ANALYSIS OF CONSUMER BEHAVIOR AND IMPROVEMENT OF MARKETING STRATEGIES BASED ON ARTIFICIAL INTELLIGENCE

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Abstract: *The rapid diffusion of artificial intelligence (AI) is transforming the way firms observe, interpret, and respond to consumer behavior. This study examines how AI-based analytics influence the effectiveness of marketing strategies. Drawing on a survey of 168 companies engaged in marketing activity, the paper develops a conceptual framework linking AI analytical technologies to consumer-behavior insights, marketing-strategy levers, and marketing outcomes. Multiple regression analysis shows that the firm-level AI Analytics Adoption Index is the strongest predictor of marketing effectiveness ($\beta = 0.451$; $p < 0.001$), and that the full model explains 58.7% of the variance in the Marketing Effectiveness Index. Companies in the highest adoption quartile reported, on average, conversion rates about 70% higher, customer-retention rates 17 percentage points higher, and marketing return on investment 1.8 times greater than firms in the lowest quartile. Despite these benefits, adoption remains uneven and is constrained mainly by cost, analytical-skills shortages, and data-quality limitations. The paper concludes with a staged set of managerial and policy recommendations for AI-driven marketing improvement.*

Keywords: *artificial intelligence, consumer behavior, marketing strategy, personalization, machine learning, marketing analytics, customer segmentation, marketing effectiveness.*

Understanding consumer behavior has always been at the core of effective marketing. Traditionally, firms inferred consumer needs from periodic market research, sales records, and managerial intuition — instruments that are slow, coarse-grained, and limited in their ability to capture the diversity and volatility of individual preferences. The digitalization of commerce and communication has changed this situation fundamentally. Every search, click, purchase, review, and interaction now leaves a trace, generating volumes of behavioral data that exceed the analytical capacity of conventional methods. Artificial intelligence has emerged as the technology capable of converting these data into timely and actionable consumer insight.

Artificial intelligence in marketing refers to the use of machine learning, natural-language processing, and related data-driven methods to analyze consumer data, predict behavior, and automate or support marketing decisions. Industry evidence indicates that AI has moved from experimentation to mainstream practice: a large majority of organizations now apply AI in some part of their operations, and a growing share of marketing budgets is allocated to AI-driven activity. Reported performance gains are substantial — AI-supported campaigns are associated with higher conversion rates, lower customer-acquisition costs, and improved return on investment relative to conventional approaches. At the same time, consumers increasingly expect personalized interaction, and are more likely to purchase from brands that meet this expectation.

Despite the strategic importance of the topic, several gaps remain. Much of the available evidence is descriptive or vendor-generated, and relatively few studies quantify, at the level of the individual firm, the relationship between AI analytical capability and marketing performance while controlling for other determinants. There is also limited research situated in developing and emerging-market contexts, where data infrastructure, analytical skills, and firm scale differ markedly from those of advanced economies. The present study addresses these gaps. Its aim is to examine how AI-based analysis of consumer behavior contributes to the improvement of marketing strategies, and to identify the factors that enable or constrain this contribution. The study pursues three objectives: (1) to develop a conceptual framework connecting AI analytics, consumer insight, marketing strategy, and marketing outcomes; (2) to estimate empirically the effect of firm-level AI adoption on marketing effectiveness; and (3) to formulate practical recommendations for firms and policymakers.

The study employs a quantitative, cross-sectional design based on a structured enterprise survey, complemented by descriptive analysis of secondary industry data. The conceptual framework, shown in Figure 1, treats AI as an analytical capability operating through a sequence of stages. AI analytical technologies — machine-learning segmentation, recommendation systems, natural-language sentiment analysis, predictive churn and customer-lifetime-value models, and conversational AI — transform raw behavioral data into consumer-behavior insights. These insights inform marketing-strategy levers such as personalization, dynamic pricing, channel optimization, and customer-experience design, which in turn shape marketing outcomes: conversion, retention, return on investment, and competitive position. A feedback loop returns performance data to retrain the analytical models, so that the system improves over time.

The central hypothesis derived from the framework is that, other factors held constant, a higher level of AI analytical adoption is associated with greater marketing effectiveness.

The dependent variable is the Marketing Effectiveness Index (MEI), a composite measure on a 0–100 scale combining managerial assessments of campaign performance, customer engagement, and goal attainment relative to plan. The principal explanatory variable is the AI Analytics Adoption Index (AAI), also scaled 0–100, which aggregates the breadth and intensity of use of AI analytical tools for consumer-behavior analysis. Four control variables are included: personalization capability, data quality and CRM integration, marketing-budget scale (a proxy for firm size), and digital-channel breadth. Both composite indices showed satisfactory internal consistency, with Cronbach's alpha of 0.87 for the AAI and 0.83 for the MEI.

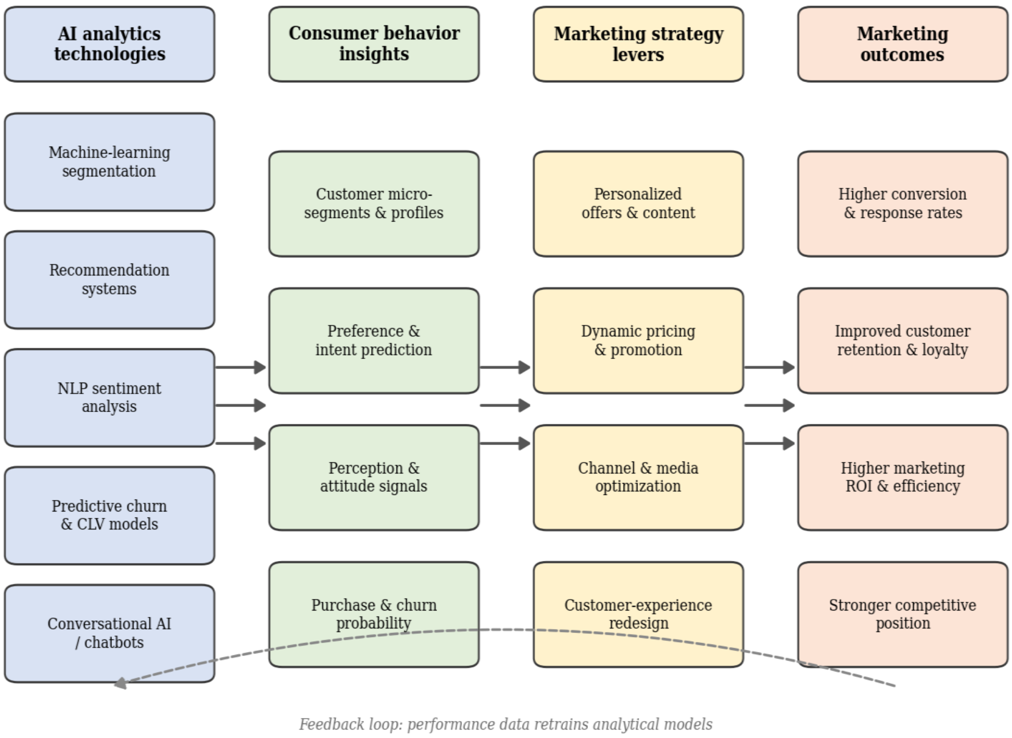

Figure 1. Conceptual framework: from AI analytics to marketing outcomes.

Primary data were collected through a structured questionnaire administered to marketing managers and decision-makers during 2025. Of 215 companies approached, 168 returned usable responses, a response rate of 78.1%. The sample spans retail and e-commerce, consumer goods, services, and food and hospitality, and includes firms of varying size. Responses were screened for completeness and consistency. Analysis proceeded in three steps: descriptive statistics and correlation analysis; ordinary-least-squares (OLS) multiple regression of the MEI on the AAI and control variables; and a quartile comparison contrasting firms with the highest and lowest levels of AI adoption. Regression diagnostics — variance inflation factors, the Durbin–Watson statistic, and residual inspection — were used to verify the assumptions of the linear model. The study is cross-sectional, and the resulting estimates should therefore be interpreted as strong, theoretically grounded associations rather than as definitive causal effects.

The relationship between AI adoption and marketing effectiveness is estimated with the following linear specification:

$$MEI_i = \beta_0 + \beta_1 \cdot AAI_i + \beta_2 \cdot PERS_i + \beta_3 \cdot DATA_i + \beta_4 \cdot CHAN_i + \beta_5 \cdot BUDG_i + \varepsilon_i$$

where MEI_i is the Marketing Effectiveness Index of firm i; AAI_i is the AI Analytics Adoption Index; $PERS_i$, $DATA_i$, $CHAN_i$, and $BUDG_i$ denote personalization capability, data quality and CRM integration, digital-channel breadth, and marketing-budget scale respectively; β_0 is the intercept; β_1–β_5 are the coefficients to be estimated; and ε_i is the error term. The coefficient of central interest is β_1: a positive and statistically significant estimate would support the study's hypothesis that greater AI analytical adoption raises marketing effectiveness, other factors held constant. Standardized coefficients are reported alongside unstandardized ones to allow the relative strength of the predictors to be compared on a common scale.

Table 1 summarizes the composition of the sample. The respondents represent a broad cross-section of consumer-facing businesses, with a balanced distribution across sectors and firm sizes, which supports the analytical use of the data.

Table 1.

Profile of surveyed companies (n = 168)

Characteristic	**Category**	**Share of firms, %**
Sector	Retail and e-commerce	33.3
	Consumer goods and manufacturing	25.0
	Services and finance	23.8
	Food and hospitality	17.9
Firm size	Small (up to 50 employees)	39.3
	Medium (51–250 employees)	38.1
	Large (over 250 employees)	22.6
Marketing function	Dedicated marketing department	61.9
	Combined / outsourced function	38.1

Source: author's enterprise survey, 2025.

Adoption of AI tools for consumer-behavior analysis is growing but remains uneven. As Figure 2 shows, conversational AI and chatbots are the most widely used technology (38.1% of firms), followed by machine-learning customer segmentation (34.5%) and recommendation systems (29.8%). More advanced predictive applications — dynamic pricing (17.9%) and predictive customer-lifetime-value modelling (15.5%) — are adopted by a much smaller minority. The mean AI Analytics Adoption Index across the sample is 31.6 (SD = 20.4), confirming that, although awareness is widespread, intensive and integrated use of AI for consumer analysis is still the exception rather than the rule.

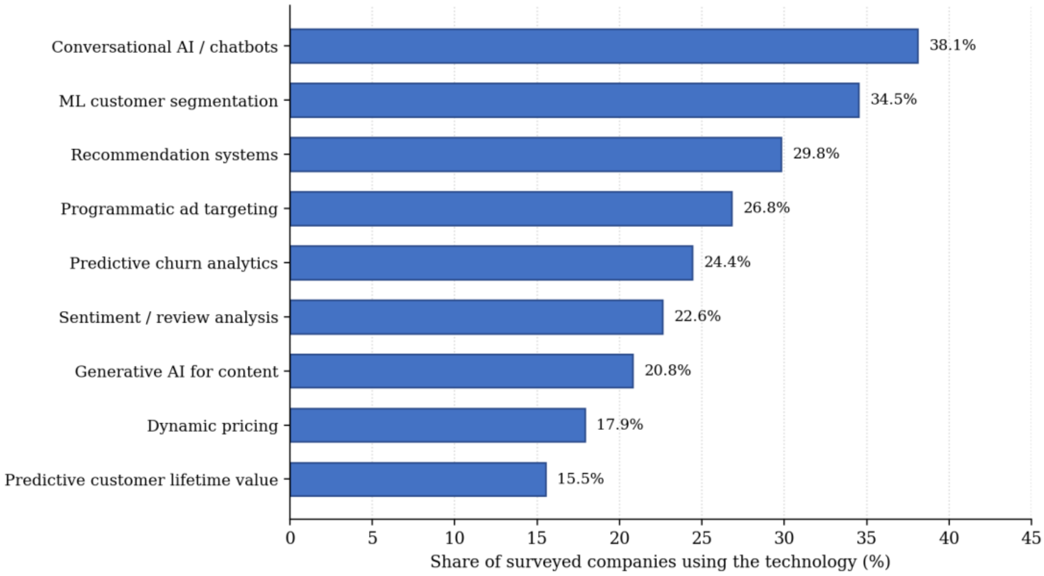

Figure 2. Adoption rates of AI technologies for consumer-behavior analysis and marketing.

Table 2 presents the descriptive statistics of the main variables together with their bivariate correlations with the Marketing Effectiveness Index. The AI Analytics Adoption Index shows the strongest positive correlation with marketing effectiveness ($r = 0.66$), ahead of personalization capability ($r = 0.49$) and digital-channel breadth ($r = 0.44$). All correlations are positive and statistically significant, providing initial support for the study's hypothesis.

Table 2.

Descriptive statistics and correlation with marketing effectiveness ($n = 168$)

Variable	Mean	SD	r with MEI
Marketing Effectiveness Index (0–100)	51.3	17.8	1.00
AI Analytics Adoption Index (0–100)	31.6	20.4	0.66
Personalization capability (0–100)	38.7	22.1	0.49
Data quality and CRM integration (0–100)	44.5	21.3	0.42
Digital-channel breadth (count)	3.8	1.9	0.44
Marketing-budget scale (1–5)	2.74	1.05	0.36

Note: all correlations significant at $p < 0.01$. Source: author's enterprise survey, 2025.

Table 3 reports the OLS regression of the Marketing Effectiveness Index on the AI Analytics Adoption Index and the four control variables. The model is statistically significant overall, $F(5, 162) = 46.08$, $p < 0.001$, and explains 58.7% of the variance in marketing effectiveness (adjusted $R^2 = 0.572$). Diagnostic checks were satisfactory: variance inflation factors ranged from 1.1 to 1.6, indicating no problematic multicollinearity, and the Durbin–Watson statistic of 1.97 indicated no autocorrelation in the residuals.

Table 3.

OLS regression results (dependent variable: Marketing Effectiveness Index)

Predictor	B	SE	β	t	p
Constant	16.20	3.40	—	4.76	<0.001
AI Analytics Adoption Index	0.388	0.058	0.451	6.69	<0.001
Personalization capability	0.205	0.064	0.208	3.20	0.002
Data quality and CRM integration	0.142	0.052	0.176	2.73	0.007
Digital-channel breadth	1.93	0.78	0.163	2.47	0.014
Marketing-budget scale	2.84	1.12	0.151	2.54	0.012

Note: $n = 168$; $R^2 = 0.587$; adjusted $R^2 = 0.572$; $F(5,162) = 46.08$, $p < 0.001$. Source: author's calculations.

All five predictors are positive and statistically significant. The AI Analytics Adoption Index has by far the largest standardized coefficient ($\beta = 0.451$), confirming that it is the dominant determinant of marketing effectiveness in the model. The unstandardized coefficient implies that, holding other factors constant, an increase of ten points in the AI adoption index is associated with an increase of about 3.9 points in the Marketing Effectiveness Index. Personalization capability is the second strongest predictor, which is consistent with the framework: personalization is one of the main channels through which AI-generated consumer insight is translated into marketing performance.

To make the magnitude of the relationship concrete, firms were divided into quartiles by their AI Analytics Adoption Index, and the top and bottom quartiles were compared on a set of marketing outcomes (Table 4). The differences are substantial. Firms in the top adoption quartile recorded a conversion rate of 4.6% against 2.7% in the bottom quartile, a customer-retention rate 17 percentage points higher, and a marketing return on investment of 3.4 against 1.9. Their composite Marketing Effectiveness Index averaged 64.8, compared with 38.1 for low-adoption firms — a gap of more than 26 points.

Table 4.

Marketing outcomes of high- and low-AI-adoption firms

Indicator	Top quartile	Bottom quartile	Difference
Average conversion rate, %	4.6	2.7	+1.9 p.p.
Customer-retention rate, %	71	54	+17 p.p.
Campaign response rate, %	9.1	5.4	+3.7 p.p.
Marketing return on investment (ratio)	3.4	1.9	×1.8
Marketing Effectiveness Index (0–100)	64.8	38.1	+26.7

Source: author's enterprise survey, 2025.

Given the evident benefits, the persistence of low average adoption constitutes an adoption paradox. Table 5 ranks the barriers reported by respondents on a five-point scale. The leading constraints are the high cost of AI tools, a shortage of data-analytics skills, and limitations in data quality and integration. Privacy and data-protection concerns and uncertainty about return on investment follow. Notably, the most binding barriers are financial, human, and infrastructural rather than technological, which suggests that they can be addressed through deliberate managerial and policy action.

Table 5.

Barriers to AI adoption ranked by perceived importance (n = 168)

Rank	Barrier	Mean (1–5)
1	High cost of AI tools and implementation	4.21
2	Shortage of data-analytics and AI skills	4.09
3	Poor data quality and weak system integration	3.91
4	Privacy and data-protection concerns	3.74
5	Uncertainty about return on investment	3.62
6	Small scale of available customer data	3.49
7	Organizational resistance to change	3.28
8	Regulatory ambiguity	3.05

Source: author's enterprise survey, 2025.

The findings confirm that AI-based analysis of consumer behavior is a powerful instrument for improving marketing strategy. The dominance of the AI Analytics Adoption Index in the regression, and its persistence after controlling for personalization, data quality, channel breadth, and budget, indicate that AI capability is not merely a reflection of firm size or marketing spending but a distinct determinant of performance in its own right. This is consistent with the resource-based and dynamic-capabilities view, under which the capacity to sense, interpret, and act on consumer signals constitutes a valuable and difficult-to-imitate organizational capability.

The mechanism revealed by the analysis follows the logic of the conceptual framework. AI technologies improve marketing in three connected ways. First, they sharpen consumer understanding: machine-learning segmentation and predictive models reveal micro-segments and individual intentions that conventional research cannot detect. Second, they enable action on that understanding at scale: recommendation systems, personalized content, and dynamic pricing apply consumer insight to millions of individual interactions in real time, something no manual process could achieve. Third, they create a learning loop: outcome data continuously retrain the models, so that targeting accuracy improves over time. The strong showing of personalization capability as the second predictor is direct evidence of the second mechanism — insight delivers value mainly when it is converted into individualized marketing action.

The quartile comparison shows that these mechanisms translate into economically meaningful results: high-adoption firms outperform low-adoption firms simultaneously on conversion, retention, response, and return on investment. The pattern indicates that AI does not improve a single metric in isolation but upgrades marketing performance broadly, by aligning offers, prices, channels, and experiences more closely with actual consumer behavior. These results are consistent with industry evidence that AI-driven campaigns achieve higher conversion and return on investment than conventional ones.

The adoption paradox — clear benefits combined with modest average adoption — is the study's central practical puzzle. Because the leading barriers are cost, skills, and data quality rather than the maturity of the technology itself, they are amenable to intervention. For firms, the evidence supports a staged approach rather than wholesale transformation: adoption should begin with mature, high-return applications such as segmentation, recommendation, and chatbot-based engagement, and extend toward predictive churn, lifetime-value, and dynamic-pricing models as data and skills accumulate. Crucially, AI should be treated as complementary to personalization and data-integration investment, since the regression shows each contributes independently. Smaller firms unable to invest individually can capture much of the benefit through shared platforms and external analytics providers. For policymakers, the priorities are to lower the cost and risk of entry through support for digital infrastructure and analytics services, to expand the supply of data-analytics skills through education and training, and to establish clear data-protection rules that sustain the consumer trust on which data-driven marketing ultimately depends.

Several limitations should be acknowledged. The cross-sectional design establishes a strong association but cannot fully exclude reverse causation, since more effective marketing organizations may also have greater capacity to adopt AI; panel data or experimental evaluation would allow firmer causal identification. The reliance on managerial self-report for some variables invites future use of objective performance data, and the single-country setting limits direct generalization. Future research could test the framework comparatively across markets, quantify the return on investment of individual AI applications, and examine the ethical dimensions of AI-based consumer analysis, including privacy, transparency, and algorithmic fairness.

Beyond its practical implications, the study contributes to marketing theory by positioning AI analytical capability as a distinct, measurable construct that mediates between data resources and competitive marketing performance. Whereas earlier frameworks treated technology mainly as an enabler of efficiency, the evidence here suggests that AI capability functions as a strategic capability that reshapes how consumer knowledge is created and deployed. The finding that personalization carries a large independent effect indicates that consumer insight and the means of acting on it are analytically separable, and that both must be present for AI to deliver value — a refinement that future models of data-driven marketing should incorporate.

This study examined how artificial intelligence improves marketing strategy through the analysis of consumer behavior. Using survey data from 168 companies, it developed and tested a framework linking AI analytical technologies to consumer insight, marketing-strategy levers, and marketing outcomes. The regression analysis showed that the firm-level AI Analytics Adoption Index is the strongest predictor of marketing effectiveness and that the model explains close to three-fifths of the variance in performance. The quartile comparison demonstrated that high-adoption firms substantially outperform low-adoption firms on conversion, retention, response rates, and return on investment.

The central message is that AI changes marketing from a periodic, intuition-based activity into a continuous, data-driven, and adaptive process. Its value, however, is realized only when analytical insight is embedded in concrete marketing action — especially personalization — and supported by adequate data and skills. The persistence of low average adoption, despite clear benefits, shows that the binding constraints are organizational and infrastructural rather than technological. Closing this gap requires coordinated effort: firms should pursue a staged, capability-building adoption path, while policymakers should reduce entry costs, expand analytical skills, and provide a trustworthy data-governance environment. Under these conditions, AI-based analysis of consumer behavior can become a durable source of marketing effectiveness and competitive advantage.

REFERENCES:

1. Davenport T., Guha A., Grewal D., Bressgott T. How artificial intelligence will change the future of marketing // Journal of the Academy of Marketing Science. – 2020. – Vol. 48. – P. 24–42.

2. Huang M.-H., Rust R.T. A strategic framework for artificial intelligence in marketing // Journal of the Academy of Marketing Science. – 2021. – Vol. 49. – P. 30–50.

3. Kumar V., Rajan B., Venkatesan R., Lecinski J. Understanding the role of artificial intelligence in personalized engagement marketing // California Management Review. – 2019. – Vol. 61(4). – P. 135–155.

4. Verma S., Sharma R., Deb S., Maitra D. Artificial intelligence in marketing: Systematic review and future research direction // International Journal of Information Management Data Insights. – 2021. – Vol. 1(1).

5. Haleem A., Javaid M., Qadri M.A. et al. Artificial intelligence (AI) applications for marketing: A literature-based study // International Journal of Intelligent Networks. – 2022. – Vol. 3. – P. 119–132.

6. Stone M., Aravopoulou E., Ekinci Y. et al. Artificial intelligence (AI) in strategic marketing decision-making // The Bottom Line. – 2020. – Vol. 33(2). – P. 183–200.

7. Chintalapati S., Pandey S.K. Artificial intelligence in marketing: A systematic literature review // International Journal of Market Research. – 2022. – Vol. 64(1). – P. 38–68.

8. De Bruyn A., Viswanathan V., Beh Y.S. et al. Artificial intelligence and marketing: Pitfalls and opportunities // Journal of Interactive Marketing. – 2020. – Vol. 51. – P. 91–105.

9. Ma L., Sun B. Machine learning and AI in marketing – Connecting computing power to human insights // International Journal of Research in Marketing. – 2020. – Vol. 37(3). – P. 481–504.

10. McKinsey & Company. The state of AI: Global survey. – 2025.

11. Salesforce. State of Marketing Report. – 2026.

12. Statista. Artificial intelligence (AI) use in marketing – statistics & facts.