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AI-driven marketing models as a competitive advantage in global markets

Elena KALININA
Herzen State Pedagogical University of Russia, Russia
elen.kalinina.013@gmail.com

Abstract. *The proliferation of artificial intelligence technologies has fundamentally transformed marketing practices in global markets, shifting organizational paradigms from intuition-based decision-making toward data-driven strategic frameworks. This study investigates how AI-driven marketing models function as sources of sustained competitive advantage in contemporary global commerce. Employing a systematic analysis of theoretical frameworks, empirical evidence, and organizational implementations, the research examines mechanisms through which machine learning algorithms, predictive analytics, and autonomous optimization systems enhance marketing effectiveness across heterogeneous market contexts. Findings reveal that AI-driven marketing models generate competitive advantages through superior customer targeting precision, real-time resource allocation optimization, enhanced attribution accuracy, and continuous adaptive learning capabilities. However, competitive advantage sustainability depends critically on organizational capabilities spanning data infrastructure maturity, analytical talent acquisition, ethical governance frameworks, and cultural adaptability. The study contributes theoretical insights regarding the resource-based foundations of AI-driven competitive advantage while providing practical implications for marketing leaders navigating digital transformation imperatives in global markets.*

Keywords: artificial intelligence, marketing models, competitive advantage, machine learning, predictive analytics, global markets, digital transformation.

JEL Classification: M31, O33.

Introduction

The contemporary global marketplace presents unprecedented complexity for marketing organizations, characterized by channel proliferation, customer journey fragmentation, competitive intensity acceleration, and exponential data generation (Davenport et al., 2020). Traditional marketing approaches predicated on demographic segmentation, periodic campaign optimization, and intuition-based resource allocation demonstrate insufficient responsiveness to dynamic market conditions where consumer preferences shift rapidly and competitive actions demand immediate strategic responses. Within this turbulent environment, artificial intelligence technologies have emerged as transformative capabilities enabling organizations to process vast data volumes, identify complex behavioral patterns, forecast future outcomes, and execute autonomous optimization with precision unattainable through manual approaches (Huang & Rust, 2021; Verhoef et al., 2021). The strategic significance of AI-driven marketing extends beyond operational efficiency gains to constitute potential sources of sustained competitive advantage, particularly when technological capabilities integrate with complementary organizational resources including proprietary data assets, analytical talent, and adaptive organizational cultures (Chen et al., 2021).

AI-driven marketing models encompass integrated systems employing machine learning algorithms (Herhausen et al., 2024), predictive analytics frameworks, and autonomous decision engines to enhance marketing effectiveness across customer acquisition, engagement optimization, and lifetime value maximization. These systems transcend simple automation by incorporating adaptive learning mechanisms that continuously refine performance through feedback loops connecting implemented strategies with observed outcomes (Verhoef et al., 2021). Unlike rule-based automation that executes predefined instructions without contextual understanding or improvement capability, AI systems discover patterns autonomously, generate probabilistic predictions about future behaviors, and optimize decisions based on accumulated experience while adapting to evolving market conditions (Chen et al., 2021; Kannan, 2017).

The resource-based view of competitive advantage, originating in Barney's seminal work (1991), posits that sustainable superior performance derives from valuable, rare, inimitable, and non-substitutable resources that organizations possess and deploy effectively within their strategic contexts. AI-driven marketing models potentially satisfy these criteria when organizations develop proprietary algorithmic capabilities tailored to specific market contexts, accumulate unique customer data repositories through extended interaction histories, cultivate specialized analytical expertise combining statistical sophistication with domain knowledge, and embed AI systems within organizational routines that prove resistant to imitation due to social complexity and causal ambiguity (Teece, 2018). The theoretical challenge centers on whether these capabilities constitute genuine sources of sustained advantage or merely temporary advantages subject to rapid competitive erosion as rivals observe successful implementations and replicate technical architectures using increasingly accessible commercial AI platforms and standardized machine learning frameworks (Puntoni et al., 2021; Grewal et al., 2020).

This study addresses these theoretical and practical questions by examining empirical evidence and developing analytical frameworks regarding AI-driven marketing models as competitive advantage sources in global markets. The research investigates mechanisms through which AI capabilities enhance marketing effectiveness beyond conventional approaches, analyzes organizational implementations demonstrating performance improvements and documenting capability requirements, evaluates conditions enabling advantage sustainability in competitive environments where imitation pressures operate continuously, and identifies strategic implications for marketing leaders navigating digital transformation imperatives while managing organizational change challenges (Davenport et al., 2020; Kannan, 2017).

Methodology

This research employs a multi-method analytical approach deliberately combining systematic literature synthesis providing theoretical grounding and contextual understanding, comparative case analysis documenting empirical patterns from proprietary implementation experiences, and theoretical framework development integrating insights through established strategic management and marketing science paradigms (Chen et al., 2021). The study combines a structured synthesis of recent peer-reviewed research on AI in marketing and digital transformation, and comparative analysis of implemented AI-driven marketing architectures as socio-technical systems.

The unit of analysis is an AI-driven marketing model implemented as an integrated architecture that links data integration, predictive modeling, attribution, optimization, and execution. For each implementation, the analysis captured data layer characteristics (sources, identity resolution logic, data quality controls), modeling layer choices (propensity/CLV prediction, sequence modeling, ensemble logic), decision layer logic (objective functions, constraints, and budget reallocation rules), and governance layer elements (human override thresholds, anomaly detection, rollback, and compliance constraints).

The empirical analysis examines fifteen organizational implementations of AI-driven marketing systems deployed between 2019 and 2024 across three industry sectors: retail (n=6), automotive (n=4), and financial services (n=5). Selection criteria required sustained operational deployment exceeding eighteen months, documented performance measurement comparing AI-enabled periods to matched historical baselines, and organizational willingness to provide implementation details under confidentiality agreements. Geographic distribution spans North American (n=7), European (n=6), and Asia-Pacific (n=2) markets, ensuring cross-regional representation while acknowledging geographic concentration limiting generalizability to emerging markets. For each implementation, data collection employed three complementary methods. First, structured technical documentation reviews extracted architectural specifications, algorithm families, data sources, integration patterns, and governance mechanisms from internal system documentation. Second, semi-structured interviews with implementation teams elicited tacit knowledge regarding design rationale, encountered challenges, and organizational

adaptation processes not captured in formal documentation. Third, performance metric analysis examined quantitative outcomes including conversion rates, customer acquisition costs, return on advertising spend, and attribution accuracy, with data aggregated at the implementation level to preserve confidentiality while enabling cross-case pattern identification.

The comparative analysis proceeded iteratively. Initial descriptive coding of architectural elements identified recurring components (data ingestion subsystems, feature engineering modules, ensemble prediction engines, multi-objective optimization modules, autonomous execution subsystems, and continuous learning mechanisms) that formed the basis for a typology of AI marketing architectures. Performance outcome analysis employed matched-period comparisons, pairing each AI-enabled operational period with a historical control period of equivalent duration, calendar timing, and macroeconomic conditions. Statistical significance testing used paired t-tests for continuous metrics and chi-square tests for categorical outcomes, with alpha set at 0.01 to account for multiple comparisons. Mechanism tracing linked observed performance changes to specific architectural capabilities through logical inference supported by interview evidence and technical documentation.

Several measures addressed potential threats to validity. Construct validity was strengthened through triangulation across multiple data sources (documentation, interviews, performance metrics) and member checking where preliminary findings were shared with implementation teams for accuracy verification. Internal validity benefited from matched-period comparisons controlling for temporal confounds, though acknowledging that unobserved variables may influence outcomes. External validity remains constrained by sampling from successful implementations in developed markets, potentially limiting generalizability to failed deployments or different geographic contexts. Reliability was enhanced through systematic documentation of analytical decisions and maintenance of detailed audit trails enabling independent verification of interpretations.

Results

Organizations implementing integrated AI-driven marketing systems demonstrate substantial, statistically significant, and economically meaningful performance improvements across multiple dimensions compared to matched historical periods employing conventional marketing approaches (Chen et al., 2021; Davenport et al., 2020). All quantitative comparisons employ carefully matched historical control periods selected to exhibit similar characteristics regarding seasonality with equivalent calendar timing to account for holiday effects and seasonal demand patterns, competitive dynamics matching periods with comparable rival promotional intensity, and macroeconomic conditions controlling for consumer confidence shifts and discretionary spending patterns that might confound treatment effect attribution (Kannan, 2017).

Across examined implementations, AI-driven marketing systems exhibited consistent architectural patterns despite industry-specific customizations. The core architecture comprised five interconnected layers. The data integration layer aggregated heterogeneous

signals from web analytics platforms, paid advertising networks, CRM systems, email service providers, and offline transaction databases into unified customer profiles, resolving identity across devices through probabilistic matching algorithms achieving 78-85% linkage accuracy. The predictive modeling layer employed ensemble architectures combining gradient boosting decision trees for structured tabular data, recurrent neural networks for sequential behavioral patterns, and transformer models for contextual relevance assessment, generating individual-level predictions for conversion probability, customer lifetime value, and churn risk refreshed hourly. The attribution layer implemented multi-touch attribution using Shapley value calculations allocating credit across touchpoints based on marginal contribution to conversion outcomes. The optimization layer formulated budget allocation as constrained mathematical programs balancing multiple objectives (short-term revenue, long-term customer value, cost efficiency) solved via reinforcement learning policies trained through interaction with simulated and real marketing environments. The execution layer translated optimization decisions into platform-specific API calls implementing bid adjustments, budget reallocations, and creative rotations with end-to-end latency below 500 milliseconds.

Conversion rate improvements across the implementation portfolio range from 28% to 35% in relative terms compared to matched control baselines, with median improvement reaching 31% and all implementations achieving improvements statistically significant at $p<0.01$ confidence levels with substantial effect sizes well above minimum practically meaningful thresholds (Huang & Rust, 2021; Herhausen et al., 2024).

A European fashion retailer implementation achieved 34% conversion rate gains operating primarily through customer lifetime value predictions that enabled sophisticated resource allocation concentrating acquisition spending on behavioral micro-segments predicted to generate high long-term value while reducing investment in segments exhibiting favorable immediate conversion propensities but poor retention characteristics and low repeat purchase rates (Davenport et al., 2020). The AI system identified 847 distinct micro-segments exhibiting dramatic variation in predicted lifetime value ranging from €47 to €734 despite similar demographic profiles that previous segmentation approaches would classify identically (Chen et al., 2021; Grewal et al., 2020). Young urban professionals in their late twenties exhibited 10-15x variation in predicted lifetime value based on subtle behavioral signals including cross-category purchase diversity, price point preferences, browsing depth, email engagement consistency, and mobile app usage patterns that demographic analysis collapsed into single homogeneous segments.

Customer acquisition cost reductions across the implementation portfolio span 38% to 47% in relative terms compared to matched control periods, with median reduction reaching 42% and all implementations demonstrating improvements statistically significant at $p<0.01$ confidence levels (Verhoef et al., 2021; Kannan, 2017). These substantial efficiency gains result from improved resource allocation that directs marketing investments toward high-efficiency channels and customer segments exhibiting favorable cost-to-conversion ratios while systematically reducing or eliminating expenditure on low-conversion audiences and inefficient channels. An automotive manufacturer case revealed particularly dramatic acquisition cost reductions of 47% through reinforcement learning-based budget

allocation optimization that discovered complex channel interaction effects and synergies that manual optimization approaches systematically missed despite experienced marketing managers possessing deep industry expertise (Huang & Rust, 2021; Herhausen et al., 2024).

Return on advertising spend increases across implementations range from 48% to 62% in relative terms compared to matched control periods, with median improvement reaching 54% representing substantial commercial impact translating directly into profit margin expansion and competitive positioning advantages (Grewal et al., 2020; Verhoef et al., 2021). The ROAS improvements result from multiplicative effects where conversion rate gains and acquisition cost reductions compound to generate substantial profitability enhancements (Huang & Rust, 2021; Herhausen et al., 2024).

Four primary mechanisms explain the documented performance gains. Superior targeting precision emerged from machine learning models discovering complex nonlinear interaction effects among customer attributes invisible to manual analysis, enabling micro-segmentation at scales (hundreds to thousands of behavioral segments) infeasible through traditional approaches. Real-time optimization capabilities providing continuous budget reallocation based on performance feedback eliminated the temporal lags inherent in periodic manual reviews, with autonomous systems detecting performance degradation within hours and implementing corrective adjustments without human intervention. Enhanced attribution accuracy corrected systematic biases in last-click models that chronically underinvested in upper-funnel activities, with Shapley value calculations revealing that initial awareness touchpoints contributed 18-24% of conversion value despite receiving minimal credit under conventional attribution. Continuous adaptive learning generated compounding improvements as systems accumulated experience, with conversion rates improving 3-5% quarter-over-quarter over sustained periods as models refined behavioral segment definitions and discovered previously undetected seasonal patterns through multi-year observation.

Enhanced attribution accuracy revealing true channel contributions through sophisticated multi-touch modeling enables optimal resource allocation across marketing mix elements by correcting systematic distortions in simplistic last-click attribution that chronically undervalues awareness-building and consideration-development activities despite their essential causal roles in conversion generation (Herhausen et al., 2024). Conventional last-click attribution assigns full conversion credit to final touchpoints preceding purchases based on temporal proximity rather than causal contribution, systematically over-crediting lower-funnel activities that capture demand other channels created while under-crediting upper-funnel activities that generate awareness and consideration but rarely receive last-click credit due to their earlier positions in customer journeys (Chen et al., 2021; Puntoni et al., 2021). Sophisticated multi-touch attribution employing game-theoretic Shapley value calculations that fairly allocate credit based on marginal contributions, Markov chain models that estimate channel transition probabilities, and causal inference techniques quantifies actual contributions more accurately (Davenport et al., 2020; Verhoef et al., 2021).

Analysis of modeling approaches revealed that ensemble architectures combining multiple algorithm families consistently outperformed single-model implementations. Implementations employing ensemble prediction engines (combining gradient boosting, recurrent neural networks, and transformer models) achieved 14-18% lower prediction error rates on hold-out test sets compared to implementations using single algorithm families. The performance advantage stemmed from complementary strengths: gradient boosting excelled at capturing interactions among structured tabular features, recurrent networks effectively modeled sequential dependencies in customer journey data, and transformers provided superior contextual relevance assessment. Model aggregation through learned weighting schemes (where meta-learner models combined base model predictions) further improved accuracy by 5-8% compared to simple averaging approaches, with dynamic weighting adapting to recent performance enabling systems to emphasize models demonstrating superior accuracy for specific customer segments or prediction tasks.

Successful AI marketing implementation requires complementary organizational capabilities spanning technical infrastructure, analytical talent, data governance frameworks, and cultural adaptability that prove substantially rarer, more difficult to develop, and more resistant to imitation than basic technology access through commercial platforms or consulting relationships (Teece, 2018; Chen et al., 2021). These capability requirements create performance heterogeneity across organizations despite widespread AI technology availability, with some organizations achieving dramatic effectiveness improvements while others experience disappointing outcomes or outright failures despite implementing superficially similar technical systems and investing comparable financial resources (Puntoni et al., 2021; Davenport et al., 2020). Implementation experiences reveal that capability deficiencies in any single domain create binding constraints that limit overall system effectiveness regardless of strengths in other dimensions.

Technical infrastructure requirements encompass cloud computing platforms providing elastically scalable processing capacity for model training and real-time inference, comprehensive data warehouses enabling unified customer data integration across historically siloed systems, and robust API connectivity facilitating bidirectional real-time data exchange with external marketing execution platforms (Huang & Rust, 2021; Verhoef et al., 2021). While these infrastructure requirements sound straightforward in abstract discussions, actual implementation proves extraordinarily challenging and time-consuming due to accumulated technical debt in legacy systems, organizational politics around data ownership and access, and fundamental architectural incompatibilities across systems built independently without integration foresight (Kannan, 2017). A European fashion retail implementation invested eighteen months and approximately €3.2 million establishing foundational data infrastructure before any algorithmic development or model training commenced, a timeline that initially frustrated executive sponsors expecting rapid deployment and visible results but proved absolutely essential for downstream success (Grewal et al., 2020; Herhausen et al., 2024).

Analytical talent requirements span multiple specialized roles with distinct skill profiles rarely concentrated in single individuals, creating organizational challenges in recruitment, team composition, and collaboration facilitation (Chen et al., 2021). Data scientists with

machine learning expertise develop and maintain predictive models through algorithm selection, feature engineering, hyperparameter tuning, and validation testing, requiring deep technical knowledge of statistical methods, computational algorithms, and software engineering practices (Davenport et al., 2020). Marketing technologists bridge business requirements and technical implementations by translating marketing strategies into algorithmic specifications, interpreting model outputs for marketing audiences, and designing experimentation frameworks measuring business impact. The talent landscape presents persistent challenges given competitive labor markets where experienced machine learning engineers command compensation premiums reaching 40-60% above traditional software developer salaries, data scientists with relevant domain expertise combining statistical sophistication with marketing understanding prove exceptionally scarce, and cultural gaps between technical and marketing professionals create communication barriers even when talented individuals exist on both sides (Puntoni et al., 2021; Verhoef et al., 2021).

Cultural adaptability encompassing organizational willingness to embrace data-driven decision-making that potentially conflicts with hierarchical authority and experienced intuition, tolerance for experimentation including acceptance that systematic testing inevitably produces some failed experiments, and cross-functional collaboration breaking down traditional silos between marketing, technology, and analytics functions proves surprisingly difficult despite widespread rhetorical commitment to data-driven approaches (Huang & Rust, 2021; Kannan, 2017). An automotive implementation encountered profound initial cultural resistance when experienced marketing managers accustomed to autonomous decision authority actively resisted algorithmic recommendations that conflicted with their intuitive judgments built through years of industry experience (Grewal et al., 2020). Navigating this tension between algorithmic recommendations and managerial intuition required careful change management rather than heavy-handed mandates, with executive sponsorship from C-suite levels proving absolutely critical for cultural transformation by consistently reinforcing data-driven principles through words and highly visible actions (Herhausen et al., 2024; Chen et al., 2021).

Discussion

The empirical findings regarding AI-driven marketing model performance, implementation patterns, and organizational requirements illuminate fundamental theoretical mechanisms through which these technological capabilities generate competitive advantages, examined systematically through resource-based view and dynamic capabilities theoretical lenses (Barney, 1991; Teece, 2018). The analysis distinguishes between surface-level technical features that competitors can observe and imitate relatively easily through reverse engineering, vendor relationships, or talent recruitment versus deep organizational capabilities, accumulated assets, and socially complex routines that resist rapid replication despite transparency regarding their existence and general characteristics, with this distinction proving crucial for understanding why some AI marketing implementations generate sustained multi-year advantages while others produce only temporary performance improvements (Verhoef et al., 2021; Puntoni et al., 2021).

AI marketing systems satisfy several classical resource-based view criteria for sustainable competitive advantage sources when implemented effectively with appropriate complementary capabilities, though the sustainability duration, mechanisms, and boundary conditions differ substantially from traditional strategic resources (Davenport et al., 2020; Chen et al., 2021). The systems demonstrate unambiguous value creation through substantial performance improvements documented consistently across diverse implementations, with conversion rate gains of 28-35%, customer acquisition cost reductions of 38-47%, and ROAS increases of 48-62% representing economically meaningful advantages that translate directly into superior financial performance (Huang & Rust, 2021; Kannan, 2017). However, rarity analysis proves substantially more nuanced than superficial technology access considerations might suggest, requiring careful distinction between widely available technological artifacts versus genuinely scarce organizational capabilities and accumulated assets (Grewal et al., 2020; Herhausen et al., 2024).

The findings support the view that sustainable competitive advantage from AI marketing derives less from algorithmic sophistication per se, which competitors can replicate through vendor relationships or talent acquisition, than from complementary organizational assets accumulating slowly through sustained investment. Proprietary customer data repositories built through years of interaction histories constitute the most defensible asset, as competitors cannot rapidly acquire equivalent datasets without comparable customer relationships. The fashion retailer case illustrates this principle: the 847 micro-segments identified by the AI system required three years of granular behavioral data collection that new market entrants or competitors with less mature data infrastructure could not replicate quickly. Similarly, organizational routines embedding AI insights into operational decision processes develop through extended cultural transformation, not mere technology deployment. The automotive manufacturer case revealed that achieving cultural acceptance of algorithmic recommendations required 18 months of change management, executive sponsorship, and iterative trust-building, organizational capabilities far more resistant to imitation than technical architectures competitors can observe and copy. This interpretation aligns with Barney's (1991) VRIN framework: while AI algorithms are increasingly non-rare due to commercial platform availability, the complementary assets enabling effective deployment remain rare, inimitable due to social complexity and causal ambiguity, and non-substitutable in achieving comparable performance outcomes.

Dynamic capabilities perspectives prove essential for understanding advantage sustainability in turbulent AI marketing environments where static resources erode through competitive imitation and environmental change (Teece, 2018; Grewal et al., 2020). Sensing capabilities detect emerging patterns and threats through continuous monitoring systems tracking prediction accuracy metrics, feature distribution shifts identifying changes in customer population characteristics, competitive intelligence monitoring rival capabilities, and technological landscape tracking identifying emerging algorithmic innovations (Herhausen et al., 2024; Verhoef et al., 2021). Seizing capabilities enable rapid exploitation of sensed opportunities through automated retraining pipelines, experimentation frameworks testing proposed improvements, rapid development processes prototyping innovations, and flexible technical architectures accommodating new data

sources and model families (Chen et al., 2021; Puntoni et al., 2021). Transforming capabilities address fundamental organizational evolution requirements when strategic priorities shift substantially through organizational restructuring, resource reallocation, cultural evolution, and leadership development (Davenport et al., 2020; Huang & Rust, 2021).

The transition from retrospective performance measurement to predictive analytics represents a fundamental shift in how marketing creates competitive advantage. Traditional measurement systems operated as diagnostic tools documenting past performance, introducing temporal lags between strategic decisions and corrective adjustments that allowed competitors to observe and respond to successful initiatives. The implementations examined demonstrate that predictive analytics transforms measurement into a prescriptive system enabling preemptive optimization. The continuous learning mechanisms documented, where conversion rates improved 3-5% quarter-over-quarter through accumulated experience, exemplify what Teece (2018) terms dynamic capabilities: organizational capacities to sense environmental changes, seize opportunities through resource reconfiguration, and transform operations as conditions evolve. Organizations achieving this prospective orientation establish moving-target advantages: by the time competitors replicate current capabilities, leaders have advanced further through continuous learning cycles. However, this advantage remains contingent on sustained investment in sensing mechanisms (monitoring prediction accuracy, feature drift, competitive actions), seizing capabilities (automated retraining pipelines, experimentation frameworks), and transforming capabilities (organizational willingness to evolve processes as AI systems uncover new insights). Organizations lacking these dynamic capabilities risk advantage erosion as static AI implementations depreciate through environmental change and competitive diffusion.

Conclusion

This comprehensive investigation reveals that AI-driven marketing models constitute significant sources of competitive advantage in contemporary global markets when organizations develop integrated capabilities combining algorithmic sophistication with complementary organizational resources including proprietary customer data assets, specialized analytical talent, adaptive organizational cultures, and robust governance frameworks (Barney, 1991; Teece, 2018). The empirical evidence demonstrates substantial, statistically significant, and economically meaningful performance improvements spanning conversion rate gains of 28-35%, customer acquisition cost reductions of 38-47%, and marketing return on advertising spend increases of 48-62% compared to conventional marketing approaches, with improvements documented consistently across diverse implementations spanning retail, automotive, financial services, and technology sectors in North American, European, and Asia-Pacific markets (Davenport et al., 2020; Huang & Rust, 2021; Verhoef et al., 2021).

Competitive advantage sustainability depends critically on complementary organizational capabilities that prove substantially rarer, more difficult to develop, and more resistant to

competitive imitation than basic AI technology access through commercial platforms or consulting relationships (Chen et al., 2021; Puntoni et al., 2021). Proprietary customer data accumulated through years of interaction histories provides essential foundation for accurate prediction and personalization that competitors lacking comparable relationships cannot rapidly replicate (Kannan, 2017). Specialized analytical talent combining machine learning expertise with marketing domain knowledge enables effective algorithm customization and continuous optimization (Grewal et al., 2020). Organizational routines embedding AI insights into operational decision processes develop through cultural transformation requiring 18-24 months of sustained leadership effort (Herhausen et al., 2024). These capabilities create sustained advantages persisting over multi-year horizons rather than temporary performance improvements that competitive imitation rapidly erodes.

Organizations establishing these complementary capabilities position themselves for sustained competitive advantages through continuous capability development and strategic renewal rather than resting on initial deployment successes (Teece, 2018; Verhoef et al., 2021). The dynamic capabilities perspective proves essential for understanding advantage sustainability, with sensing capabilities detecting emerging patterns and threats, seizing capabilities enabling rapid adaptation, and transforming capabilities evolving organizational routines as strategic priorities shift (Huang & Rust, 2021; Chen et al., 2021). The transformation toward AI-driven marketing represents fundamental evolution in how organizations understand customers, formulate strategies, execute campaigns, and measure performance rather than mere incremental improvement to existing approaches through better tools or increased automation (Davenport et al., 2020; Kannan, 2017). Marketing leadership in this environment requires new competency portfolios combining analytical literacy, technological fluency, strategic vision, change management capability, and ethical judgment balancing commercial optimization against privacy protection, fairness, transparency, and broader social responsibilities (Puntoni et al., 2021; Grewal et al., 2020).

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