strategic alignment of digital resources, adaptive capabilities, and market-oriented capability deployment.

5. CONCLUSION

This study provides a comprehensive understanding of how strategic capabilities influence marketing performance among SMEs in emerging markets, offering valuable insights for practitioners and researchers. The results suggest that marketing performance is not equally influenced by all capabilities, but rather by a specific combination of key abilities. Specifically, the most influential drivers are product exploration capabilities, digital capabilities, and future adaptation capabilities, with exploratory innovation, digital integration, and adaptive responsiveness emphasized as the most important. Furthermore, this study reveals that digital capabilities are not a universal enabler. The moderating role of these factors is limited and context-dependent, with only one significant interaction (FAC × DC) that negatively affects performance. This implies a substitution effect or diminishing returns, suggesting that higher digital capabilities may reduce the marginal contribution of certain adaptive capabilities. These findings build on the RBV and DCV by showing that capabilities are organized in a selective and contingent manner, rather than serving as a uniform reinforcement mechanism. From a practical perspective, SMEs should prioritize aligning digital initiatives with specific strategic capabilities, rather than assuming that digitalization alone will improve performance. Managers should focus on strengthening exploratory and adaptive capabilities and on digital integration. The study is limited in several ways. It is cross-sectional and focuses on SMEs in a single emerging market, which limits the generalizability of the results. Future research should adopt a longitudinal design, explore cross-country comparisons, and analyze the dynamic interactions among capabilities over time to improve the understanding of capability orchestration in digital environments.

1. THEORETICAL CONTRIBUTIONS

The paper contributes to the current literature by offering an extended perspective on integrated capability orchestration, building on the RBV and the DCV. The results of this study suggest that strategic capabilities do not consistently affect marketing performance. Instead, they appear to influence outcomes selectively, depending on their configuration and how well they complement one another. This contradicts the common assumption that capabilities always have a positive effect on performance. Furthermore, it highlights the bias of assuming that all capabilities are prioritized equally. Additionally, this study clarifies that digital capabilities function as a conditional, context-dependent mechanism rather than a context-free driver. This contributes to a deeper understanding of PLS-SEM moderation effects in emerging markets.

2. POLICY IMPLICATIONS

The study highlights that SMEs should be selective when building their capabilities. To achieve better performance, companies ought to focus on product exploration, digital integration, and adaptive responsiveness instead of trying to develop every strategic capability. Additionally, aligning digital capabilities with chosen organizational strengths is crucial. This requires a deliberate approach, making specific decisions to optimize particular outcomes. Moreover, digital transformation programs should be tailored to develop targeted capabilities, rather than expecting all firms to improve uniformly.

3. POLICY IMPLICATIONS

These findings highlight the need for more targeted policy interventions to build SME capabilities. Rather than providing broad, one-size-fits-all support, policymakers should prioritize strengthening key capabilities such as product exploration, digital integration, and adaptability, which have been shown to have the most significant impact on performance. Furthermore, digital transformation initiatives must be context-specific to ensure alignment between digital adoption and companies' existing strategic capabilities. It is crucial to enhance resource use by implementing programs that focus on digital skills development, innovation support, and capability alignment. To achieve sustainable competitiveness in emerging markets, SME policies must emphasize selective capability development and strategic orchestration.

Funding Statement

This research received no external funding.

Author Contributions

Sudarwati: Conceptualization, Methodology, Investigation, Formal analysis, Original draft writing, Review & editing. Septiana Novita Dewi: Data curation, software development, validation, and writing—including review and editing. Aris Tri Haryanto: Visualization, Resources, Project administration, Writing – review & editing. Muhammad Kholid Arif Rozaq: Investigation, Formal analysis, Writing – review & editing. Agus Dwianto: Methodology, Validation, Supervision, Writing – review & editing. Mukdad Ibrahim: Conceptualization, Supervision, Writing – review & editing. Gehad Mohammed Sultan Saif: Validation, Writing – review & editing.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could appear to influence the work reported in this paper.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgment

The authors gratefully acknowledge support from Universitas Islam Batik Surakarta and collaborating institutions throughout this research. This study did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors also sincerely thank all MSME respondents and participants for their valuable contributions to this study. In addition, the authors extend their appreciation to the local and international co-authors for their meaningful collaboration, intellectual contributions, and shared commitment to advancing knowledge and fostering academic cooperation across institutions and countries.

REFERENCES

1. Moore, S. B., & Manring, S. L. (**2009**). Strategy development in small and medium sized enterprises for sustainability and increased value creation. *Journal of Cleaner Production*, *17*(2).
2. Narver, J. C., & Slater, S. F. (**1990**). The effect of a market orientation on business profitability. *Journal of Marketing*, *54*(4).
3. Vorhies, D. W., & Morgan, N. A. (**2005**). Benchmarking marketing capabilities for sustainable competitive advantage. *Journal of Marketing*, *69*(1).

4. Calantone, R. J., Cavusgil, S. T., & Zhao, Y. (**2002**). Learning orientation, firm innovation capability, and firm performance. *Industrial Marketing Management, 31*(6), 515–524.
5. Moreira, A., Navaia, E., & Ribau, C. (**2024**). Innovation capabilities and their dimensions: A systematic literature review. *International Journal of Innovation Studies*.
6. Baker, W. E., & Sinkula, J. M. (**2009**). The complementary effects of market orientation and entrepreneurial orientation on profitability in small businesses. *Journal of Small Business Management, 47*(4), 443–464.
7. Jaworski, B. J., & Kohli, A. K. (**1993**). Market orientation: Antecedents and consequences. *Journal of Marketing, 57*(3), 53–70.
8. Granstrand, O. (**1998**). Towards a theory of the technology-based firm. *Research Policy, 27*(5), 465–489.
9. Jørgensen, F., & Ulhøi, J. P. (**2010**). Enhancing innovation capacity in SMEs through early network relationships. *Creativity and Innovation Management, 19*(4), 397–404.
10. Nalmpanti, A. D., Wong, C. Y., & Oghazi, P. (**2024**). Collaborating for innovation: The inhibiting role of constraints. *Journal of Innovation and Knowledge, 9*(3).
11. Porter, C. E., & Donthu, N. (**2006**). Using the technology acceptance model to explain how attitudes determine Internet usage: The role of perceived access barriers and demographics. *Journal of Business Research, 59*(9), 999–1007.
12. Dalgic, T., & Leeuw, M. (**1994**). Niche marketing revisited: Concept, applications and some European cases. *European Journal of Marketing, 28*(4), 39–55.
13. Hudson, K., Kumar, V., & Morgan, R. E. (**2024**). An evolutionary perspective on capabilities for fluid product-markets: The contingent effects of routinization and renewal in marketing, R&D, and operations. *Long Range Planning, 57*(6).
14. Oh, G. E., Aliyev, M., Kafouros, M., & Au, A. K. M. (**2022**). The role of consumer characteristics in explaining product innovation performance: Evidence from emerging economies. *Journal of Business Research, 149*, 470–482.
15. Rahimi, R. A., & Oh, G. S. (**2025**). Beyond theory: A systematic review of strengths and limitations in technology acceptance models through an entrepreneurial lens. *Journal of Marketing Analytics, 13*(4).
16. Vecchiato, R., & Roveda, C. (**2010**). Strategic foresight in corporate organizations: Handling the effect and response uncertainty of technology and social drivers of change. *Technological Forecasting and Social Change, 77*(9), 1527–1539.
17. Cunningham, J. A., Damij, N., Modic, D., & Olan, F. (**2023**). MSME technology adoption, entrepreneurial mindset and value creation: A configurational approach. *The Journal of Technology Transfer, 48*(5), 1517–1542.
18. Khabbaz, L., Kuran, O., & Youness, H. (**2026**). The adaptive enactment of value propositions in fragile economies: Evidence from sustainable MSMEs. *Sustainable Technology and Entrepreneurship, 5*(2), Article 100135.
19. Probohudono, A. N., Suhardjanto, D., Aligarh, F., Chayati, N., & Putra, A. A. (**2025**). Navigating MSMEs' performance through innovation and digital IT capabilities in business strategy. *Social Sciences & Humanities Open, 12*.
20. Helfat, C. E. (**2011**). Dynamic capabilities and strategic management: Organizing for innovation and growth. By David J. Teece. *R&D Management, 41*(2), 213–214.
21. Teece, D. J., Pisano, G., & Shuen, A. (**1997**). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533.
22. Liang, Z., Du, J., & Hua, Y. (**2025**). The impact of digital marketing capability on firm performance: Empirical evidence from Chinese listed manufacturing firms. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(3).
23. Dwianto, A., Qurrota A'yun, A., & Sabila, I. (**2025**). Mobile AI applications to support QRIS literacy and financial growth of traditional market SMEs. *Journal Economic Business Innovation, 2*(1).
24. Veiga, P. M., Marnoto, S., Guerra-Mota, M., & Rexhepi, G. (**2024**). Building new business models in MSMEs: Digital capabilities, global value chains integration and the moderating role of entrepreneurial failure. *Journal of Small Business and Enterprise Development, 31*(3), 478–500.
25. Amperawati, E. D., Rahmawati, Hariningsih, E., Winarno, W. W., Airawaty, D., & Dwianto, A. (**2024**). Role of gender in shaping consumer responses to doctor influencer: Insights into brand perceptions and repurchase intentions in the Indonesian mineral water industry. *Qubahan Academic Journal, 4*(3).
26. Venkatesh, V., Brown, S. A., & Bala, H. (**2013**). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly, 37*(1), 21–54.
27. Hair, J. F., Howard, M. C., & Nitzl, C. (**2020**). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109*, 101–110.
28. Creswell, J. W., & Plano Clark, V. L. (**2017**). *Designing and conducting mixed methods research* (3rd ed.). Sage Publications.
29. Schoonenboom, J., & Johnson, R. B. (**2017**). How to construct a mixed methods research design. *Kölner Zeitschrift für Soziologie und Sozialpsychologie, 69*(Suppl. 2), 107–131.
30. Akdeniz, M. B., Gonzalez-Padron, T., & Calantone, R. J. (**2010**). An integrated marketing capability benchmarking approach to dealer performance through parametric and nonparametric analyses. *Industrial Marketing Management, 39*(1), 150–160.
31. Eisenhardt, K. M., & Martin, J. A. (**2000**). Dynamic capabilities: What are they? *Strategic Management Journal, 21*(10–11), 1105–1121.
32. Pitelis, C., & Wang, C. L. (**2019**). Dynamic capabilities: What are they and what are they for? *British Journal of Management, 30*(4), 785–806.
33. Sambamurthy, V., Bharadwaj, A., & Grover, V. (**2003**). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS Quarterly, 27*(2), 237–263.

34. Li, L., Su, F., Zhang, W., & Mao, J. Y. (**2018**). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal, 28*(6), 1129–1157.
35. Carayannis, E. G., Dumitrescu, R., Falkowski, T., Papamichail, G., & Zota, N. R. (**2025**). Enhancing SME resilience through artificial intelligence and strategic foresight: A framework for sustainable competitiveness. *Technology in Society, 81*.
36. Kim, J., & Jin, W. (**2024**). Impact of digital capabilities on entrepreneurial performance in SMEs. *Journal of Innovation and Knowledge, 9*(4).
37. Wang, S., & Zhang, H. (**2025**). Enhancing SMEs sustainable innovation and performance through digital transformation: Insights from strategic technology, organizational dynamics, and environmental adaptation. *Socio-Economic Planning Sciences*.
38. Soykoth, M. W., Sim, W., & Frederick, S. (**2025**). Research trends in market intelligence: A review through a data-driven quantitative approach. *Journal of Marketing Analytics, 13*(1).
39. Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (**2013**). Digital business strategy: Toward a next generation of insights. *MIS Quarterly, 37*(2), 471–482.
40. Sohn, S. (**2024**). Consumer perceived risk of using autonomous retail technology. *Journal of Business Research, 171*, Article 114389.
41. Hokmabadi, H., Rezvani, S. M. H. S., & de Matos, C. A. (**2024**). Business resilience for small and medium enterprises and startups by digital transformation and the role of marketing capabilities—A systematic review. *Systems, 12*(6).
42. Maya, Z. D., & Rahmawati, Y. (**2025**). Financial literacy, digital payment adoption, and trust in advancing MSME growth. *Journal Economic Business Innovation, 2*(2).
43. Ihsan, H. Z., & Rahmawati, Y. (**2025**). Female entrepreneurs role in enhancing halal MSME growth and profitability. *Journal International Economic Sharia, 2*(1).
44. Istiqomah, Y., & Pawitri, W. (**2025**). Green orientation and digital capabilities driving regional MSME sustainability. *Journal Economic Business Innovation, 2*(3).
45. Mao, H., Liu, S., & Gong, Y. (**2024**). Balancing structural IT capabilities for organizational agility in digital transformation: A resource orchestration view. *International Journal of Operations & Production Management, 44*(1), 315–344.
46. Awad, J. A. R., & Martín-Rojas, R. (**2024**). Digital transformation influence on organisational resilience through organisational learning and innovation. *Journal of Innovation and Entrepreneurship, 13*(1).
47. Hanoum, S., Palalic, R., Durman, T. Y., & Shubbak, M. (**2025**). Enhancing SME performance through e-business: The interplay of ambidexterity and entrepreneurial orientation in technology parks. *Journal of Innovation and Entrepreneurship, 14*(1).
48. Febriani, A., Sopha, B. M., & Wibisono, M. A. (**2025**). Dynamic capabilities for omnichannel transformation in MSMEs: A comparative case study of fashion and furniture sectors. *Journal of Open Innovation: Technology, Market, and Complexity, 11*(1).
49. Candraningtyas, M. A., & Rahmawati, Y. (**2025**). Digital capabilities, Islamic financial literacy, and halal orientation driving online MSME sustainability. *Journal Economic Business Innovation, 2*(3).
50. Ibrahim, F. A., Fadli, A., & Saputri, H. (**2025**). Digital transformation as a catalyst for MSME competitiveness and development. *Advances in Management Innovation, 1*(2).
51. Alajmi, N. H. (**2026**). Resource-centered transformation paths: The role of digital transformation in optimizing SME resources for sustainable entrepreneurship. *Business Strategy and the Environment*.
52. Phi Nga, L., & Phan Thanh, T. (**2025**). Applied data science for exploring technological advancements and innovations affecting green logistics management: A case study logistics enterprises in Vietnam. *Qubahan Academic Journal, 5*(4), 152–176.
53. Teece, D., Peteraf, M., & Leih, S. (**2016**). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California Management Review, 58*(4), 13–35.
54. Fetters, M. D., Curry, L. A., & Creswell, J. W. (**2013**). Achieving integration in mixed methods designs: Principles and practices. *Health Services Research, 48*(6, Part 2), 2134–2156.
55. Sekaran, U. (**2003**). *Research methods for business: A skill-building approach* (4th ed.). John Wiley & Sons.
56. Chen, X., Shi, Y., & Zhao, D. (**2026**). Influence of digital innovation on entrepreneurial performance in small and medium-sized manufacturing enterprises. *Sustainable Technology and Entrepreneurship, 5*(2), Article 100130.
57. Utami, A. T., Pramuktisari, N., & Aini, N. (**2024**). The role of cooperatives in supporting micro, small, and medium enterprises (MSMEs) in Indonesia. *Researcher Academy Innovation Data Analysis (RAIDA), 1*(1).
58. Panjaitan, J. M. P., Darwin, M., Sumiyana, S., Wiva, W., & Setyowati, S. M. (**2025**). Measuring the Indonesian SMEs' capabilities for sociodynamic and disruptive innovation: The case for gaining resilience and sustainability. *Journal of Innovation and Entrepreneurship, 14*(1).
59. Shmueli, G., Ray, S., Velasquez Estrada, J. M., Chatla, S. B., & others. (**2019**). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347.
60. Jie, H., Gooi, L. M., & Lou, Y. (**2025**). Digital maturity, dynamic capabilities and innovation performance in high-tech SMEs. *International Review of Economics & Finance, 99*.
61. Hurley, R. F., & Hult, G. T. M. (**1998**). Innovation, market orientation, and organizational learning: An integration and empirical examination. *Journal of Marketing, 62*(3), 42–54.
62. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (**2019**). *Multivariate data analysis* (8th ed.). Cengage Learning.

63. Sarstedt, M., Radomir, L., Moisescu, O. I., & Ringle, C. M. (**2022**). Latent class analysis in PLS-SEM: A review and recommendations for future applications. *Journal of Business Research, 138*, 740–755.
64. Hubona, G. S., Schuberth, F., & Henseler, J. (**2021**). A clarification of confirmatory composite analysis (CCA). *International Journal of Information Management, 61*, Article 102399.
65. Henseler, J., Lee, N., Roemer, E., Kemény, I., Dirsehan, T., & Cadogan, J. W. (**2024**). Beware of the Woozle effect and belief perseverance in the PLS-SEM literature! *Electronic Commerce Research, 24*(2), 859–878.
66. World Medical Association. (**2013**). World Medical Association declaration of Helsinki: Ethical principles for medical research involving human subjects. *JAMA, 310*(20), 2191–2194.
67. Curran, P. J., West, S. G., & Finch, J. F. (**1996**). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods, 1*(1), 16–29.
68. Arraya, M. (**2025**). Distinctive capabilities system in MSMEs' business model adaptation: Evidence of the moderating and mediating effect of adaptive capability. *Central European Management Journal, 33*(2).
69. Qohar, R. Z. S., & Darmawan, B. A. (**2024**). Digital platforms as enablers of MSMEs' business model innovation: Revealing the role of capability reconfigurations. *Asian Journal of Economics, Business and Accounting, 24*(7).

Appendix 1. Respondent Profile and Data Collection Details

Table A1. Respondents detailed demographic distribution.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	386	55.1
	Female	314	44.9
Age	20–29 years	145	20.7
	30–39 years	235	33.6
	40–49 years	235	33.6
	≥50 years	85	12.1
Business Location	Jakarta	140	20
	West Java	165	23.6
	Central Java	130	18.6
	Yogyakarta	125	17.9
	East Java	140	20
Business Experience	<2 years	80	11.4
	2–5 years	210	30
	>5 years	410	58.6
Sector Type	Food	410	58.6
	Beverage	290	41.4

Table A2. Data collection procedure.

Stage	Description
Instrument Development	Questionnaire developed based on validated literature and adapted to MSME context
Pilot Testing	Initial testing conducted to ensure clarity and reliability of items
Sampling	Purposive sampling targeting MSME owners/managers
Data Collection Method	Online and offline questionnaire distribution
Sample Size	700 valid responses
Qualitative Support	In-depth interviews with selected MSME practitioners
Data Screening	Missing data, outliers, and response bias checked before analysis

Table A3. Respondent eligibility criteria.

Criteria	Description
Business Type	MSMEs in food and beverage sector
Role	Owner or manager involved in strategic decisions
Experience	Minimum operational experience required
Digital Exposure	Familiarity with basic digital tools/platforms

Table A4. Research timeline and data collection phases.

Phase	Period	Activity Description
Instrument Development	January – March 2024	Development of the survey instrument based on validated scales from prior literature (RBV and DCV frameworks), followed by content refinement to ensure contextual relevance for MSMEs
Pilot Testing	Apr-24	Preliminary testing of the questionnaire to assess clarity, reliability, and wording accuracy; minor revisions were made based on pilot feedback
Qualitative Data Collection	May – August 2024	In-depth semi-structured interviews with selected MSME practitioners to explore capability configurations and support construct validation
Survey Distribution	September 2024 – November 2025	Large-scale data collection through online and offline survey distribution across five major regions in Indonesia
Data Screening and Cleaning	Dec-25	Data validation procedures including completeness checks, outlier detection, and response consistency assessment
Final Dataset and Analysis	Jan-26	Final dataset preparation (N = 700 valid responses) and structural model analysis using PLS-SEM (SmartPLS 4)

Appendix 2. Detailed Measurement Items (Operational Indicators)

Table A1. Measurement items and Likert scale.

Construct	Code	Measurement Item	1	2	3	4	5
Product Innovation Capability (PIC)	PIC1	Ability to generate new products	☐	☐	☐	☐	☐
	PIC2	Ability to design innovative formats	☐	☐	☐	☐	☐
	PIC3	Development of new customer bases	☐	☐	☐	☐	☐
	PIC4	Modification with alternative materials	☐	☐	☐	☐	☐
	PIC5	Product uniqueness in quality and pricing	☐	☐	☐	☐	☐
Market Intelligence (MI)	MI1	Monitoring competitor promotions	☐	☐	☐	☐	☐
	MI2	Observation of product launches	☐	☐	☐	☐	☐
	MI3	Feedback collection from market	☐	☐	☐	☐	☐
	MI4	Competitor sales analysis	☐	☐	☐	☐	☐
	MI5	Monitoring marketing strategies	☐	☐	☐	☐	☐

Construct	Code	Measurement Item	1	2	3	4	5
Product Exploration Capability (PEC)	PEC1	Benchmarking with other firms	☐	☐	☐	☐	☐
	PEC2	Acquiring new insights	☐	☐	☐	☐	☐
	PEC3	Discovering market opportunities	☐	☐	☐	☐	☐
	PEC4	Developing product prototypes or experiments	☐	☐	☐	☐	☐
Technology Accessibility (TA)	TA1	Access to innovation technologies	☐	☐	☐	☐	☐
	TA2	Production of superior products	☐	☐	☐	☐	☐
	TA3	Speed and efficiency of service acquisition	☐	☐	☐	☐	☐
	TA4	Facility accessibility	☐	☐	☐	☐	☐
	TA5	Awareness of customer location	☐	☐	☐	☐	☐
Collaboration Network Strength (CNS)	CNS1	Dedicated collaboration teams	☐	☐	☐	☐	☐
	CNS2	Policy-supported collaboration systems	☐	☐	☐	☐	☐
	CNS3	Proactive cooperation	☐	☐	☐	☐	☐
	CNS4	Sustainable partnership commitments	☐	☐	☐	☐	☐
	CNS5	Long-term collaboration mindset	☐	☐	☐	☐	☐
Market Literacy (ML)	ML1	Understanding of trends	☐	☐	☐	☐	☐
	ML2	Identification of consumer needs	☐	☐	☐	☐	☐
	ML3	Explanation of market rejection	☐	☐	☐	☐	☐
	ML4	Interpretation of demand increase	☐	☐	☐	☐	☐
	ML5	Understanding of customer behavior	☐	☐	☐	☐	☐
Consumer Preference Orientation (CPO)	CPO1	Loyalty development	☐	☐	☐	☐	☐
	CPO2	Consumer education	☐	☐	☐	☐	☐
	CPO3	Attraction of new users	☐	☐	☐	☐	☐
	CPO4	Control over consumer behavior	☐	☐	☐	☐	☐
	CPO5	Adjustment to preferences	☐	☐	☐	☐	☐
Niche Market Mastery (NMM)	NMM1	Market expansion strategies	☐	☐	☐	☐	☐
	NMM2	Product/service specialization	☐	☐	☐	☐	☐
	NMM3	Market share protection	☐	☐	☐	☐	☐
	NMM4	Market growth	☐	☐	☐	☐	☐
	NMM5	Adaptation strategy	☐	☐	☐	☐	☐
Future Adaptation	FAC1	Quick responsiveness	☐	☐	☐	☐	☐

Construct	Code	Measurement Item	1	2	3	4	5
Capability (FAC)							
	FAC2	Flexibility to change	☐	☐	☐	☐	☐
	FAC3	Understanding evolving needs	☐	☐	☐	☐	☐
	FAC4	Predictive capability	☐	☐	☐	☐	☐
Digital Capability (DC)	DC1	Adoption of digital platforms	☐	☐	☐	☐	☐
	DC2	Integration of digital tools	☐	☐	☐	☐	☐
	DC3	Data-driven decision-making	☐	☐	☐	☐	☐
	DC4	Agility in digital trends	☐	☐	☐	☐	☐
	DC5	Digital skills of employees	☐	☐	☐	☐	☐
Marketing Performance (MP)	MP1	Sales volume growth	☐	☐	☐	☐	☐
	MP2	Customer base expansion	☐	☐	☐	☐	☐
	MP3	Profitability	☐	☐	☐	☐	☐
	MP4	Market share capture	☐	☐	☐	☐	☐
	MP5	Market competitiveness	☐	☐	☐	☐	☐