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Artificial Intelligence-Enabled Digital Marketing Strategies: An Empirical Investigation of Competitive Advantage and Marketing Performance

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ABSTRACT

Purpose. This study examines how AI-enabled digital marketing strategies (AI personalization, predictive analytics, AI digital advertising, AI content automation and AI marketing automation) relate to competitive advantage and marketing performance, and whether competitive advantage transmits part of the effect of AI-enabled marketing on marketing performance.

Design. A cross-sectional survey design was specified using a 38-item questionnaire (8 profile items and 30 five-point Likert items). The analysis used a simulated sample of 250 marketing professionals and was run in Microsoft Excel: descriptive statistics, Cronbach's alpha, Pearson correlations, chi-square tests of independence, one-way ANOVA with Bonferroni post hoc comparisons, multiple and simple linear regression, and a Sobel test of mediation.

Findings. All constructs were reliable ($\alpha = .76–.83$). The five AI strategies jointly explained 42.4% of the variance in marketing performance; AI personalization ($\beta = .30$), AI digital advertising ($\beta = .22$) and predictive analytics ($\beta = .16$) were significant, whereas content automation ($\beta = .11$, $p = .060$) and marketing automation ($\beta = .05$, $p = .438$) were not. AI-enabled marketing predicted competitive advantage ($\beta = .56$), competitive advantage predicted marketing performance ($\beta = .50$), and the indirect effect was significant (Sobel $z = 3.47$, $p < .001$), indicating partial mediation. AI adoption differed by organization size, $\chi^2(6, N = 250) = 29.66$, $p < .001$, Cramér's $V = .24$.

Implications. Competitive value from AI appears to come from customer-facing, insight-driven applications rather than from automation alone.

Originality. The study tests several AI marketing applications in one integrated model rather than in isolation.

Keywords: artificial intelligence; digital marketing; competitive advantage; marketing performance; personalization; predictive analytics; mediation analysis

1. Introduction

Artificial intelligence (AI) has become an important technology in contemporary digital marketing. Machine learning, predictive analytics, natural language processing, recommendation systems, generative AI and intelligent automation enable organizations to analyze customer data, personalize communication, optimize advertising, automate marketing activities and support faster decision-making. AI is therefore increasingly viewed not only as a technological tool but also as a strategic marketing capability (Davenport et al., 2020; Huang & Rust, 2021).

AI-driven personalization can improve the relevance of content, recommendations and offers by using customer characteristics and behavioral data. Predictive analytics can help firms forecast customer behavior, demand and campaign responses. AI-enabled advertising can improve targeting and campaign optimization, while generative AI can support scalable content creation. Marketing automation further enables organizations to automate repetitive activities and respond to customers more efficiently.

However, adoption of AI does not automatically create competitive advantage. Its strategic value depends on how organizations integrate technology with data, human expertise, marketing knowledge and organizational processes (Manis & Madhavaram, 2023). Existing research often examines individual AI applications in isolation, resulting in a fragmented understanding of how AI-enabled digital marketing strategies collectively influence competitive advantage and marketing performance.

1.1 Problem statement

Organizations are investing in several AI marketing applications at once, yet it is unclear which of them are associated with better marketing outcomes, and whether those outcomes arise directly or through the competitive position that AI helps the firm build.

1.2 Research objectives

RO1. To examine the extent to which organizations adopt AI-enabled digital marketing strategies.

RO2. To examine the effect of AI-driven personalization on marketing performance.

RO3. To determine the influence of predictive analytics and AI-driven customer insights on marketing performance.

RO4. To investigate the effect of AI-enabled digital advertising on marketing performance.

RO5. To examine the influence of AI-driven content automation on marketing performance.

RO6. To assess the effect of AI-enabled marketing automation on marketing performance.

RO7. To examine the relationship between AI-enabled digital marketing strategies and competitive advantage.

RO8. To investigate whether competitive advantage mediates the relationship between AI-enabled digital marketing strategies and marketing performance.

RO9. To examine whether competitive advantage contributes to marketing performance.

RO10. To develop and empirically test an integrated model explaining how AI-enabled digital marketing strategies contribute to competitive advantage and marketing performance.

1.3 Contribution and structure

The study contributes an integrated test of five AI marketing applications within one mediation model, and it provides a reproducible Excel workflow that practitioners and students can apply to their own survey data. Section 2 reviews the literature and develops hypotheses; Section 3 presents the conceptual framework; Section 4 describes the methodology; Section 5 reports the results; Section 6 discusses them; Sections 7 and 8 give implications and limitations; Section 9 concludes.

2. Review of Literature and Hypothesis Development

2.1 AI and digital marketing

AI has evolved from a supporting technology into a strategic component of digital marketing. Major applications include predictive analytics, recommendation systems, conversational agents, programmatic advertising, personalization, content generation and customer analytics. Huang and Rust (2021) distinguish mechanical, thinking and feeling AI and argue that marketing strategy, from research to segmentation, targeting and positioning, can be supported at each level. Davenport et al. (2020) similarly describe how AI changes the nature of marketing tasks and customer interactions. The literature increasingly treats AI as a capability that can improve the speed, scale and intelligence of marketing decisions.

2.2 Theoretical foundation

The study draws on the Resource-Based View (RBV) and the dynamic capabilities perspective. RBV holds that sustained advantage comes from resources that are valuable, rare, difficult to imitate and organized for use (Barney, 1991). Dynamic capabilities theory adds that firms must integrate, build and reconfigure resources to respond to changing environments (Teece et al., 1997). AI technologies, data and related organizational resources create value when combined with complementary marketing capabilities; competitive advantage is therefore expected to arise not from technology adoption alone but from how AI is embedded in marketing processes.

2.3 AI-enabled marketing strategies and marketing performance

AI-driven personalization. Personalization uses customer characteristics, browsing behavior, purchase history and engagement data to tailor messages, recommendations and offers. Kumar et al. (2019) argue that AI-based personalized engagement can improve relevance and customer experience. Personalization is therefore expected to improve marketing performance. **H1: AI-driven personalization has a significant positive effect on marketing performance.**

Predictive analytics. Predictive analytics enables firms to forecast customer behavior, demand, churn and campaign responses. By converting large datasets into actionable insights, it supports proactive decisions and better resource allocation (Wedel & Kannan, 2016). **H2: AI-driven predictive analytics has a significant positive effect on marketing performance.**

AI-enabled digital advertising. AI supports audience segmentation, automated targeting, programmatic advertising, campaign optimization and real-time decision-making, which can improve advertising efficiency and effectiveness. **H3: AI-enabled digital advertising has a significant positive effect on marketing performance.**

AI content automation. Generative AI can create and adapt text, images, video, product descriptions and advertising copy at scale. Benefits include speed, personalization and cost efficiency, although quality, ethics, privacy and governance remain concerns. **H4: AI-driven content automation has a significant positive effect on marketing performance.**

AI marketing automation. AI-enabled automation covers customer segmentation, lead nurturing, email communication, campaign scheduling and customer interactions, and adds predictive and adaptive decision-making to conventional automation. **H5: AI-enabled marketing automation has a significant positive effect on marketing performance.**

2.4 Competitive advantage as a mediating variable

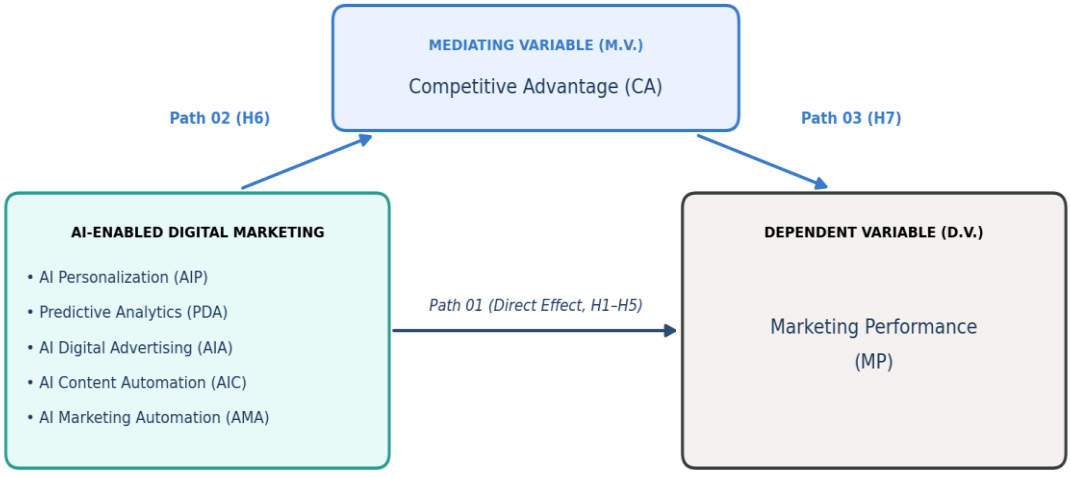
AI can strengthen a firm's ability to sense customer and market changes and respond quickly (Teece et al., 1997), and capabilities built on AI can help firms differentiate and strengthen their market position (Manis & Madhavaram, 2023). **H6: AI-enabled digital marketing strategies have a significant positive effect on competitive advantage.** A firm that has achieved a stronger market position, better differentiation and faster customer response should in turn realize better campaign effectiveness, engagement, conversion and return on marketing investment. **H7: Competitive advantage has a significant positive effect on marketing performance.** Taken together, competitive advantage may transmit part of the effect of AI-enabled marketing on performance. **H8: Competitive advantage significantly mediates the relationship between AI-enabled digital marketing strategies and marketing performance.** The reverse ordering (performance leading to advantage) is also plausible; a cross-sectional design cannot rule it out (see Section 8).

2.5 Research gap

Existing studies frequently focus on individual AI applications or customer-level outcomes. There remains a need for integrated empirical research examining multiple AI-enabled digital marketing strategies together and linking them with competitive advantage and marketing performance. This study addresses that gap.

3. Conceptual Framework

Figure 1 presents the structural mediation framework. The five AI strategies form the independent variables, competitive advantage is the mediating variable and marketing performance is the dependent variable. Path 01 is the direct effect, and Paths 02 and 03 form the indirect route through competitive advantage.



4. Research Methodology

4.1 Research design

The study uses a quantitative, cross-sectional, explanatory survey design. Constructs were measured with multi-item five-point Likert scales (1 = strongly disagree, 5 = strongly agree), and hypotheses were tested with correlation, regression and mediation analysis.

4.2 Population and sample

The target population is marketing, sales, digital marketing, management and IT professionals working in organizations that use, or plan to use, AI in digital marketing. For a real administration, purposive and snowball sampling through professional networks is suggested, with an online questionnaire distributed through Google Forms. A sample of 250 is adequate for a regression with five predictors (more than 20 cases per predictor; Hair et al., 2019).

4.3 Data used in this draft

Because no field data had been collected, the analysis uses a **simulated dataset of 250 respondents** generated in Python with a fixed random seed. Profile characteristics were drawn from plausible distributions; latent scores for the five AI strategies, competitive advantage and marketing performance were generated with moderate correlations consistent with the proposed model, and item responses were produced by adding measurement error and rounding to the 1–5 scale. The dataset therefore demonstrates the analytical workflow and the form of the results; its effect sizes are assumptions, not findings.

4.4 Instrument and measures

The questionnaire has three sections: respondent profile (8 items), AI-enabled digital marketing strategies and outcomes (30 Likert items) and an overall assessment (3 Likert items and 2 open questions, not analyzed here). Table 1 lists the constructs and their reliability. The items are given in Appendix A.

Table 1. Constructs and reliability (n = 250)

Construct	Items	Cronbach α	Interpretation
AI Personalization (AIP)	4	.805	Good
Predictive Analytics (PDA)	4	.793	Acceptable
AI Digital Advertising (AIA)	4	.763	Acceptable
AI Content Automation (AIC)	4	.795	Acceptable
AI Marketing Automation (AMA)	4	.812	Good
Competitive Advantage (CA)	5	.803	Good
Marketing Performance (MP)	5	.831	Good
All AI strategy items (AIP–AMA)	20	.903	Excellent

Note. α ≥ .70 is acceptable (Nunnally, 1978). Alpha was computed in Excel from item variances and total-score variance (Cronbach, 1951).

4.5 Analytical procedures

All analysis was carried out in Microsoft Excel (workbook supplied with this paper). Composite scores were computed as the mean of each construct's items. The procedures were: (1) frequencies and descriptive statistics; (2) Cronbach's alpha; (3) Pearson correlations with two-tailed p-values; (4) chi-square tests of independence with Cramér's V; (5) one-way ANOVA with eta squared and Bonferroni-adjusted pairwise t-tests; (6) ordinary least squares regression estimated with LINEST, with standardized coefficients and variance inflation factors (VIF); and (7) mediation analysis following the causal-steps logic of Baron and Kenny (1986) with a Sobel (1982) test of the indirect effect. The significance level was α = .05. Results were cross-checked against an independent calculation in Python (scipy/numpy) and matched to at least four decimal places.

4.6 Ethical considerations

In a real administration, participation would be voluntary and anonymous, a consent statement would precede the questionnaire, and names or e-mail addresses would not be collected unless the protocol requires them. Responses would be used only for academic purposes.

5. Data Analysis and Results

5.1 Respondent profile

Table 2. Respondent profile (N = 250)

Characteristic	Distribution, n (%)
Age	18–25: 53 (21.2%) / 26–35: 87 (34.8%) / 36–45: 69 (27.6%) / 46–55: 31 (12.4%) / Above 55: 10 (4.0%)
Gender	Male: 124 (49.6%) / Female: 120 (48.0%) / Prefer not to say: 4 (1.6%) / Other: 2 (0.8%)
Qualification	Undergraduate: 105 (42.0%) / Postgraduate: 117 (46.8%) / Doctorate: 12 (4.8%) / Other: 16 (6.4%)
Job role	Marketing: 55 (22.0%) / Sales: 29 (11.6%) / Digital Marketing: 59 (23.6%) / Management: 41 (16.4%) / IT: 39 (15.6%) / Other: 27 (10.8%)
Industry	Retail: 35 (14.0%) / Banking & Finance: 35 (14.0%) / IT & Software: 45 (18.0%) / Education: 17 (6.8%) / Healthcare: 18 (7.2%) / Manufacturing: 22 (8.8%) / E-commerce: 55 (22.0%) / Other: 23 (9.2%)
Organization size	Micro: 23 (9.2%) / Small: 75 (30.0%) / Medium: 70 (28.0%) / Large: 82 (32.8%)
Experience (years)	Less than 2: 51 (20.4%) / 2–5: 71 (28.4%) / 6–10: 67 (26.8%) / More than 10: 61 (24.4%)
AI use in digital marketing	Yes: 144 (57.6%) / Planning to adopt: 67 (26.8%) / No: 39 (15.6%)

Of the 250 respondents, 144 (57.6%) reported that their organization currently uses AI in digital marketing, 67 (26.8%) were planning to adopt it and 39 (15.6%) did not use it (RO1). Most respondents worked in medium or large organizations.

5.2 Descriptive statistics

Table 3. Descriptive statistics of constructs (1–5 scale)

Construct	M	SD	Min	Max	Skewness	Kurtosis
AI Personalization	3.60	0.72	1.50	5.00	-0.25	-0.24
Predictive Analytics	3.57	0.70	2.00	5.00	-0.16	-0.68
AI Digital Advertising	3.60	0.69	1.25	5.00	-0.37	-0.13
AI Content Automation	3.57	0.70	1.50	5.00	-0.10	-0.33
AI Marketing Automation	3.59	0.72	1.25	5.00	-0.38	0.28
AI-Enabled Digital Marketing Index	3.58	0.53	1.90	4.80	-0.34	0.00
Competitive Advantage	3.55	0.68	1.40	5.00	-0.22	-0.08
Marketing Performance	3.61	0.68	1.80	5.00	-0.19	-0.44

Note. Skewness and kurtosis within ±1 indicate approximately normal distributions suitable for parametric tests.

Mean scores for all constructs were between 3.55 and 3.61, above the scale midpoint of 3, indicating moderately high agreement with the AI-related statements. Skewness (-0.38 to -0.10) and kurtosis (-0.68 to 0.28) were within acceptable limits.

5.3 Correlation analysis

Table 4. Pearson correlations among study variables

Variable	1	2	3	4	5	6	7	8
1. AIP	–							
2. PDA	.45***	–						
3. AIA	.47***	.49***	–					
4. AIC	.43***	.40***	.45***	–				
5. AMA	.51***	.51***	.50***	.41***	–			
6. AI Index	.76***	.75***	.77***	.71***	.78***	–		
7. CA	.47***	.44***	.40***	.37***	.44***	.56***	–	
8. MP	.55***	.47***	.51***	.42***	.44***	.64***	.50***	–

*Note. *p < .05, **p < .01, ***p < .001 (two-tailed). AI Index = mean of the five AI strategy scores.*

All correlations were positive and significant ($p < .001$). The five AI strategies correlated with marketing performance between $r = .42$ and $r = .55$, and the AI Index correlated with competitive advantage ($r = .56$) and marketing performance ($r = .64$). Correlations among the strategies ($r = .40$–$.51$) were moderate, so multicollinearity was not expected to be a problem.

5.4 Chi-square tests of independence

Table 5. AI use in digital marketing by organization size, n (row %)

Organization size	Yes	Planning to adopt	No	Total
Micro	6 (26.1%)	8 (34.8%)	9 (39.1%)	23
Small	37 (49.3%)	22 (29.3%)	16 (21.3%)	75
Medium	38 (54.3%)	23 (32.9%)	9 (12.9%)	70
Large	63 (76.8%)	14 (17.1%)	5 (6.1%)	82
Total	144 (57.6%)	67 (26.8%)	39 (15.6%)	250

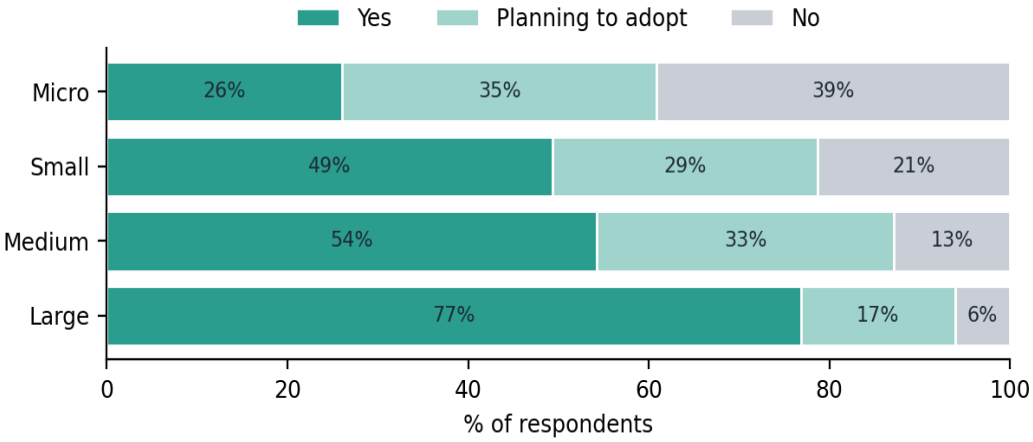


Figure 2. AI use in digital marketing by organization size (row percentages).

Test 1 – organization size and AI use. The association was significant, $\chi^2(6, N = 250) = 29.66$, $p < .001$, Cramér's V = .24, a medium effect (Cohen, 1988). Current use rose from 26.1% in micro organizations to 76.8% in large organizations, while the share not using AI fell from 39.1% to 6.1%. One of 12 cells (8.3%) had an expected count below 5 (minimum = 3.59), within the usual tolerance of 20%.

Test 2 – industry group and AI use. No significant association was found, $\chi^2(6, N = 250) = 7.94$, $p = .243$, Cramér's V = .13; all expected counts were at least 5 (minimum = 5.46). Industry groups were Technology & E-commerce (IT & Software and E-commerce), Banking & Finance, Retail and Other sectors (Education, Healthcare, Manufacturing and Other).

5.5 One-way ANOVA

Table 6. ANOVA 1 – AI-Enabled Digital Marketing Index by organization size

Group	n	M	SD
Micro	23	3.12	0.53
Small	75	3.48	0.55
Medium	70	3.61	0.48
Large	82	3.79	0.46

Source	SS	df	MS	F	p	η^2
Between groups	9.38	3	3.128	12.48	< .001	.132
Within groups	61.65	246	0.251			
Total	71.04	249				

Note. Bonferroni-adjusted pairwise comparisons significant at .05: Micro - Small (−0.36, adjusted p = .016), Micro - Medium (−0.49, adjusted p < .001), Micro - Large (−0.67, adjusted p < .001), Small - Large (−0.31, adjusted p < .001). Ratio of largest to smallest group SD = 1.18.

Table 7. ANOVA 2 – Marketing Performance by organization size

Group	n	M	SD
Micro	23	3.41	0.67
Small	75	3.47	0.65
Medium	70	3.61	0.70
Large	82	3.78	0.66

Source	SS	df	MS	F	p	η^2
Between groups	4.81	3	1.604	3.60	.014	.042
Within groups	109.57	246	0.445			
Total	114.38	249				

Note. Bonferroni-adjusted pairwise comparisons significant at .05: Small - Large (−0.31, adjusted p = .023). Ratio of largest to smallest group SD = 1.08.

Table 8. ANOVA 3 – Marketing Performance by industry group

Group	n	M	SD
Technology & E-commerce	100	3.77	0.70
Banking & Finance	35	3.45	0.70
Retail	35	3.65	0.67
Other sectors	80	3.46	0.60

Source	SS	df	MS	F	p	η^2
Between groups	5.17	3	1.724	3.88	.010	.045
Within groups	109.21	246	0.444			
Total	114.38	249				

Note. Bonferroni-adjusted pairwise comparisons significant at .05: Technology & E-commerce - Other sectors (+0.31, adjusted p = .015). Ratio of largest to smallest group SD = 1.17.

ANOVA 1. The AI Index differed significantly across organization sizes, $F(3, 246) = 12.48$, $p < .001$, $\eta^2 = .132$ (medium to large). Micro organizations scored lowest (M = 3.12) and large organizations highest (M = 3.79). Micro organizations differed from all other groups, and small organizations differed from large ones; small–medium and medium–large differences were not significant after Bonferroni correction.

ANOVA 2. Marketing performance also differed by organization size, $F(3, 246) = 3.60$, $p = .014$, $\eta^2 = .042$, a small-to-medium effect. After correction, only the difference between small (M = 3.47) and large organizations (M = 3.78) was significant.

ANOVA 3. Marketing performance differed by industry group, $F(3, 246) = 3.88$, $p = .010$, $\eta^2 = .045$. Technology & E-commerce organizations (M = 3.77) reported higher performance than those in Other sectors (M = 3.46). Group standard deviations were similar in all three analyses (largest-to-smallest ratio 1.18, 1.08 and 1.17), so the homogeneity-of-variance assumption was judged reasonable.

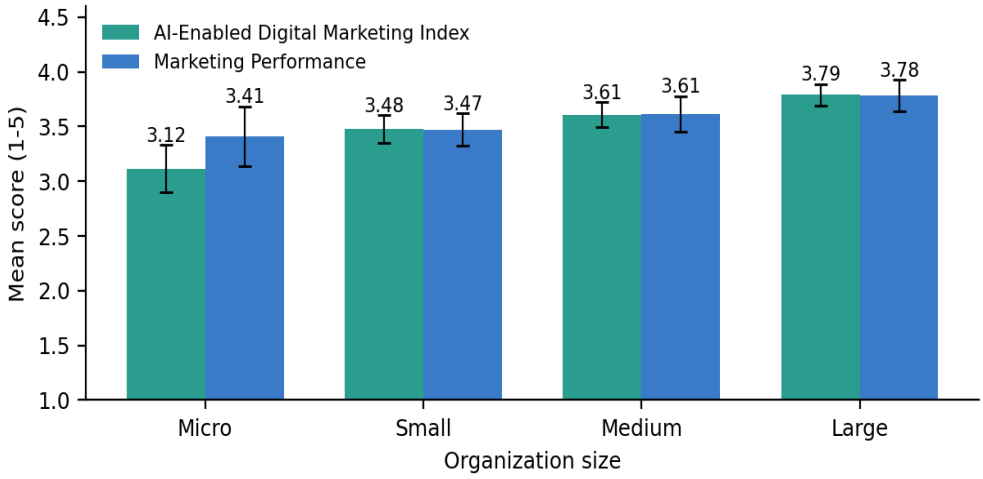


Figure 3. Mean AI Index and marketing performance by organization size (error bars = 95% CI).

5.6 Multiple linear regression: AI strategies and marketing performance (H1–H5)

Table 9. Regression of marketing performance on the five AI strategies (Model 1)

Predictor	B	SE	β	t	p	VIF
AI personalization	0.282	0.057	.301	4.93	< .001 ***	1.58
Predictive analytics	0.158	0.059	.163	2.67	.008 **	1.57
AI digital advertising	0.215	0.061	.220	3.55	< .001 ***	1.63
AI content automation	0.105	0.056	.109	1.89	.060	1.42
AI marketing automation	0.046	0.059	.049	0.78	.438	1.67
Constant	0.716	0.224				

*Note. $R^2 = .424$, adjusted $R^2 = .412$, $F(5, 244) = 35.91$, $p < .001$. *p < .05, **p < .01, ***p < .001. B = unstandardized, β = standardized coefficient.*

The model was significant and explained 42.4% of the variance in marketing performance (adjusted $R^2 = .412$), a large effect ($f^2 = 0.74$). VIF values (1.42–1.67) were far below 5, so collinearity was not a concern. AI personalization (β = .301, p < .001), AI digital advertising (β = .220, p < .001) and predictive analytics (β = .163, p = .008) had significant positive effects, supporting H1, H3 and H2. AI content automation (β = .109, p = .060) fell just short of significance and AI marketing automation (β = .049, p = .438) was clearly not significant, so H4 and H5 were not supported.

5.7 Mediation analysis: competitive advantage (H6–H8)

Table 10. Regression results for the mediation model

Model / path	B	SE	β	t	p
Model 2 – Path a (H6): AI Index → CA	0.711	0.067	.561	10.66	< .001
Model 3 – Path b (H7): CA → MP	0.503	0.055	.502	9.15	< .001
Model 4 – Total effect c: AI Index → MP	0.808	0.062	.637	13.00	< .001
Model 5 – Direct effect c′: AI Index → MP (controlling CA)	0.657	0.073	.518	8.98	< .001
Model 5 – Path b: CA → MP (controlling AI Index)	0.212	0.058	.212	3.67	< .001

Note. R^2: Model 2 = .314, Model 3 = .252, Model 4 = .405, Model 5 = .436 (adjusted .432). Indirect effect (a × b) = 0.151; Sobel SE = 0.043; z = 3.47, p < .001; proportion mediated = 18.7%.

AI-enabled digital marketing strongly predicted competitive advantage (β = .561, p < .001; R^2 = .314), supporting H6, and competitive advantage predicted marketing performance (β = .502, p < .001), supporting H7. The total effect of AI-enabled marketing on performance (c = 0.808) was reduced to c′ = 0.657 when competitive advantage was added, yet remained significant, while competitive advantage itself remained a significant predictor (β = .212, p < .001). The indirect effect was 0.151 (Sobel z = 3.47, p < .001), accounting for about 19% of the total effect. H8 was supported, and the pattern indicates **partial mediation**. Figure 4 summarizes the estimated model.

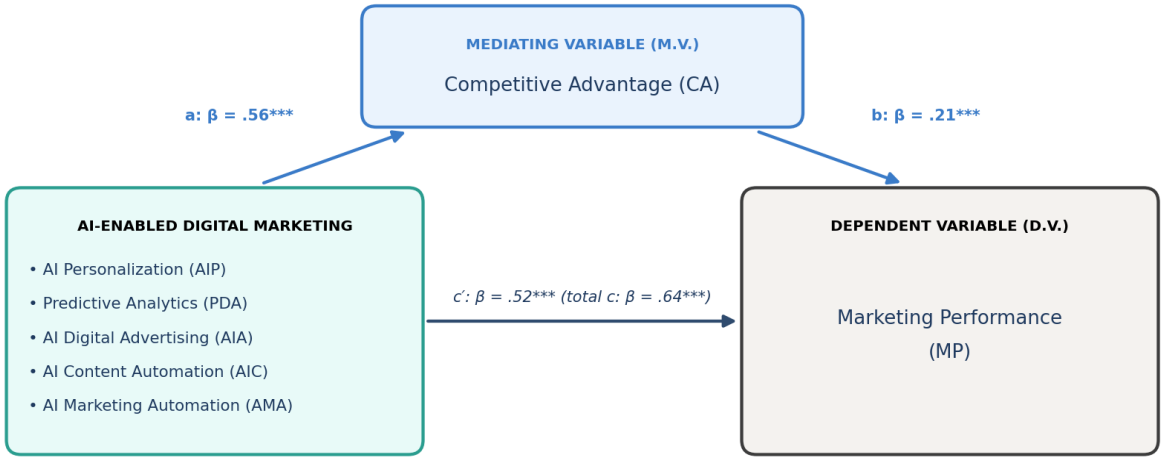


Figure 4. Estimated mediation model (standardized coefficients; *** p < .001).

5.8 Summary of hypothesis tests

Table 11. Hypothesis test summary

Hypothesis	Statement	Estimate	p	Decision
H1	AI personalization → Marketing performance	.301	< .001	Supported
H2	Predictive analytics → Marketing performance	.163	.008	Supported
H3	AI digital advertising → Marketing performance	.220	< .001	Supported
H4	AI content automation → Marketing performance	.109	.060	Not supported
H5	AI marketing automation → Marketing performance	.049	.438	Not supported
H6	AI-enabled digital marketing → Competitive advantage	.561	< .001	Supported
H7	Competitive advantage → Marketing performance	.502	< .001	Supported
H8	Competitive advantage mediates AI-enabled digital marketing → Marketing performance (Sobel test)	0.151	< .001	Supported

Note. Estimates for H1–H7 are standardized β; the estimate for H8 is the unstandardized indirect effect (a × b). Decision rule: supported if the effect is positive and p < .05.

Six of the eight hypotheses were supported (H1, H2, H3, H6, H7, H8); H4 and H5 were not.

6. Discussion

The results (from the simulated dataset) illustrate how the proposed model would be interpreted. First, AI adoption was uneven. Larger organizations were more likely to use AI in digital marketing and scored higher on the AI Index, consistent with the idea that scale gives firms the data, budget and specialist staff needed to deploy AI (RO1). Industry group, by contrast, was not associated with adoption status in this sample.

Second, the strategies did not contribute equally to marketing performance (RO2–RO6). Personalization, advertising optimization and predictive analytics each had a unique positive effect, while content automation and marketing automation did not once the other strategies were controlled. All five were positively correlated with performance (r = .42–.55) and VIF values were low, so the weaker coefficients reflect overlapping rather than unstable effects: automation tools appear to add little beyond what customer-facing and insight-driven applications already deliver. A plausible interpretation is that personalization, targeting and prediction change *what* the customer experiences and *which* decisions the firm makes, whereas content and workflow automation mainly change the *cost and speed* of doing so. This interpretation is speculative and should be tested with real data.

Third, AI-enabled marketing was strongly associated with competitive advantage (H6), which in turn was associated with better marketing performance (H7). The significant indirect effect, accounting for about 19% of the total effect, is consistent with the RBV and dynamic-capabilities argument that AI creates value partly through the competitive position it helps build, but the persistence of a significant direct effect shows that AI also improves marketing results through routes the model does not capture, such as operational efficiency or customer experience (RO7–RO10). Group comparisons showed that marketing performance was higher in large organizations and in technology and e-commerce firms, although these differences were small (η^2 of .042 and .045).

7. Implications

7.1 Theoretical implications

The framework extends AI-marketing research from single-application studies to an integrated model and positions competitive advantage as a channel through which AI capabilities influence performance. It also shows how the RBV logic can be operationalized with measurable AI marketing capabilities. If the real data confirm the differentiated effects, theory should distinguish insight-driven AI capabilities from automation-oriented ones.

7.2 Managerial implications

If confirmed with real data, managers should prioritize AI applications that improve what customers see and which customers are targeted (personalization, advertising optimization and prediction) and judge automation investments on their cost and speed benefits rather than expecting direct performance gains. Smaller organizations, which reported lower AI use, can start with a single customer-facing application. Because competitive advantage carried part of the effect, firms should also pair AI with differentiation and positioning decisions rather than treating it as a stand-alone tool.

8. Limitations and Future Research

(1) **Simulated data.** The most important limitation is that the results come from simulated data, so none of the effect sizes can be interpreted as evidence about real organizations. (2) **Cross-sectional design.** Causal direction cannot be established; performance may also build competitive advantage. Longitudinal or experimental designs are needed. (3) **Self-reported, single-source data.** Perceptual measures and a single respondent per organization may cause common-method bias (Podsakoff et al., 2003); Harman's single-factor test or marker-variable checks should be added. (4) **Measurement.** Only Cronbach's alpha was computed; confirmatory factor analysis, composite reliability, average variance extracted and HTMT discriminant validity (originally proposed for SmartPLS) are needed for a full validation. (5) **Mediation test.** The Sobel test assumes a normal sampling distribution for the indirect effect; bootstrapped confidence intervals (for example in PROCESS or SmartPLS) are preferred. (6) **Item wording.** Some competitive-advantage and performance items refer to AI directly, which may inflate their association with the AI items. Future studies could use outcome measures that are independent of AI wording, objective performance data and moderators such as data maturity and AI governance.

9. Conclusion

This paper developed and illustrated an integrated model of AI-enabled digital marketing, competitive advantage and marketing performance. In the simulated analysis, personalization, advertising optimization and predictive analytics were the strongest correlates of performance, competitive advantage partially mediated the effect of AI-enabled marketing, and AI adoption increased with organization size. The workflow, from questionnaire to Excel analysis to hypothesis decisions, is ready to be re-run with real survey responses, after which Sections 4–7 should be revised to report the actual findings.

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