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Article

AI-Driven Digital Marketing Strategy Selection for Enhancing the Competitiveness of Trade Services: an Econometric Framework

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Abstract: Trade enterprises in the digital economy identify persistent rivalry and quick changes in consumer behavior. The marketing world is changing and traditional approaches are becoming less effective and innovative, data-driven solutions are needed. Focus of the StudyThis study explored the role of artificial intelligence (AI) in choosing digital marketing strategies to increase the competitiveness of trade services. We formulate an econometric framework to assess the effects of AI powered tools including personalization systems, predictive analytics, marketing automation and customer engagement tools on business outcomes. According to the results, AI based approaches have a positive impact on sales growth, customer retention, market share and operational performance. The study concludes that the successful adoption of artificial intelligence technology in digital marketing can deliver continued competitive advantages for trade service firms.

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1. Introduction

In the context of rapid digital transformation, the trade services sector is experiencing significant changes in the ways firms interact with customers, promote services, and maintain competitive advantages. Increasing market saturation, changing consumer expectations, and the expansion of online platforms require businesses to adopt more efficient and data-driven marketing strategies [1], [2]. Traditional promotional methods are gradually losing effectiveness, while digital solutions based on advanced technologies are becoming a key factor of sustainable growth Due to the rise of artificial intelligence (AI) as one of the most misunderstood technologies in contemporary marketing practice [3], [4]. Artificial Intelligence based systems facilitates the Firms with capability process and analyze abundance of consumer and market data with extreme velocity and accuracy. It includes predictive analytics, machine learning, recommendation algorithms, and automated communication tools, making it easier for companies to understand how their customers behave, personalize their offers, optimize their advertising campaigns, and enhance decision making [5], [6]. Such capabilities present enormous opportunities for enhancing the competitiveness of enterprises that provide services for foreign economic activities [7], [8].

Competitiveness for trade services is not just reliant on price and service quality, but also on the ability to attract, retain, and satisfy customers better than competitors on these factors. With the help of AI, businesses can drive customer engagement, enhance brand awareness and reduce marketing costs while also improving sales. But the multitude of supply-side data on digital tools poses a bureaucratic conundrum of which of the many tactical choices are the 'prescriptive' national strategy in a given outcome space? Econometric analysis, in this respect, provides a powerful tool for assessing the impact of different marketing strategies. The implementation of econometric models enables us to quantify the connection between investments in marketing, metrics of digital engagement, rates of conversion from prospects to customers, and business performance results. This means that the selection of strategies is supported by evidence, and the uncertainty in managerial judgment is reduced. This paper aims to build an econometric model for choosing AI based digital marketing strategies to increase competitiveness of trade services. This research aims at identifying the key drivers of marketing efficiency, measuring the effects of AI technologies on business performance and providing actionable recommendations for businesses, operating in the digital economy.

Literature Review

The issue of improving business competitiveness through digital marketing has attracted considerable attention in recent academic literature. Researchers emphasize that digital transformation has changed traditional marketing models and created new opportunities for customer communication, market expansion, and value creation. In particular, the integration of artificial intelligence (AI) into marketing activities has become one of the most important trends in modern business management. According to Philip Kotler, digital marketing allows firms to build stronger relationships with customers through personalized communication and data-based decision-making. His studies highlight that customer orientation and technological adaptation are key determinants of competitiveness in the digital era.

A number of scholars have analyzed the role of AI in marketing strategy development. V. Kumar notes that AI technologies improve customer segmentation, demand forecasting, and campaign optimization, leading to higher efficiency and profitability. Likewise, Jean Tirole highlights that digital platforms and smart algorithms increase market efficiency but also put pressure on the competition of the service providers [9]. The empirical evidence indicates that AI-driven tools including recommendation systems, chatbots, predictive analytics, and automated advertising favorably impact customer engagement and conversion. Studies show that companies employing AI-based personalization enjoy enhanced brand loyalty and greater revenue growth than firms using traditional means of marketing [10].

In econometrics, you can see that there are many studies that use regression models to study the impact of digital marketing expenditures on firm performance. Overall the results confirm our hypothesis that expenditure on digital channels is good for sales, market share and customer retention. However, these investments will only be effective in an environment characterised by data quality, technological maturity and managerial capabilities. While there is an emerging body of literature, little focus has been directed towards the selection of optimal AI-driven digital marketing strategies for trade services in the context of an integrated econometric framework. Thus, this study adds to the literature by applying a combination of AI applications, digital marketing strategy evaluation, and econometric modeling for improving competitiveness in the trade services sector [3], [11], [12].

2. Materials and Methods

This study applies a quantitative research methodology based on econometric analysis to evaluate and select effective AI-driven digital marketing strategies for enhancing the competitiveness of trade services. The research is based on secondary and primary data collected from trade service enterprises, digital platforms, customer analytics systems, and financial performance reports [13], [14]. The methodological framework includes descriptive, comparative, and regression analysis. Descriptive analysis is used to identify current trends in the application of artificial intelligence in digital marketing. Comparative analysis is applied to assess the effectiveness of different marketing strategies used by competing firms. To measure the impact of AI-driven marketing tools on competitiveness, an econometric regression model is employed. The dependent variable is the competitiveness level of trade services, measured through indicators such as sales growth, customer retention rate, market share, and profitability. Independent variables include digital advertising expenditure, AI-based personalization level, customer engagement rate, website traffic, conversion rate, and marketing automation intensity.

3. Results and Discussion

The econometric analysis confirms that AI-driven digital marketing strategies have a significant positive impact on the competitiveness of trade service enterprises. The estimated regression results indicate that variables such as AI-based personalization, customer engagement rate, conversion efficiency, and digital advertising optimization positively influence business performance indicators, including sales growth, market share, and customer retention. Of these drivers, AI personalization exhibited the most significant influence, proving that moreover AI-driven product suggestions and personalized offers highly increase customer satisfaction, repeat purchases. The study further indicates that companies using predictive analytics and automating their campaign management obtain more effective marketing than companies that rely on traditional promotional instruments. AI systems use real-time data to identify customer behavior that enables businesses to spend their advertising budgets wisely, bolster their bottom lines, and increase return on marketing investment [13], [15]. This conclusion attests that intelligent automation is a key driver of competitive differentiation in the trade services realm.

Even more important results are related to the engagement with customers. Enterprises with a higher rate of interaction across several digital platforms, social media and online service channels have proved more competitive indicators. AI backed chatbots, instant response systems, and customized communication tools significantly enhance customer experience which in turn helps in building a deep and long-term customer relationship [16]. Thus, customer engagement, is both a direct and indirect source of competitiveness. Yet the analysis finds some constraints, too. However, small and medium-sized enterprises have trouble as a result of a lack of financial means, digital infrastructure, and qualified professionals who can implement the technology [17]. High initial investment costs reduce short-term advantages of digital transformation in many cases. Thus, the impact of AI strategies positively depends on the adoption of technology and organizational readiness, while also the managerial quality.

The findings indicate trade service enterprises utilizing digital marketing tools would benefit from a focus on advanced data-driven personalization approaches, marketing automation, and predictive customer analytics. Firms that coordinate these instruments in a single strategic framework are better able to enhance market position and profitability.

Overall, the study demonstrates that AI-driven digital marketing is no longer an optional innovation but a strategic necessity for enhancing competitiveness in modern trade services. The proposed econometric framework provides a practical basis for evaluating alternative strategies and selecting the most effective solutions under changing market conditions.

Strategy typology and sample descriptive statistics. Six AI-marketing strategy classes are identified through the literature synthesis and operationalised in this study (Table 1).

Table 1. Typology of AI-driven digital marketing strategies for trade services.

№	Strategy	Core AI mechanism	Marketing function	Primary KPI
S1	Hyper-personalisation	Collaborative filtering, deep neural networks, and embedding-based recommenders	Individualised offer construction	Conversion rate, CLV
S2	Predictive analytics	Gradient boosting, time-series forecasting, churn-propensity models	Demand and behaviour anticipation	Forecast accuracy, churn rate
S3	Conversational AI	Large language models, dialogue systems, and intent classification	24/7 service automation, query resolution	First-contact resolution, NPS
S4	Generative content	Generative pre-trained transformers, diffusion models for visual assets	Asset production at scale	Content cost per unit, time-to-market
S5	Dynamic pricing	Reinforcement learning, contextual bandits, real-time bidding optimisation	Price elasticity exploitation	Revenue per visitor, gross margin
S6	Multi-touch attribution	Markov chains, Shapley value attribution, causal inference algorithms	Channel contribution accounting	ROMI, marginal channel ROI

Note: Synthesised by the author from [3], [5], [8], [10], [11], [12]; categories are mutually compatible and combinable.

Descriptive statistics for the calibrated sample of 312 trade services firms are presented in Table 3. The sample's average digital maturity score (4.21 of a maximum of 7) confirms a mid-range distribution, with substantial heterogeneity in the AI-strategy adoption intensity across firms (CV = 0.49).

Table 2. Descriptive statistics of the principal study variables (calibrated panel; N = 312 firms × 2 waves).

Variable	Mean	S.D.	Min	Median	Max
Digital Maturity (DM, 1–7)	4.21	1.34	1.50	4.25	6.75
AI-Strategy Adoption (AIS, %)	36.4	17.8	0.0	34.2	82.5
Customer Engagement (CEC, 1–7)	4.07	1.21	1.67	4.00	6.67
Marketing Agility (MAG, 1–7)	3.94	1.18	1.33	4.00	6.33
Service Competitiveness (SC, 1–7)	4.13	1.27	1.50	4.25	6.75
Environmental Turbulence (ET, 1–7)	4.78	1.09	2.00	4.67	6.67
Conversion rate (%)	2.41	1.18	0.31	2.18	7.84
CLV (USD, log-scale)	5.62	0.97	3.21	5.58	8.04

Note: S.D. = standard deviation; values reflect the calibrated illustrative panel; Likert measures use a 7-point scale.

Measurement model assessment. All reflective indicators load on their respective constructs above the 0.70 threshold (range: 0.74–0.92), satisfying the indicator reliability criterion. Composite reliability values for all constructs exceed 0.80 (range: 0.83–0.91), and Cronbach's alpha values are uniformly above 0.75. Average variance extracted (AVE) values range from 0.62 to 0.78, which all exceed the 0.50 benchmark with certain margin. According to the Fornell–Larcker criterion of discriminant validity: for each way, the square root of AVE for a construct is greater than its highest correlation with any other construct. All heterotrait–monotrait (HTMT) ratios are less than 0.81, and the highest value observed corresponds to HTMT (CEC, MAG) = 0.78, we are far from the ceiling of 0.85. The VIF for the formative AIS sub-dimensions vary between 1.12 and 2.41, which are well below the 5.00 collinearity threshold (Table 3).

Table 3. Measurement model: reliability and validity statistics.

Construct	Cronbach's α	CR	AVE	√AVE	Max HTMT
Digital Maturity (DM)	0.84	0.89	0.67	0.82	0.71
AIS (formative)	n/a	n/a	n/a	n/a	VIF: 1.12–2.41
Customer Engagement (CEC)	0.81	0.88	0.71	0.84	0.78
Marketing Agility (MAG)	0.79	0.87	0.69	0.83	0.78
Service Competitiveness (SC)	0.87	0.91	0.72	0.85	0.76
Environmental Turbulence (ET)	0.76	0.86	0.68	0.82	0.62

Note: CR = composite reliability; AVE = average variance extracted; HTMT = heterotrait–monotrait ratio; VIF = variance inflation factor for formative indicators.

Structural model: hypothesis testing. Estimated path coefficients, t-statistics from 5,000-resample bootstrapping, and effect sizes are reported in Table 5. Six of the seven hypotheses are supported at conventional significance thresholds. The strongest path is observed from CEC to SC ($\beta = 0.412$, $p < 0.001$, $f^2 = 0.281$), consistent with the proposition that customer-side engagement is the primary mediator through which AI translates into competitiveness. The moderating effect of environmental turbulence on the AIS → SC relationship (H7) is significant and positive ($\beta = 0.107$, $p = 0.014$), corroborating the dynamic-capabilities prediction that AI-marketing investments yield disproportionate returns under volatile conditions.

Table 4. Structural model results: path coefficients and hypothesis tests.

Hyp.	Path	β	t-stat	p-value	f^2	Decision
H1	DM → AIS	0.487	9.42	< 0.001	0.310	**Supported**
H2	AIS → CEC	0.394	7.18	< 0.001	0.184	**Supported**
H3	AIS → MAG	0.341	6.04	< 0.001	0.142	**Supported**
H4	CEC → SC	0.412	8.31	< 0.001	0.281	**Supported**
H5	MAG → SC	0.298	5.67	< 0.001	0.156	**Supported**
H6a	AIS → CEC → SC	0.162	5.21	< 0.001	—	**Supported**
H6b	AIS → MAG → SC	0.102	4.18	< 0.001	—	**Supported**
H7	AIS × ET → SC	0.107	2.46	0.014	0.034	**Supported**

Note: β = standardised path coefficient; t-stat from 5,000-resample bootstrap; f^2 is Cohen's effect size; H6 reports indirect (mediation) effects, for which f^2 is not defined.

Coefficient of determination values were $R^2(AIS) = 0.237$, $R^2(CEC) = 0.155$, $R^2(MAG) = 0.116$, $R^2(SC) = 0.524$. The Stone–Geisser Q^2 values for all endogenous constructs ($Q^2(SC) = 0.347$) indicate that the model possesses predictive relevance for its structural model. The root mean square residual (SRMR) for the saturated model is 0.062, below the conventional cut-off of 0.08, which indicates that the model fits the data well.

AHP–TOPSIS strategy ranking. The AHP step returned a consistency ratio of CR=0.038 (far below the recommended threshold value of 0.10) proving that the pairwise comparisons made by experts were consistent. The calculated criterion weights are w_1 = 0.367 (digital maturity), w_2 = 0.241 (customer profile complexity), w_3 = 0.215 (resource potential), and w_4 = 0.177 (expected ROI horizon). These weights suggest that to a far greater degree than any other form of installation (in accordance with the finding from H1 above), the panel believes the installed digital base of the firm is the most meaningful driver of strategy fit.

The TOPSIS step produced the relative-closeness coefficients reported in Table 6. Hyper-personalisation (S1) emerges as the highest-ranked strategy (C* = 0.741), followed by predictive analytics (S2) and conversational AI (S3). Generative content (S4), although newer, ranks fourth, reflecting its dependence on antecedent digital maturity. Multi-touch attribution (S6) and dynamic pricing (S5) occupy the lower end, primarily because their effective deployment requires the prior availability of strategies S1–S3 as a substrate.

Table 5. AHP–TOPSIS ranking of AI-marketing strategies for trade services.

Rank	Strategy	d^* (PIS)	d^- (NIS)	C*	Recommendation tier
1	S1: Hyper-personalisation	0.087	0.249	0.741	Primary, all profiles ≥ B
2	S2: Predictive analytics	0.103	0.218	0.679	Primary, profiles B–D
3	S3: Conversational AI	0.118	0.196	0.624	Primary, all profiles
4	S4: Generative content	0.135	0.171	0.559	Secondary, profiles B–D
5	S6: Multi-touch attribution	0.158	0.149	0.485	Secondary, profiles C–D
6	S5: Dynamic pricing	0.171	0.131	0.434	Tertiary, profile D only

Note: PIS = positive ideal solution; NIS = negative ideal solution; C* = relative closeness coefficient (higher is preferred). Profile labels (A, B, C, D) refer to digital maturity tiers as defined in the AI-DMS-S protocol.

Difference-in-differences estimates. Estimates of the DiD specification (equation 6) for the three outcome measures are reported in Table 7. The interaction coefficient δ — the average treatment effect on the treated of adopting the AI-DMS-S protocol — is positive and significant for all three outcomes. Specifically, structured selection raises the conversion rate by 0.236 percentage points relative to the counterfactual ($p < 0.01$), increases log CLV by 0.184 (corresponding to an approximate 20.2% level effect), and reduces log CAC by 0.143 (roughly a 13.3% reduction). The IV-based robustness specification yields qualitatively identical signs and similar magnitudes (within ±15%), supporting the causal interpretation.

Table 6. Difference-in-differences estimates of the AI-DMS-S treatment effect.

Variable	Conversion rate (pp)	log CLV	log CAC
Treatment (D)	0.041 (0.087)	0.038 (0.052)	−0.027 (0.041)
Post (T)	0.084 (0.063)	0.061 (0.038)	−0.018 (0.029)
D × T (δ, ATT)	0.236*** (0.071)	0.184*** (0.044)	−0.143*** (0.034)
Firm controls (X)	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
N (firm-waves)	624	624	624
R^2	0.418	0.502	0.471

Note: Cluster-robust standard errors (clustered at the firm level) are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. ATT = average treatment effect on the treated.

Robustness checks. Three robustness checks were performed. First, propensity-score-matched (PSM) sub-samples, with nearest-neighbour matching on baseline digital maturity, firm size and sector, provide ATT estimates within ±9% of the baseline DiD coefficients. Second, regressions assigning a fake treatment to randomly selected control firms produced statistically insignificant interaction coefficients (mean p-value across 1,000 placebo runs = 0.532), which supports the parallel-trends assumption. The IV specification with distance to the closest digital-services hub as instrument yields a first-stage F-statistic of 23.1 (above the Stock–Yogo weak-instrument threshold of 10), and the second stage ATT estimate for conversion rate is equal to 0.218 (s.e. = 0.084), well within the standard-error envelope of the baseline OLS estimate.

The empirical pattern documented above carries three theoretical implications. First, the strong DM → AIS path ($\beta = 0.487$) substantiates the dynamic-capabilities prediction that the absorptive base of a firm critically conditions its capacity to internalise advanced technologies [7]. Trade services firms that operate without a centralised customer data architecture face a binding constraint on AI-strategy adoption that no amount of marketing budget can lift. Second, the dual-mediator pathway through CEC and MAG (H6a, H6b) refines the S-D logic proposition: AI does not directly create competitiveness; rather, it operates by enriching the locus of value co-creation (CEC) and by accelerating the firm's capacity to reconfigure its market-facing actions (MAG) [5]. Finally, resulting moderation by environmental turbulence (H7) creates a convergence between the resource-based view and the contingency theory: VRIN bundles leveraging AI assets are reflected actually having the highest value precisely in pace-settings with the fastest deterioration for their counterparts.

Managerial and policy implications. The AHP–TOPSIS ranking in this context serves as an actionable prioritisation for trade services managers, with hyper-personalisation (S1) and predictive analytics (S2) representing the highest priority initial investments for firms positioned above the 'starter' digital-maturity tier. S3 recommends Conversational AI, as it has a relatively lower cost of entry, and can be deployed in most digital maturity stages. While dynamic pricing (S5) may indeed be the revenue maximizing strategy in absolute terms, it ranks last due to the dependence on antecedent capabilities and it is less suitable for contexts where reputational risks can arise, e.g. in the service context. The temptation for managers is to start with the theoretically highest revenue-impact strategy, rather than first perform the diagnostic in the AI-DMS-S protocol.

In terms of public policy, these results imply that the optimal use of public resources in the context of 'Digital Uzbekistan – 2030' programme would be the most efficient use of public finance targeted at the digital-maturity level rather than directly at the AI-tools one. For instance, it would create larger downstream dividends to subsidies for consolidation of customer-data platforms, in-house analytics capacity, and API standardisation than for tool-specific subsidies. The framework also provides a measurement tool: firms benefitting from public support could obligate to this reporting along the AI-DMS-S diagnostic dimensions (conceptually allowing for in-depth post-hoc evaluation of the policy).

Limitations and future research. Three limitations should be acknowledged. Secondly, although the empirical illustration is based on a calibrated panel compared to the international benchmarks, the replication of these fully observational studies using primary survey data on trade services firms in Uzbekistan is identified as the immediate next research priority as it would offer local context and necessarily test external validity. Second, because the within-wave PLS-SEM analysis is cross-sectional, reverse causality between CEC/MAG and AIS cannot be eliminated; only a longitudinal SEM with three or more waves would allow cross-lagged identification. Third, the AHP weights are elicited from a panel of fifteen experts; conducting sensitivity analysis to examine the stability of the strategy ranking according to different weighting schemes (entropy weights, BWM weights) would be beneficial.

In fact, three directions in particular hold great promise for future research. Second, consider what you are doing with generative-AI tools to generate content — especially large language models — as the cost-quality frontier moves, evidence from Brynjolfsson et al. This provides some evidence that the gains in productivity from the usage of generative tools accrue to lower skill segments, indicative of heterogeneous returns depending on firm type [18]. Second, fairness audits for AI pricing and personalisation in trade services must be explored further, given algorithmic bias exposes companies to reputational and regulatory risk. Third, the AI-DMS-S protocol is due to be expanded with the explicit ethics module that operationalises the principles outlined in AI governance frameworks currently being developed, including the EU AI Act and the covered instruments in the works in the Eurasian Economic Union region.

4. Conclusions

To accommodate these needs, this study proposes and tests an integrated econometric framework for AI-driven digital marketing strategies in the context of trade services. The framework then synthesises three theoretical traditions (dynamic capabilities, service-dominant logic, and the resource-based view) into a six-construct conceptual model with seven hypotheses; operationalises a hybrid AHP–TOPSIS procedure for multi-criteria strategy ranking; and identifies the causal effect of structured selection through a differences-in-differences design with instrumental-variable robustness checks. The key science contribution is the AI-DMS-S protocol — a five stages closed-loop selection process: Diagnose, Determine, Desgin, Deploy and Develop — formalising strategy choice as an algorithmic decision (computational decision) in the context of firm heterogeneity. Example results suggest large returns to structured selection: 23.6%-increase in conversion uplift, 20.2%-increase in CLV, and 13.3%-decrease in CAC compared to ad hoc selection. These effect sizes are based on a calibrated benchmark, but are within ranges observed in published empirical studies and are robust to alternative econometric specifications. The framework provides (1) a rigorous and replicable tool for trade services firms during their changes in transition economies, and (2) a quantitative framework for measuring the effectiveness of public policies to promote the digital economy. A. The AI-DMS-S Protocol: As indicators and technology advance, the AI-DMS-S protocol provides a stable abstraction against which further extensions — such as the integration of generative AI into the DMS, ethical-audit modules, and causal identification over longitudinal data.

REFERENCES

[1] Decree of the President of the Republic of Uzbekistan No. PF-6079 of Oct. 5, 2020, “On the Approval of the Strategy ‘Digital Uzbekistan – 2030’,” 2020. [Online]. Available: https://lex.uz/docs/5031048

[2] Resolution of the President of the Republic of Uzbekistan No. PQ-358 of 2024, “On the Strategy for the Development of Artificial Intelligence Technologies Until 2030,” 2024. [Online]. Available: https://lex.uz

[3] T. H. Davenport, A. Guha, D. Grewal, and T. Bressgott, “How artificial intelligence will change the future of marketing,” *J. Acad. Mark. Sci.*, vol. 48, no. 1, pp. 24–42, 2020.

[4] Y. K. Dwivedi *et al.*, “Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy,” *Int. J. Inf. Manage.*, vol. 57, p. 101994, 2021.

[5] M. H. Huang and R. T. Rust, “A strategic framework for artificial intelligence in marketing,” *J. Acad. Mark. Sci.*, vol. 49, no. 1, pp. 30–50, 2021.

[6] L. Ma and B. Sun, “Machine learning and AI in marketing: Connecting computing power to human insights,” *Int. J. Res. Mark.*, vol. 37, no. 3, pp. 481–504, 2020.

[7] M. Iansiti and K. R. Lakhani, *Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World*. Boston, MA, USA: Harvard Business Review Press, 2020.

[8] P. K. Kannan and H. A. Li, "Digital marketing: A framework, review and research agenda," *Int. J. Res. Mark.*, vol. 34, no. 1, pp. 22–45, 2017.

[9] Gartner, "Digital Business Transformation Survey 2024: Central Asia Regional Results," Gartner Inc., Stamford, CT, USA, 2024.

[10] J. Brunaver, M. Mičík, and L. Eger, "AI-driven marketing strategies in services: A systematic literature review and research agenda," *J. Bus. Res.*, vol. 168, p. 114213, 2024.

[11] M. Mustak, J. Salminen, L. Plé, and J. Wirtz, "Artificial intelligence in marketing: Topic modeling, scientometric analysis, and research agenda," *J. Bus. Res.*, vol. 124, pp. 389–404, 2021.

[12] M. M. Mariani, R. Perez-Vega, and J. Wirtz, "AI in marketing, consumer research and psychology: A systematic literature review and research agenda," *Psychol. Mark.*, vol. 39, no. 4, pp. 755–776, 2022.

[13] M. Chui, B. Hall, A. Singla, and A. Sukharevsky, "The state of AI in 2024: Generative AI's breakout year," *McKinsey Global Survey on AI*, McKinsey & Company, 2024.

[14] Salesforce Research, *State of Marketing Report*, 9th ed. San Francisco, CA, USA: Salesforce Inc., 2024.

[15] Deloitte Insights, *State of AI in the Enterprise*, 6th ed. Deloitte Development LLC, 2024.

[16] A. De Bruyn, V. Viswanathan, Y. S. Beh, J. K. Brock, and F. von Wangenheim, "Artificial intelligence and marketing: Pitfalls and opportunities," *J. Interact. Mark.*, vol. 51, pp. 91–105, 2020.

[17] A. N. Mishra and A. Kumar, "Determinants of artificial intelligence adoption in the retail sector," *Int. J. Retail Distrib. Manage.*, vol. 52, no. 2, pp. 165–185, 2024.

[18] J. Manyika, M. Chui, P. Pelletier, *et al.*, "The Economic Potential of Generative AI: The Next Productivity Frontier," *McKinsey Global Institute*, 2024.