Journal of Economics, Entrepreneurship, Management Business and Accounting, 2026, 4(6),1589-1614
https://doi.org/10.61255/jeemba.v4i6.2114

AI Marketing Routines, Sensing, Adaptation, and Perceived Competitive Performance

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ABSTRACT

Purpose – This study examines how enacted AI-supported marketing routines relate to perceived competitive marketing performance through market sensing capability (MSC) and adaptive marketing capability (AMC) among tourism-oriented businesses in North Sulawesi.

Design/methodology/approach – We analysed 320 businesses recruited through an MSME-oriented field frame using PLS-SEM. We specified the seven-activity AIDMC index as a Mode B composite and MSC, AMC, and perceived competitive marketing performance as reflective measures. We compared reduced AIDMC compositions with an integrated marketing-agility alternative.

Findings/Results – AIDMC showed positive associations with MSC and AMC, and MSC with AMC. Both MSC and AMC related positively to respondent-perceived competitive performance. The additional direct AIDMC–performance association was nonsignificant ($\beta = 0.055$, $p = 0.322$), while three theory-ordered indirect associations were significant. The separated model explained 35.9% of performance variance versus 34.7% for the integrated model; paired CVPAT found no significant predictive-loss difference ($p = 0.1345$).

Originality/Value – Separating market interpretation from adaptive marketing action adds analytical granularity without establishing predictive superiority or temporal capability conversion. The heterogeneously weighted AIDMC composite captures reported activities, not a verified higher-order dynamic capability. Competitive performance reflects one informant's appraisal, and the recruitment frame does not independently establish statutory MSME status.

ARTICLE INFO

Keywords:
Social Adaptive Marketing, AI-enabled Marketing, Perceived Competitive Marketing Performance, Market Sensing, Tourism-Oriented Businesses

Article Information:
Received: 16/09/2026
Revise: 20/10/2026
Accepted: 16/11/2026

ISSN:
2985-3168 (Online)
2985-3222 (Print)

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1. Introduction

Digital adoption has become part of the operating environment of Indonesian MSMEs, but digital access and advanced AI use are not equivalent. In August 2024, Indonesia's communications ministry reported that 27 million MSMEs had adopted digital technology and set a national target of 30 million for that year (Ministry of Communication and Informatics, 2024). In August 2025, the Ministry of Creative Economy reported that more than 90% of Indonesian MSMEs had not yet optimized artificial intelligence (AI) use, indicating that broad digital adoption still coexists with limited AI utilization (Ministry of Creative Economy, 2025). The tourism context in North Sulawesi is simultaneously active and variable: official statistics recorded 1.31 million domestic tourist trips and 3,742 foreign tourist visits in June 2025, while domestic trips in January-June 2025 reached 6.76 million, 63.77% above the same period of 2024 (BPS North Sulawesi, 2025). These national and regional indicators describe the study context rather than the sample itself; together, they establish a setting in which digital access is widespread, AI-enabled marketing capability remains uneven, and tourism demand shifts rapidly.

Prior research rejects a simple technology-to-performance account, but it does so for different reasons. Davenport et al. (2020) and Huang and Rust (2021) map AI across marketing research, strategy, and action, whereas Mikalef and Gupta (2021) model AI capability as an organizational resource linked to creativity and performance. Homburg and Wielgos (2022) show that digital marketing capabilities add performance value beyond classic marketing capabilities, yet their evidence concerns a broader digital capability domain rather than AI-enabled routines. More recent studies shift attention toward intervening processes: Chen et al. (2025) connect AI adoption intensity with marketing performance through dynamic marketing capabilities, Abdul Wahab and Radmehr (2024) identify absorptive capacity and customer agility as mechanisms linking AI assimilation with SME performance, and Neiroukh et al. (2025) place decision-making speed and quality between AI capability and organizational performance. Zhang et al. (2026), on the other hand, demonstrate that AI-enabled marketing communication does not generate uniform performance benefits because customer uncertainty and heterogeneity condition its value. The literature therefore supports a capability-based explanation while leaving the specific sequence from AI-supported marketing routines to market interpretation and adaptive market action unresolved.

The present study isolates that unresolved sequence by separating market interpretation from market-facing action. Market sensing capability (MSC) captures recurring collection and interpretation of customer, competitor, and market information, whereas adaptive marketing capability (AMC) captures changes in marketing activity after a relevant market shift is recognized. This separation matters because adjacent literatures often combine the two functions. Kalaignanam et al. (2021), for example, conceptualize marketing agility as rapid iteration between market sensemaking and marketing decisions. That integrated concept clarifies why speed and iteration matter, but it does not estimate the distinct association of interpretation and adaptive action with performance. The present model therefore treats MSC and AMC as related but non-equivalent capabilities, consistent with the dynamic capabilities view (DCV) distinction between sensing and subsequent seizing/reconfiguration.

The tourism-business setting sharpens this distinction. Tourism demand changes with seasonality, destination events, platform visibility, reviews, and visitor composition, so firms face repeated information and response problems rather than a one-time technology-adoption decision. Bulchand-Gidumal et al. (2024) show that hotel AI marketing spans personalization, customer interaction, analytics, and operational challenges. Kim et al. (2025) similarly identify

organizational decision making and AI in marketing as central research directions in hospitality and tourism, while Demir and Demir (2025) show that tourism-SME owners and managers differ in how they frame AI investment and implementation. At the strategic level, Succurro (2026) finds that tourism SMEs gain more from combining digital adoption with an explicit digital strategy than from technology adoption alone. Indonesian evidence also links social-media marketing with MSME performance (Tatik & Setiawan, 2025), but it does not distinguish market sensing from adaptive marketing. Together, these studies justify examining how AI-supported marketing routines sit inside a capability system rather than treating tourism AI use as a homogeneous input.

Three close empirical streams define the study's incremental contribution. Chen et al. (2025) connect AI adoption intensity to marketing performance through a broad dynamic-marketing-capability mechanism. Abdul Wahab and Radmehr (2024) examine AI assimilation through absorptive capacity and customer agility, while Mu and Zhang (2025) examine AI-marketing usage and firm performance through customer-related mechanisms. These studies already establish that AI–performance relationships can operate through intervening organizational and market mechanisms. The present study therefore makes a narrower claim: it separates a market-interpretation capability (MSC) from a market-facing adaptive-action capability (AMC) within one tourism-business model and models AIDMC as a composite of enacted AI-supported marketing routines. We use 'capability conversion' only as an author-proposed explanatory framing grounded in the dynamic capabilities view. It is not an established construct, is not measured separately, and does not imply that this cross-sectional design observes a temporal conversion event.

Accordingly, the study asks two research questions: RQ1, how is AIDMC associated with MSC, AMC, and perceived competitive marketing performance among tourism-oriented businesses recruited through an MSME-oriented frame? RQ2, are the AIDMC–performance associations concentrated in separate and serial indirect paths through MSC and AMC? Using 320 firms in North Sulawesi, the analysis tests these questions with a theory-ordered PLS-SEM model and predictive diagnostics. The design is cross-sectional, so the ordering is interpreted as a theoretically specified association rather than an observed temporal sequence.

2. Literature Review & Hypothesis Development

2.1. AI-enabled marketing routines as an enacted activity composite

The conceptual separation imposes a falsifiable boundary: if AI routines merely record the frequency of task use, their association with outcomes should depend on independently measured information interpretation and response activities; any stand-alone capability claim requires longitudinal evidence of routinization, coordination and reproducibility. Future measurement work should ask about recurrent cross-role workflows, exception handling, knowledge retention and adjustment under market disruption rather than infer these capacities from task use.

DCV separates resource possession from the organizational capabilities used to sense change, seize opportunities, and reconfigure activity (Teece et al., 1997; Teece, 2007). Digital-transformation research reaches a similar conclusion from a different route: digital technologies create value when firms develop complementary organizational assets and routines rather than when they merely install or access technology (Verhoef et al., 2021). This distinction is especially visible in SMEs. Eller et al. (2020) find that digitalization is associated with SME financial performance but that individual resources do not translate uniformly into

outcomes, while Matarazzo et al. (2021) identify sensing and learning capabilities as pillars through which SMEs use digital transformation to create customer value. The implication for AI marketing is specific: access to generative, analytical, targeting, or decision-support functions cannot substitute for the routines that organize those functions into repeatable marketing work.

In this study, AIDMC is the operational label for a composite of seven enacted AI-supported marketing routines: creating or adjusting digital content, finding prospective customers, identifying customer groups, tailoring messages or offers, responding to customers, evaluating promotions, and using AI output in subsequent marketing decisions. The indicators establish reported execution across distinct tasks. They do not independently measure repeatability across episodes, cross-functional coordination, organizational memory, or resource reconfiguration. We therefore treat AIDMC as an enactment-focused marketing-routine composite rather than direct evidence that the firm possesses a higher-order dynamic capability. The Mode B specification captures heterogeneity in activity content, but neither Mode B nor statistically significant paths turns AI use into an organizational dynamic capability. This distinction limits the scope of the DCV interpretation (Teece, 2007; Mikalef & Gupta, 2021; Homburg & Wielgos, 2022).

2.2. From AI-enabled marketing to market sensing

Market sensing is the recurring work of gathering, monitoring, interpreting, and sharing information about customers, competitors, and market trends (Day, 1994). AI-supported routines can expose patterns in customer interaction, targeting, promotional response, and external information, but exposure is not equivalent to organizational interpretation. Matarazzo et al. (2021) place sensing and learning at the center of SME digital transformation, while Abdul Wahab and Radmehr (2024) show that AI assimilation is associated with absorptive capacity and customer agility. These studies support an information-processing route without collapsing the technology-related capability into the sensing capability itself. That distinction also addresses item-content adjacency in the present instrument: AIDMC3, AIDMC6, and AIDMC7 touch activities near sensing or adaptation, but MSC represents a broader recurring capability to collect and interpret market information. The overlap is therefore tested empirically rather than assumed away.

For small firms with limited formal market-research capacity, AI-supported routines can reduce the effort required to organize customer and promotional information and generate alternatives for managerial attention. Chen et al. (2025) report a positive link between AI adoption intensity and dynamic marketing capabilities, while Neiroukh et al. (2025) show that decision processes help explain how organizational AI capability relates to performance. Neither study tests the present AIDMC–MSC relationship directly, but both challenge a purely technological account and support testing whether enacted AI marketing routines are positively associated with market sensing.

H1: The composite of enacted AI-enabled marketing routines (AIDMC) is positively associated with market sensing capability.

2.3. From sensing to adaptive marketing action

Recognizing a market shift is conceptually distinct from changing what the firm does. AMC captures changes to marketing activities, strategy, programs, or offers after a relevant market change is recognized. Within DCV, AMC represents a market-facing expression of the action side of seizing and reconfiguring: seizing concerns committing resources to a response, whereas reconfiguring concerns altering routines and resource deployment (Teece, 2007).

AMC does not exhaust either higher-order function. This boundary also distinguishes AMC from the broader marketing-agility construct. Kalaignanam et al. (2021) combine sensemaking, marketing decisions, speed, and iteration within marketing agility, whereas the present model separates interpretation from adaptive action so that their associations can be estimated independently. Bekos et al. (2026) and Zhou et al. (2019) likewise connect strategic/marketing adaptation with changing market conditions, and recent multisource evidence links marketing agility with longer-run firm performance through customer outcomes (Agag et al., 2025).

AI can reduce the time and effort required to draft alternatives, personalize messages, review promotional results, or generate response options. Huang and Rust (2021) place AI applications across marketing strategy and action; Bulchand-Gidumal et al. (2024) document tourism applications that span personalization, communication, and analytics; and Demir and Demir (2025) show that tourism-SME implementation depends on managerial judgments about strategy and operational feasibility. These studies support expecting AIDMC to be associated with AMC, while the separate MSC–AMC path captures the theoretical proposition that interpreting a market change and changing marketing activity remain distinct organizational tasks.

H2: The composite of enacted AI-enabled marketing routines (AIDMC) is positively associated with adaptive marketing capability.

H3: Market sensing capability is positively associated with adaptive marketing capability.

2.4. Market sensing, adaptive marketing, and perceived competitive marketing performance

Perceived competitive marketing performance (CMP) is a single informant's comparative appraisal of the firm's customer-base growth, acquisition of new customers, sales from existing customers, and total sales revenue relative to that informant's perceived main competitor during the preceding twelve months. The instrument did not standardize competitor identification or independently validate the comparative information. Consequently, CMP represents perceived relative performance, not verified growth. Capability–performance studies motivate the theoretical expectation (Morgan et al., 2009; Vorhies & Morgan, 2005; Homburg & Wielgos, 2022; Agag et al., 2025), but their measures and research designs do not validate this study's competitive referent.

MSC can support performance by directing managerial attention toward changes in customer preferences, competitor moves, and market conditions. Yet interpretation alone does not change an offer, message, channel emphasis, or promotional program. AMC captures that market-facing response. Emerging-market evidence reinforces the distinction: Wilopo et al. (2026) show that strategic agility, marketing agility, and market-driving capability do not contribute uniformly to SME performance, while Matarazzo et al. (2021) show that digital value creation in SMEs depends on dynamic-capability processes. The present model therefore expects both MSC and AMC to relate positively to competitive marketing performance but does not assume equal effect sizes.

A direct AIDMC–performance association remains theoretically plausible because AI-supported routines can reduce effort in content production, customer response, prospect targeting, and campaign evaluation. Mikalef and Gupta (2021), Homburg and Wielgos (2022), Mu and Zhang (2025), and Tatik and Setiawan (2025) each report positive links between AI/digital capabilities or digital marketing activity and performance-related outcomes. Yet a second empirical stream qualifies that expectation. Chen et al. (2025) emphasize dynamic marketing capabilities, Abdul Wahab and Radmehr (2024) identify absorptive capacity and customer agility, Neiroukh et al. (2025) identify decision-process mechanisms, and Zhang et al. (2026) identify customer-related boundary conditions. H6 therefore serves as a direct benchmark. Its rejection would not imply that

AIDMC lacks an overall association with performance; it would indicate that an additional direct association is not evident after MSC and AMC enter the model.

H4: Market sensing capability is positively associated with perceived competitive marketing performance.

H5: Adaptive marketing capability is positively associated with perceived competitive marketing performance.

H6: The composite of enacted AI-enabled marketing routines (AIDMC) is positively associated with perceived competitive marketing performance.

2.5. Indirect capability pathways and the proposed capability-conversion framing

There are several plausible indirect routes from AIDMC to performance, and prior studies specify different mechanisms linking AI-related capability with performance. Chen et al. (2025) emphasize dynamic marketing capabilities; Abdul Wahab and Radmehr (2024) emphasize absorptive capacity and customer agility; Neiroukh et al. (2025) emphasize decision speed and quality; and Mu and Zhang (2025) identify customer acquisition and satisfaction mechanisms. Ameen et al. (2024) adds a complementary insight by showing that AI capability produces different creative outcomes when coupled with strategic agility. None of these studies tests the identical AIDMC→MSC→AMC→CMP sequence. The present study therefore does not claim a new universal mediation mechanism. It tests whether the covariance pattern in tourism businesses is consistent with three distinct indirect associations: through MSC, through AMC, and through a theory-ordered MSC-to-AMC sequence. 'Capability conversion' labels this author-proposed interpretation of the pattern; it does not denote a separately measured construct or an observed temporal event.

We assess the integrated higher-order agility alternative as a competing measurement architecture; reciprocal and longitudinal explanations require different research designs.

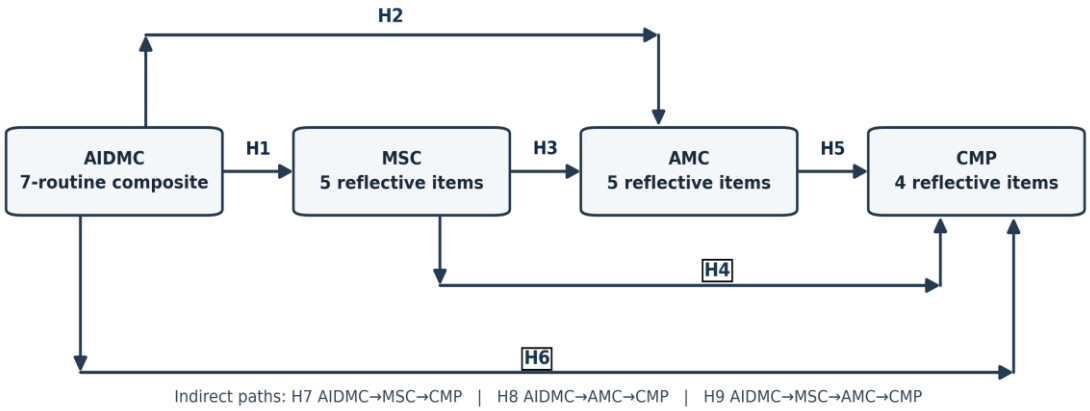
Competing-model evidence now permits a direct assessment of the integrated-agility rival. We compared the original separated MSC–AMC model (M0) with a two-dimensional higher-order marketing-agility model (M31), retaining the same 320 observations and outcome indicators. Rather than establishing the empirical dominance of one architecture, this comparison tests whether separating interpretation and action offers a meaningful explanatory or predictive increment. The cross-sectional design still cannot adjudicate reciprocal or temporal mechanisms.

H7: The AIDMC routine composite has a positive indirect association with perceived competitive marketing performance through market sensing capability.

H8: The AIDMC routine composite has a positive indirect association with perceived competitive marketing performance through adaptive marketing capability.

H9: The AIDMC routine composite has a positive theory-ordered serial indirect association with perceived competitive marketing performance through MSC and AMC, in that order.

Figure 1. Conceptual model, construct specification, and hypotheses



Source: Authors' conceptualization.

3. Methodology

3.1. Research design, context, and respondents

The unit of analysis was the business, represented by one respondent involved in marketing decisions. The recruited sample comprised tourism-oriented businesses that the MSME-oriented field frame identified as eligible and that reported active AI-assisted marketing. The research does not establish their legal MSME classification. The survey did not collect the business-capital or annual-sales information needed to verify MSME status under Government Regulation No. 7/2021. Hence the sample is not a legally verified MSME cohort, and our estimates generalize only to the eligible recruited businesses. Recruitment used purposive location and business-type balancing, not probability sampling. Planning documents specified outreach to approximately 500–600 businesses, at least 350 completed questionnaires, and about 300 usable cases; the retained analytical archive confirms 320 usable cases but does not preserve an exact approached count, recruitment-channel log, survey-mode breakdown, or complete dated fieldwork log. We do not reconstruct missing documentation retrospectively. The field instrument was administered in Bahasa Indonesia.

Area and business-type quotas functioned as balancing targets, not as equal-probability strata or fixed equal-size cells. Recruitment covered Manado, Tomohon, Minahasa, North Minahasa, Bitung, and other represented locations in North Sulawesi, together with culinary, café/restaurant, souvenir/local-product, craft/creative, tourism-service, tourism-support retail, and other tourism-oriented businesses. The retained design material does not contain a numeric cell-by-cell quota matrix. We therefore report the achieved margins in Table 1 and the achieved business type×location, business type×firm size, and location×firm size cross-tabulations in Appendix C. No quota targeted gender or age, so their near-equal marginal distributions cannot be attributed to a planned equal-allocation design.

Eligibility required at least one year of business operation, use of digital marketing channels, a tourism/visitor customer orientation, and active use of at least one AI or AI-assisted marketing function during the preceding six months. The six-month phrase defined a recency window, not a minimum duration of accumulated AI experience. A firm reporting less than six months of total AI-marketing experience therefore remained eligible if it actively used a qualifying AI function within that window. A follow-up function screen excluded respondents

whose only exposure involved passive platform algorithms. The final analytical dataset contained no missing values in the variables used for the model, so no imputation was applied.

The respondent-role option 'Other' captured marketing decision-makers whose job titles did not match owner, owner-manager, or manager. Every retained respondent, including those in 'Other', passed the screening requirement of direct involvement in marketing decisions. The dataset does not preserve finer job-title detail or a separate informant-knowledge scale for those 95 cases, so we do not retrospectively relabel them. Instead, we evaluate role-related robustness by re-estimating the complete model after excluding all 'Other' respondents (N=225).

Informant qualification rested on a broad involvement-in-marketing-decision screen, not a validated informant-competence scale. No retained field records establish decision authority, tenure in the specific marketing function, access to competitor accounts, or confidence in estimating relative performance for the 95 'Other' responses. The N = 225 exclusion model checks coefficient sensitivity; it cannot validate what the excluded or included respondents knew about the firms.

The questionnaire informed respondents about the academic purpose of the study, voluntary participation, aggregate analysis, and the right to discontinue at any point; continuing the questionnaire constituted informed consent. Re-checking the retained project archive did not identify a verifiable institutional ethics-approval or exemption record for this specific survey. We therefore do not report an approval identifier or infer a formal status that the archive cannot substantiate. This documentary limitation does not alter the recorded consent procedure, but it remains a reporting limitation. The de-identified analytical data are not publicly deposited; access requests can be directed to the corresponding author subject to participant confidentiality and applicable institutional requirements. Potential non-response bias was assessed by comparing the first and last 160 usable responses using Welch tests for the focal construct scores and chi-square tests for categorical characteristics.

Balanced demographic and firm-category margins describe the realized purposive sample, not independent evidence of fabrication or random-sample representativeness.

Table 1. Respondent and firm profile

Characteristic	Category	n (%)
Position	Owner	70 (21.9%)
Position	Owner-manager	85 (26.6%)
Position	Manager	70 (21.9%)
Position	Other	95 (29.7%)
Gender	Male	100 (31.2%)
Gender	Female	120 (37.5%)
Gender	Prefer not to answer	100 (31.2%)
Age group	<25	64 (20.0%)
Age group	25–34	68 (21.2%)
Age group	35–44	66 (20.6%)
Age group	45–54	59 (18.4%)
Age group	≥55	63 (19.7%)
Education	High school	63 (19.7%)
Education	Diploma	69 (21.6%)
Education	Bachelor	70 (21.9%)
Education	Master/Doctoral	51 (15.9%)
Education	Other	67 (20.9%)

Characteristic	Category	n (%)
Management tenure	<1 year	56 (17.5%)
Management tenure	1–3 years	70 (21.9%)
Management tenure	4–6 years	45 (14.1%)
Management tenure	7–10 years	57 (17.8%)
Management tenure	>10 years	92 (28.7%)
Location	Manado	46 (14.4%)
Location	Tomohon	54 (16.9%)
Location	Minahasa	37 (11.6%)
Location	North Minahasa	60 (18.8%)
Location	Bitung	50 (15.6%)
Location	Other North Sulawesi	73 (22.8%)
Business type	Culinary	38 (11.9%)
Business type	Café/restaurant	54 (16.9%)
Business type	Souvenir/local product	44 (13.8%)
Business type	Craft/creative	52 (16.2%)
Business type	Tourism service	51 (15.9%)
Business type	Tourism-support retail	44 (13.8%)
Business type	Other	37 (11.6%)
Firm size	1–4 employees	77 (24.1%)
Firm size	5–19 employees	79 (24.7%)
Firm size	20–49 employees	79 (24.7%)
Firm size	≥50 employees	85 (26.6%)
Digital-marketing experience	<1 year	93 (29.1%)
Digital-marketing experience	1–3 years	73 (22.8%)
Digital-marketing experience	4–6 years	80 (25.0%)
Digital-marketing experience	>6 years	74 (23.1%)
AI-marketing experience	<6 months	78 (24.4%)
AI-marketing experience	6–12 months	77 (24.1%)
AI-marketing experience	1–2 years	87 (27.2%)
AI-marketing experience	>2 years	78 (24.4%)

Notes: The location category "Other" denotes other locations within North Sulawesi not separately listed. Percentages may differ slightly from 100 because of rounding.

Source: Main survey dataset, n = 320.

For legal context, Government Regulation of the Republic of Indonesia No. 7/2021 classifies MSMEs using business-capital or annual-sales criteria. Excluding land and buildings used for the business, micro enterprises have business capital up to Rp1 billion, small enterprises more than Rp1 billion to Rp5 billion, and medium enterprises more than Rp5 billion to Rp10 billion. The corresponding annual-sales thresholds are up to Rp2 billion for micro enterprises, more than Rp2 billion to Rp15 billion for small enterprises, and more than Rp15 billion to Rp50 billion for medium enterprises (Government of the Republic of Indonesia, 2021). Employee headcount is not the general classification rule under Article 35, although Article 36 permits ministries or agencies to use employment and other criteria for specific purposes. Accordingly, the 85 firms reporting >=50 employees cannot be classified as non-MSMEs from headcount alone. However, the survey did not collect the capital and annual-sales fields required to independently re-verify legal status. The term MSME therefore reflects the study's field recruitment frame, and this classification limitation remains explicit.

3.2. Measurement development

Instrument development proceeded in stages. Four experts reviewed item relevance and clarity in two rounds. In the second round, the 28 then-current substantive items reached I-CVI=1.000 for both relevance and clarity and S-CVI/Ave=1.000 for both dimensions. Five AI-using MSMEs then participated in contextual interviews, followed by a cognitive pretest with 15 respondents. A separate pilot survey (n=50) evaluated the measurement model; pretest and pilot participants were excluded from the 320-case main sample. Several AIDMC items were simplified after the earlier expert-review wording. We therefore report the CVI values as instrument-development history rather than as fresh validation of the final post-pilot wording. The field instrument used Bahasa Indonesia. Because no separate English field version was administered, conventional back-translation was not applicable; Appendix A presents an author translation for reporting.

Content-validity continuity and final wording. Four experts evaluated relevance and clarity across two rounds, with the second-round 28-item instrument reaching I-CVI = 1.000 and S-CVI/Ave = 1.000 for the assessed items. Subsequently, five AI-using businesses completed contextual interviews, 15 participants completed a cognitive pretest, and an independent group of 50 respondents completed the pilot test; these respondents did not enter the 320-case main analysis. After expert assessment, wording refinements simplified language and enhanced respondent comprehension without changing the intended meanings, conceptual content, or substantive coverage of the AIDMC indicators, as confirmed by the authors. The early CVI results therefore remain relevant to the item content, although they do not constitute an independent second rating of the exact final phrasing. We explicitly distinguish continuity of content from a claim of newly obtained expert scores. The primary seven-item Mode B specification preserves complementary AI-supported marketing task domains; a nonsignificant relative weight alone does not remove an indicator's conceptual contribution. Nevertheless, the item set measures enacted AI-supported marketing routines rather than resource orchestration or higher-order organizational renewal in full.

AIDMC was estimated as a composite (Mode B) because its seven indicators represent distinct AI-supported marketing routines that jointly define the capability domain rather than interchangeable manifestations of one latent trait. A separate global item, AIDMC-G, served only as the redundancy criterion and was excluded from the substantive H1–H9 model. Pilot evidence supported continued use of the measures: AIDMC indicator loadings ranged from 0.612 to 0.800, VIFs from 1.537 to 2.333, and the redundancy coefficient was 0.881 ($p<0.001$); MSC, AMC, and CMP had composite reliabilities of 0.924, 0.916, and 0.897 and AVEs of 0.710, 0.687, and 0.685, respectively, with a maximum HTMT of 0.789. These pilot statistics support instrument progression but do not replace the main-sample measurement assessment.

MSC used five reflective items covering collection and interpretation of customer, competitor, and market-trend information. AMC used five reflective items on marketing adjustment after a recognized market change. Perceived competitive marketing performance (CMP) used four reflective items asking a single respondent to compare customer-base growth, new-customer acquisition, sales from existing customers, and total sales-revenue growth with the respondent's perceived main competitor over the preceding 12 months. The retained questionnaire and study archive do not establish a standardized main-competitor identification procedure, an independent competitor-knowledge screen, or validation against financial statements, booking counts, transaction records, or platform analytics. Accordingly, CMP is an informant-reported relative appraisal, not verified firm performance. AIDMC,

MSC, and AMC used seven-point agreement scales; CMP used a seven-point relative-to-competitor scale. Appendix A records the author-translated wording and response frames.

Table 2. Construct specification and measurement

Construct	Role	Specification	Indicators	Response frame
AIDMC	Exogenous capability	Composite (Mode B)	7	Agreement, 1–7
MSC	Mediator 1	Reflective	5	Agreement, 1–7
AMC	Mediator 2	Reflective	5	Agreement, 1–7
CMP	Endogenous outcome	Reflective	4	Relative to main competitor, 1–7
AIDMC-G	Auxiliary criterion	Single item	1	Used only for redundancy analysis

Notes: AIDMC = composite of enacted AI-enabled digital marketing activities; MSC = market sensing capability; AMC = adaptive marketing capability; CMP = perceived competitive marketing performance, an informant-rated relative outcome. AIDMC-G was excluded from the substantive structural model.

Source: Research instrument and authors' specification.

3.3. Common-method safeguards and analytical procedure

The questionnaire applied procedural safeguards against common-method bias: respondents did not see the proposed structural model, predictor, mediator, and outcome items were separated, responses were confidential, and CMP used a comparative response frame distinct from the agreement scales used for AIDMC, MSC, and AMC (Podsakoff et al., 2003). These procedures reduce obvious sources of consistency and evaluation apprehension but cannot remove common-method variance. We therefore retain full-collinearity VIF only as a supplementary diagnostic. The project did not collect a theoretically unrelated marker variable prospectively, and we did not create a post-hoc marker by relabelling substantive indicators. The absence of a marker or latent-method-factor design remains a limitation.

Estimation was carried out in SmartPLS 4. The model combines a composite (Mode B) AIDMC with reflective MSC, AMC, and CMP measures (Hair et al., 2020; Hair et al., 2022; Sarstedt et al., 2022). AIDMC assessment used indicator collinearity, outer weights, outer loadings, and redundancy analysis. Reflective measurement assessment used item loadings, Cronbach's alpha, rho_A, composite reliability (rho_c), AVE, HTMT, and cross-loadings. Structural assessment used inner VIFs, standardized path coefficients, R^2, f^2, and 10,000 bias-corrected and accelerated (BCa) bootstrap resamples. Specific indirect associations were evaluated from bootstrap confidence intervals rather than causal-steps logic. Because the design is cross-sectional, these tests quantify conditional association patterns rather than temporal mediation. Prediction was assessed with PLSpredict using 10 folds and 10 repetitions and with CVPAT against both indicator-average and linear-model benchmarks (Liengaard et al., 2021; Shmueli et al., 2019; Sharma et al., 2023). IPMA for CMP was used only as a descriptive managerial diagnostic, with indicator-level results reported in Appendix G. Sample-size planning preceded the main survey. A conventional a priori power calculation for up to seven predictors, f^2=0.15, α=0.05, and power=0.95 yielded a requirement of approximately 153 observations. The design target of about 300 usable cases and final N=320 therefore exceeded that analytical requirement; we do not use the PLS '10-times rule' as the sample-size justification.

Robustness assessment proceeded in five layers without replacing the theory-driven primary model. First, the pre-specified PLS control model added dummy-coded management tenure, firm size, digital-marketing experience, and AI-marketing experience to the endogenous constructs. Second, a supplementary score-based standardized regression added business type, location, respondent role, and education to those controls. Exact firm age was not independently recorded: the retained field labelled 'FirmAge' duplicates management tenure exactly, so it is not reinterpreted as a distinct firm-age variable. Third, the structural model was re-estimated after excluding all 95 respondents classified as 'Other' (N=225). Fourth, the model was re-estimated without AIDMC6 and AIDMC7, the two indicators with the clearest sensing/adaptive-action adjacency. Fifth, Gaussian-copula terms were examined as an endogeneity sensitivity diagnostic following Hult et al. (2018). None of these checks establishes causality; each tests whether the focal pattern is sensitive to a specific modelling or sample concern.

Gaussian-copula applicability requires non-normality of the tested potentially endogenous regressor and transparent generation of the corresponding copula control term in each endogenous equation. The supplied archive account reports six estimated terms but no auditable predictor-level non-normality tests or full term-construction specifications. Without those checks, the six estimates cannot establish identification or exogeneity; accordingly, this manuscript treats them as descriptive sensitivity results rather than evidence that reverse causality has been addressed. In the absence of regressor-level distribution checks and reproducible model-specific term construction, these estimates do not constitute a validated endogeneity correction. They remain descriptive archival results only.

4. Results and Discussion

4.1. Sample diagnostics and measurement model assessment

An early–late response comparison used the first and last 160 usable cases as a diagnostic for systematic response differences. Welch tests were nonsignificant for AIDMC ($p=0.188$), MSC ($p=0.606$), AMC ($p=0.151$), and CMP ($p=0.844$), and chi-square tests for categorical respondent and firm characteristics were also nonsignificant (all $p \geq 0.064$). These results provide no evidence of early–late differences in the observed sample, but they do not establish the absence of non-response bias because the exact approached-firm frame was not retained. Appendix B reports construct means, standard deviations, and correlations; Appendix C reports the business-type, location, and firm-size cross-tabulations.

Interpretation of the sample profile. The relatively balanced category margins, including the three gender groups of 100, 120, and 100, are descriptive properties rather than evidence of duplication, fabrication, or representativeness. Recruitment balanced geographic areas and business types but did not impose gender or age quotas; accordingly, we do not attribute those margins to a nonexistent quota. The N = 320 analytical file had no item-level missing values, and the first-versus-last-half comparisons did not identify statistically significant observed differences. Neither finding proves the provenance of individual responses. Original respondent-level metadata, exact approach counts, and timing or device records are unavailable in the retained study account. We refrain from claiming a technical duplicate, straightlining, IP, or completion-time audit that the archive cannot document.

The composite (Mode B) AIDMC indicators showed no collinearity problem, with VIFs from 1.233 to 1.474. Bootstrapped outer weights were statistically significant for AIDMC1, AIDMC5, and AIDMC7; AIDMC3 approached the conventional .05 threshold; AIDMC2, AIDMC4, and

AIDMC6 had nonsignificant relative weights. All seven outer loadings were positive and statistically significant. Because a formative/composite indicator can contribute through absolute content even when its relative weight is weak, the primary model retains all seven indicators for domain coverage and uses sensitivity analysis to test whether weak or concept-adjacent indicators drive the structural conclusions.

Convergent validity for the composite was evaluated in a separate redundancy model. The AIDMC→AIDMC-G coefficient was 0.730 ($p<0.001$), and AIDMC explained 53.3% of the variance in the global criterion. We use the redundancy coefficient as the convergent-validity evidence and report R^2 only as descriptive explained variance in the auxiliary criterion. The result supports convergence of the seven-indicator composite with the global criterion while remaining compatible with uneven relative indicator weights.

Table 3. Composite (Mode B) assessment of AI-enabled digital marketing capability

Item	Outer weight	p (weight)	Outer loading	VIF	Decision
AIDMC1	0.396	<0.001	0.710	1.275	Retained
AIDMC2	0.005	0.959	0.410	1.233	Retained for content coverage
AIDMC3	0.226	0.058	0.668	1.430	Retained
AIDMC4	0.152	0.159	0.572	1.322	Retained
AIDMC5	0.329	0.005	0.715	1.474	Retained
AIDMC6	−0.038	0.730	0.478	1.398	Retained for content coverage
AIDMC7	0.362	0.002	0.722	1.355	Retained

Notes: All outer loadings were statistically significant at $p < 0.001$. Separate redundancy analysis: AIDMC → AIDMC-G = 0.730, $p < 0.001$; R^2(AIDMC-G) = 0.533.

Source: Authors' SmartPLS 4 calculations, n = 320.

For the reflective constructs, item loadings ranged from 0.770 to 0.837 for MSC, 0.775 to 0.815 for AMC, and 0.749 to 0.834 for CMP. Composite reliability (rho_c) ranged from 0.883 to 0.905 and AVE from 0.640 to 0.657. Every HTMT estimate and its bootstrap upper bound remained below 0.85. Appendix D reports all item-level loadings and cross-loadings. AIDMC is not evaluated with reflective discriminant-validity criteria; potential overlap with MSC and AMC is instead examined through construct correlations, item-content comparison, item-level correlations for AIDMC3/AIDMC6/AIDMC7, and structural sensitivity re-estimation.

Table 4. Reflective measurement quality

Construct	Loading range	Cronbach's α	rho_A	rho_c	AVE
MSC	0.770–0.837	0.869	0.873	0.905	0.657
AMC	0.775–0.815	0.860	0.860	0.899	0.640
CMP	0.749–0.834	0.823	0.827	0.883	0.654

Source: Authors' SmartPLS 4 calculations, n = 320.

Table 5. HTMT discriminant-validity assessment

Construct pair	HTMT	95% bootstrap CI	Decision
MSC – AMC	0.632	0.540–0.719	Supported
MSC – CMP	0.541	0.439–0.636	Supported

Construct pair	HTMT	95% bootstrap CI	Decision
AMC – CMP	0.678	0.599–0.752	Supported

Source: Authors' SmartPLS 4 calculations, n = 320.

The supplementary full-collinearity check produced VIFs of 1.339 for AIDMC, 1.662 for MSC, 1.795 for AMC, and 1.561 for CMP. These values do not indicate severe collinearity, but they are not treated as proof that common-method bias is absent. No prospective marker variable was collected. This design limitation is retained explicitly.

Construct-level raw-score correlations were moderate (AIDMC–MSC=0.440; AIDMC–AMC=0.376; AIDMC–CMP=0.302), and item-level correlations for the reviewer-identified content-adjacent indicators were also modest: AIDMC3 with MSC items reached at most 0.266, AIDMC6 with MSC items at most 0.197, and AIDMC7 with AMC items at most 0.295 (its maximum with MSC items was 0.319). A sensitivity model removed AIDMC6 and AIDMC7, the two clearest sensing/action-adjacent items. The direct coefficients changed only modestly (AIDMC→MSC 0.447; AIDMC→AMC 0.169; MSC→AMC 0.474; MSC→CMP 0.193; AMC→CMP 0.447; AIDMC→CMP 0.050), H7–H9 remained significant, and R^2 for CMP remained 0.359. These results reduce, but do not eliminate, the concern that the focal pathway is an artefact of content overlap. Appendix E reports the sensitivity results.

Alternative composite specifications (ACS). We compared the seven-item primary specification (M0) with two post-estimation sensitivity reductions: M1 retained AIDMC1–AIDMC5, excluding the two indicators with sensing/action adjacency; M2 retained AIDMC1, AIDMC3, AIDMC5, and AIDMC7, excluding AIDMC2, AIDMC4, and AIDMC6 with weak relative weights. Each specification used the same 320 cases, retained MSC, AMC, and CMP measurement, and preserved the same structural relations. Estimated AIDMC→MSC coefficients were 0.471, 0.447, and 0.465 for M0, M1, and M2; AIDMC→AMC coefficients were 0.180, 0.169, and 0.186; AIDMC→CMP coefficients were 0.055, 0.050, and 0.045. R^2 for CMP rounded to 0.359 in all three specifications. In M2, the five paths significant in M0 remained significant, AIDMC→CMP remained nonsignificant ($p=0.415$), and all three specific indirect associations remained significant (H7 $\beta=0.090$, H8 $\beta=0.083$, H9 $\beta=0.096$; each $p<0.001$). These comparisons indicate descriptive stability of substantive structural conclusions, not equivalence of latent scores or formal statistical equivalence of competing models.

Predictive sensitivity. Using 10-fold PLSpredict with 10 repetitions, all four CMP indicators showed positive Q^2predict for M0, M1, and M2. The CMP1–CMP4 Q^2predict values were M0 [0.0548, 0.0595, 0.0516, 0.0485], M1 [0.0524, 0.0556, 0.0455, 0.0470], and M2 [0.0577, 0.0623, 0.0542, 0.0481]. Corresponding RMSE values were M0 [1.1069, 1.1311, 1.1055, 1.1030], M1 [1.1082, 1.1334, 1.1090, 1.1039], and M2 [1.1052, 1.1294, 1.1040, 1.1033]. Differences across specifications were small and do not demonstrate predictive superiority or statistical equivalence. Because M0 preserves wider task coverage without materially changing structural conclusions or predictive accuracy, we retain M0 as the substantively preferred primary composite and treat M1/M2 strictly as robustness checks. CVPAT comparisons against separate benchmark models are not interpreted as paired tests between M0, M1, and M2.

4.2. Structural model and hypothesis tests

Inner VIFs ranged from 1.000 to 1.606, so structural collinearity was not a concern. The model accounted for 22.2% of MSC variance, 32.7% of AMC variance, and 35.9% of CMP variance.

SRMR was 0.043 and NFI 0.897; both are reported as descriptive diagnostics rather than as stand-alone acceptance rules for the PLS model.

The direct paths followed a differentiated pattern. AIDMC was positively associated with MSC (β=0.471, p<0.001) and AMC (β=0.180, p<0.001), while MSC was positively associated with AMC (β=0.464, p<0.001). Both MSC (β=0.190, p<0.001) and AMC (β=0.445, p<0.001) were positively associated with CMP. A paired test using the same 10,000 bootstrap draws showed that AMC→CMP exceeded MSC→CMP by Δβ=0.255, with a 95% bootstrap interval of [0.078, 0.430] and p=0.005. H6 differed from the other direct hypotheses: AIDMC→CMP was small (β=0.055, f^2=0.004), and its 95% BCa interval crossed zero [−0.048, 0.172]. The data therefore provide no evidence of an additional direct AIDMC–CMP association after MSC and AMC are included; they do not establish that the population coefficient equals zero.

The outcome estimates refer to one respondent's perceptions of relative competitive results. The coefficients should not be interpreted as independently verified growth in revenue or customers. Shared managerial appraisal of adaptive behavior and relative success remains a plausible source of covariance even when structural VIF values are low.

Figure 2. Estimated structural model (standardized coefficients and R^2)

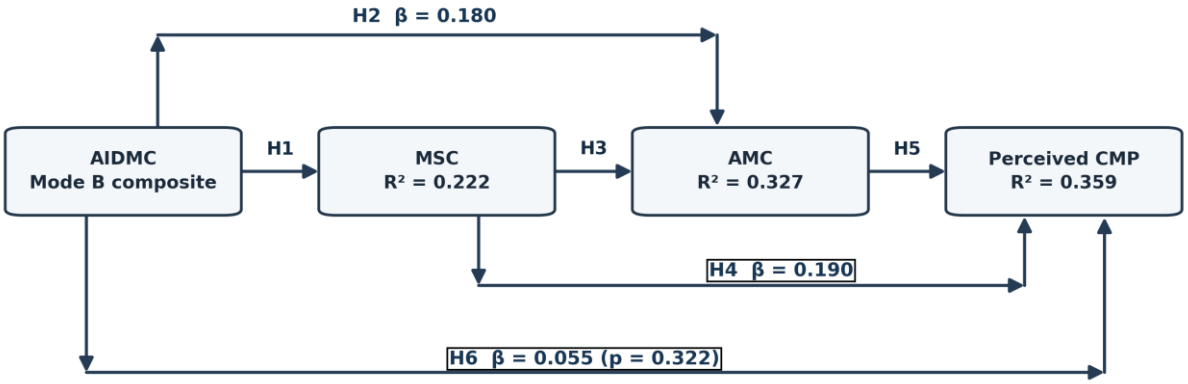


Table 6. Direct structural relationships

Hypothesis	Path	β	t	p	95% CI	f^2	Decision
H1	AIDMC → MSC	0.471	10.876	<0.001	0.391–0.562	0.286	Consistent with hypothesis
H2	AIDMC → AMC	0.180	3.493	<0.001	0.090–0.292	0.037	Consistent with hypothesis
H3	MSC → AMC	0.464	9.453	<0.001	0.362–0.553	0.249	Consistent with hypothesis
H4	MSC → CMP	0.190	3.604	<0.001	0.085–0.290	0.035	Consistent with hypothesis

Hypothesis	Path	β	t	p	95% CI	f^2	Decision
H5	AMC → CMP	0.445	9.011	<0.001	0.347–0.541	0.208	Consistent with hypothesis
H6	AIDMC → CMP	0.055	0.991	0.322	−0.048–0.172	0.004	No evidence for H6

Notes: BCa bootstrap with 10,000 resamples; two-tailed inference. R^2: MSC = 0.222; AMC = 0.327; CMP = 0.359.
Source: Authors' SmartPLS 4 calculations, n = 320.

4.3. Indirect capability pathways to performance

The indirect results clarify why the weak H6 coefficient should not be interpreted as absence of an overall AIDMC–CMP association. The specific association through MSC was 0.089 (p=0.001), through AMC 0.080 (p=0.002), and through the ordered AIDMC→MSC→AMC→CMP path 0.097 (p<0.001). The total indirect association was 0.267 and the total association 0.322. Each focal specific indirect coefficient is small in standardized magnitude, so statistical significance is not equated with large practical impact. Their substantive value lies in the recurrence of the same capability-pathway pattern across separate indirect routes and robustness checks.

Zhao et al. (2010) would classify this coefficient pattern as an indirect-only statistical configuration. In this cross-sectional study, we interpret that terminology as a description of direct and indirect associations rather than as evidence of temporal mediation.

Table 7. Specific indirect associations and hypothesis tests

Hypothesis	Indirect path	β	t	p	95% CI	Decision
H7	AIDMC → MSC → CMP	0.089	3.228	0.001	0.040–0.148	Consistent with hypothesis
H8	AIDMC → AMC → CMP	0.080	3.125	0.002	0.038–0.139	Consistent with hypothesis
H9	AIDMC → MSC → AMC → CMP	0.097	5.351	<0.001	0.066–0.137	Consistent with hypothesis
—	MSC → AMC → CMP	0.207	6.626	<0.001	0.147–0.268	Additional indirect effect
—	Total indirect AIDMC → CMP	0.267	—	<0.001	—	Significant
—	Total effect AIDMC → CMP	0.322	6.571	<0.001	0.238–0.430	Significant

Source: Authors' SmartPLS 4 calculations, n = 320.

4.4. Robustness checks

The archival Gaussian-copula terms had reported p-values of .123–.504, but the retained documentation does not verify their distributional prerequisites or construction. We therefore

exclude those terms from claims of validated endogeneity control. Appendix E preserves them solely as transparently qualified historical outputs; the independently interpretable control and indicator-sensitivity checks remain the robustness evidence.

Table 8. Robustness comparison: primary versus controlled model

Hypothesis	Primary β	Controlled β	Δβ	Controlled p
H1: AIDMC → MSC	0.471	0.460	-0.011	<0.001
H2: AIDMC → AMC	0.180	0.171	-0.009	0.001
H3: MSC → AMC	0.464	0.474	+0.010	<0.001
H4: MSC → CMP	0.190	0.167	-0.023	0.002
H5: AMC → CMP	0.445	0.446	+0.001	<0.001
H6: AIDMC → CMP	0.055	0.058	+0.003	0.311
H7: AIDMC → MSC → CMP	0.089	0.077	-0.012	0.005
H8: AIDMC → AMC → CMP	0.080	0.076	-0.004	0.003
H9: AIDMC → MSC → AMC → CMP	0.097	0.097	~0.000	<0.001

Notes: Controls were dummy-coded. Reference categories were <1 year management tenure, 1-4 employees, <1 year digital-marketing experience, and <6 months AI-marketing experience. Δβ = controlled β - primary β.

Source: Authors' SmartPLS 4 calculations, n = 320.

4.5. Predictive assessment and importance-performance results

PLSpredict produced positive construct-level Q^2predict values for MSC (0.198), AMC (0.136), and CMP (0.085), and every endogenous indicator had positive Q^2predict. Against the indicator-average benchmark, CVPAT loss differences were negative and statistically significant for MSC, AMC, and CMP. Against the linear-model benchmark, the loss difference was nonsignificant for MSC (p=0.144) but significant for AMC (p=0.039) and CMP (p=0.001). The model therefore shows positive predictive relevance, but incremental predictive performance relative to a linear benchmark is outcome-dependent rather than uniformly superior. Table 9 summarizes the construct-level comparison, and Appendix F provides the complete indicator-level PLSpredict and CVPAT results.

IPMA is treated as a descriptive diagnostic rather than a resource-allocation ranking. For CMP, total importance was approximately 0.315 for AIDMC, 0.400 for MSC, and 0.446 for AMC, while construct performance values were 61.21, 63.42, and 61.14, respectively. The roughly two-point performance spread is too small to support categorical claims that one construct is decisively weakest or strongest. Table 10 therefore reports the construct-level results descriptively, while Appendix G provides the full indicator-level importance and performance values, including AIDMC7 as a diagnostic signal rather than an automatic intervention priority.

Table 9. Predictive assessment for endogenous constructs

Assessment	MSC	AMC	CMP	Interpretation
Q^2predict (construct)	0.198	0.136	0.085	Positive predictive relevance
CVPAT vs indicator average: loss difference (p)	−0.1708 (<.001)	−0.1219 (.001)	−0.0730 (.010)	PLS lower predictive loss for all three
CVPAT vs linear model: loss difference (p)	−0.0161 (.144)	−0.0209 (.039)	−0.0304 (.001)	Evidence over LM for AMC and CMP, not MSC

Table 10. Importance–performance map results for CMP

Construct	Total importance	Performance	Reading

AIDMC	0.315	61.21	Meaningful importance; performance close to AMC
MSC	0.400	63.42	Meaningful importance; slightly higher performance
AMC	0.446	61.14	Largest total importance; similar performance to AIDMC

Source: Authors' PLSpredict, CVPAT, and IPMA calculations, n = 320.

4.6. Discussion

The results document associations between reported AI-supported marketing routines, market sensing, adaptive marketing, and perceived competitive marketing performance rather than an observed capability-conversion process. AIDMC related positively to MSC and AMC, MSC related positively to AMC, and both capabilities related positively to a single informant's competitive-performance appraisal. Although the AMC–CMP coefficient exceeded the MSC–CMP coefficient in a paired bootstrap comparison, the subjectively selected competitor and shared informant restrict interpretation of the difference to perceived relative performance. Common-source appraisal remains a rival explanation that the collinearity diagnostics do not exclude.

The positive AIDMC–MSC association aligns with studies that connect AI capability, AI assimilation, or digital transformation with information-processing and dynamic-capability mechanisms (Mikalef & Gupta, 2021; Abdul Wahab & Radmehr, 2024; Matarazzo et al., 2021). Chen et al. (2025) similarly link AI adoption intensity with a broader dynamic-marketing-capability mechanism. The present study narrows that mechanism by isolating market sensing as a distinct interpretive capability. The overlap diagnostics strengthen this interpretation: the sensing-adjacent AIDMC items showed modest item-level correlations with MSC, and deleting AIDMC6 and AIDMC7 left the focal structural pattern essentially unchanged.

The positive MSC–AMC coefficient distinguishes the two operational definitions within the separated specification, not two empirically verified stages of organizational development. Teece (2007) distinguishes sensing from seizing and reconfiguring, whereas Kalaignanam et al. (2021) incorporate iterative interpretation and action into marketing agility. The paired bootstrap comparison shows a larger AMC–CMP coefficient ($\Delta\beta = 0.255$, 95% CI [0.078, 0.430], $p = 0.005$), but the paired CVPAT did not detect a statistically significant predictive-loss difference between the separated and integrated models ($p = 0.1345$). Separation therefore supplies more granular coefficients and clearer managerial distinctions, without evidence that this architecture predicts perceived performance better than its integrated rival.

H6 provides the principal empirical contrast with a simple direct AI-performance account. Mikalef and Gupta (2021), Homburg and Wielgos (2022), Mu and Zhang (2025), and Tatik and Setiawan (2025) report positive AI- or digital-marketing relationships with performance-related outcomes. In this sample, however, AIDMC did not retain an additional direct association with CMP after MSC and AMC entered the model (β=.055, f^2=.004, BCa 95% CI [−.048,.172]). That result accords more closely with studies that place intervening capabilities, decision processes, or boundary conditions between AI resources and performance (Abdul Wahab & Radmehr, 2024; Chen et al., 2025; Neiroukh et al., 2025; Zhang et al., 2026). The model specification and the active-AI-user sampling frame offer plausible contextual explanations, but the data do not identify either explanation as the cause of H6's result.

The archived copula estimates do not resolve endogeneity without verified distributional prerequisites or construction records. Reverse causality and omitted-variable explanations therefore remain open.

Tourism businesses recruited through the MSME-oriented field frame operate amid seasonal demand, destination events, platform visibility, customer reviews, and changing visitor profiles. These contextual features make both market interpretation and adaptive responses plausible managerial concerns. The survey did not test seasonality, platform dependence, or visitor-mix volatility as moderators; it also did not verify each business's legal MSME classification. Accordingly, the discussion does not generalize the coefficients to all legally classified tourism MSMEs.

4.7. Theoretical contributions

The first contribution is analytical rather than an assertion of architectural superiority. Building on Teece (2007), the study separately operationalizes market sensing (interpretation) and adaptive marketing (action), allowing their conditional associations with perceived competitive performance to differ within one model. Kalaignanam et al. (2021), in contrast, theorize an integrated marketing-agility process. Our matched higher-order alternative fits the same 320 businesses and showed no statistically detectable difference in paired predictive loss (direct model-comparison CVPAT p = 0.1345). Thus the separated specification offers explanatory granularity, not demonstrated predictive superiority or proof of universally distinct sequential capabilities.

The second contribution places explicit limits around the proposed capability-conversion framing. Three positive specific indirect associations are consistent with the theoretical order AIDMC → MSC → AMC → perceived CMP, but all constructs were measured simultaneously from one informant. The results do not identify temporal direction. Adaptive firms may improve sensing, relatively successful firms may increase AI activity, and MSC and AMC may express one broader agility capability. The matched integrated model reinforces the plausibility of the latter alternative. The archived Gaussian-copula outputs lack the documented prerequisites necessary to dismiss endogeneity. Accordingly, capability conversion remains an interpretation to test longitudinally, not an observed process or separately validated construct.

The third contribution concerns an association pattern in tourism-oriented businesses recruited through an MSME-oriented frame, not a verified legal MSME population. AIDMC showed a positive total association with informant-rated competitive performance, while the additional direct coefficient was small and nonsignificant after MSC and AMC entered the model. This result focuses attention on complementary market-facing capabilities. It does not establish that AI activity lacks direct economic value or that changes in AI routines cause sales or customer growth.

The predictive tests provide a separate empirical check on model usefulness. Every endogenous construct produced positive Q^2predict. CVPAT also showed lower predictive loss than the indicator-average benchmark for MSC, AMC, and CMP, while the linear-model comparison supported incremental predictive performance for AMC and CMP but not MSC. These results add outcome-specific predictive evidence to the explanatory findings without converting prediction into evidence of causality.

4.8. Competing-model comparison: separated capabilities versus integrated marketing agility

To evaluate the higher-order marketing-agility alternative, we compared the theory-ordered separated MSC–AMC specification (M0) with a second-order, two-dimensional integrated model (M31). Both models used the same 320 observations, AIDMC and CMP indicators, and matched prediction settings, as reported in the existing model-comparison results. In M31, market sensing and adaptive marketing loaded on the higher-order marketing-agility construct (loadings 0.872 and 0.888; composite reliability 0.873; AVE 0.774). The integrated model linked AIDMC to marketing agility ($\beta = 0.493$), marketing agility to perceived competitive marketing performance ($\beta = 0.566$), and retained the direct AIDMC–CMP relationship ($\beta = 0.045$, $p = 0.427$). The indirect AIDMC–agility–CMP association was 0.279 ($p < 0.001$).

The separated specification explained 35.9% of CMP variance, compared with 34.7% for the integrated higher-order marketing-agility model. Although the separated model produced slightly lower RMSE values for all four CMP indicators, the paired model-comparison CVPAT found no statistically significant difference (M0 1.235788; M31 1.237092; $\Delta = -0.001303$; $t = 1.5004$; $p = 0.1345$). BIC estimates were −120.462 and −120.158, respectively. These values neither establish predictive superiority nor prove equivalence. The value of separation lies in estimating distinct conditional paths for interpretation and action, while the integrated model remains a credible rival explanation. Appendix I reports its specification and prediction comparisons.

4.9. Managerial implications

For practice, the findings justify piloting linked routines rather than prescribing a causal sequence. Managers can examine AI-assisted content, targeting, customer responses, and campaign review alongside explicit market-signal interpretation and documented adjustments. They should evaluate whether these routines improve independently recorded customer acquisition, repeat sales, or revenue before treating the observed questionnaire associations as operational effects. AIDMC indicators carry uneven relative weights, so no single AI activity or uniform seven-routine package receives causal endorsement from the composite score.

IPMA adds a descriptive diagnostic to the structural results. AMC produced the largest construct-level total importance for CMP, while AIDMC, MSC, and AMC showed closely grouped performance scores. The small performance differences do not justify a categorical ranking or a mechanical reallocation of resources. At indicator level, AIDMC7 combines meaningful importance with a comparatively lower performance value, so managers can treat it as a prompt for diagnosis and local validation rather than as an automatic intervention priority.

Tourism-support agencies and business associations can develop training exercises that connect specific AI-assisted tasks to interpreting market signals and testing adaptive responses. They should target businesses according to documented needs rather than assume every recruited firm satisfies a statutory MSME category. Any program should evaluate costs, realized outcomes, and differential responses across AI activity types. The survey provides associative evidence to motivate such pilots, not a verified estimate of their economic benefits.

5. Conclusion and Implications

The analysis covers 320 tourism-oriented businesses recruited through an MSME-oriented field frame in North Sulawesi; the survey did not verify legal MSME status. Reported AI-supported marketing activity was positively associated with market sensing and adaptive

marketing, and both capability scores were positively associated with one respondent's perceived competitive marketing performance. The additional direct AIDMC–CMP coefficient was nonsignificant ($\beta = 0.055$, $p = 0.322$), whereas the three theory-ordered indirect associations were positive. The separated model explained 35.9% of CMP variance versus 34.7% for the integrated agility alternative, without a significant predictive advantage (CVPAT $p = 0.1345$). These results support analytical differentiation of sensing and adaptation, not empirically superior architecture, verified firm growth, or temporal conversion.

Managers can use the two-function specification as a diagnostic language: identify customer and competitor signals, then test and record market-facing adjustments. The study does not establish that implementing these steps causes higher sales or customer growth. Future research should follow businesses over time, obtain transaction and platform records or a second knowledgeable informant, standardize the competitive reference, test reciprocal MSC–AMC paths, and independently verify legal firm classification where MSME-specific inference is intended.

6. Limitations and Future Research

The archival Gaussian-copula terms are not treated as evidence of exogeneity because the accompanying identification prerequisites and construction details have not been independently verified.

The sample also limits generalization and creates composition uncertainty. The purposive design covered tourism-oriented active AI users across multiple North Sulawesi locations and business types, but it does not provide population-representative estimates. The retained archive cannot explain the unusually balanced marginal distributions beyond the documented area and business-type balancing strategy, and it does not preserve an exact approached-firm count or detailed job titles for the 95 respondents classified as 'Other'. The N=225 sensitivity analysis preserved the substantive pathway pattern after excluding that group, but it cannot reconstruct information that the study did not retain. The survey also omitted the capital and sales variables required to independently verify legal MSME status under Government Regulation No. 7/2021 and did not record exact firm age separately from management tenure.

The matched higher-order marketing-agility model remains a plausible alternative: the separated and integrated specifications showed no statistically significant difference in paired predictive loss (CVPAT $p = 0.1345$). The present data distinguish two sets of measured activities analytically but do not establish two temporally ordered, empirically superior capabilities.

The AIDMC Mode B composite combines heterogeneous enacted AI-marketing activities, and its seven indicators do not contribute equal relative information: AIDMC2 (weight = 0.005, $p = 0.959$), AIDMC4 ($p = 0.159$), and AIDMC6 (weight = −0.038, $p = 0.730$) lack significant relative weights. Their retention preserves content coverage, while four- and five-item alternatives establish structural stability of the fitted relationships, not definitive domain validation, not one definitive domain definition. Conceptual adjacency to sensing and action also remains. Future research should differentiate generative, predictive, analytical, personalization, communication, and decision-support activities; verify competitive outcomes using accounts, bookings, platform metrics, or another informed respondent; pre-specify the main competitor; measure legal MSME classification; and compare longitudinal and reciprocal capability models. The single-informant design leaves common-method covariance possible even with low full-collinearity VIFs.

Acknowledgement
The authors thank the leadership of Universitas Sam Ratulangi for supporting the research environment. We also acknowledge the research team for its contributions to data collection and analysis, the experts and pretest participants who helped refine the questionnaire, and the tourism-business respondents who shared their time and insights.

Funding Statement
The Institute for Research and Community Service (LPPM), Universitas Sam Ratulangi, funded this research through the Budget Implementation List (DIPA) of Universitas Sam Ratulangi for Fiscal Year 2025. The authors take full responsibility for the interpretations and conclusions presented in this article, which do not necessarily reflect the views of the funding institution.

Conflict of Interest Statement
The authors declare that they have no conflicts of interest.

Declaration of AI and AI-assisted technologies in the writing process
In preparing this work, the authors used ChatGPT (OpenAI) strictly as an editorial aid for linguistic coherence and readability. The authors generated all substantive content, empirical findings, and theoretical interpretations independently. Following the use of this tool, the authors audited the manuscript and assume full accountability for its published content.

Data availability statement
The de-identified analytical data are not publicly deposited. Requests for access may be directed to the corresponding author and will be considered subject to participant confidentiality and applicable institutional requirements.

Ethics and informed consent
The retained project archive does not contain a verifiable institutional ethics-approval or exemption record for this specific survey; therefore, no approval identifier or unsupported formal status is reported. Participation was voluntary; the questionnaire stated the academic purpose of the study, aggregate use of responses, and the right to stop at any time. Continuing the questionnaire constituted informed consent.

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