

Digital Value Resonance and Customer Participation: Key Drivers of Marketing Performance and Distinctive Management Competencies

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ABSTRACT

Purpose – This study examines the association between customer participation and perceived marketing performance among Indonesian MSMEs through distinctive management competencies and the moderating role of digital value resonance, drawing on Service-Dominant Logic (S-DL).

Design/methodology/approach – Survey data from 175 Indonesian MSME owners/managers, obtained through purposive online sampling, were analyzed using PLS-SEM in SmartPLS. Moderated mediation and sensitivity analyses were conducted with 5,000 bootstrap resamples.

Finding/Results – Customer participation is positively associated with management competencies. Its relationship with perceived marketing performance is negative at low digital value resonance, insignificant at the mean ($\beta = -0.068$), and positive but insignificant at high levels. Management competencies show a positive indirect association ($\beta = 0.427$ at the mean), which weakens as digital value resonance increases (index = -0.129 , 95% CI [-0.263 , -0.027]). Digital value resonance strengthens the participation–performance association ($\beta = 0.196$) but weakens the competencies–performance association ($\beta = -0.186$). Partial discriminant validity warrants caution.

Originality/Value – The study extends S-DL by identifying contrasting, conditional roles of digital value resonance across participation and competency pathways. Given its cross-sectional, single-source design, the findings indicate associations rather than causal effects.

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1. Introduction

Optimal marketing performance is a key indicator of business success in today's competitive market (Oduro & Mensah-Williams, 2023). Customer participation drives new product development (Heng et al., 2020; Morgan et al., 2019) and is a key factor in product innovation that adapts to market needs (Zhang et al., 2024). Understanding how customer participation affects marketing performance is crucial for business owners. However, its success relies on effective integration of digital technologies and distinctive management competencies. This study addresses the gap in how these factors synergize within MSMEs, proposing that (1) customer participation enhances distinctive management competencies, (2) distinctive management competencies mediate the association between participation and perceived marketing performance, and (3) digital value resonance moderates both the direct participation–performance path and the competencies–performance path, so that the indirect effect is conditional on digital value resonance. Throughout the paper, marketing performance refers to perceived (self-reported) marketing performance. Adequate technological infrastructure is essential to support the process of value creation from customer participation (Kamasak, 2017; Sashi, 2021). Previous research on customer participation and marketing performance has produced contradictory results, indicating a need for further research to explain and bridge these discrepancies.

Previous research shows mixed results on customer participation's impact on marketing performance. Some studies report positive outcomes (Samuelsson, 2023), while others show inconsistent or negative outcomes (Dong & Wu, 2015). Therefore, this study poses two questions:

RQ1: How can the controversy surrounding the findings on the role of customer participation in enhancing marketing performance be addressed?

RQ2: What are the concrete strategies for business owners to create customer value or mitigate threats in the environment?

Distinctive management competencies, within service-dominant logic (S-DL), enable managers to co-create value, integrate resources, and drive innovation. These competencies involve stakeholder collaboration, technology utilization, and customer prioritization (Lusch et al., 2007; Waheed & Kausar, 2020). In the context of SMEs, distinctive management competencies play a crucial role in enhancing marketing performance. These competencies allow SMEs to analyze customer data and refine their service offerings, resulting in more personalized experiences. Moreover, fostering a culture of innovation helps SMEs to continually improve their processes, and remain competitive in the market. The application of these competencies within the S-DL framework can significantly enhance firm performance and competitive advantage (Karpen et al., 2012; Khan et al., 2019; Wilden et al., 2017). Therefore, the role of distinctive management competencies presents a new leverage point for the relationship between customer participation and marketing performance.

Research suggests customer participation can improve marketing performance through stronger brand orientation and collaboration (Carlson et al., 2018; Chang et al., 2018). However, some studies indicate it can cause stress and dissatisfaction, negatively affecting performance (Blut et al., 2020). This mixed evidence highlights the need for further investigation into how customer participation can be optimized to enhance performance. Wang et al. (2020) argue that participation accelerates innovation, while Dong et al. (2015) note that decreased service quality can negatively affect participation. Negative involvement can also reduce marketing capabilities Rahman et al. (2022) found that negative customer

involvement can reduce a company's marketing capabilities, indicating the ambivalent impact of customer participation. Thus, empirical testing of the value creation process is needed to resolve these discrepancies.

This study empirically tests distinctive management competencies as mediators and digital value resonance as a moderator. Adopting the service-dominant logic (S-DL) it emphasizes that value is created through interactions between companies and customers, where customers act as co-creators (Vargo & Lusch, 2004). Within this framework, customer participation is regarded as a valuable resource that possesses knowledge and skills to co-create value with the company (Vargo & Lusch, 2008a). Digital value resonance enhances collaboration via digital platforms, optimizing participation and improving marketing performance (Lusch & Vargo, 2006; Lusch et al., 2007). This approach is especially relevant to SMEs in Indonesia, offering insights on leveraging management competencies and digital technology for marketing excellence. This research focuses on SMEs in sectors such as trade, culinary arts, products, and services in Indonesia. It aims to deepen understanding of how customer participation impacts marketing performance in these dynamic business contexts. Recent studies on value co-creation emphasize the growing importance of digital platforms for enhancing customer engagement and performance (Gallarza et al., 2023; Liu & Tan, 2023; Pandey & Kumar, 2020; Pham et al., 2022). This study argues that valuable resources are generated through the collaboration between management and customers, strengthening marketing performance.

This research aims to examine the role of value creation mechanisms in explaining the relationship between customer participation and marketing performance. It proposes that participation is associated with performance through distinctive management competencies and that digital value resonance conditions this pathway. Firms that involve customers and develop effective management strategies may be better placed to achieve marketing success, although the cross-sectional design supports associations and not causal effects. This study offers a new perspective on the mediation mechanisms linking customer engagement to marketing outcomes. This manuscript is structured as follows: The introduction provides the research context, focusing on customer participation in MSMEs and its effect on marketing performance, alongside the roles of management competencies and digital value resonance. The literature review discusses the S-DL framework and its relevance. The methodology outlines the quantitative approach, including structural equation modeling (SEM) and sampling. The results emphasize the mediating role of distinctive management competencies, the moderating effect of digital value resonance, and the resulting conditional indirect effects. The discussion interprets the findings, and the conclusion summarizes the contributions and future research directions.

2. Literature Review & Hypothesis Development

2.1. A Perspective Service-Dominant Logic (S-DL)

S-DL suggests that value is co-created through interactions between businesses and consumers, with both active participating. This is crucial for MSMEs, which relies on customer engagement to enhance competitiveness and marketing performance. Distinctive management competencies mediate this relationship by integrating customer input into business operations, improving service delivery and innovation (Ponsignon et al., 2021). By adopting these processes, MSMEs can better align their offerings with market demands, boosting marketing performance.

Digital value resonance enhances the impact of customer participation by enabling seamless interactions through digital platforms, increasing engagement and satisfaction (Gao et al., 2023). Digital tools support value co-creation, helping MSMEs harness customer input more effectively. Studies show that digital marketing capabilities significantly improve MSME performance by enhancing customer outreach (Sashi, 2021). Thus, integrating digital tools with S-DL principles fosters a collaborative environment, driving better marketing outcomes and sustainable growth.

Construct definitions and boundaries. Four constructs are used, each under a single term throughout the manuscript. Customer participation (CP) is the extent to which customers actively contribute feedback, ideas, and knowledge to the firm's offerings (Ajmal et al., 2023; Bagherzadeh et al., 2020; Xie et al., 2020). Marketing performance (MP) is perceived marketing performance: the owner's or manager's self-reported assessment of sales growth, revenue improvement, customer advocacy, and market-coverage expansion relative to previous periods (Farida & Prabawani, 2021; Heng et al., 2020; Rosita et al., 2023); it is not audited sales, accounting, or market-share data.

Digital value resonance (DVR) is defined as the degree to which a firm's digital interactions resonate with customers' value expectations, that is, the extent to which digital channels allow the firm and its customers to align expectations, exchange value continuously, and jointly create value (Panjaitan et al., 2021). The term "resonance" follows the relational logic of brand resonance, in which a deep and mutually reinforcing bond between customer and firm results from interaction (Cheng et al., 2019), and it is applied here to the digital interface of value co-creation under S-DL (Lusch & Vargo, 2006; Vargo & Lusch, 2008a). DVR is therefore an interaction-quality construct and is distinguished from neighboring constructs by what it describes. Digital readiness or technology readiness is an antecedent disposition to adopt technology; digital capability and digital marketing capability are the firm's stock of resources and processes for using digital tools (Apasrawirote et al., 2022); and customer-engagement technology is the tool itself. DVR does not measure whether such resources exist but whether digital interactions align customer expectations with the firm's offerings and sustain value exchange. Its measurement draws on Cheng et al. (2019) and Panjaitan et al. (2021) and was elaborated for this study into four reflective items (Table 2), whose dimension labels were revised to match the item wording. Because the construct is relatively new and its scale history is limited, its distinctiveness is treated as supported but not unequivocal (see the discriminant validity results and the limitations).

Distinctive management competencies (DMC) refers to managers' capability to integrate customer knowledge, adapt strategic decisions, and coordinate organizational resources to support value creation and market performance (Ng et al., 2020; Raza Bilal et al., 2017). In this study DMC is specified as a reflective construct: its five indicators (idea exploration, strategy adaptation, technology adaptation, target setting, and customer-oriented promotion) are treated as interchangeable manifestations of one underlying customer-oriented managerial capability, consistent with their moderately high and similar loadings (0.730–0.798). The reflective specification rests on three arguments. First, DMC is defined as a general, customer-oriented managerial capability that is a property of how the owner-manager runs the business; in owner-managed MSMEs the same person evaluates ideas, adapts strategy and technology, sets targets, and designs promotion, so a higher level of this capability is expected to show up in all five behaviors at the same time, which is the common-cause logic of reflective measurement (Jarvis et al., 2003). Second, the items covary strongly (Cronbach's alpha 0.828;

loadings 0.730–0.798) and each is a manifestation of the same domain, customer-oriented adaptive management, so that removing one item should not change the meaning of the construct. Third, a composite specification gives virtually identical estimates (Section 3.5). Against this, the five behaviors are distinct activities, and a formative view in which each competence contributes separately to the capability is equally defensible (Diamantopoulos & Winklhofer, 2001); the evidence does not settle this question, and it is reported as a limitation. Four of the five DMC items (idea exploration, strategy adaptation, target setting, and customer-oriented promotion) refer to customer ideas, needs, insights, or knowledge, and therefore share part of their content domain with customer participation; this overlap is examined in the Discussion.

2.2. Customer Participation and Marketing Performance

Customer participation is central to S-DL, where customers act as co-creators of value (Vargo & Lusch, 2004). Increased customer involvement in product development and feedback leads to better alignment with customer needs, improving satisfaction and loyalty (Cheung & To, 2016). This collaboration enhances service quality, competitive advantage, and ultimately, marketing performance (Ercsey, 2017). Recent studies reinforce this link. For example, Adeoye et al. (2022); Wu and Feiyan (2018), show that active customer participation boosts marketing metrics such as retention and sales growth. Additionally, Mishra et al. (2020); Zhang et al. (2015), demonstrated that leveraging customer input in marketing strategies increases brand trust and market share. These findings highlight the key role of customer involvement in marketing success within the S-DL framework. Therefore, we hypothesize:

H1: Higher customer participation is associated with higher perceived marketing performance at the mean level of digital value resonance

2.2 Customer Participation and Distinctive Management Competencies

Customer participation is a fundamental component of S-DL, emphasizing the role of customers as co-creators of value in service exchanges (Vargo & Lusch, 2004). Research indicates that increased customer participation enhances marketing performance by fostering deeper engagement and collaboration between customers and firms. For instance, greater customer involvement in product development and feedback processes leads to a better alignment of products and services with customers' needs, resulting in increased customer satisfaction and loyalty (Cheung & To, 2016). This collaborative strategy increases reliability and competitiveness, enhancing marketing performance (Ercsey, 2017). Recent research shows that client cooperation improves the results of organizations. For example, research by Adeoye et al. (2022); Wu and Feiyan (2018), found that active customer interaction in the value-sharing stages boosts marketing performance measures, such as customer retention and sales growth. These findings underscore the vital role of client participation in leveraging marketing success within the S-DL framework. Therefore, we hypothesize:

H2: Higher customer participation is associated with higher distinctive management competencies

2.3. The Moderating Role of Digital Value Resonance Between Customer Participation and Marketing Performance

Digital value resonance, which enhances interactions through digital platforms, amplifies the positive impact of customer participation on marketing performance (Sashi, 2021). Digital tools enable personalized customer interactions, increasing participation in value co-creation. Digital interactions can personalize exchanges and improve engagement, and customer participation and value creation in online brand communities have been shown to improve

brand relationship performance (Carlson et al., 2019). Sashi (2021) likewise argues that digital communication enables value co-creation and customer engagement in business networks. These findings suggest that digital tools can increase the benefit that firms obtain from customer participation. These findings underscore the importance of digital tools in maximizing customer participation's benefits in marketing. Therefore, we hypothesize:

H3: Digital value resonance moderates the relationship between customer participation and marketing performance

2.4. The Moderating Role of Digital Value Resonance Between Distinctive Management Competencies and Marketing Performance

How digital value resonance conditions the payoff of managerial competencies is theoretically open. On a complementarity view, digital data and interaction channels help managers identify and evaluate customer ideas and execute marketing strategies more precisely, so digital resonance should amplify the competencies–performance link (Lichtenthaler, 2021; Rantala et al., 2019). On a substitution view, digital interfaces embed part of the sensing and coordination work that managerial judgment otherwise performs, so the marginal contribution of managerial competencies should diminish as digital resonance rises (diminishing returns or digital managerial redundancy), and digital transformation pays off only when technological resources are aligned with managerial processes (Hughes, 2019). Because these arguments predict opposite signs, the direction of the moderation is treated as an empirical question. Therefore, we hypothesize:

H4: Digital value resonance moderates the relationship between distinctive management competencies and marketing performance.

2.5. Digital Value Resonance and Marketing Performance

In S-DL, digital value resonance influences marketing performance by leveraging digital tools for co-creating value with customers. Digital marketing strategies, such as data analytics and social media, help SMEs tailor offerings, improving customer loyalty and marketing effectiveness (Apasrawirote et al., 2022; Saura et al., 2021). By using digital technologies, SMEs gain better insights into customer behavior, resulting in more effective advertising. Aligning digital strategies with sustainability goals is key for long-term success, as S-DL emphasizes co-creating value while ensuring sustainability. SMEs adopting digital technologies can enhance their marketing performance and overall competitiveness, fostering sustainable growth (Suciu et al., 2021).

H5: Higher digital value resonance leads to higher marketing performance

2.6. Distinctive Management Competencies and Marketing Performance

Distinctive management competencies focus on customer-centricity, innovation, and service quality to create value and enhance marketing performance. Within S-DL, these competencies are vital for facilitating value co-creation between businesses and customers (Cheung & To, 2016). S-DL shifts focus from goods to services, with value emerging when customers use the resources provided by businesses (Bürkel & Zimmermann, 2021; Kristensen & Remmen, 2019). These competencies integrate services and goods within a customer-centric framework, driving service quality and satisfaction (Huarng & Más-Verdú, 2018). The focus on intangible services highlights the importance of cultivating these abilities to improve marketing strategies and competitiveness. Therefore, we hypothesize:

H6: Higher distinctive management competencies lead to higher marketing performance

2.7. Customer Participation in Marketing Performance through Distinctive Management Competencies

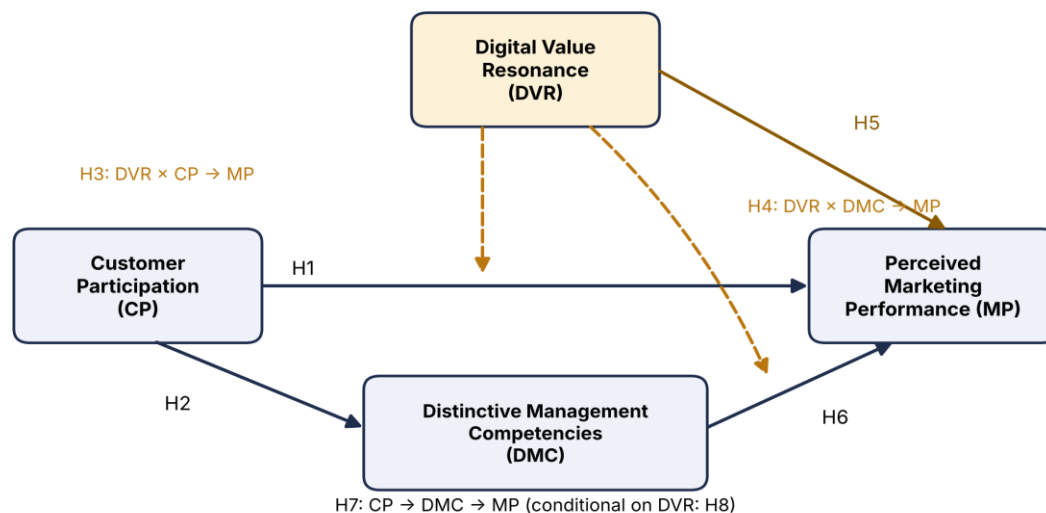
Customer participation may be associated with higher marketing performance through the development of distinctive management competencies. By involving customers in value co-creation, businesses can adapt management practices to better meet market demands. Research shows that customer-driven management processes improve service quality, innovation, and overall performance, leading to better marketing outcomes (Prebensen et al., 2016). Evidence on customer participation in new product development indicates that its effects on performance operate through intermediate mechanisms and key contingencies (Morgan et al., 2018), and managerial competencies have been linked to SME growth decisions (Raza Bilal et al., 2017). Distinctive management competencies are therefore expected to be the channel through which customer inputs are converted into marketing outcomes. So, that argument can then be explained in this relationship:

H7: Distinctive management competencies mediate the relationship between customer participation and marketing performance.

Because digital value resonance is hypothesized to moderate the DMC $\rightarrow$ MP path (H4), the indirect effect of customer participation on marketing performance through DMC (H7) is not constant but depends on the level of digital value resonance; this is a second-stage moderated-mediation (conditional indirect-effect) structure (Hayes, 2015; Preacher et al., 2007). Whether the mediating role of DMC becomes stronger or weaker as digital resonance rises follows from the sign of the DVR $\times$ DMC interaction and is evaluated with the index of moderated mediation, defined as the product of the CP $\rightarrow$ DMC path and the DVR $\times$ DMC $\rightarrow$ MP coefficient. Therefore, we hypothesize:

H8: The indirect effect of customer participation on marketing performance through distinctive management competencies is conditional on digital value resonance (moderated mediation).

Figure 1. Conditional-process (moderated-mediation) research model, H1–H8



Note: Solid arrows are direct paths; dashed arrows are the moderating effects of digital value resonance (DVR) on the CP $\rightarrow$ MP path (H3) and on the DMC $\rightarrow$ MP path (H4). H7 is the indirect effect CP $\rightarrow$ DMC $\rightarrow$ MP and H8 states that this indirect effect is conditional on DVR. CP = customer participation; DMC = distinctive management competencies; MP = perceived marketing performance.

3. Methodology

3.1 Data Analysis

The data analysis followed several key steps. First, the measurement model was evaluated for reliability and validity. Outer loadings above 0.7 were deemed satisfactory, though slightly lower loadings were accepted if they contributed significantly to the construct (Hair et al., 2010). Reliability was confirmed with Cronbach's Alpha and Composite Reliability values, all exceeding the 0.7 threshold (Kiliç, 2016). Next, the structural model was tested to assess relationships between constructs. The R^2 values for DMC and MP were 0.482 and 0.603, respectively, explaining 48.2% and 60.3% of the variance. Adjusted R^2 values were slightly lower but still indicated strong explanatory power. Global goodness-of-fit (GoF) was not used as evidence of model validity because it cannot reliably distinguish valid from invalid models (Henseler & Sarstedt, 2013); the structural model is instead judged from collinearity (inner VIF), R^2 , effect sizes (f^2), and bootstrapped path estimates (Hair et al., 2019b). In summary, this study used a quantitative approach, analyzing data with SEM using SmartPLS. PLS-SEM was chosen because the model contains a mediator, two interaction terms, and a relatively new construct, for which variance-based estimation is appropriate (Hair et al., 2019b). The adequacy of the sample size is justified separately in the sample section.

Estimation settings. The model was estimated with SmartPLS 3 (Ringle et al., 2015) using the path weighting scheme (maximum 300 iterations; stop criterion 10^{-7}) on 175 complete cases. Significance was tested with the basic nonparametric bootstrap (5,000 subsamples of 175 cases; Streukens & Leroi-Werelds, 2016), two-tailed tests at $\alpha = 0.05$, and 95% confidence intervals; the percentile intervals (2.5% and 97.5%) are reported in Tables 9 to 12. Bias-corrected and accelerated (BCa) intervals were also computed and lead to the same significance decisions for every coefficient in Table 9 and for the index of moderated mediation; the only exception is the conditional direct effect of CP on MP at -1 SD of DVR, whose BCa interval $([-0.496, 0.003])$ just includes zero. The bootstrap for the baseline model (Tables 9 and 10) is the SmartPLS 3 output with 5,000 subsamples (BCa and percentile intervals, two-tailed, path weighting scheme); a first SmartPLS run with 500 subsamples gave the same signs and the same significance decisions. The conditional effects and the index of moderated mediation are not reported by SmartPLS; they were calculated from the 5,000 SmartPLS bootstrap path coefficients (a , b , c , and both interaction terms), so the same resamples feed every interval. The sensitivity models of Section 3.5 and the out-of-sample prediction were run with an implementation of the SmartPLS two-stage algorithm in Python that reproduces the SmartPLS path coefficients, outer loadings, and interaction-term scaling of the baseline model to the fourth decimal. The two interaction terms ($DVR \times CP$ and $DVR \times DMC$) were created with the two-stage approach (Henseler & Chin, 2010): latent-variable scores of the main effects were estimated first, standardized, and multiplied to form single-indicator interaction terms in the structural model, so that simple slopes are expressed in standard-deviation units. Conditional effects were evaluated at the mean and at ± 1 SD of DVR: within each of the 5,000 bootstrap samples (each re-estimating the measurement model, the two-stage interaction terms, and the structural model) the conditional direct, indirect, and total effects and the index of moderated mediation were recomputed from the bootstrapped path coefficients, and their percentile intervals were taken from the resulting distributions. The index of moderated mediation is the product of the $CP \rightarrow DMC$ path and the $DVR \times DMC \rightarrow MP$ coefficient (Hayes, 2015). Discriminant validity was assessed among the four substantive constructs only, using the

Fornell–Larcker criterion and HTMT (Henseler et al., 2015); interaction terms belong to the structural analysis and were excluded from that assessment.

3.2 Common Method Bias Assessment

Component	Eigenvalue	% of Variance	Cumulative %
1	11.947	49.780	49.780

Source: Data Processed (2026)

Because all constructs were measured using a single questionnaire completed by the same respondents, potential common method bias was assessed using Harman’s single-factor test. All measurement items were entered into an exploratory factor analysis, and the first factor accounted for 49.780% of the total variance. This value lies just below the conventional 50% cut-off, and Harman’s single-factor test is an insensitive diagnostic that cannot demonstrate the absence of common method variance (Podsakoff et al., 2003). It is therefore interpreted only as showing that no single factor accounted for the majority of the covariance; common method bias cannot be ruled out, and it is treated as a limitation. Procedural remedies were applied during questionnaire administration: respondents were assured of anonymity and confidentiality and of voluntary participation; the cover page stated that there were no right or wrong answers; items were short, unambiguous, and pre-tested with a small group of MSMEs; and the outcome block (marketing performance) was placed after the predictor blocks. Harman’s test was also repeated on the 19 indicators retained in the final measurement model: the first unrotated factor then accounts for 47.5% of the variance (eigenvalue 9.018). As a stronger diagnostic suited to PLS-SEM, the full-collinearity assessment of Kock (2015) was run on the latent-variable scores (each construct regressed on all other constructs). The full-collinearity VIFs are 2.52 for CP, 2.90 for DVR, 2.37 for MP, and 3.46 for DMC. Three values are below the 3.3 threshold, but the VIF of DMC slightly exceeds it, which indicates that common method bias cannot be excluded for the DMC measures and that the DMC-related estimates should be read with caution. (The inner VIFs in Table 7, maximum 2.994, are not a full-collinearity test.) The very large CP → DMC association ($\beta = 0.694$) and the high correlations among DVR, DMC, and MP are particularly exposed to shared-method variance because the same owner or manager rated all constructs.

3.3 Research instruments

The research instrument was a structured questionnaire designed to capture customer participation behavior, including customer involvement in knowledge sharing, feedback contribution, idea generation, and value co-creation activities. It was developed based on established scales from previous studies and adapted to the context of Indonesian MSMEs. Respondents evaluated their experiences using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was pre-tested with a small group of MSMEs to ensure clarity and relevance. A Cronbach’s Alpha value of over 0.7 confirmed reliability, though 0.6 was acceptable (Hair et al., 2010). Digital value resonance was measured as the extent to which digital interactions facilitate shared value creation, alignment between customer expectations and firm offerings, and continuous value exchange between customers and firms (Ajmal et al., 2023; Bagherzadeh et al., 2020; Xie et al., 2020). Digital value resonance was operationalized with four reflective items covering needs alignment through digital platforms, joint digital value exchange, technology-enabled identification of market opportunities, and continuous digital interaction (Cheng et al., 2019; Panjaitan et al., 2021). The dimension labels in Table 2 were revised to match the wording of the items; the items themselves and all statistics are unchanged. Distinctive management competencies (DMC)

represent managerial capabilities to integrate customer knowledge, adapt strategic decisions, and coordinate organizational resources to support value creation and market performance (Ng et al., 2020; Raza Bilal et al., 2017); DMC is specified as a reflective construct (see the construct definitions in the Literature Review). Marketing performance was measured as perceived (self-reported) marketing performance, that is, the owner's or manager's Likert-scale assessment of sales growth, revenue improvement, customer advocacy, and market-coverage expansion relative to the previous period; it is not based on audited sales figures, accounting records, or market-share statistics (Farida & Prabawani, 2021; Heng et al., 2020; Rosita et al., 2023).

3.3 Sample and data collection

This study employed a purposive sampling technique to recruit MSMEs operating in Indonesia. The sample selection was based on specific criteria: MSMEs must have been operating for more than two years and be involved in sectors such as trade, culinary, creative industries, and services. The eligibility criteria were verified during the respondent screening process before questionnaire distribution. An online closed questionnaire was used to collect data from March to May 2026. A total of 190 questionnaires were distributed, and 175 usable responses were obtained, resulting in a response rate of 92.1%. Although this response rate reflects strong participation among the invited respondents, the purposive sampling design does not allow the sample to be considered statistically representative of the entire Indonesian MSME population. Therefore, the findings should be interpreted within the context of the sampled MSMEs rather than generalized to all Indonesian MSMEs.

Sampling coverage. Respondents were recruited through purposive online sampling. The questionnaire did not record the respondent's province or city, so the geographic distribution of the sample cannot be reported and the sample may be concentrated in the researchers' professional networks. Sectoral representation is uneven: creative industries account for 44.6% of respondents (Table 1). Legal form, ownership characteristics, and number of employees were also not collected, so the business-age, income, and sector profile in Table 1 is the only descriptive information available. The findings are therefore interpreted as applying to the sampled Indonesian MSMEs and not to the national MSME population.

Sample size justification. The most complex endogenous equation (MP) receives five structural paths (CP, DVR, DMC, DVR $\times$ CP, and DVR $\times$ DMC), so the ten-times rule requires at least 50 cases. A power analysis for a regression with five predictors (F test of a single predictor's increment, $\alpha = 0.05$, $n = 175$; Cohen, 1988) gives descriptive power of 0.86 and 0.89 for the observed interaction effects ($f^2 = 0.053$ for DVR $\times$ DMC and 0.059 for DVR $\times$ CP), and a minimum detectable f^2 of about 0.045 at 80% power; power for the small direct CP effect ($f^2 = 0.005$) is only about 0.15. With the inverse square-root method (Kock & Hadaya, 2018), detecting a path of $|\beta| = 0.196$ at the 5% level with 80% power requires about 161 cases, whereas $|\beta| = 0.186$ requires about 179, slightly more than the 175 available. The interaction estimates are therefore adequately but not generously powered, and the non-significant CP $\rightarrow$ MP coefficient at the mean level of DVR should not be read as evidence of no effect.

Table 1. Demographic Information of the Respondents

No	Characteristics	Total	%
1	Sex	Male	111
		Female	64
2	Age	< 20 years old	23

		> 20 to 30 years old	40	22.9
		> 30 to 40 years old	34	19.4
		> 40 to 50 years old	46	26.3
		> 50 years old	32	18.3
3	Education	Senior High School	42	24.0
		Bachelor's degree	43	24.6
		Master's degree	52	29.7
		Doctoral Degree	38	21.7
4	The duration of the business	>2 to 3 years	17	9.7
		> 3 to 5 years	53	30.3
		> 5 to 10 years	69	39.4
		> 10 years	36	20.6
5	Income/month	< IDR 10 million	79	45.1
		>IDR 10 million to 25 million	64	36.6
		>IDR. 25 million to 100 million	23	13.1
		> IDR 100 million to 200 million	7	4.0
		> IDR 200 million	2	1.1
6	Business Sector	Creative Industry	78	44.6
		Trading	43	24.6
		Culinary	32	18.3
		Others	22	12.6

Sources: Collected Data (2026)

All respondents satisfied the minimum business-age criterion of more than two years. Of the 175 participating MSMEs, 17 (9.7%) had operated for more than two and up to three years, 53 (30.3%) for more than three and up to five years, 69 (39.4%) for more than five and up to ten years, and 36 (20.6%) for more than ten years.

Diagnostic Test

Several diagnostic tests were conducted to ensure the robustness of the model:

- **Convergent Validity:** This was assessed through the AVE for each construction. A value of AVE greater than 0.5 was used as the threshold, confirming that the indicators converge on a common latent construct.
- **Discriminant Validity:** Fornell–Larcker criterion and HTMT (0.85 and 0.90 thresholds) were applied among the four substantive constructs (CP, DVR, DMC, and MP) to ensure that each construct is distinct from the others; interaction terms were excluded from this

assessment. The square root of each construct's AVE was compared to the correlations with other constructs, confirming adequate discriminant validity.

- **Reliability:** Cronbach's Alpha and Composite Reliability (CR) were calculated for each construct, with values exceeding the 0.7 cut-off, indicating strong internal consistency.

Table 2. Variable Measurement Instruments

Variable	Dimension	Indicator	Sources
Customer Participation (X1)	Feedback channels (X1.1)	Customers actively provide feedback that contributes to improving our products or services.	Ajmal et al. (2023); Bagherzadeh et al. (2020); Xie et al. (2020)
	Engagement contact (X1.2)	Customers frequently provide suggestions and ideas that influence our product or service improvements	
	Inquiry Hotline (X1.3)	Customers actively communicate their needs, experiences, and opinions to support business improvement	
	Product Discussion (X1.4)	Customers participate in discussions regarding product features, improvements, and new offerings	Elaborated from
	Feature Meetings (X1.5)	Customers contribute ideas and opinions during product development and improvement discussions	
		Customer suggestions are	

Variable	Dimension	Indicator	Sources
Digital Value Resonance (X2)	Improvement suggestions (X1.6)	incorporated into our product improvement and decision-making processes	Cheng et al. (2019); Panjaitan et al. (2021)
	Needs alignment (X2.1)	Digital platforms help us understand customer needs and align our products or services with customer expectations.	
		Digital interactions enable customers and our firm to jointly create and exchange value.	
	Joint value exchange (X2.2)	We find market opportunities faster with technology compared to face-to-face interactions.	
	Market-opportunity identification (X2.3)	Our digital channels support continuous interaction and value exchange with customers.	Elaborated from Ng et al. (2020);
		Our managers systematically identify and evaluate customer-driven ideas for improving products or services.	Raza Bilal et al. (2017)
	Continuous interaction (X2.4)		
	Idea exploration (X3.1)	Our managers adapt organizational strategies based on changing customer	

Variable	Dimension	Indicator	Sources
Distinctive Management Competencies (X3)		needs and market conditions	
	Strategy adaptation (X3.2)	Our leadership will always adapt to the latest technology.	
	Technology adaptation (X3.3)	Our managers establish strategic objectives that incorporate customer insights and market opportunities	
	Target setting (X3.4)	Our managers develop customer-oriented marketing strategies based on accumulated customer knowledge	Farida and Prabawani (2021); Heng et al. (2020); Rosita et al. (2023)
	Customer Promotion (X3.5)	Our actual sales volume has increased compared with the previous year	
Marketing Performance (Y)		Our actual revenue growth has improved compared with previous business periods	
	Annual Sales (Y.1)	Our customers actively recommend our products or services to other potential customers	
	Revenue Growth (Y.2)	Our business has successfully expanded its market	

Variable	Dimension	Indicator	Sources
		coverage during recent period.	
	Product Advocacy (Y.3)		
	Coverage expansion (Y.4)		

Source: Data Elaborated, Note: Dimension labels for DVR and DMC were revised to match item wording. The Y items are self-reported perceptions of sales, revenue, advocacy, and coverage; they are not audited data.2026

4. Result and Discussion

4.1 Discriminant Validity

Discriminant validity was assessed using both the Fornell and Larcker (1981a) and the heterotrait-monotrait ratio (HTMT; Henseler et al., 2015), as presented in Tables 3 and 4. According to the Fornell-Larcker criterion, the square root of the average variance extracted (AVE) for each construct exceeded its correlations with the other constructs. Specifically, the square root of AVE for Customer Participation (CP) was 0.765, which was higher than its correlations with Digital Value Resonance (DVR = 0.740), Distinctive Management Competencies (DMC = 0.694), and Marketing Performance (MP = 0.514). Similarly, the square root of AVE for DVR was 0.795, exceeding its correlations with CP (0.740), DMC (0.732), and MP (0.625). The square root of AVE for DMC was 0.770, which was greater than its correlations with CP (0.694), DVR (0.732), and MP (0.748). Finally, the square root of AVE for MP was 0.865, exceeding its correlations with CP (0.514), DVR (0.625), and DMC (0.748). These results indicate that the Fornell-Larcker criterion was satisfied for all four substantive constructs.

The HTMT analysis (Table 4; Henseler et al., 2015) provided an additional and more stringent assessment among the four substantive constructs. The values were CP–DVR = 0.870, CP–DMC = 0.795, CP–MP = 0.573, DVR–DMC = 0.894, DVR–MP = 0.716, and DMC–MP = 0.869. All values remained below the liberal 0.90 threshold, but three pairs (DVR–DMC, CP–DVR, and DMC–MP) exceed the more conservative 0.85 criterion, which is the more appropriate benchmark when constructs are conceptually close. The interaction term $DVR \times CP$ was removed from Table 4 because interaction terms are created for the structural moderation analysis and are not substantive constructs; discriminant validity was therefore evaluated first among CP, DVR, DMC, and MP.

Taken together, the evidence shows that construct separation is only partially supported. The Fornell-Larcker criterion is met and every indicator correlates most strongly with its own construct (Table 11, Section 3.5), but the HTMT ratios of three theoretically central pairs (DVR–DMC, CP–DVR, and DMC–MP) exceed 0.85. Bootstrapped HTMT inference (5,000 resamples

of the 175 cases; percentile 95% intervals) gives CP–DVR = 0.870 [0.781, 0.954], CP–DMC = 0.795 [0.696, 0.896], CP–MP = 0.573 [0.434, 0.717], DVR–DMC = 0.894 [0.798, 0.986], DVR–MP = 0.716 [0.540, 0.870], and DMC–MP = 0.869 [0.793, 0.942]. Every upper limit is below 1.00, so no pair of constructs is empirically identical, but the upper limits for CP–DVR, DVR–DMC, and DMC–MP exceed 0.90, so a value below 0.90 cannot be demonstrated for these pairs. Discriminant validity is therefore not described as satisfied: DVR, DMC, and CP are related but separable constructs. This matters for interpretation. If DVR and DMC (or DVR and CP) partly capture overlapping perceptions of the same digital and managerial practices, the interaction coefficients may partly reflect differences among closely related perceptions rather than clearly differentiated organizational mechanisms, and the conditional-process results should be read as association patterns among related perceptions. Cross-loadings, an item-level mapping, and sensitivity re-estimations (Section 3.5) are reported for this reason.

Item-level conceptual mapping. Three of the four DVR items (X2.1 needs alignment, X2.2 joint value exchange, and X2.4 continuous interaction) describe the exchange of value between customers and the firm through digital channels, which is the interaction-resonance domain defined in the Literature Review. X2.3 (finding market opportunities faster with technology) describes a firm-side technological capability, is conceptually closest to digital capability, and has the lowest DVR loading (0.662). On the DMC side, X3.3 (adapting to the latest technology) belongs to the digital domain, and four items (X3.1, X3.2, X3.4, and X3.5) refer to customer ideas, needs, insights, or knowledge, which overlaps with the content of the CP items. These overlaps are the content-based reasons for the high HTMT ratios.

Table 3. Discriminant Validity

Fornell-Larcker Criterion	Customer Participation	Digital Value Resonance	Distinctive Management Competencies	Marketing Performance
Customer Participation	0.765			
Digital Value Resonance	0.740	0.795		
Distinctive Management Competencies	0.694	0.732	0.770	
Marketing Performance	0.514	0.625	0.748	0.865

Source: Data Processed (2026)

Table 4. HTMT Discriminant Validity

Construct	CP	DVR	DMC	MP
DVR	0.870			
DMC	0.795	0.894		
MP	0.573	0.716	0.869	

Source: Data Processed (2026)

4.2. Convergent Validity

The results demonstrated satisfactory validity and reliability for the constructs, as shown in Table 5. Most outer loadings were above the 0.7 threshold for indicator reliability (Hair et al., 2019a) except for X1.5 (0.678) and X2.3 (0.662), which, though slightly below 0.7, were still acceptable due to their proximity. Cronbach's Alpha values ranged from 0.804 for DVR to 0.888 for MP, all exceeding the 0.7 benchmark, indicating good internal consistency. Composite Reliability values also surpassed 0.7, with CR ranging from 0.871 for DVR to 0.922 for MP, supporting the constructs' reliability Bagozzi and Yi (1988). Average Variance Extracted (AVE) values were all above the 0.5 threshold, suggesting the constructs captured a significant proportion of variance, with AVE values ranging from 0.586 for CP to 0.749 for MP Fornell and Larcker (1981a). These results confirmed that the measurement model was both reliable and valid, ensuring the robustness of the constructs. The indicator X2.3 (0.662; technology-enabled identification of market opportunities) is conceptually closest to a generic digital capability; it is retained for content validity, and the AVE of DVR (0.631) remains above 0.50.

Table 5. Composite Reliability, Cronbach's Alpha, and AVE

Variable	Indicator	Outer Loading	Conclusion	CA	CR	AVE
Customer Participation (X1)	X1.1	0.719	valid	0.860	0.894	0.586
	X1.2	0.817	valid			
	X1.3	0.756	valid			
	X1.4	0.819	valid			
	X1.5	0.678	valid			
Digital Value Resonance (X2)	X1.6	0.792	valid	0.804	0.871	0.631
	X2.1	0.740	valid			
	X2.2	0.886	valid			
	X2.3	0.662	valid			
Distinctive Management Competencies (X3)	X2.4	0.869	valid	0.828	0.879	0.593
	X3.1	0.798	valid			
	X3.2	0.730	valid			
	X3.3	0.778	valid			
	X3.4	0.797	valid			
Marketing Performance (Y)	X3.5	0.744	valid	0.888	0.922	0.749
	Y.1	0.800	valid			
	Y.2	0.878	valid			
	Y.3	0.877	valid			
	Y.4	0.903	valid			

Source: Data Processed (2026)

The predictive relevance of the endogenous constructs was assessed using the blindfolding procedure in SmartPLS. The Q^2 values were calculated based on the SSO and SSE values, following the Stone-Geisser criterion. Values greater than zero indicate predictive relevance of the model. SmartPLS also allows for the evaluation of both direct and indirect effects, making it a powerful tool for investigating mediation and moderation effects, such as those presented in this study. These Q^2 values express in-sample (Stone-Geisser) predictive relevance and not out-of-sample predictive performance; out-of-sample prediction is assessed separately below. The model is therefore evaluated at three levels that should not be conflated: (i) in-sample explanatory power (R^2 and f^2 ; Tables 6 and 8), (ii) in-sample Stone-Geisser predictive relevance (Q^2), and (iii) out-of-sample prediction, assessed with a PLSpredict-type procedure (Shmueli et al., 2019) using 10 folds repeated 10 times and the direct-antecedents approach. Out-of-sample prediction was assessed for two specifications: the main-effects model ($CP \rightarrow DMC \rightarrow MP$, $CP \rightarrow MP$, and $DVR \rightarrow MP$) and the full conditional-process model that adds $DVR \times CP$ and $DVR \times DMC$. For the four marketing-performance indicators (Y.1 to Y.4), the RMSE was 0.479, 0.429, 0.522, 0.494 for the main-effects model, 0.474, 0.428, 0.522, 0.488 for the full model, and 0.479, 0.431, 0.525, 0.488 for the linear-model (LM) benchmark, against 0.612, 0.604, 0.636, 0.621 for a naive mean benchmark. Both PLS specifications therefore predict held-out cases clearly better than the naive benchmark ($Q^2_{predict} = 0.387, 0.495, 0.328, 0.367$ for the main-effects model and $0.401, 0.498, 0.328, 0.384$ for the full model) and about as well as the LM benchmark; adding the two interaction terms reduced RMSE by at most 0.006. The out-of-sample evidence thus shows moderate, benchmark-level predictive accuracy and does not show that the interaction terms improve prediction; their contribution is explanatory and in-sample. No claim of high predictive power is made. The calculations used a Python implementation of the PLS algorithm that reproduces the SmartPLS outer loadings and path coefficients and should be confirmed with the PLSpredict module of SmartPLS.

Table 6. Coefficient of Determination and Predictive Relevance

Endogenous Construct	R^2	Adjusted R^2	SSO	SSE	Q^2
Distinctive Management Competencies	0.482	0.479	875.000	633.084	0.276
Marketing Performance	0.603	0.591	700.000	403.544	0.424

Source: Data Processed (2026)

The model explained 48.2% of the variance in distinctive management competencies ($R^2 = 0.482$) and 60.3% of the variance in marketing performance ($R^2 = 0.603$). The blindfolding procedure showed positive Q^2 values for distinctive management competencies (0.276) and marketing performance (0.424), indicating in-sample predictive relevance ($Q^2 > 0$).

Table 7. Inner VIF Assessment

Predictor Construct	Outcome Construct	VIF
Customer Participation	DMC	1.000
Customer Participation	MP	2.555
DVR $\times$ CP	MP	2.767
Digital Value Resonance	MP	2.994
Distinctive Management Competencies	MP	2.573

Predictor Construct	Outcome Construct	VIF
DVR × DMC	MP	2.566

Source: Data Processed (2026)

The inner VIF values ranged from 1.000 to 2.994, which are below the recommended threshold of 5.00. Therefore, the structural model does not suffer from multicollinearity problems.

Table 8. Effect Size

Relationship	f ²	Interpretation
Customer Participation → DMC	0.930	Large
Customer Participation → MP	0.005	Negligible
DVR × CP → MP	0.059	Small
DVR → MP	0.054	Small
DMC → MP	0.369	Large
DVR × DMC → MP	0.053	Small

Source: Data Processed (2026)

The effect size analysis showed that customer participation had a large effect on distinctive management competencies ($f^2 = 0.930$), while distinctive management competencies had a substantial effect on marketing performance ($f^2 = 0.369$). The interaction effects of digital value resonance showed small effect sizes ($f^2 = 0.059$ and 0.053). The very large f^2 for CP → DMC follows mechanically from the R^2 of DMC (0.482) with a single predictor ($f^2 = R^2/(1 - R^2)$) and may partly reflect conceptual overlap between customer-participation and customer-oriented competency items and shared-method variance (see the Discussion and limitations).

4.3. Hypothesis Testing

The hypothesis-testing results show that customer participation did not have a statistically significant association with perceived marketing performance at the mean level of digital value resonance ($\beta = -0.068$, $t = 0.683$, $p = 0.494$, 95% CI [-0.268, 0.122]). Because the model contains the DVR × CP interaction, this coefficient is the association of customer participation with perceived marketing performance at the reference (mean) level of digital value resonance and not a general direct effect; H1 is therefore not supported at the mean level of digital value resonance. The interval includes zero, so customer participation has no statistically distinguishable direct association with perceived marketing performance at average digital value resonance, but H3 shows that this association is conditional: it is significantly negative at low digital value resonance (-0.264), approximately zero at the mean, and positive but not significant at high digital value resonance (0.128) (Table 10). In contrast, customer participation had a strong and significant positive effect on distinctive management competencies ($\beta = 0.694$, $t = 17.028$, $p < 0.001$, 95% CI [0.617, 0.776]), supporting H2. Digital value resonance significantly moderated the relationship between customer participation and marketing performance ($\beta = 0.196$, $t = 2.357$, $p = 0.018$, 95% CI [0.032, 0.358]), supporting H3. The positive interaction coefficient indicates that higher digital value resonance strengthens the association between customer participation and marketing performance.

The interaction between digital value resonance and distinctive management competencies was also statistically significant ($\beta = -0.186$, $t = 2.315$, $p = 0.021$, 95% CI [-0.357, -0.040]), supporting H4. However, the negative coefficient indicates an attenuating moderation effect: as digital value resonance increases, the positive relationship between distinctive management

competencies and marketing performance becomes weaker. Therefore, this effect should not be described as an amplification or strengthening effect. Digital value resonance had a significant positive association with perceived marketing performance ($\beta = 0.254$, $t = 2.046$, $p = 0.041$, 95% CI [0.018, 0.503]), supporting H5. Distinctive management competencies also had a strong positive association with perceived marketing performance ($\beta = 0.615$, $t = 6.794$, $p < 0.001$, 95% CI [0.456, 0.816]), supporting H6. Finally, the indirect relationship between customer participation and marketing performance through distinctive management competencies was statistically significant ($\beta = 0.427$, $t = 5.641$, $p < 0.001$), supporting H7. The bootstrapped 95% confidence interval of this indirect effect, [0.305, 0.608] (Table 9), excludes zero. Combined with the nonsignificant direct CP $\rightarrow$ MP coefficient, this is consistent with an indirect-only mediation structure at the mean level of digital value resonance. Because digital value resonance moderates the DMC $\rightarrow$ MP path, however, the indirect effect is conditional on digital value resonance (H8; see the next subsection). The full structural model of this study is illustrated in Figure 2 below.

Table 9. Hypothesis Testing and Bootstrap Confidence Intervals

Hypothesis	Relationship	β	T Statistics	P-Value	2.5% CI	97.5% CI	Result
H1	CP $\rightarrow$ MP	-0.068	0.683	0.494	-0.268	0.122	Not Supported at mean DVR (conditional; see H3)
H2	CP $\rightarrow$ DMC	0.694	17.028	<0.001	0.617	0.776	Supported
H3	DVR $\times$ CP $\rightarrow$ MP	0.196	2.357	0.018	0.032	0.358	Supported – Positive Moderation
H4	DVR $\times$ DMC $\rightarrow$ MP	-0.186	2.315	0.021	-0.357	-0.040	Supported – Negative Moderation
H5	DVR $\rightarrow$ MP	0.254	2.046	0.041	0.018	0.503	Supported
H6	DMC $\rightarrow$ MP	0.615	6.794	<0.001	0.456	0.816	Supported
H7	CP $\rightarrow$ DMC $\rightarrow$ MP	0.427	5.641	<0.001	0.305	0.608	Supported

Source: Data Processed (2026)

Description: CP = customer participation; DMC = distinctive management competencies; DVR = digital value resonance; MP = marketing performance Intervals are percentile 95% intervals from 5,000 bootstrap subsamples. The CP $\rightarrow$ MP coefficient (H1) is conditional on the mean level of DVR because the model contains the DVR $\times$ CP interaction.

4.4 Conditional Indirect Effects (Moderated Mediation)

Because digital value resonance moderates the DMC $\rightarrow$ MP path (H4), the indirect effect in H7 is conditional on digital value resonance, and the single coefficient of 0.427 in Table 9 is the effect at the mean of digital value resonance only. Table 10 reports the conditional effects at -1 SD, the mean, and $+1$ SD. The indirect effect of CP on MP through DMC is positive at every level but declines as digital value resonance rises: 0.556 at -1 SD (95% CI [0.386, 0.825]), 0.427 at the mean ([0.305, 0.608]), and 0.297 at $+1$ SD ([0.145, 0.461]); all three intervals exclude zero. The index of moderated mediation, the product of the CP $\rightarrow$ DMC path (0.694) and the DVR $\times$ DMC $\rightarrow$ MP coefficient (-0.186), is -0.129 (bootstrap 95% CI [-0.263 , -0.027]; $t = 2.16$, $p = 0.031$); the interval excludes zero, which supports H8: the mediating role of DMC becomes weaker, not stronger, as digital value resonance increases. In contrast, the conditional direct path from

CP to MP moves from -0.264 at -1 SD (95% CI $[-0.518, -0.017]$) to 0.128 at $+1$ SD ($[-0.141, 0.389]$) (H3), so the conditional total effect rises modestly from 0.292 to 0.425 ; the direct effect is significantly negative only at low digital value resonance and is not distinguishable from zero at the mean and at $+1$ SD (the negative effect at -1 SD is borderline under BCa intervals; Section 2.1). At higher levels of digital value resonance, customer participation therefore appears to be converted into perceived marketing performance more through the direct (digital) route and less through the managerial route, although the net association remains positive at all three levels.

Table 10. Conditional Direct, Indirect, and Total Effects of CP on MP at Levels of DVR

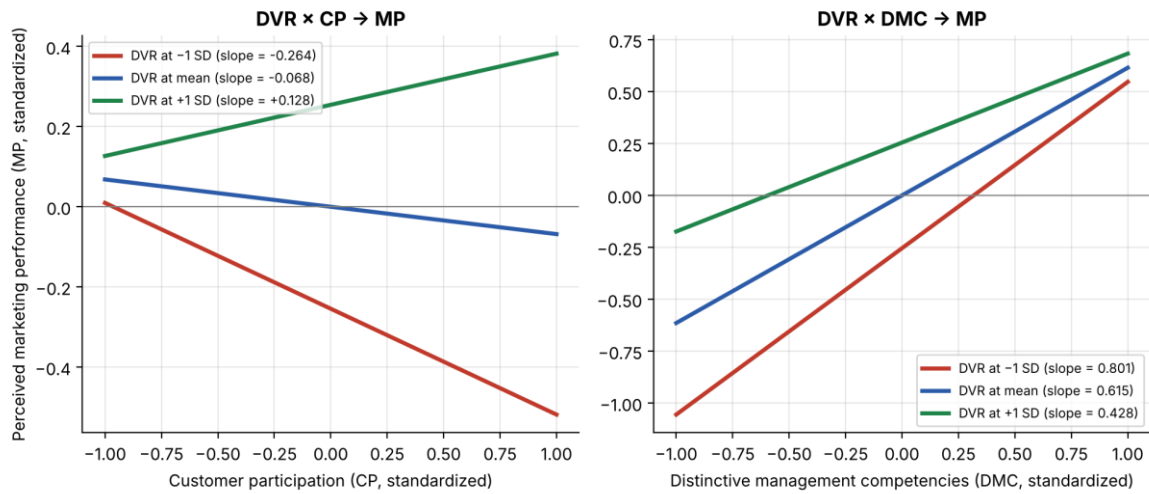
DVR level	Direct effect CP → MP [95% CI]	Indirect effect CP → DMC → MP [95% CI]	Total effect [95% CI]	DMC → MP slope [95% CI]
-1 SD	$-0.264 [-0.518, -0.017]$	$0.556 [0.386, 0.825]$	$0.292 [0.070, 0.536]$	$0.801 [0.582, 1.107]$
Mean	$-0.068 [-0.268, 0.122]$	$0.427 [0.305, 0.608]$	$0.359 [0.133, 0.584]$	$0.615 [0.456, 0.816]$
+1 SD	$0.128 [-0.141, 0.389]$	$0.297 [0.145, 0.461]$	$0.425 [0.161, 0.681]$	$0.428 [0.210, 0.644]$
Index of moderated mediation	–	$-0.129 [-0.263, -0.027]$	–	–

Source: Computed from the 5,000 bootstrap samples (standardized scores; interaction created with the two-stage approach).

Note: Conditional indirect effect = $CP \rightarrow DMC \text{ path} \times (DMC \rightarrow MP \text{ path} + DVR \times DMC \text{ coefficient} \times DVR \text{ level})$; conditional direct effect = $CP \rightarrow MP \text{ path} + DVR \times CP \text{ coefficient} \times DVR \text{ level}$; index of moderated mediation = $CP \rightarrow DMC \text{ path} \times DVR \times DMC \text{ coefficient}$. Each quantity was recomputed in all 5,000 bootstrap samples, and percentile 95% intervals are reported (the interval for the mean-level indirect effect equals the SmartPLS interval for the specific indirect effect in Table 9).

Figure 2 plots the simple slopes of the two interactions (standardized scores). For $CP \rightarrow MP$ (left panel), the slope is negative at -1 SD of digital value resonance (-0.264), close to zero at the mean (-0.068), and positive at $+1$ SD (0.128): the slope is significantly negative at -1 SD, not distinguishable from zero at the mean, and positive but not significant at $+1$ SD (Table 10); the positive interaction ($\beta = 0.196$) therefore shifts the association from negative toward positive as digital value resonance rises, but does not make it significantly positive within the observed range. For $DMC \rightarrow MP$ (right panel) the pattern is reversed: the slope is steepest at -1 SD (0.801), 0.615 at the mean, and flattest at $+1$ SD (0.428), as implied by the negative interaction ($\beta = -0.186$). Higher digital value resonance therefore attenuates the marginal association between managerial competencies and performance. This slope effect must be distinguished from the level effect: because digital value resonance also has a positive direct association with marketing performance ($\beta = 0.254$), the line for high digital value resonance lies above the line for low digital value resonance across the plotted range of DMC (at $DMC = +1$ SD, predicted MP is 0.68 versus 0.55), but the gap narrows as DMC increases. The pattern suggests diminishing returns or partial substitution between digital resources and managerial competencies rather than simple technological complementarity. Both interactions are statistically significant ($p < 0.05$) but small in size ($f^2 = 0.059$ and 0.053 ; Table 8) (Hair et al., 2011).

Figure 2. Simple Slopes of the Moderating Effect of Digital Value Resonance (–1 SD, Mean, +1 SD) on the CP → MP and DMC → MP Relationships



Note: Lines are plotted from the standardized coefficients in Table 9 ($MP = -0.068 CP + 0.254 DVR + 0.615 DMC + 0.196 DVR \times CP - 0.186 DVR \times DMC$, with the other predictor at its mean); they reproduce the SmartPLS slope-analysis output. For CP → MP the slope rises with DVR (–0.264, –0.068, 0.128); for DMC → MP it falls with DVR (0.801, 0.615, 0.428).

4.5. Robustness and Sensitivity Analyses

Cross-loadings. Table 11 reports the correlation of every indicator with every construct score. Each indicator is most strongly correlated with its own construct, so the cross-loading criterion is met. The margins are smallest for X3.3 (0.099; it correlates 0.679 with DVR), X3.5 (0.107; 0.637 with MP), and X2.3 (0.132; 0.530 with CP); all other margins exceed 0.14. The margin of X3.3 reflects the DVR–DMC proximity seen in the HTMT ratios.

Table 11. Cross-Loadings (Correlations of Indicators with Construct Scores)

Indicator	CP	DVR	DMC	MP
X1.1	0.719	0.505	0.444	0.313
X1.2	0.817	0.675	0.652	0.495
X1.3	0.756	0.550	0.483	0.341
X1.4	0.819	0.664	0.619	0.422
X1.5	0.678	0.345	0.332	0.282
X1.6	0.792	0.569	0.562	0.442
X2.1	0.554	0.740	0.520	0.430
X2.2	0.637	0.886	0.643	0.623
X2.3	0.530	0.662	0.518	0.332
X2.4	0.636	0.869	0.640	0.538
X3.1	0.578	0.579	0.798	0.574
X3.2	0.500	0.503	0.730	0.527
X3.3	0.583	0.679	0.778	0.566
X3.4	0.526	0.563	0.797	0.574
X3.5	0.481	0.488	0.744	0.637

Indicator	CP	DVR	DMC	MP
Y.1	0.401	0.538	0.626	0.800
Y.2	0.446	0.564	0.718	0.878
Y.3	0.473	0.487	0.612	0.877
Y.4	0.459	0.567	0.620	0.903

Source: Data Processed (2026)

Note: The largest value in each row is the indicator's correlation with its own construct. CP = customer participation (X1.1–X1.6); DVR = digital value resonance (X2.1–X2.4); DMC = distinctive management competencies (X3.1–X3.5); MP = perceived marketing performance (Y.1–Y.4). Construct scores are standardized latent-variable scores.

Bootstrap stability. The results in Tables 9 and 10 are the SmartPLS output with 5,000 bootstrap subsamples. They agree with the first SmartPLS run with 500 subsamples: all signs are identical and every coefficient that was significant remains significant (the p-values of the two interactions change from 0.012 and 0.015 to 0.018 and 0.021, and that of DVR → MP from 0.040 to 0.041), while the non-significant CP → MP path remains non-significant ($p = 0.494$). The index of moderated mediation is -0.129 in both runs (95% CI $[-0.244, -0.021]$ with 500 and $[-0.263, -0.027]$ with 5,000 subsamples). The conditional slopes are unchanged (CP → MP: $-0.264, -0.068$, and 0.128 ; DMC → MP: $0.801, 0.615$, and 0.428). The intervals differ only in the second decimal, so the conclusions do not depend on the number of subsamples.

Digital value resonance without X2.3. Because X2.3 is conceptually closest to digital capability and has the weakest DVR loading, the model was re-estimated with a three-item DVR (X2.1, X2.2, and X2.4; Cronbach's alpha 0.806, composite reliability 0.885, AVE 0.721). The moderation results are essentially unchanged (Table 12): DVR × CP = $0.201 [0.026, 0.384]$, DVR × DMC = $-0.179 [-0.362, -0.024]$, and the index of moderated mediation = $-0.124 [-0.266, -0.017]$, although the p-value of the index (0.050) is at the margin of 0.05. The direct association of DVR with MP becomes stronger ($\beta = 0.300 [0.079, 0.514]$). The HTMT ratios of DVR fall (CP–DVR = $0.835 [0.731, 0.944]$; DVR–DMC = $0.865 [0.766, 0.956]$), but the upper limits remain above 0.90, so this sensitivity analysis does not remove the discriminant-validity concern; it shows that the moderation findings do not depend on X2.3. The interpretation of DVR does not need to be reconsidered on this basis, but the reservations about its boundary remain.

Composite specification of DMC. DMC was re-estimated as a composite with regression (Mode B) weights. All five weights are positive (X3.1 = 0.27, X3.2 = 0.21, X3.3 = 0.31, X3.4 = 0.15, and X3.5 = 0.35); four are significant at the 5% level and X3.4 is not (95% CI $[-0.047, 0.347]$), although its loading is 0.76. The indicator VIFs are 1.64 to 2.01, well below 3.3, so collinearity among the indicators is not a problem. The composite score correlates 0.996 with the reflective score and the structural results hardly change (Table 12): CP → DMC = 0.693, DMC → MP = 0.635, DVR × DMC = $-0.199 [-0.351, -0.035]$, and the index of moderated mediation = $-0.138 [-0.257, -0.024]$. The DVR → MP coefficient falls to the margin of significance ($\beta = 0.234$, 95% CI $[0.000, 0.480]$). The conclusions therefore do not depend on treating DMC as reflective rather than as a composite.

Refined DMC with less content overlap. To reduce the overlap with customer participation, DMC was re-estimated with three items (X3.2 strategy adaptation, X3.3 technology adaptation, and X3.4 target setting; Cronbach's alpha 0.737, composite reliability 0.851, AVE 0.655). The two items that explicitly refer to customer-driven ideas and accumulated customer knowledge (X3.1 and X3.5) were removed; X3.2 and X3.4 still mention customer needs or insights, so the overlap is reduced and not eliminated. The CP → DMC path falls from 0.694 to 0.667 (R^2 of DMC from 0.482 to 0.445; f^2 from 0.930 to 0.80), the DMC → MP path falls to $0.432 [0.245, 0.672]$,

and the indirect effect at the mean of DVR falls from 0.427 to 0.288 [0.159, 0.481], about two-thirds of its baseline size. The interactions keep their signs: $\text{DVR} \times \text{CP} = 0.234$ [0.041, 0.450] and $\text{DVR} \times \text{DMC} = -0.205$ [-0.444, -0.031]; the index of moderated mediation is -0.137 [-0.317, -0.020] ($p = 0.072$), and the conditional indirect effect at +1 SD of DVR is no longer distinguishable from zero (0.151 [-0.051, 0.349]). The HTMT ratio of DVR–DMC rises to 0.924 [0.796, 1.049] because X3.3 (technology adaptation) overlaps with DVR. Combining the three-item DVR with the refined DMC (Table 12) gives $\text{DVR} \times \text{DMC} = -0.195$ [-0.443, -0.026] and an index of -0.130 [-0.316, -0.017] ($p = 0.091$). The mediation mechanism therefore remains meaningful after the conceptual redundancy is reduced, so it is not simply a product of overlapping item content, but part of the baseline $\text{CP} \rightarrow \text{DMC} \rightarrow \text{MP}$ association and the precision of the moderated-mediation result depend on the customer-oriented items. H4 and H8 are supported in the baseline specification and are directionally consistent, but less precisely estimated, in the refined specification.

Table 12. Sensitivity Analyses: Main Coefficients with Percentile 95% Confidence Intervals (5,000 Bootstrap Subsamples)

Specification	CP $\rightarrow$ DMC	DVR $\times$ CP $\rightarrow$ MP	DVR $\times$ DMC $\rightarrow$ MP	Indirect effect CP $\rightarrow$ DMC $\rightarrow$ MP (mean DVR)	Index of moderated mediation
Baseline (reflective DMC; 4-item DVR)	0.694 [0.617, 0.776]	0.196 [0.032, 0.358]	-0.186 [-0.357, -0.040]	0.427 [0.305, 0.608]	-0.129 [-0.263, -0.027]
DVR without X2.3 (3 items)	0.694 [0.617, 0.777]	0.201 [0.026, 0.384]	-0.179 [-0.362, -0.024]	0.415 [0.304, 0.586]	-0.124 [-0.266, -0.017]
DMC as composite (Mode B)	0.693 [0.621, 0.778]	0.204 [0.033, 0.357]	-0.199 [-0.351, -0.035]	0.440 [0.329, 0.622]	-0.138 [-0.257, -0.024]
Refined DMC (X3.2, X3.3, X3.4)	0.667 [0.573, 0.759]	0.234 [0.041, 0.450]	-0.205 [-0.444, -0.031]	0.288 [0.159, 0.481]	-0.137 [-0.317, -0.020]
Three-item DVR and refined DMC	0.667 [0.573, 0.759]	0.227 [0.034, 0.461]	-0.195 [-0.443, -0.026]	0.276 [0.155, 0.469]	-0.130 [-0.316, -0.017]

Source: Data Processed (2026)

Note: Each specification was re-estimated with the two-stage approach and 5,000 bootstrap subsamples; values are standardized coefficients with percentile 95% confidence intervals. The signs of all interactions and of the index of moderated mediation are the same in all five specifications.

4.6. Discussion

The relationship between customer participation and distinctive management competencies revealed a significant correlation. This indicated that higher customer participation was associated with stronger distinctive management competencies. These findings aligned with Boaventura and Brito (2018); Palma et al. (2018), who explained that customer participation was crucial for creating value and enhancing service quality and innovation. However, Blinda et al. (2019) found that excessive participation could reduce the willingness to pay, suggesting that customer sacrifices may outweigh perceived benefits. Additionally, Mustak et al. (2016) also noted that customer participation can have both positive and negative outcomes, depending on how well it is managed. This suggested that customer interaction and distinctive management competencies were not always straightforward and positive. The findings show

that higher levels of customer participation are associated with stronger distinctive management competencies, but, at average digital value resonance, not directly with perceived marketing performance. However, given the cross-sectional design, the direction of these relationships should be interpreted cautiously. Moreover, this contradicted previous studies that indicated negative or inconsistent impacts of customer participation on distinctive management competencies, emphasizing the importance of understanding customer input and its implications in S-DL's implementation.

The results indicate that customer participation has no statistically distinguishable direct association with perceived marketing performance at the mean level of digital value resonance ($\beta = -0.068$, $p = 0.494$); because of the DVR $\times$ CP interaction, this coefficient is a conditional rather than a general direct effect. The conditional estimates show that the association is significantly negative at low digital value resonance (-0.264), approximately zero at the mean, and positive but not significant at high digital value resonance (0.128) (Table 10). This finding suggests that customer participation alone may not be associated with better marketing outcomes among MSMEs unless digital conditions are favorable. Although customer participation provides firms with valuable knowledge, feedback, and market information, its effectiveness depends on how organizations integrate and utilize these customer-generated resources. Previous studies have demonstrated that customer participation may produce different outcomes depending on contextual factors, including the degree of customer involvement, task complexity, and the firm's capability to manage customer contributions (Blut et al., 2020; Chang & Taylor, 2016). Therefore, the absence of a distinguishable direct association at average digital value resonance suggests that customer participation requires appropriate organizational capabilities, and favorable digital conditions, to be associated with better marketing outcomes. The findings further indicate that digital value resonance plays an important role in shaping the relationship between customer participation and marketing performance. The positive moderation effect of digital value resonance ($\beta = 0.196$, $p = 0.018$) suggests that customer participation becomes more valuable when supported by digital value creation mechanisms that facilitate interaction, information exchange, and value alignment between firms and customers. Consistent with the Service-Dominant Logic perspective, customer participation represents a process of resource integration in which customers contribute knowledge and experiences that firms can incorporate into value creation activities (Grönroos & Gummerus, 2014; Vargo & Lusch, 2008a). Previous studies also indicate that digital platforms can strengthen customer engagement by improving communication and enabling collaborative value creation (Carlson et al., 2019). Therefore, the findings suggest that digital value resonance does not replace customer participation but is associated with more favorable conditions for the link between customer involvement and marketing outcomes. At low digital value resonance the association of customer participation with performance was negative (-0.264), which is consistent with evidence that participation can impose costs on customers and firms when it is poorly supported (Blinda et al., 2019; Mustak et al., 2016); the present data cannot identify the mechanism.

Furthermore, customer participation demonstrated a strong positive association with distinctive management competencies ($\beta = 0.694$, $p < 0.001$). This finding suggests that customer involvement provides valuable knowledge resources that support managerial learning and capability development. From the Service-Dominant Logic perspective, customers contribute operand resources, such as knowledge, experiences, and feedback, which firms can integrate into their value creation processes (Vargo & Lusch, 2008a). For MSMEs,

continuous interaction with customers may enhance managers' ability to identify market needs, adapt strategies, and develop customer-oriented practices. Therefore, the findings indicate that customer participation is more strongly associated with internal managerial capability development rather than with marketing performance at the mean level of digital value resonance.

The moderating effect of digital value resonance on the relationship between distinctive management competencies and marketing performance was significant but negative ($\beta = -0.186$, $p = 0.021$). This finding indicates that higher levels of digital value resonance weaken the positive association between distinctive management competencies and marketing performance. Although digital transformation provides opportunities for value creation, digital resources do not automatically enhance the effectiveness of managerial capabilities. As suggested by Hughes (2019), digital transformation requires organizational adaptation and alignment between technological resources and managerial processes. The conditional estimates (Table 10) show the same pattern: the DMC $\rightarrow$ MP slope falls from 0.801 at -1 SD to 0.428 at $+1$ SD. Three interpretations are consistent with this attenuation, and the present data cannot separate them: (i) substitution, in which digital interfaces take over part of the sensing and coordination work that managers otherwise perform; (ii) diminishing returns, in which the marginal gain from managerial competencies falls because digital value resonance already lifts performance (its positive level effect, $\beta = 0.254$); and (iii) digital managerial redundancy or misalignment, in which digital practices and managerial processes overlap or are poorly integrated (Hughes, 2019). A ceiling effect on the self-reported performance scale at high digital resonance may also contribute.

Digital value resonance may support marketing outcomes by facilitating customer interaction, accessibility, and value exchange processes ($\beta = 0.254$, $p = 0.041$). This finding indicates that digital-enabled interactions and value exchange mechanisms may support improved marketing outcomes among MSMEs. Digital resources can facilitate customer engagement, improve accessibility, and strengthen firms' ability to respond to market changes. However, the contribution of digital value resonance depends on the alignment between digital practices and organizational capabilities. Previous research suggests that digital transformation creates performance benefits when firms are able to integrate technological resources with appropriate strategic and managerial processes (Hughes, 2019).

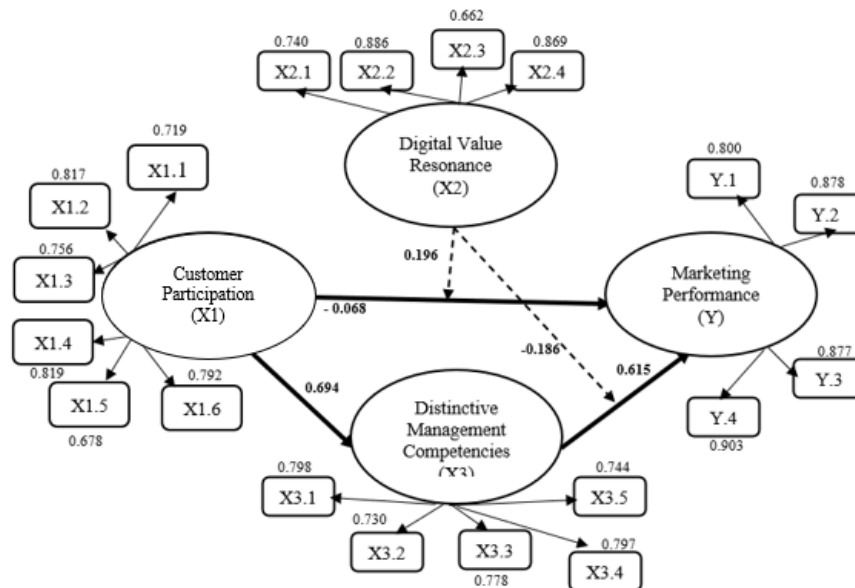
From the perspective of S-DL, distinctive management competencies are positively associated with marketing performance because they enable firms to integrate resources, adapt strategies, and respond to changing market conditions. Market orientation had a strong and positive relationship with the sales growth of SMEs in the UK. These findings highlighted the crucial role of the competitive environment in determining SME performance (Amadasun & Mutezo, 2022). Additionally, research by Raza Bilal et al. (2017) demonstrated that distinctive management competencies had a significant mediating role linking capable fiscal policies and SMEs' business growth, indicating that unique managerial decisions could enhance SMEs' performance. Conversely, some studies indicated that distinctive management competencies did not always have a significantly positive impact on marketing performance. Study by Wilden and Gudergan (2017) found that while a service-dominant orientation enhanced marketing capabilities, its impact could be diminished if companies overly relied on dynamic capabilities that might not always align with distinctive management competency strategies. This occurs because an excessive focus on dynamic capabilities could lead to strategic misalignment and the misallocation of resources, ultimately undermining the benefits of

distinctive management competencies. Therefore, the findings of this study explain that distinctive management competencies was positively associated with SMEs' marketing performance through efficient managerial decisions. Furthermore, the effectiveness of distinctive management competencies varies, depending on the balance of dynamic capabilities and financial strategies within the company.

The mediation analysis indicates that distinctive management competencies provide an indirect pathway linking customer participation and marketing performance ($\beta = 0.427$, $p < 0.001$). This finding suggests that customer participation may contribute to marketing outcomes when firms possess the managerial capabilities required to interpret and utilize customer-generated knowledge. Rather than showing a direct association with marketing performance at average digital value resonance, customer participation appears to be associated with marketing outcomes through the development of internal competencies. This indirect association is conditional: it is strongest when digital value resonance is low (0.556 at -1 SD) and weakest when it is high (0.297 at $+1$ SD) (Table 10), and the negative index of moderated mediation (-0.129 ; 95% CI $[-0.263, -0.025]$) shows that the managerial route is partly substituted by digital resources. Customer participation thus converts into perceived marketing performance through different routes at different digital levels. However, given the cross-sectional nature of the data, this indirect relationship should be interpreted as an empirical association rather than a confirmed causal mechanism. This finding is consistent with previous research emphasizing that the effectiveness of customer participation depends on firms' ability to manage customer involvement and transform external knowledge into organizational resources (Chang & Taylor, 2016; Morgan et al., 2018). Therefore, the results highlight the importance of distinctive management competencies as an internal mechanism that enables MSMEs to benefit from customer participation.

Interpretive cautions. First, marketing performance is self-reported and perceived; the associations reported here are with owners' or managers' perceptions of sales, revenue, advocacy, and coverage, and statements that customer participation, digital capabilities, or DMC "improve" performance should be read in this limited sense. Second, the CP $\rightarrow$ DMC association ($\beta = 0.694$; $f^2 = 0.930$) is exceptionally large. Part of it may reflect conceptual overlap, because four DMC items refer to customer ideas, needs, insights, or knowledge, which is also the content domain of the customer-participation items, and part may reflect shared-method variance because the same respondent rated both constructs. The discriminant evidence (square roots of AVE of 0.765 and 0.770 against a correlation of 0.694; HTMT = 0.795) shows that the two constructs are distinguishable but not independent. Third, HTMT ratios above 0.85 for DVR–DMC, CP–DVR, and DMC–MP mean that the conceptual distinctiveness of DVR, which underlies its moderating role, Fourth, the sensitivity analyses (Section 3.5) show that the signs of the interactions and of the index of moderated mediation are stable when the DVR and DMC measures are modified, but that the moderated-mediation estimates become less precise when DMC is refined to reduce overlap with customer participation (index = -0.137 , $p = 0.072$), and the upper HTMT limit for DVR–DMC stays above 0.90 in every specification (0.956 to 1.049). The interaction results should therefore be read as patterns among closely related perceptions of digital and managerial practices and not as separately identified organizational mechanisms. is only partially supported.

Figure 3. Full Structural Model of Perceived Marketing Performance (Standardized Path Coefficients and Outer Loadings; Dashed Arrows = Moderating Effects of DVR)



Note: Standardized path coefficients and outer loadings from SmartPLS (CP → MP -0.068; CP → DMC 0.694; DMC → MP 0.615; DVR × CP → MP 0.196; DVR × DMC → MP -0.186). Dashed arrows are moderating effects. The negative DVR × DMC coefficient means that higher DVR attenuates the DMC → MP relationship. X1 = CP, X2 = DVR, X3 = DMC, and Y = MP.

5. Conclusion and Suggestion

This study provides empirical evidence that customer participation is associated with marketing performance through distinctive management competencies within the Service-Dominant Logic (S-DL) perspective. The findings show that customer participation is positively associated with distinctive management competencies, which in turn are positively associated with perceived marketing performance, whereas the association between customer participation and perceived marketing performance is conditional on digital value resonance: it is not distinguishable from zero at average digital value resonance, negative at low digital value resonance, and positive but not significant at high digital value resonance. Customer involvement and managerial capabilities are thus jointly associated with stronger perceived marketing outcomes; the cross-sectional, single-source data do not show that changing these variables would improve performance. Furthermore, digital value resonance conditions these relationships in opposite directions: it strengthens the association between customer participation and perceived marketing performance ($\beta = 0.196$) but weakens the association between distinctive management competencies and perceived marketing performance ($\beta = -0.186$), so that the indirect effect through competencies declines as digital value resonance rises (0.556 at -1 SD to 0.297 at +1 SD; index of moderated mediation = -0.129). Digital value resonance also has a positive direct association with perceived performance ($\beta = 0.254$). The results are therefore more consistent with diminishing returns or partial substitution between digital resources and managerial competencies than with simple complementarity. Thus, this study extends the S-DL framework by highlighting that value co-creation is conditional: it depends not only on customer involvement but also on firms' internal capabilities to manage customer-generated resources and on the digital conditions under which these capabilities pay off. These conclusions are tempered by the partial support for construct separation (upper HTMT limits above 0.90 for DVR–DMC, CP–DVR, and DMC–MP) and by sensitivity analyses that give the same signs but less precise moderated-mediation estimates when DMC is refined to reduce overlap with customer participation.

The main implication of this study is descriptive: customer participation, managerial competencies, and digital interaction quality are associated with perceived marketing outcomes in different ways depending on the level of digital value resonance. At average digital value resonance, customer participation is not associated with higher perceived performance on its own; it is associated with stronger managerial competencies, and these competencies are most strongly associated with perceived performance where digital value resonance is low. Because the data are observational, cross-sectional, and single-source, these patterns should be treated as hypotheses for managers to test and not as evidence that developing competencies or digital channels will raise performance.

6. Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design and single-source perceptual measures limit the ability to establish temporal causality among customer participation, digital value resonance, distinctive management competencies, and marketing performance. Reverse causality and common method bias cannot be completely excluded. Second, the use of purposive sampling focusing on Indonesian MSMEs across selected sectors may limit the generalizability of the findings to other business contexts, industries, or geographical regions. Future research should consider longitudinal designs and broader samples across different regions and industries to validate the proposed model and examine how customer participation evolves over time. In addition, future studies may incorporate other emerging digital capability constructs, such as virtual reality, augmented reality, artificial intelligence adoption, or technological readiness, to further explore how digital transformation enables value co-creation based on resource-based and resource advantage perspectives.

Further limitations concern measurement, inference, and sampling. First, marketing performance is self-reported and perceived; future research should combine perceptual measures with archival indicators such as percentage sales growth, revenue growth, customer-retention rates, market-share changes, or digital-conversion metrics. Second, Harman's single-factor test (first factor 49.78%) cannot rule out common method bias, and the full-collinearity VIF of DMC (3.46) is slightly above 3.3; future studies should use multi-source or time-separated data and a marker variable. Third, digital value resonance and distinctive management competencies are conceptually broad; HTMT ratios above 0.85 for three construct pairs and the possible overlap between customer-participation and customer-oriented competency items and upper HTMT limits above 0.90 for these pairs call for further scale validation; the sensitivity analyses in Section 3.5 (a three-item DVR, a composite DMC, and a refined DMC) did not remove these concerns, and construct separation is only partially supported. Fourth, Q^2 reflects in-sample predictive relevance only, and the out-of-sample assessment shows benchmark-level accuracy for the main-effects and full models without any gain from the interaction terms; it was computed outside SmartPLS and should be confirmed with the PLSpredict module of SmartPLS. Global GoF was not used as evidence of model fit, and no SRMR is reported because it was not part of the available output. Fifth, the interaction estimates are adequately but not generously powered ($n = 175$) and the conditional-effect intervals are wide; one conditional direct effect ($CP \rightarrow MP$ at -1 SD of DVR) is significant under percentile but not under BCa intervals, and replication with larger samples is recommended. Sixth, geographic location, legal form, ownership, and number of employees were not

recorded, creative industries make up 44.6% of the sample, and the sample was recruited online by purposive sampling, so the findings apply to the sampled MSMEs and should not be generalized to all Indonesian MSMEs.

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT (OpenAI) solely for language refinement, including improving sentence structure, grammar, and clarity of expression during the writing process. The tool was not used to generate scientific ideas, analyze data, interpret results, or develop the conclusions of the study. After using this tool/service, the author(s) thoroughly reviewed and edited the content as needed and take(s) full responsibility for the accuracy, originality, and integrity of the content of the publication.

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