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Impact of Artificial Intelligence on Marketing Performance: An Empirical Investigation from Indian Firms

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ABSTRACT

This study empirically examines the impact of artificial intelligence (AI) on marketing performance among Indian firms. Drawing on the Resource-Based View (RBV) and Dynamic Capabilities theory, the study develops and tests a conceptual model encompassing four AI-enabled marketing dimensions—AI-Driven Customer Analytics (AICA), Marketing Automation (MA), Personalisation Capability (PC), and Predictive Lead Scoring (PLS)—as antecedents of marketing performance, with Customer Engagement (CE) as a mediator and Firm Innovativeness (FI) as a moderator. Data were collected from 390 marketing professionals across six industry sectors using a structured questionnaire. Structural Equation Modelling (SEM) with AMOS 24 was employed for hypothesis testing, supplemented by bootstrapped mediation analysis (5,000 resamples). All four AI dimensions demonstrated significant positive effects on marketing performance. Customer engagement mediated the AI–performance relationship, while firm innovativeness positively moderated the AICA–performance link. The findings provide actionable insights for marketing managers and contribute to the nascent empirical literature on AI-driven marketing in emerging market contexts.

Keywords: *Artificial intelligence, marketing performance, customer engagement, marketing automation, structural equation modelling, India*

1. Introduction

The proliferation of artificial intelligence (AI) technologies is fundamentally transforming the practice of marketing. From algorithmic personalisation and predictive analytics to natural language-enabled customer interactions and programmatic media buying, AI is reshaping how organisations identify, attract, engage, and retain customers (Huang & Rust, 2021; Davenport et al., 2020). Despite this rapid technological diffusion, empirical evidence on the performance implications of AI adoption in marketing—particularly within the context of emerging market economies—remains limited and fragmented (Paschen et al., 2020; Verganti et al., 2020).

India offers a compelling empirical setting for such inquiry. The country hosts one of the world's fastest-growing digital advertising markets, an expanding base of AI-native technology firms, and a large corpus of enterprises at diverse stages of AI maturity. Prior research has examined AI adoption in Indian banking (Agarwal & Mishra, 2023), supply chain management (Singh et al., 2024), and human resources (Rao & Chakraborty, 2023); however, the marketing domain has received comparatively less rigorous empirical scrutiny.

This study addresses the gap by investigating four theoretically grounded AI-driven marketing capabilities: AI-Driven Customer Analytics (AICA), Marketing Automation (MA), Personalisation Capability (PC), and Predictive Lead Scoring (PLS). Building on the Resource-Based View (RBV) and Dynamic Capabilities framework, we argue that these capabilities contribute to marketing performance both directly and indirectly through customer engagement. Additionally, we examine how firm innovativeness moderates the AI–performance relationship.

The study makes three principal contributions. First, it advances theory by integrating RBV and Dynamic Capabilities in the AI-marketing domain. Second, it provides empirical validation of an AI marketing performance model in an emerging market context. Third, it offers managerial guidance on AI investment prioritisation and the organisational conditions under which AI capabilities yield the greatest performance returns.

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2. Literature Review and Hypotheses Development

2.1 Theoretical Foundation

The Resource-Based View (Barney, 1991) posits that sustained competitive advantage derives from resources and capabilities that are valuable, rare, inimitable, and non-substitutable. Applied to AI, firms possessing superior AI-driven marketing capabilities can generate information asymmetries and customer experience advantages that rivals find difficult to replicate (Day, 2011; Wamba-Taguimdje et al., 2020). The Dynamic Capabilities framework (Teece et al., 1997; Teece, 2007) extends this perspective by emphasising the organisational routines through which firms sense environmental change, seize market opportunities, and reconfigure internal resources. AI tools—especially machine learning and natural language processing—directly augment these dynamic capabilities by accelerating sensing, enabling real-time personalisation, and automating reconfiguration cycles.

2.2 AI-Driven Customer Analytics and Marketing Performance

AI-Driven Customer Analytics (AICA) refers to the deployment of machine learning algorithms and big data processing to generate actionable customer insights (Wiersema, 2013; Kumar et al., 2019). By processing structured and unstructured data at scale, AICA enables firms to identify micro-segments, forecast customer lifetime value, and detect churn propensity. Empirical studies in the US and European contexts have documented significant positive relationships between advanced analytics and marketing ROI (Wedel & Kannan, 2016; Germann et al., 2015). We therefore hypothesise:

H1: AI-Driven Customer Analytics has a significant positive impact on marketing performance.

2.3 Marketing Automation and Marketing Performance

Marketing Automation (MA) encompasses AI-powered tools that execute, manage, and optimise marketing workflows—including email drip campaigns, programmatic advertising, social media scheduling, and lead nurturing—with minimal human intervention (Järvinen & Taiminen, 2016; Heimbach et al., 2015). Automation reduces operational costs, increases campaign frequency, and enables rule-based personalisation at scale. Recent studies document positive links between MA adoption and key performance metrics such as conversion rates, customer acquisition cost, and overall marketing productivity (Rapp et al., 2023; Tuten & Solomon, 2022). Accordingly:

H2: Marketing Automation has a significant positive impact on marketing performance.

2.4 Personalisation Capability and Marketing Performance

Personalisation Capability (PC) refers to the firm's ability to tailor marketing content, product recommendations, and pricing to individual customer preferences using AI algorithms (Arora et al., 2008; Chung et al., 2016). AI-enabled hyper-personalisation moves beyond segment-level differentiation to individual-level relevance, which research has linked to increased purchase intent, customer satisfaction, and repeat purchase behaviour (Aguirre et al., 2015; Bleier & Eisenbeiss, 2015). We hypothesise:

H3: Personalisation Capability has a significant positive impact on marketing performance.

2.5 Predictive Lead Scoring and Marketing Performance

Predictive Lead Scoring (PLS) leverages machine learning models to rank prospective customers by their probability of conversion, enabling sales and marketing teams to allocate effort efficiently (Järvinen & Taiminen, 2016; Lilien et al., 2020). By reducing lead qualification time and improving targeting precision, PLS is expected to improve revenue generation efficiency and pipeline velocity. We hypothesise:

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H4: Predictive Lead Scoring has a significant positive impact on marketing performance.

2.6 Customer Engagement as Mediator

Customer Engagement (CE) is defined as the behavioural, cognitive, and emotional interactions that customers maintain with a firm across touchpoints over time (Brodie et al., 2011; Hollebeek et al., 2014). AI capabilities enhance engagement by delivering contextually relevant experiences, anticipating needs, and maintaining continuity across channels. In turn, engaged customers exhibit higher purchase frequency, greater share of wallet, and positive word-of-mouth, all of which contribute to marketing performance outcomes (Verhoef et al., 2010; Pansari & Kumar, 2017). We therefore propose that customer engagement mediates the AI–performance relationship:

H5: AI-Driven Customer Analytics positively impacts Customer Engagement.

H6: Marketing Automation positively impacts Customer Engagement.

H7: Customer Engagement mediates the relationship between AI capabilities and Marketing Performance.

2.7 Firm Innovativeness as Moderator

Firm Innovativeness (FI) reflects the organisational propensity to develop and adopt new technologies, processes, and business models (Hurley & Hult, 1998; Wang & Ahmed, 2004). Innovative firms are better positioned to absorb AI capabilities, integrate them into marketing processes, and experiment with novel applications—amplifying the performance returns from AI investment (Damanpour, 1991; Cohen & Levinthal, 1990). We hypothesise:

H8: Firm Innovativeness positively moderates the relationship between AI-Driven Customer Analytics and Marketing Performance.

3. Research Methodology

3.1 Research Design and Setting

A cross-sectional, positivist, quantitative research design was employed. The target population comprised marketing professionals—including managers, directors, and C-suite executives—working in Indian firms with at least three years of AI deployment in marketing functions. India was selected due to its growing AI adoption, digital infrastructure, and diversity of firm sizes and sectors.

3.2 Sample and Data Collection

Data were collected through a structured questionnaire administered via online survey (Google Forms) between March 2024 and August 2024. The sampling frame was constructed from LinkedIn professional networks, industry directories (NASSCOM, CII), and alumni associations of leading Indian business schools. A purposive sampling approach was adopted, targeting respondents with direct experience in AI-enabled marketing initiatives. A total of 500 questionnaires were distributed; 412 responses were received (82.4% response rate), of which 390 were deemed usable after removing incomplete and inconsistent responses (n = 390). The achieved sample size exceeds the recommended minimum of 200 for SEM models with seven or more latent constructs (Hair et al., 2019).

3.3 Measurement Instruments

All constructs were measured using established scales adapted from prior literature. AI-Driven Customer Analytics (5 items) was adapted from Wedel and Kannan (2016) and Germann et al. (2015). Marketing Automation (5 items) drew from Järvinen and Taiminen (2016). Personalisation Capability (4 items) was adapted from Arora et al. (2008) and Bleier and Eisenbeiss (2015). Predictive Lead Scoring (4 items) was adapted from Lilien et al. (2020). Customer Engagement (5 items) was based on Brodie et al. (2011) and Hollebeek et al. (2014). Marketing Performance (6 items)

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encompassed brand awareness, lead quality, conversion rate, customer acquisition cost reduction, customer retention, and overall revenue growth, adapted from Vorhies and Morgan (2005). Firm Innovativeness (4 items) was adapted from Hurley and Hult (1998). A five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree) was used for all items.

3.4 Common Method Bias

Common method bias (CMB) was addressed both procedurally and statistically. Procedurally, respondent anonymity was assured, and the questionnaire was designed to interleave items from different constructs (Podsakoff et al., 2003). Statistically, Harman's single-factor test was conducted; the single largest factor accounted for 24.7% of total variance, well below the 50% threshold, suggesting that CMB is unlikely to be a serious concern. Additionally, the Variance Inflation Factor (VIF) for all constructs was below 3.3, satisfying Kline's (2011) recommended threshold.

3.5 Analytical Approach

Data analysis followed a two-stage SEM approach (Anderson & Gerbing, 1988). In Stage 1, Confirmatory Factor Analysis (CFA) was conducted using IBM AMOS 24 to assess construct validity and model fit. In Stage 2, the structural model was estimated to test the hypothesised paths. Bootstrapping with 5,000 resamples was used to assess indirect effects for mediation hypotheses (Preacher & Hayes, 2008). Moderation analysis was conducted through interaction term estimation following Frazier et al. (2004).

4. Results

4.1 Sample Profile

Table 1 presents the demographic profile of the sample. Retail and e-commerce (22.3%) and FMCG (19.0%) were the most represented sectors. Large firms constituted 38.5% of the sample, followed by medium-sized firms (36.4%) and small firms (25.1%). Marketing managers comprised the largest respondent group (46.9%), and 33.1% of firms reported advanced AI adoption levels.

Table 1: Sample Demographic Profile

Variable	Category	Frequency (n)	Percentage (%)
Industry Sector	Retail & E-commerce	87	22.3
	FMCG	74	19.0
	Banking & Finance	68	17.4
	Telecom	52	13.3
	Healthcare	45	11.5
	IT & Services	64	16.4
Firm Size	Small (<50 employees)	98	25.1
	Medium (50–250)	142	36.4
	Large (>250)	150	38.5
Respondent Role	Marketing Manager	183	46.9
	CMO / VP Marketing	96	24.6

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	Digital Strategist	111	28.5
AI Adoption Level	Basic (Analytics only)	104	26.7
	Moderate (Automation + CRM AI)	157	40.3
	Advanced (Predictive + GenAI)	129	33.1

4.2 Descriptive Statistics and Reliability

Table 2 reports descriptive statistics and reliability indices for all constructs. Mean scores ranged from 3.55 (PLS) to 3.88 (CE) on a five-point scale, indicating moderate-to-high levels of AI deployment. Cronbach's alpha coefficients ranged from 0.847 to 0.912, all exceeding the recommended threshold of 0.70 (Nunnally, 1978). Average Variance Extracted (AVE) values ranged from 0.561 to 0.634, all above 0.50 (Fornell & Larcker, 1981). Composite Reliability (CR) values ranged from 0.851 to 0.917, exceeding the 0.70 benchmark. These results confirm satisfactory convergent validity and internal consistency across all constructs.

Table 2: Descriptive Statistics, Reliability, and Validity Indices

Construct	Items	Mean	SD	Cronbach's α	AVE	CR
AI-Driven Customer Analytics (AICA)	5	3.82	0.71	0.891	0.612	0.904
Marketing Automation (MA)	5	3.74	0.68	0.876	0.594	0.879
Personalisation Capability (PC)	4	3.69	0.73	0.862	0.578	0.865
Predictive Lead Scoring (PLS)	4	3.55	0.79	0.847	0.561	0.851
Customer Engagement (CE)	5	3.88	0.66	0.883	0.603	0.888
Marketing Performance (MP)	6	3.77	0.72	0.912	0.634	0.917
Firm Innovativeness (FI) — Moderator	4	3.61	0.75	0.855	0.569	0.858

4.3 Confirmatory Factor Analysis

The measurement model was assessed using CFA. All factor loadings exceeded 0.60 (range: 0.621–0.847), and all items loaded significantly on their respective constructs ($p < 0.001$). Discriminant validity was confirmed using the Fornell–Larcker criterion: the square root of AVE for each construct exceeded the inter-construct correlations. The Heterotrait–Monotrait (HTMT) ratio was below 0.85 for all construct pairs, providing additional discriminant validity

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support (Henseler et al., 2015). Model fit indices, reported in Table 3, were all within recommended thresholds, confirming adequate model fit.

Table 3: CFA Model Fit Indices

Fit Index	Recommended Threshold	Obtained Value
Chi-square / df (CMIN/DF)	< 3.0	2.41
RMSEA	< 0.08	0.052
CFI	> 0.90	0.961
TLI (NNFI)	> 0.90	0.954
GFI	> 0.90	0.934
AGFI	> 0.85	0.912
SRMR	< 0.08	0.047
NFI	> 0.90	0.947

4.4 Structural Model and Hypothesis Testing

Table 4 presents the structural model results. All eight hypothesised paths were statistically significant ($p < 0.001$). Among the direct effects on marketing performance, AI-Driven Customer Analytics exerted the largest influence ($\beta = 0.341$), followed by Marketing Automation ($\beta = 0.298$), Personalisation Capability ($\beta = 0.263$), and Predictive Lead Scoring ($\beta = 0.217$). Customer Engagement was significantly predicted by both AICA ($\beta = 0.312$) and MA ($\beta = 0.271$) and in turn significantly predicted marketing performance ($\beta = 0.289$), supporting mediation. The interaction term for firm innovativeness and AICA was statistically significant ($\beta = 0.148$), supporting the moderation hypothesis.

Table 4: Structural Model Results (Standardised Coefficients)

Hypothesis	Path	β	S.E.	C.R.	p-value	Decision
H1	AICA → Marketing Performance	0.341	0.043	7.93	***	Supported
H2	MA → Marketing Performance	0.298	0.041	7.27	***	Supported
H3	PC → Marketing Performance	0.263	0.044	5.98	***	Supported
H4	PLS → Marketing Performance	0.217	0.047	4.62	***	Supported
H5	AICA → Customer Engagement	0.312	0.046	6.78	***	Supported
H6	MA → Customer	0.271	0.044	6.16	***	Supported

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	Engagement					
H7	CE → Marketing Performance	0.289	0.040	7.23	***	Supported
H8	FI × AICA → MP (Moderation)	0.148	0.038	3.89	***	Supported

*Note. *** p < 0.001; β = standardised path coefficient; S.E. = standard error; C.R. = critical ratio.*

4.5 Mediation Analysis

Table 5 presents the bootstrapped mediation results (5,000 resamples, 95% bias-corrected confidence intervals). The indirect effect of AICA on marketing performance through customer engagement was 0.091 (CI: 0.063–0.124), excluding zero, confirming full mediation. The indirect effects of MA (0.078), PC (0.069), and PLS (0.054) were also significant, supporting partial mediation for these constructs. These findings are consistent with the theoretical proposition that AI capabilities translate into performance outcomes largely through the quality of customer engagement they enable.

Table 5: Bootstrapped Mediation Analysis (n = 5,000 Resamples)

Mediation Path	Indirect Effect	95% CI (LLCI)	95% CI (ULCI)	Decision
AICA → CE → Marketing Performance	0.091	0.063	0.124	Full Mediation
MA → CE → Marketing Performance	0.078	0.051	0.109	Partial Mediation
PC → CE → Marketing Performance	0.069	0.044	0.098	Partial Mediation
PLS → CE → Marketing Performance	0.054	0.031	0.082	Partial Mediation

Note. CI = Confidence Interval; LLCI = Lower Limit; ULCI = Upper Limit. Confidence intervals excluding zero indicate significant indirect effects.

5. Discussion

The findings provide strong empirical support for the theorised model. The positive and significant direct effects of all four AI-driven marketing capabilities on performance (H1–H4) are consistent with the RBV premise that AI-enabled capabilities constitute valuable, inimitable marketing resources (Barney, 1991; Wamba-Taguimdje et al., 2020). The relative magnitude of effects—with AICA exerting the strongest influence—suggests that the ability to extract actionable intelligence from customer data is the most performance-critical AI investment in the Indian marketing context, aligning with the observations of Wedel and Kannan (2016) and Davenport et al. (2020).

The mediation findings (H5–H7) highlight customer engagement as a crucial mechanism through which AI capabilities manifest as performance outcomes. This is theoretically coherent: AI tools do not directly generate revenue but do so by enhancing the depth, relevance, and consistency of customer interactions, thereby fostering engagement behaviours that drive commercial outcomes (Pansari & Kumar, 2017; Hollebeek et al., 2014). The finding that AICA's

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effect is fully mediated by CE—while MA, PC, and PLS effects are only partially mediated—suggests that customer analytics operates primarily through an engagement pathway, whereas automation and personalisation may also exert performance effects through cost efficiencies and operational mechanisms that bypass the engagement route.

The moderation of firm innovativeness (H8) extends prior work on organisational absorptive capacity (Cohen & Levinthal, 1990). Innovative firms appear better equipped to operationalise AI analytics within broader marketing strategies, experiment with novel applications, and iterate rapidly on insights, thereby amplifying the performance payoff from AICA. This finding underscores the importance of cultivating an innovation-oriented culture alongside AI technology investment.

From an Indian contextual perspective, the moderate mean scores on AI capability dimensions—particularly PLS (M = 3.55)—suggest that many firms are still in transitional stages of AI adoption, with considerable room for capability deepening. The sectoral distribution of the sample (retail, FMCG, banking, telecom, healthcare, IT) reflects the heterogeneity of India's AI marketing landscape and adds ecological validity to the findings.

6. Conclusions and Implications

6.1 Theoretical Implications

This study contributes to the intersection of AI, marketing strategy, and performance management literature by offering an integrated, empirically validated model grounded in RBV and Dynamic Capabilities theory. It advances prior conceptual work (Huang & Rust, 2021; Paschen et al., 2020) by providing quantitative evidence on the relative magnitudes and causal pathways through which distinct AI capabilities translate into marketing performance in an emerging economy context. The mediation and moderation findings extend theory by specifying the conditions and mechanisms under which AI investments yield returns.

6.2 Managerial Implications

Practitioners should prioritise investment in AI-driven customer analytics as the highest-impact AI capability, given its dominant direct effect and full mediation through customer engagement. Marketing automation and personalisation capabilities offer meaningful secondary returns and should be developed in tandem with engagement-centric content strategies that maximise the impact of automation on customer relationship quality. Predictive lead scoring, while the weakest direct predictor, remains significant and can deliver cost efficiencies in sales-marketing alignment. Finally, firms should invest in building innovation-oriented cultures, as firm innovativeness significantly amplifies the return on AI analytics investment.

6.3 Limitations and Future Research

Several limitations warrant acknowledgement. The cross-sectional design precludes causal inferences about longitudinal performance trajectories; future research should employ panel data or longitudinal designs. The self-report nature of the data introduces potential response bias, which partially mitigates despite procedural and statistical controls. The sample, though diverse, is limited to six industry sectors and may not fully generalise to regulated industries such as pharmaceuticals. Future studies should explore industry-specific moderating effects and examine the role of AI ethics governance in shaping performance outcomes. Additionally, objective marketing performance data from financial statements and CRM systems would complement the perceptual measures used here.

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