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An Integrated Social Media, AI, and Data Analytics Marketing Capability Model for Enhancing MSME Performance and SDG Achievement

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The author(s) declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

ABSTRACT

Purpose: This study develops and empirically tests an integrated marketing capability model to explain how Social Media Marketing Capability, Artificial Intelligence Marketing Capability, and Data Analytics Capability jointly influence the marketing performance of MSMEs.

Research Method: An explanatory sequential mixed-methods design was employed. The qualitative phase involved in-depth interviews and focus group discussions with 12 MSMEs to refine and validate the research instruments. The quantitative phase surveyed 75 digitally based MSMEs in West Sulawesi, Indonesia. Data were analyzed using SEM-PLS with SmartPLS 4.0.

Results and Discussion: The model explains 72.3% of the variance in marketing performance. Data Analytics Capability showed the strongest effects on Customer Insight Quality, Marketing Agility, and Marketing Performance. Social Media Marketing Capability significantly influenced all three outcomes, while AI Marketing Capability significantly affected only Customer Insight Quality. Customer Insight Quality and Marketing Agility also served as significant mediators.

Implications: MSME development programs should prioritize data analytics capability, strengthen strategic social media practices, and implement AI adoption gradually.

Originality: This study integrates three digital marketing capabilities with customer insight and marketing agility within a single empirical model for digitally based MSMEs.

1) Introduction

The digital transformation of micro, small, and medium enterprises (MSMEs) in Indonesia represents both an imperative and a persistent challenge. While the adoption of digital technologies has accelerated significantly, particularly following the pandemic-induced shift toward online commerce, the mere presence of technology does not guarantee enhanced marketing performance. Hendrawan et al. (2024) documented that many Indonesian MSMEs utilize social media platforms without strategic planning, resulting in tactical rather than strategic marketing activities. Similarly, Masitoh et al. (2025), through their systematic literature review, identified that digital transformation in the MSME sector remains fragmented, with technology adoption frequently outpacing capability development. This disconnect between technological access and organizational capability creates what may be termed a "digital capability gap" that undermines the potential benefits of digitalization.

The practical manifestations of this gap are observable across multiple dimensions. Research conducted by Purba (2025) demonstrated that while MSMEs increasingly integrate e-wallets and social media into their operations, the integration remains superficial, often limited to transactional functions rather than strategic marketing purposes. Adesoye (2024, 2025) further emphasized that small businesses struggle to leverage innovative marketing technologies because they lack the foundational capabilities to plan, implement, and evaluate digital marketing initiatives effectively. In the context of West Sulawesi, preliminary qualitative exploration conducted by the research team with 12 digitally-based MSMEs confirmed three fundamental problems: social media utilization remains tactical and unplanned; data analytics capabilities for extracting customer insights are minimal; and artificial intelligence applications for personalization and behavioral prediction are virtually nonexistent.

Recent scholarship has increasingly recognized the strategic importance of digital marketing capabilities. Studies examining social media marketing have established its role in customer engagement and brand building (Novitasari et al., 2025; Sabila et al., 2025). Research on AI in marketing has explored its potential for personalization and predictive analytics, though predominantly in the context of large enterprises (Cherian, 2025; Vamshi & Chakravorty, 2025; Anssuini Morales et al., 2024). Data-driven decision-making has received considerable attention, with scholars such as Borges et al. (2021), Johanes & Siallagan (2024), and Rosário & Cruz (2025) demonstrating how analytics can enhance marketing effectiveness. Soraya Tanjung (2024) and ur Rahaman (2024) emphasized the importance of customer insights in strategic marketing management.

However, these bodies of literature have largely developed in parallel rather than in integration. Adesoye (2024, 2025) examined social media capabilities in isolation, while Aini et al. (2025) and Mittal (2025) focused on AI applications without fully considering how they interact with other capabilities. Zein et al. (2024) acknowledged the need for integrated approaches to SME marketing and customer relationship management, yet their proposed frameworks remain conceptual rather than empirically validated in the Indonesian context. Onesi-Ozigagun et al. (2024) and Thapaliya & Adhikari (2025) highlighted the importance of data-driven agility, but the specific mechanisms through which digital capabilities translate into marketing agility remain underexplored.

This fragmentation in the literature presents a significant gap. The current body of knowledge does not adequately explain how social media, AI, and data analytics capabilities interact within a unified system to influence MSME marketing performance. Furthermore, the mediating mechanisms through which these capabilities affect performance—particularly the roles of customer insight quality and marketing agility—remain insufficiently theorized and empirically tested. Khomein Singh & Anees (2025) and Bhavsar et al. (2025) observed that the drivers and barriers to digital transformation in MSMEs are context-specific, yet most existing models are derived from studies conducted in developed economies or on large corporations.

The present research addresses these gaps by developing and empirically validating an Integrated Marketing Capability Strengthening Model. Three research questions guide the inquiry: (1) How do Social Media Marketing Capability, AI Marketing Capability, and Data Analytics Capability influence Customer Insight Quality, Marketing Agility, and Marketing Performance? (2) Do Customer Insight Quality and Marketing Agility mediate the relationships between digital marketing capabilities and performance? (3) What are the implications of these relationships for MSME development and SDG achievement?

The novelty of this research is threefold. First, it integrates three digital marketing capabilities within a single empirically validated system, moving beyond the partial approaches characteristic of prior work. Second, it identifies and tests the dual mediation mechanism through which customer insight quality and marketing agility translate capabilities into performance. Third, it contextualizes these relationships within the Indonesian MSME sector, specifically in an eastern Indonesian region, contributing to the limited literature on digital transformation in non-urban and developing economy settings. This model is also explicitly linked to Sustainable Development Goals 8 (decent work and economic growth), 9 (industry, innovation, and infrastructure), and 12 (responsible consumption and production), as advocated by Sukoco et al. (2024).

2) Literature Review and Hypothesis Development

Theoretical Foundations

The conceptual model developed in this research rests on three established theoretical perspectives. Each offers a distinct lens. Together, they provide a comprehensive framework for understanding how MSMEs develop and deploy digital marketing capabilities. Resource-Based View (RBV) anchors the theoretical foundation. Barney (1991) argued that sustained competitive advantage emerges from firm-specific resources and capabilities. These must be valuable, rare, imperfectly imitable, and non-substitutable—the well-known VRIN criteria. Within digital marketing, social media capability, AI capability, and data analytics capability fit this description. When properly developed and deployed, these strategic resources can generate meaningful competitive advantage. Adesoye (2024, 2025) applied RBV logic to show that small businesses achieve market differentiation through innovative marketing technologies. Novitasari et al. (2025) similarly demonstrated that marketing capabilities function as valuable organizational assets influencing MSME performance. For this study, the three digital capabilities are treated as distinct yet interconnected VRIN resources that collectively contribute to marketing success.

Dynamic Capability Theory builds on RBV. It explains how organizations reconfigure their resource base in response to environmental change. Teece et al. (1997) defined dynamic capabilities as the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. This perspective proves especially relevant to digital marketing. Technological evolution and shifting consumer behaviors demand organizational responsiveness. Onesi-Ozigagun et al. (2024) and Novitasari et al. (2025) emphasized that marketing agility—a key dynamic capability—enables firms to sense and respond effectively to market changes. In the present model, Marketing Agility is positioned as a manifestation of dynamic capability. It mediates the relationship between digital marketing capabilities and marketing performance.

Technology-Organization-Environment (TOE) Framework provides the third pillar. Tornatzky and Fleischer (1990) proposed that technology adoption decisions are influenced by three contextual factors. Technological context refers to the availability and characteristics of technologies. Organizational context covers firm resources, managerial commitment, and organizational structure. Environmental context includes competitive pressure, regulatory environment, and external support. This framework has been applied fruitfully to understand digital adoption in MSMEs (Komar Priatna et al., 2025; Zein et al., 2024). The TOE perspective is incorporated into the present model to acknowledge a crucial point. Digital marketing capabilities develop within specific technological, organizational, and environmental contexts. Effective integration demands attention to all three dimensions.

Conceptual Definitions

Social Media Marketing Capability (SMMC) refers to the MSME's capacity to strategically plan, implement, and evaluate marketing activities through social media platforms. Drawing on Adesoye (2024, 2025) and Purba (2025), this capability encompasses three dimensions. The first is strategic planning. This involves developing content calendars, setting specific objectives, and scheduling publications. The second is implementation. This covers designing engaging content, using varied content formats, and actively responding to customer interactions. The third is evaluation. This includes regularly monitoring engagement metrics, assessing content effectiveness, and adjusting strategies based on evaluation results. This multidimensional conceptualization recognizes a fundamental insight. Effective social media marketing extends beyond mere presence. It encompasses systematic and reflective practice.

AI Marketing Capability (AIMC) denotes the MSME's capacity to leverage artificial intelligence technologies to support marketing activities. These include automation, personalization, and predictive analytics. Following Aini et al. (2025), Cherian (2025), and Vamshi & Chakravorty (2025), this capability comprises three dimensions. Automation involves using AI-powered tools for automated customer response, scheduled promotional messaging, and product recommendations. Personalization entails employing AI to deliver differentiated content and offers based on identified preferences. Predictive analytics involves utilizing AI to forecast purchase trends, identify potential customers, and analyze behavioral patterns. This conceptualization acknowledges that AI marketing capability exists on a continuum. It ranges from basic automation to sophisticated prediction and personalization.

Data Analytics Capability (DAC) is defined as the MSME's capacity to collect, manage, and analyze customer data to support marketing decision-making. Adapting from Alimkhodjaeva (2022), Borges et al. (2021), and Johanes & Siallagan (2024), this capability is conceptualized to reflect MSME operational realities. The focus is on "small data" rather than "big data." Three dimensions are identified. Data collection involves recording purchase data, gathering preference information, and storing communication histories. Data management covers organizing data in accessible formats, updating information regularly, and segmenting customers. Data analysis entails examining purchase patterns, comparing sales across periods, and utilizing analytical findings for marketing strategy. This emphasis on small data is deliberate. It ensures the capability is accessible to MSMEs with limited resources.

Customer Insight Quality (CIQ) refers to the quality of insights derived from deep customer understanding. It encompasses accuracy, depth, timeliness, and usefulness of customer information. Drawing upon ur Rahaman (2024) and Soraya Tanjung (2024), this construct acknowledges an important distinction. Not all customer information constitutes valuable insight. Four dimensions are identified. Accuracy means information corresponds to customer reality. Depth involves understanding of purchase motivations and loyalty factors. Timeliness refers to prompt awareness of behavioral changes and competitor switching. Usefulness means insights are directly applicable to decision-making and strategy formulation.

Marketing Agility (MA) denotes the MSME's capacity to respond to market and customer changes rapidly, flexibly, and effectively. Synthesizing from Novitasari et al. (2025), Onesi-Ozigagun et al. (2024), and Zein et al. (2024), this construct comprises three dimensions. Responsiveness speed refers to the ability to rapidly change marketing strategy and adjust offerings. Flexibility involves the capacity to reallocate marketing resources and change marketing channels. Effectiveness means changes produce visible improvements and maintain customer relationships. This conceptualization recognizes a crucial point. Agility involves not just speed but also the quality and effectiveness of responses.

Marketing Performance (MP) encompasses the MSME's marketing outcomes. These include both financial and non-financial dimensions. Following Borges et al. (2021) and Johanes & Siallagan (2024), three dimensions are identified. Sales growth includes increasing sales volume, new customer acquisition, and average purchase value. Market expansion covers reaching customers beyond geographic boundaries and extending marketing reach. Customer satisfaction and loyalty is evidenced by satisfaction, repurchase behavior, and recommendations. This multi-dimensional conceptualization acknowledges that marketing performance extends beyond immediate sales. It encompasses market development and customer relationship outcomes.

Hypothesis Development

The conceptual model integrates the three theoretical foundations and conceptual definitions to propose twelve hypotheses. Resource-Based View suggests that SMMC, AIMC, and DAC, as VRIN resources, should directly contribute to performance outcomes. Dynamic Capability Theory suggests these relationships may be mediated by marketing agility. The TOE framework underscores that the development and effectiveness of these capabilities depend on contextual factors.

The hypotheses are organized into four categories. These cover direct effects of capabilities on customer insight quality, direct effects of capabilities on marketing agility, direct effects on marketing performance, and mediating effects through insight quality and agility.

Direct Effects on Customer Insight Quality

Customer insight quality represents the extent to which MSMEs develop accurate, timely, and actionable understanding of their customers. Social media platforms serve as rich sources of customer data. Interactions, comments, and behavioral patterns all contribute (Adesoye, 2024; Purba, 2025). MSMEs with stronger social media marketing capabilities are better positioned to systematically extract and interpret this data. This generates higher quality customer insights. Similarly, AI technologies enhance insight generation. They do this through automated data processing, pattern recognition, and predictive modeling (Aini et al., 2025; Cherian, 2025). Data analytics capabilities directly improve insight quality. They enable structured collection, management, and analysis of customer information (Borges et al., 2021; Johanes & Siallagan, 2024). Therefore:

H1: Social Media Marketing Capability positively influences Customer Insight Quality.
H4: AI Marketing Capability positively influences Customer Insight Quality.
H7: Data Analytics Capability positively influences Customer Insight Quality.

Direct Effects on Marketing Agility

Marketing agility requires rapid sensing and responding to market changes. Social media platforms enable real-time monitoring of customer sentiment and competitive activity. This facilitates agile responses (Adesoye, 2024, 2025). AI technologies can accelerate response times. They do this through automated content generation, personalization, and decision support (Novitasari et al., 2025; Onesi-Ozigagun et al., 2024). Data analytics provides the evidence base for timely decision-making. It enables organizations to adjust strategies based on current information rather than intuition (Zein et al., 2024; Soraya Tanjung, 2024). These considerations suggest:

H2: Social Media Marketing Capability positively influences Marketing Agility.
H5: AI Marketing Capability positively influences Marketing Agility.
H8: Data Analytics Capability positively influences Marketing Agility.

Direct Effects on Marketing Performance

The direct effects of digital marketing capabilities on performance have been documented in various contexts. Social media marketing has been consistently linked to sales growth, customer acquisition, and brand development (Purba, 2025; Novitasari et al., 2025). AI applications have demonstrated potential for improving marketing effectiveness. They do this through personalization and predictive targeting (Cherian, 2025; Vamshi & Chakravorty, 2025). Data-driven marketing strategies are associated with improved decision quality and performance outcomes (Rosário & Cruz, 2025; Borges et al., 2021). The integration of these capabilities suggests:

H3: Social Media Marketing Capability positively influences Marketing Performance.
H6: AI Marketing Capability positively influences Marketing Performance.
H9: Data Analytics Capability positively influences Marketing Performance.

Mediation Effects

The theoretical framework suggests that the relationship between digital marketing capabilities and performance is not entirely direct. Customer insight quality represents the cognitive output of data processing. It enables more informed marketing decisions (ur Rahaman, 2024; Soraya Tanjung, 2024). Marketing agility represents the behavioral output—the capacity to act on insights (Novitasari et al., 2025; Onesi-Ozigagun et al., 2024). The sequential logic suggests a clear pathway. Capabilities generate insights (CIQ). Insights enable agility (MA). Agility produces performance (MP). This yields:

H10: Customer Insight Quality positively influences Marketing Agility.
H11: Customer Insight Quality positively influences Marketing Performance.
H12: Marketing Agility positively influences Marketing Performance.

The mediation hypotheses are implicit in the proposed direct and mediating relationships. Specifically, Customer Insight Quality is hypothesized to mediate the effects of SMMC, AIMC, and DAC on Marketing Agility and Performance. Marketing Agility is hypothesized to mediate the effects of all preceding variables on Marketing Performance.

3) Research Design and Methodology

Research Approach

An explanatory sequential mixed-methods design was employed. This approach was selected to achieve both depth and generalizability. The qualitative phase, conducted initially, served to validate and enrich the measurement instruments by ensuring that constructs were contextualized to the West Sulawesi MSME environment. The quantitative phase, conducted subsequently, tested the hypothesized relationships using a larger sample and statistical modeling.

Qualitative Exploration

The qualitative phase involved in-depth interviews and focus group discussions with 12 MSME owners and managers from Majene and surrounding areas. Participants were selected purposively based on criteria including: operation for at least two years, active use of social media for marketing, and demonstrated engagement with digital technologies. Interviews followed a semi-structured protocol addressing each of the six constructs. Observations were conducted at business premises to document digital marketing practices and data management activities. Findings from this phase informed the refinement of measurement indicators and confirmed the relevance of all six constructs to the local MSME context.

Quantitative Survey

The quantitative phase surveyed 75 MSME owners or managers in West Sulawesi. The sample was selected using purposive sampling based on the following criteria: (1) business operation of at least two years, (2) active use of social media platforms for marketing, (3) owner or manager involvement in marketing decisions, and (4) willingness to participate in the research. The sample size of 75 exceeds the minimum requirements for SEM-PLS analysis, which typically recommends 5-10 cases per indicator or a minimum of 30-50 cases for simple models.

Respondents represented diverse business types including culinary (32%), fashion (24%), crafts (24%), and services (20%). Most businesses employed 1-3 people (78.7%) and had been operating for 3-6 years (68%). Instagram was the most commonly used platform (84%), followed by WhatsApp Business (68%) and TikTok (40%). Monthly revenue ranged from less than Rp 5 million (25.3%) to Rp 5-25 million (56%) and above Rp 25 million (18.7%).

Research Instrument

The instrument consisted of six sections measuring the six constructs, plus a demographic section. A 5-point Likert scale was employed (1 = Strongly Disagree to 5 = Strongly Agree). The instrument was developed through adaptation from existing literature and refined based on qualitative findings:

- SMMC (9 items): Adapted from Adesoye (2024, 2025) and Purba (2025)
- AIMC (9 items): Adapted from Aini et al. (2025), Cherian (2025), and Vamshi & Chakravorty (2025)
- DAC (9 items): Adapted from Alimkhodjaeva (2022), Borges et al. (2021), and Johanes & Siallagan (2024)
- CIQ (8 items): Adapted from ur Rahaman (2024) and Soraya Tanjung (2024)
- MA (8 items): Adapted from Novitasari et al. (2025), Onesi-Ozigagun et al. (2024), and Zein et al. (2024)
- MP (8 items): Adapted from Borges et al. (2021) and Johanes & Siallagan (2024)

Data Collection Procedure

Data collection was conducted over a four-month period (April-July 2026). A mixed-mode approach was employed to maximize response rates. In-person administration was conducted for respondents with limited digital literacy, using trained enumerators who followed standardized protocols. Online administration via Google Forms was offered to respondents comfortable with digital platforms. Each respondent was provided with clear instructions and the opportunity to ask clarification questions. Follow-up reminders were sent to improve response rates.

Data Analysis

Quantitative data were analyzed using Structural Equation Modeling-Partial Least Squares (SEM-PLS) with SmartPLS 4.0. PLS-SEM was selected as the analytical approach for several reasons: (1) the research is exploratory in nature, aiming to predict key target constructs, (2) the model includes multiple constructs with multiple indicators, (3) the sample size of 75 is adequate for PLS-SEM but may be insufficient for covariance-based SEM, and (4) PLS-SEM accommodates non-normal data distributions. The analysis proceeded in two stages: assessment of the measurement model (outer model) for validity and reliability, followed by assessment of the structural model (inner model) for hypothesis testing and mediation analysis.

4) Resultsand Discussion

a) Results

Assessment of Measurement Model

The measurement model was assessed for convergent validity, discriminant validity, and reliability. Convergent validity was evaluated using outer loadings and Average Variance Extracted (AVE). All 51 indicators had outer loadings above 0.70, ranging from 0.712 to 0.856, indicating that each indicator significantly represents its construct. AVE values ranged from 0.587 to 0.654, exceeding the 0.50 threshold for all constructs, confirming convergent validity.

Discriminant validity was assessed using the Fornell-Larcker criterion. The square root of AVE for each construct (diagonal values) exceeded the correlations between constructs (off-diagonal values), confirming that each construct is distinct from others. For example, the square root of AVE for DAC was 0.796, exceeding its highest correlation with another construct (0.684 with SMMC). These results indicate adequate discriminant validity.

Reliability was assessed using Cronbach's Alpha and Composite Reliability (CR). All constructs demonstrated Cronbach's Alpha values ranging from 0.867 (CIQ) to 0.912 (MP), and CR values ranging from 0.922 to 0.948, all well above the 0.70 threshold. These results confirm that the measurement instrument is reliable for all six constructs.

Assessment of Structural Model

The structural model was assessed for predictive relevance and explanatory power. The R^2 values indicate the proportion of variance explained in endogenous constructs: Customer Insight Quality (R^2=0.634), Marketing Agility (R^2=0.678), and Marketing Performance (R^2=0.723). These values exceed the 0.50 threshold and are considered substantial, indicating that the model explains a significant proportion of variance in all three endogenous constructs.

Predictive relevance was assessed using Stone-Geisser's Q^2 values obtained through blindfolding procedures. Q^2 values for CIQ (0.412), MA (0.456), and MP (0.489) all exceeded zero, confirming the model's predictive relevance. Effect sizes (f^2) indicated that Data Analytics Capability had a medium effect on CIQ (0.234), while Social Media Marketing Capability had a small-to-medium effect, and AI Marketing Capability had a small effect.

Hypothesis Testing Results

The structural model was evaluated using path coefficients, t-statistics, and p-values derived from bootstrapping procedures with 5,000 resamples. Table 1 presents the results of the hypothesis tests.

Table 1. Structural Model Estimation Results

Hypothesis	Path	Path Coefficient	Standard Error	t-value	p-value	Support
H1	SMMC → CIQ	0.312***	0.087	3.586	0.000	Yes
H2	SMMC → MA	0.234*	0.092	2.543	0.011	Yes
H3	SMMC → MP	0.156*	0.078	2.000	0.046	Yes
H4	AIMC → CIQ	0.187*	0.076	2.461	0.014	Yes
H5	AIMC → MA	0.145	0.081	1.790	0.074	No
H6	AIMC → MP	0.089	0.072	1.236	0.217	No
H7	DAC → CIQ	0.356***	0.083	4.289	0.000	Yes
H8	DAC → MA	0.267**	0.089	3.000	0.003	Yes
H9	DAC → MP	0.178*	0.082	2.171	0.030	Yes
H10	CIQ → MA	0.289**	0.088	3.284	0.001	Yes
H11	CIQ → MP	0.234**	0.084	2.786	0.005	Yes
H12	MA → MP	0.312***	0.091	3.429	0.001	Yes

****p < 0.001, *p < 0.01, p < 0.05. n=75*
***Source:** Primary data processed (2026)*

Ten of the twelve hypothesized relationships were supported. H5 and H6, which proposed direct effects of AI Marketing Capability on Marketing Agility and Marketing Performance, were not supported. All other hypotheses were supported at p < 0.05 or better.

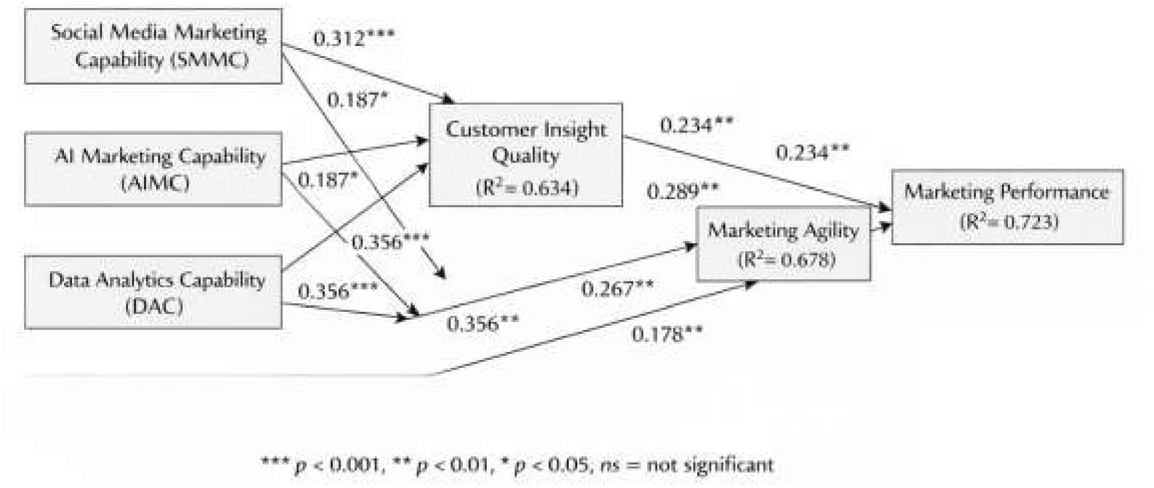

Figure 1. Structural Path Model with Coefficients
Source: *Primary data processed (2026)*

b) **Discussion**

The findings provide empirical support for the Integrated Marketing Capability Strengthening Model and offer several insights into how MSMEs can enhance their marketing performance through digital capability development. The discussion organizes the findings around three themes: the primacy of data analytics capability, the nuanced role of AI, and the critical mediating functions of customer insight quality and marketing agility.

The Primacy of Data Analytics Capability

The most robust finding from this study is the dominant influence of Data Analytics Capability across all outcomes. DAC demonstrated the strongest direct effect on Customer Insight Quality (β=0.356), Marketing Agility (β=0.267), and Marketing Performance (β=0.178). This finding suggests that for MSMEs in the Indonesian context, the ability to systematically collect, manage, and analyze customer data serves as the foundational capability upon which other digital marketing capabilities depend.

This finding resonates with the theoretical reasoning of Borges et al. (2021), who argued that data-driven decision making constitutes the foundation of effective contemporary marketing. Johanes & Siallagan (2024) similarly demonstrated that businesses with structured data management practices achieved better marketing outcomes through improved decision quality. The present study extends these arguments by contextualizing them in the MSME sector, demonstrating that even with limited resources and "small data," systematic data practices yield significant performance benefits.

Several mechanisms may explain this finding. First, data collection practices such as recording purchase histories and customer preferences create a memory of customer interactions that enables more personalized marketing. Second, data management practices such as customer segmentation allow MSMEs to tailor their offerings to different customer groups, increasing relevance and effectiveness. Third, data analysis practices such as trend identification and period comparison support evidence-based decision-making, reducing reliance on intuition and guesswork. These mechanisms collectively suggest that DAC functions as a capability-enabling capability, strengthening the effectiveness of other digital marketing activities.

The strong influence of DAC on Marketing Agility is particularly noteworthy. MSMEs that systematically analyze customer data are better positioned to detect market changes and adjust their strategies accordingly. This finding supports the argument of Onesi-Ozigagun et al. (2024) that data-driven organizations are more agile in responding to customer needs and competitive dynamics.

The Persistent Role of Social Media Marketing Capability

Social Media Marketing Capability consistently influenced all three outcomes, though with smaller effect sizes than DAC. SMMC positively influenced Customer Insight Quality (β=0.312), Marketing Agility (β=0.234), and Marketing Performance (β=0.156). This finding confirms that social media platforms serve not merely as communication channels but as strategic resources for customer insight generation and agile marketing.

The influence of SMMC on CIQ suggests that strategic social media use enables MSMEs to develop deeper understanding of their customers. Through careful monitoring of engagement metrics, analysis of customer interactions, and evaluation of content effectiveness, MSMEs can extract valuable insights about customer preferences and behaviors. This aligns with Adesoye's (2024, 2025) argument that social media marketing requires strategic planning and evaluation rather than merely posting content.

The significant but smaller direct effect of SMMC on MP (β=0.156) compared to its indirect effects suggests that much of the performance benefit of social media marketing flows through the mechanisms of customer insight and marketing agility. In other words, the performance impact of social media marketing is not simply about increasing visibility; it is about using social media to understand customers better and respond more quickly to their needs. This interpretation suggests that MSMEs should evaluate their social media effectiveness not just by engagement metrics but by how social media activities contribute to insight development and agile response.

The Nascent State of AI Marketing Capability

The finding that AI Marketing Capability influences Customer Insight Quality (β=0.187) but not Marketing Agility or Marketing Performance represents one of the most instructive results of this study. This pattern suggests that AI adoption among MSMEs in the study context is still in its early stages. MSMEs may be beginning to use AI for basic insight generation—such as analyzing customer behavior patterns or suggesting content variations—but have not yet integrated AI into their marketing workflows sufficiently to enhance agility or directly improve performance.

Several interpretations are possible. First, the AI tools accessible to MSMEs in West Sulawesi may be relatively basic, limited to consumer applications such as ChatGPT for content creation or simple automation features. Vamshi & Chakravorty (2025) noted that sophisticated AI applications for personalization and predictive analytics remain concentrated among large enterprises with substantial technological resources. Cherian (2025) similarly cautioned that AI's transformative potential in marketing is not yet widely realized among small businesses.

Second, the organizational readiness for AI integration may be limited. Implementing AI effectively requires not just technological tools but also complementary investments in skills, process redesign, and organizational learning. Khomein Singh & Anees (2025) identified that MSMEs face numerous barriers to technology adoption including limited technical skills, financial constraints, and insufficient awareness of benefits. The present study's findings suggest that MSMEs may be using AI in isolated applications without systematic integration into marketing decision-making processes.

Third, the relatively low levels of AI capability in the sample (mean scores were significantly lower for AIMC than for other constructs) may reflect the early adoption stage of AI in the Indonesian MSME sector. Masitoh et al. (2025) observed that while digital transformation is progressing, the adoption of advanced technologies such as AI remains limited. As AI technologies become more accessible and MSMEs gain experience with their applications, the effects of AI capability on agility and performance may strengthen over time.

The non-significant findings for H5 and H6 do not imply that AI is irrelevant to MSME marketing. Rather, they suggest a phased trajectory of capability development: initial AI adoption may support insight generation (H4 supported), but achieving marketing agility and performance benefits requires more advanced integration and complementary capability development. This interpretation is consistent with the TOE framework's emphasis on organizational context—technology alone does not generate value; it must be aligned with organizational processes and capabilities.

The Mediating Functions of Customer Insight Quality and Marketing Agility

The supported mediation hypotheses (H10, H11, H12) confirm the theoretical logic that digital marketing capabilities influence performance through the development of customer insight and marketing agility. The significant relationships CIQ → MA (β =0.289), CIQ → MP (β =0.234), and MA → MP (β =0.312) establish a sequential logic: capabilities generate insights (CIQ), insights enable agility (MA), and agility produces performance (MP).

The mediating role of Customer Insight Quality suggests that raw capabilities—such as having social media platforms or data management tools—are insufficient to generate performance improvements. These capabilities must be translated into meaningful understanding of customers. MSMEs that collect data but do not analyze it for insights will not realize the performance benefits of their digital investments. Soraya Tanjung (2024) emphasized this point by distinguishing between data possession and insight utilization, arguing that insights, not data, drive marketing effectiveness.

The mediating role of Marketing Agility reflects the dynamic capability perspective. In rapidly changing markets, the ability to respond quickly and effectively to customer preferences is a critical success factor. Onesi-Ozigagun et al. (2024) and Novitasari et al. (2025) demonstrated that agile organizations outperform their less agile counterparts because they can adjust to changing conditions more effectively. The present study extends this understanding by identifying the antecedents of agility—specifically, digital capabilities and customer insight quality.

The strong effect of MA on MP (β=0.312) confirms that agility is not merely a theoretical concept but a practical driver of performance. MSMEs that can adapt their marketing strategies quickly, allocate resources flexibly, and respond to market changes effectively achieve better sales growth, market expansion, and customer satisfaction. This finding underscores the importance of organizational agility in the digital marketing context.

5) Conclusion

This research set out to develop and empirically validate an Integrated Marketing Capability Strengthening Model. The model explains how three digital capabilities—social media marketing, AI marketing, and data analytics—collectively shape MSME marketing performance. Testing the model with data from 75 MSMEs in West Sulawesi yielded encouraging results. The model accounted for 72.3% of the variance in marketing performance. Ten of the twelve hypothesized relationships found support. This confirms the overall validity of the proposed framework.

The most telling finding concerns Data Analytics Capability. It emerged as the dominant influence—the foundational capability upon which other digital marketing capabilities depend. MSMEs that systematically collect, manage, and analyze customer data achieve superior outcomes across the board. They enjoy better customer insight quality, greater marketing agility, and stronger performance. Social Media Marketing Capability also contributed consistently, though with smaller effect sizes. This confirms that social media matters strategically, not just as a presence exercise. AI Marketing Capability showed a more nuanced pattern. It influenced customer insight quality but showed no direct effects on agility or performance. This suggests that AI adoption among MSMEs remains in its early stages.

The mediating roles of Customer Insight Quality and Marketing Agility received empirical confirmation. This establishes the mechanisms through which digital capabilities translate into performance improvements. The logic is sequential and clear. Capabilities generate insights. Insights enable agility. Agility produces performance. This chain provides a crisp theoretical explanation. It helps explain why some MSMEs succeed in digital marketing while others fail, despite similar technological investments.

Theoretical Contributions

This research makes several contributions to the academic literature. Three deserve particular emphasis. First, the study integrates three distinct digital marketing capabilities within a single empirically validated model. This addresses the fragmentation that characterized prior research. Previous studies tended to examine social media, AI, or data analytics in isolation. By bringing them together, the model reveals how they interact and collectively shape performance. The integration of

RBV, Dynamic Capability Theory, and the TOE Framework provides a comprehensive theoretical foundation. Future research can build on this integrated perspective.

Second, the identification and empirical testing of the dual mediation mechanism through CIQ and MA contributes to understanding the "black box" between digital capabilities and performance. The findings reveal something important. Digital capabilities do not directly produce performance improvements. Rather, they generate insights. These insights enable agile responses. Agile responses, in turn, enhance performance. This finding refines both RBV and Dynamic Capability perspectives. It specifies the mechanisms through which resources and capabilities create value. The theoretical contribution lies in making these mechanisms explicit and empirically testable.

Third, the study contextualizes these relationships in the Indonesian MSME sector, specifically in an eastern Indonesian region. This addresses a notable gap in the literature. Most digital transformation research focuses on urban areas or developed economies. By examining a non-urban, developing economy context, the study demonstrates that theoretical models developed in Western contexts are applicable but require contextual adaptation. The emphasis on "small data" rather than "big data" is one such adaptation. This contextualization enriches the literature and provides a foundation for comparative studies.

Practical Implications

The findings offer several practical implications for MSME owners, policymakers, and business mentors. Five implications stand out. First, MSMEs should prioritize the development of Data Analytics Capability. This does not require sophisticated technology. Simple, accessible practices yield significant benefits. Recording customer transactions, organizing customer information in spreadsheets, and regularly analyzing purchase patterns—these are within reach of most MSMEs. Training programs and mentoring should emphasize these foundational capabilities. The return on investment appears substantial.

Second, social media marketing training needs redesign. It should move beyond technical instruction on posting. Strategic planning and evaluation deserve equal attention. MSMEs should be guided to set specific objectives for social media activities, monitor engagement metrics, and adjust strategies based on results. The evaluation dimension of SMMC is particularly important. It links social media activity to insight generation. Without evaluation, social media remains tactical rather than strategic.

Third, AI adoption in MSMEs should be approached as a phased process. Expecting immediate transformation is unrealistic. Initial adoption may focus on basic automation and insight generation. More advanced AI integration can be pursued as organizational capabilities develop. Policymakers and technology providers should offer accessible AI tools and training appropriate to MSME capacity. The goal should be gradual capability building, not overnight revolution.

Fourth, capacity-building programs should emphasize the development of customer insight and marketing agility. Technical skills alone are insufficient. MSMEs need to systematically analyze customer data for insights. They also need to use those insights to rapidly adjust marketing strategies. This dual emphasis on insight and agility is crucial. It is the mechanism through which digital capabilities translate into performance. Programs that focus solely on technical skills miss this essential connection.

Fifth, the findings support integrated rather than fragmented capability development. Social media, AI, and data analytics should be developed as interconnected components of a unified marketing system. They should not be treated as separate initiatives. Program design and resource allocation should reflect this integration. The whole is greater than the sum of its parts. Developing capabilities in isolation risks missing the synergies that drive performance.

Limitations and Future Research Directions

Several limitations of this study should be acknowledged. Each suggests directions for future research. First, the cross-sectional design captures relationships at a single point in time. This cannot establish causality with certainty. Future research employing longitudinal designs would strengthen causal inference. Such designs would also capture the temporal dynamics of capability development. How do capabilities evolve over time? What sequences of development are most effective? These questions remain open.

Second, the sample was drawn from a specific geographic region—West Sulawesi. This may limit generalizability to other contexts. Future studies should extend the sample to other regions of Indonesia. Urban areas and regions with different economic and technological characteristics would provide valuable comparisons. Testing the model's generalizability across diverse contexts would strengthen its external validity.

Third, the sample size of 75, while adequate for PLS-SEM, limits statistical power for detecting smaller effects. Future research with larger samples would enable more robust estimation. It would also allow testing of more complex models. Additional mediating or moderating variables could be incorporated. The current model could be extended and refined with larger samples.

Fourth, the measurement instrument, while psychometrically sound, was developed for the specific MSME context. Adaptation for use with larger enterprises or other sectors may be required. Future research could explore the applicability of the instrument in different contexts. Cross-sector validation would enhance the instrument's utility and generalizability.

Fifth, the study focused on the Indonesian MSME sector. Research in other developing economy contexts would contribute to understanding whether the findings are context-specific or generalizable. Comparative studies across countries would be particularly valuable. They would reveal which aspects of the model are universal and which are context-dependent.

Sixth, future research could explore the specific mechanisms through which AI marketing capability develops over time. The current findings suggest AI adoption is still in early stages. Longitudinal studies tracking AI adoption and integration would provide valuable insights. How does AI capability evolve? What factors accelerate or impede its development? How do its effects on agility and performance change over time? These questions merit investigation.

Seventh, the relationship between MSME capability development and SDG achievement warrants further investigation. This study provided conceptual linkages. Empirical research specifically measuring SDG outcomes would strengthen the connection between digital capability and sustainable development. Does enhanced marketing capability contribute to decent work, economic growth, innovation, or responsible consumption? These questions have important policy implications.

Eighth, future research could employ qualitative methods more extensively. Understanding the lived experiences of MSME owners in developing digital capabilities would add depth. Such research could identify specific barriers, facilitators, and learning processes that quantitative methods cannot capture. The stories behind the numbers would enrich our understanding and inform more effective interventions.

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Statement on the Use of Generative Artificial Intelligence (AI)

During the preparation of this manuscript, the authors used **ChatGPT (OpenAI) and Grammarly** solely to support language editing, grammar correction, clarity, and readability. All AI-assisted content was critically reviewed, revised, and validated by the authors. These tools were not used as authors or as substitutes for scientific judgment, data analysis, interpretation of findings, or the formulation of conclusions. The authors take full responsibility for the accuracy, originality, integrity, and final content of the manuscript. This disclosure complies with the journal's Policy on the Use of Generative Artificial Intelligence (GenAI).

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