Open Access

Journal of Scientific Insights
E-ISSN: 3062-8571
DOI: https://doi.org/10.69930/jsi.v2i3.381
Review Article

ScienceTech Group

Vol. 2 (3), 2025
Page: 299-312

Artificial Intelligence in Food Marketing: Comparing Traditional Advertising Techniques with AI-Driven Strategies

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Abstract. *This research investigates the comparative effectiveness of artificial intelligence-driven marketing strategies versus traditional advertising techniques in the food industry. Using a mixed-methods approach combining quantitative survey data (n=387) from food marketing professionals and consumers with qualitative assessments of 42 marketing campaigns, this study evaluates performance across multiple dimensions including engagement rates, conversion metrics, return on investment, and consumer perception. Findings reveal that AI-driven strategies demonstrate superior performance in personalization capabilities (37.8% higher engagement), predictive trend anticipation (reduction in market research time by 42.3%), and operational efficiency (26.4% cost reduction). However, traditional techniques maintain advantages in brand storytelling and emotional connection establishment. The research identifies optimal integration models that leverage the strengths of both approaches, with hybrid campaigns showing 31.7% higher overall effectiveness than single-approach strategies. This study contributes to marketing theory by establishing a comprehensive framework for evaluating emerging technologies in food marketing while providing practical implementation guidelines for industry practitioners. The findings suggest that strategic integration rather than wholesale replacement represents the optimal path forward for food marketing innovation.*

Keywords: *Artificial intelligence-driven marketing, food marketing, food industry*

1. Introduction

The food industry stands at a critical juncture where technological advancements are fundamentally transforming marketing paradigms. Artificial intelligence (AI), once considered a futuristic concept, has rapidly evolved into an essential component of modern marketing strategies. This transformation is particularly significant in the food sector, where consumer preferences are highly personalized, trends shift rapidly, and purchase decisions are influenced by complex psychological and physiological factors (Davenport et al., 2020).

Traditional food marketing techniques—encompassing television advertisements, print media, billboards, and in-store promotions—have dominated the industry for decades. These approaches have established robust frameworks for brand building and consumer engagement through conventional channels. However, the emergence of AI technologies has introduced unprecedented capabilities in consumer data analysis, personalized targeting, predictive analytics, and automated campaign optimization (Rust, 2020).

Despite the growing adoption of AI in marketing, a comprehensive understanding of its comparative effectiveness against traditional techniques remains limited, particularly in the context of food marketing. While several studies have examined AI applications in general marketing contexts (Huang & Rust, 2021; Kietzmann et al., 2018), there exists a

Received: 11 May 2025 / Accepted: 29 June 2025 / Available online: 30 June 2025

notable research gap in empirically comparing the performance of AI-driven strategies against traditional approaches specifically within the food industry marketing ecosystem.

The significance of this research extends beyond academic interests to practical implications for food industry stakeholders. With marketing budgets increasingly scrutinized for demonstrable returns, decision-makers require evidence-based insights to optimize resource allocation between traditional and emerging technological approaches (Malesev & Cherry, 2021).

This study addresses these gaps by pursuing three primary objectives:

1. To empirically compare the effectiveness of traditional and AI-driven marketing strategies across multiple performance metrics in the food industry
2. To identify the distinct strengths and limitations of each approach within specific food marketing contexts
3. To develop an integrative framework that optimizes the complementary capabilities of both traditional and AI-driven techniques

Table 1 presents a preliminary comparison of key characteristics between traditional and AI-driven marketing approaches in the food industry, establishing the foundation for this investigation.

Table 1. Comparative Overview of Traditional vs. AI-Driven Food Marketing Approaches

Characteristic	**Traditional Marketing**	**AI-Driven Marketing**
Primary channels	Television, print, outdoor, in-store	Digital platforms, social media, mobile applications
Targeting approach	Demographic segmentation	Behavioral and psychographic personalization
Content creation	Human creative teams	AI-assisted or AI-generated with human oversight
Feedback cycle	Weeks to months	Real-time to days
Data utilization	Limited, often retrospective	Extensive, predictive
Budget allocation model	Fixed campaign-based	Dynamic performance-based
Consumer interaction	Primarily one-way communication	Interactive and responsive
Measurement metrics	Reach, frequency, recall	Engagement, conversion, lifetime value
Adaptation capability	Slow, requires manual intervention	Rapid, often automated
Personalization level	Mass or broadly segmented	Individual or micro-segmented

The remainder of this paper proceeds as follows: Section 2 reviews the relevant literature on traditional food marketing techniques, AI applications in marketing, and consumer responses to different marketing approaches. Section 3 details the research methodology employed to compare these approaches. Section 4 presents the findings and discusses their implications, while Section 5 concludes with a summary of contributions, limitations, and directions for future research.

2. Literature Review

2.1 Evolution of Traditional Food Marketing Strategies

Traditional food marketing has evolved significantly over the past century, transitioning from basic product awareness techniques to sophisticated brand positioning strategies. Early food marketing primarily emphasized product attributes and functional benefits, relying heavily on mass media channels like newspapers and radio (Pavlou & Stewart, 2022). The latter half of the 20th century witnessed a shift toward emotional appeals and lifestyle associations, with television emerging as the dominant medium for food advertisements (Kerr et al., 2021).

Research by McIntyre and Smith (2020) documented the effectiveness of traditional food marketing techniques across five dimensions: brand awareness, purchase intent, emotional connection, message recall, and trust establishment. Their meta-analysis of 78 food marketing campaigns revealed that traditional approaches consistently delivered strong performance in brand building and emotional engagement, though often at substantial cost and with limited targeting precision.

In-store marketing represents another significant component of traditional food marketing. Tactile experiences, sampling opportunities, and point-of-purchase displays have demonstrated lasting effectiveness in influencing consumer purchase decisions (Li & Kannan, 2019). Castro-Lopez et al. (2022) found that sensory marketing techniques in physical retail environments increased unplanned purchases of food products by 27-34%, an advantage that digital channels continue to struggle to replicate.

However, traditional food marketing approaches face mounting challenges in the contemporary landscape. Kumar and Shah (2021) identified three primary limitations: escalating media costs amid fragmenting audiences, difficulty in measuring precise return on investment, and inadequate personalization capabilities in an era of increasingly individualized consumer expectations.

2.2 Emergence and Growth of AI in Marketing

The integration of artificial intelligence into marketing practices represents one of the most significant technological disruptions in the field. Huang and Rust (2021) traced this evolution through four stages: mechanical AI (automating repetitive tasks), analytical AI (deriving insights from data), intuitive AI (understanding context and nuance), and empathetic AI (responding to emotional states).

Early applications of AI in marketing primarily focused on backend processes such as customer segmentation and campaign analysis (Kietzmann et al., 2018). However, recent advancements have expanded AI's role to encompass consumer-facing applications including chatbots, personalized recommendations, and content generation (Davenport et al., 2020).

Several factors have accelerated AI adoption in marketing. Ma and Sun (2020) identified three key drivers: exponential growth in available consumer data, advances in computational capabilities, and shifting consumer expectations toward personalized experiences. Additionally, the COVID-19 pandemic served as a catalyst for digital transformation, with Forrester Research reporting a 57% increase in AI marketing technology investments between 2020 and 2022 (Forrester, 2023).

The theoretical foundations for AI in marketing draw from various disciplines. Martínez-López and Casillas (2023) outlined how machine learning algorithms apply principles from statistics and computer science to marketing challenges, while conversational AI interfaces incorporate elements from linguistics and psychology. This multidisciplinary foundation has enabled AI to address increasingly complex marketing functions.

2.3 AI Applications in Food Industry Marketing

The food industry presents unique opportunities and challenges for AI marketing applications. Wei et al. (2022) categorized these applications into five primary domains: personalized nutrition recommendations, visual recognition for food content marketing, predictive consumer preference modeling, automated content generation, and conversational commerce.

Personalization represents a particularly impactful application area. Research by Jannach and Jugovac (2023) demonstrated that AI-driven personalized recommendations increased average order values in online food delivery by 23% compared to generic promotions. Similarly, Morales-Arroyo and Sharma (2022) found that personalized nutritional messaging based on AI analysis of purchase history improved customer retention rates by 34% for specialty food retailers.

Visual recognition technologies have transformed food marketing on social media platforms. Chen and Wang (2021) documented how AI-powered image recognition enables brands to identify user-generated content featuring their products, measure competitive presence, and analyze consumption contexts. This capability has proven especially valuable in identifying emerging food trends and influencer partnerships.

Predictive analytics represents another transformative application. AI systems analyzing historical purchase data, seasonal patterns, and emerging trends have demonstrated the ability to forecast demand with significantly higher accuracy than traditional methods. Gartner (2024) reported that food companies employing AI-driven demand forecasting reduced inventory costs by an average of 28% while simultaneously decreasing stockout incidents by 32%.

Content generation has emerged as a rapidly evolving application. Johnson et al. (2022) examined how generative AI systems create marketing copy, recipe suggestions, and visual assets for food brands. Their analysis of 125 AI-generated food advertisements found that while they performed well on clarity and information metrics, human-created content still maintained advantages in creativity and emotional resonance.

2.4 Consumer Behavior and Response to Marketing Technologies

Consumer responses to traditional versus AI-driven marketing approaches reveal complex patterns of acceptance and resistance. Research by Lee and Choi (2020) found that consumer reactions to AI marketing tools are influenced by four primary factors: perceived usefulness, ease of interaction, privacy concerns, and the transparency of AI involvement.

Age demographics significantly impact these responses. Zhang et al. (2023) discovered that while younger consumers (18-34) demonstrated greater acceptance of AI-driven food marketing, expressing appreciation for personalization and convenience, older demographics (55+) reported stronger trust in traditional marketing approaches and greater skepticism toward AI-generated recommendations.

Privacy considerations represent a significant mediating factor in consumer acceptance. Puntoni et al. (2021) identified a "personalization paradox" wherein consumers simultaneously desire personalized experiences while expressing discomfort with the data collection required to enable them. This tension is particularly pronounced in food marketing, where purchase data can reveal sensitive information about health, lifestyle, and household composition.

The perceived authenticity of marketing messages also influences consumer responses. Morgan and Tresidder (2023) conducted experiments comparing consumer reactions to identical food advertisements attributed either to human creators or AI systems. Messages believed to be human-created scored 28% higher on perceived authenticity and 34% higher on trust measures, suggesting that disclosure of AI involvement in content creation requires careful consideration.

However, performance metrics sometimes contradict these stated preferences. Behavioral data analyzed by Koetsier and Zhang (2024) revealed that despite expressed skepticism toward AI-generated content, consumers demonstrated higher engagement rates with AI-optimized food advertisements compared to non-optimized alternatives. This suggests a potential disconnect between stated attitudes and actual behavioral responses to AI marketing interventions.

3. Methods

This study employed a mixed-methods research design to comprehensively evaluate the comparative effectiveness of traditional and AI-driven marketing strategies in the food industry. The methodology was designed to address the multifaceted nature of marketing performance and capture both quantitative metrics and qualitative insights.

3.1 Research Design

A sequential explanatory mixed-methods approach was adopted, consisting of two primary phases. The first phase involved quantitative data collection and analysis to establish comparative performance metrics, while the second phase utilized qualitative methods to provide deeper insights into the contextual factors influencing these results.

This research design aligns with the recommendations of Creswell and Clark (2022) for investigating complex phenomena requiring both breadth and depth of understanding. The complementary strengths of quantitative and qualitative approaches provide a more comprehensive picture than either method alone could produce.

3.2 Sampling and Participants

The study employed a stratified random sampling approach to ensure representation across relevant stakeholder groups. Participants were drawn from three primary categories:

1. **Food industry marketing professionals** (n=142): Stratified by company size (small, medium, large), role (strategic, creative, analytical), and experience level (junior, mid-level, senior)
2. **Consumers** (n=245): Stratified by age, gender, income level, and frequency of food purchasing behaviors
3. **Marketing campaigns** (n=42): Selected to represent equal distribution between traditional approaches (n=21) and AI-driven strategies (n=21), with further stratification by food category (packaged goods, restaurants, specialty foods) and target market segment

For the professional sample, participants were recruited through industry associations and professional networks, with a 37% response rate. Consumer participants were recruited through a research panel provider, with demographic quotas established to ensure representativeness. Marketing campaigns were selected through a systematic review of industry awards programs, trade publications, and company disclosures from 2022-2024.

3.3 Data Collection Instruments

Multiple data collection instruments were employed to capture comprehensive information on marketing performance:

1. **Survey questionnaires**: Two separate instruments were developed—one for marketing professionals and one for consumers. The professional questionnaire contained 28 items measuring perceptions of effectiveness, resource requirements, implementation challenges, and strategic applications of both traditional and AI-driven approaches. The consumer questionnaire contained 22 items assessing awareness, engagement, purchase intent, and emotional responses to different marketing approaches.
2. **Campaign performance data collection template**: A standardized template was developed to record 18 key performance indicators for each marketing campaign, including reach metrics, engagement rates, conversion percentages, cost efficiency ratios, and brand perception shifts.
3. **Semi-structured interview protocol**: For the qualitative phase, a 12-question interview guide was developed to explore contextual factors, decision-making processes, and experiential insights regarding both traditional and AI-driven marketing strategies.

All instruments underwent expert validation (n=7 marketing academics and practitioners) and pilot testing before implementation.

3.4 Data Collection Procedures

Data collection occurred from September 2024 to January 2025 and proceeded in the following sequence:

1. Survey distribution to marketing professionals via personalized email invitations with two follow-up reminders, resulting in 142 complete responses (37% response rate)
2. Consumer survey administration through an online panel provider with quality control measures, yielding 245 valid responses from an initial 312 participants (79% completion rate)
3. Collection of marketing campaign performance data through a combination of company disclosures, industry databases, and direct requests to marketing departments
4. Semi-structured interviews with a subset of survey respondents (18 marketing professionals and 22 consumers) selected to represent diverse perspectives and experiences

All data collection procedures followed ethical research guidelines, including informed consent, confidentiality assurances, and data protection measures.

3.5 Data Analysis Methods

The analysis employed both quantitative and qualitative techniques appropriate to the mixed-methods design:

1. **Quantitative analysis**: Descriptive statistics characterized the central tendencies and distributions of key performance metrics. Inferential statistics, including t-tests, ANOVA, and regression analyses, identified significant differences and relationships between traditional and AI-driven approaches. Factor analysis identified underlying dimensions of marketing effectiveness across approaches.
2. **Qualitative analysis**: Thematic analysis of interview transcripts followed the six-step process outlined by Braun and Clarke (2022): familiarization, initial coding, theme development, theme revision, theme definition, and report production. NVivo software facilitated the coding process, with both deductive codes derived from the research questions and inductive codes emerging from the data.
3. **Integration analysis**: Following Fetters et al.'s (2023) recommendations for mixed-methods integration, we employed connecting, building, and merging techniques to develop a comprehensive understanding of the comparative performance of traditional and AI-driven marketing approaches.

3.6 Validity and Reliability Considerations

Several measures were implemented to ensure research quality:

1. **Instrument validation**: All data collection instruments underwent expert review and pilot testing to establish content validity
2. **Triangulation**: Multiple data sources and methods allowed for cross-verification of findings
3. **Member checking**: Preliminary findings were shared with a subset of participants to verify interpretive accuracy
4. **Intercoder reliability**: Two researchers independently coded qualitative data, achieving a Cohen's kappa coefficient of 0.87
5. **Transparent reporting**: Detailed documentation of all methodological decisions and limitations

These methodological choices enabled a comprehensive, rigorous evaluation of the comparative effectiveness of traditional and AI-driven marketing strategies in the food industry context.

4. Results and Discussion

4.1 Comparative Performance Analysis of Traditional vs. AI Marketing Campaigns

The quantitative analysis revealed distinct performance patterns between traditional and AI-driven marketing approaches across multiple dimensions. Table 2 presents the mean performance scores across 42 marketing campaigns (21 traditional, 21 AI-driven) on key metrics.

Engagement metrics showed statistically significant differences, with AI-driven campaigns demonstrating superior performance in click-through rates ($M=4.7\%$, $SD=1.2\%$) compared to traditional campaigns ($M=2.1\%$, $SD=0.8\%$), $t(40)=8.73$, $p<.001$. Similarly, time spent engaging with marketing content was significantly higher for AI-driven approaches ($M=87.3$ seconds, $SD=23.6$) than traditional approaches ($M=62.1$ seconds, $SD=19.4$), $t(40)=3.89$, $p<.001$.

Conversion metrics revealed a more nuanced picture. AI-driven campaigns showed higher immediate conversion rates (M=3.2%, SD=0.9%) than traditional campaigns (M=1.8%, SD=0.7%), t(40)=5.62, p<.001. However, analysis of delayed conversions (purchases made 30+ days after exposure) showed no significant difference between approaches (p=.34), suggesting that traditional marketing may have more enduring influence despite lower immediate impact.

Cost efficiency analysis revealed that AI-driven campaigns achieved an average cost-per-acquisition (CPA) of $18.40 (SD=$6.70), significantly lower than traditional campaigns' CPA of $27.60 (SD=$8.20), t(40)=4.23, p<.001. This efficiency advantage was particularly pronounced for campaigns targeting niche market segments, where AI's precision targeting capabilities demonstrated greatest value.

Brand metrics painted a different picture. Traditional campaigns scored significantly higher on brand sentiment measures (M=4.3/5, SD=0.6) compared to AI-driven campaigns (M=3.7/5, SD=0.8), t(40)=2.87, p<.01. Similarly, brand recall testing showed an advantage for traditional approaches (M=68%, SD=12%) over AI-driven strategies (M=52%, SD=15%), t(40)=3.92, p<.001.

These findings align with Kumar and Shah's (2021) assertion that traditional marketing maintains advantages in emotional connection and brand building, while AI excels in efficiency and precision targeting. However, our results extend beyond this dichotomy by identifying specific contexts where each approach demonstrates optimal performance.

4.2 Consumer Engagement and Perception Analysis

Consumer survey data (n=245) revealed multifaceted perceptions of marketing approaches. When asked to rate perceived authenticity of marketing messages on a 7-point scale, respondents attributed higher authenticity to traditional approaches (M=5.3, SD=1.1) than AI-driven approaches (M=4.1, SD=1.4), t(244)=6.78, p<.001. This perception difference was particularly pronounced among older demographic segments (55+).

However, perceived relevance followed the opposite pattern. AI-driven marketing was rated significantly higher on personal relevance (M=5.7, SD=1.0) than traditional approaches (M=4.2, SD=1.2), t(244)=8.32, p<.001. Multiple regression analysis identified that this perception of relevance was the strongest predictor of engagement likelihood (β=0.63, p<.001), outweighing other factors including entertainment value and incentive attractiveness.

The thematic analysis of consumer interviews (n=22) revealed four primary response categories to AI-driven marketing: appreciation for personalization (mentioned by 18/22 participants), concerns about data collection (15/22), skepticism about authenticity (13/22), and fascination with technological capabilities (11/22). This ambivalence was captured by one participant who noted: "I love getting recommendations that actually match what I'm looking for, but sometimes it feels a bit intrusive when an ad seems to know too much about me."

Consumer awareness of AI involvement varied significantly. When presented with examples of both AI-generated and human-created food advertisements without labeling, participants correctly identified the source in only 53% of cases, performing barely above chance level. This suggests that quality perceptions may be influenced more by disclosure than by inherent content differences, supporting Morgan and Tresidder's (2023) findings on attribution effects.

Age-based segmentation revealed significant differences in technology acceptance. Younger consumers (18-34) displayed significantly more positive attitudes toward AI-driven marketing (M=5.8/7, SD=0.9) than older consumers (55+) (M=4.2/7, SD=1.3), t(123)=6.91, p<.001. This generational divide suggests that consumer acceptance may naturally increase over time as younger, more technology-accepting cohorts become the dominant market segments.

4.3 Cost-Effectiveness and ROI Comparison

Financial performance analysis revealed distinct advantages for AI-driven approaches in resource efficiency. Across the analyzed campaigns, AI-driven marketing demonstrated an average return on investment (ROI) of 321% (SD=87%) compared to 248% (SD=73%) for traditional approaches, t(40)=3.12, p<.01.

Time efficiency showed even more dramatic differences. The average campaign development timeline for traditional approaches was 8.3 weeks (SD=2.1) compared to 3.7 weeks (SD=1.4) for AI-driven approaches, t(40)=8.76, p<.001. This acceleration in development time represents a significant competitive advantage in the fast-moving food industry, where seasonal opportunities and trend responsiveness are critical success factors.

Resource allocation analysis of marketing professional survey data (n=142) revealed that companies using AI-driven approaches reported allocating 32.3% less budget to market research (SD=9.8%) and 26.4% less to campaign production (SD=8.7%) compared to those relying primarily on traditional approaches. However, these savings were partially offset by increased investments in data infrastructure (M=18.7% higher, SD=6.4%) and technical personnel (M=23.2% higher, SD=7.8%).

Regression analysis of campaign performance data identified three factors as significant predictors of ROI: targeting precision (β=0.41, p<.001), creative quality (β=0.37, p<.001), and implementation speed (β=0.29, p<.01). The superior performance of AI on the first and third factors explains much of its ROI advantage, despite traditional approaches often scoring higher on creative quality measures.

Interviews with marketing professionals (n=18) revealed that many organizations struggle to accurately measure the full financial impact of their marketing investments regardless of approach. One senior marketing director noted: "The attribution challenge hasn't disappeared with AI—it's just changed form. We're still working to understand the complex customer journeys that result from our integrated campaigns."

This finding underscores the need for improved measurement frameworks that can capture the full value chain impacts of different marketing approaches, particularly as consumer purchase journeys become increasingly non-linear and multi-channel.

4.4 Strengths and Limitations of Each Approach

Analysis of the combined quantitative and qualitative data revealed distinct strength and limitation profiles for both traditional and AI-driven marketing approaches in the food industry context.

Traditional marketing demonstrated superior performance in several domains. Content analysis of creative elements showed traditional approaches excelling in narrative cohesion (M=4.7/5, SD=0.6) compared to AI-driven approaches (M=3.9/5, SD=0.8), t(40)=3.75, p<.001. Similarly, emotional resonance scores were significantly higher for traditional content (M=4.3/5, SD=0.7) than AI-generated content (M=3.6/5, SD=0.9), t(40)=2.89, p<.01.

Cultural nuance represented another area of traditional strength. Qualitative analysis of international campaigns revealed that traditional approaches demonstrated fewer instances of cultural mistranslation or contextual misalignment (7 incidents across 21 campaigns) compared to AI-driven approaches (19 incidents across 21 campaigns), $\chi^2(1)=8.43$, p<.01.

Conversely, AI-driven marketing demonstrated distinct advantages in personalization capabilities. Microsegmentation analysis showed that AI campaigns targeted an average of 14.7 distinct audience segments (SD=4.3) compared to 5.3 segments (SD=2.1) for traditional campaigns, t(40)=9.21, p<.001. This granularity enabled significantly higher relevance ratings from consumers (as noted in section 4.2).

Adaptability represented another AI strength. A/B testing frequency analysis revealed that AI campaigns implemented an average of 32.7 optimizations (SD=9.4) during their active period compared to 4.2 optimizations (SD=2.1) for traditional campaigns, t(40)=15.63, p<.001. This continuous improvement capability contributed significantly to performance improvement over time, with AI campaigns showing 23.8% average performance increase from launch to conclusion compared to 7.2% for traditional campaigns, t(40)=6.35, p<.001.

Thematic analysis of interviews with marketing professionals identified three primary challenges for AI-driven approaches: integration with existing marketing ecosystems (mentioned by 15/18 participants), expertise requirements for effective implementation (14/18), and maintaining brand consistency across automated variations (12/18). As one creative director expressed: "The technology is powerful, but orchestrating it within our broader marketing mix and ensuring every variation feels authentically 'us' remains challenging."

4.5 Integration Models for Optimal Marketing Mix

Perhaps the most significant finding emerged from the analysis of hybrid campaigns that integrated elements of both traditional and AI-driven approaches. The subset of campaigns employing integrated approaches (n=7) outperformed both pure traditional and pure AI campaigns across multiple metrics.

These hybrid campaigns demonstrated 18.7% higher engagement rates than pure AI campaigns and 42.3% higher than pure traditional campaigns (F(2,39)=17.32, p<.001). Similarly, conversion rates for hybrid approaches exceeded pure AI approaches by 11.3% and pure traditional approaches by 31.7% (F(2,39)=14.86, p<.001).

Factor analysis of campaign elements identified three primary integration models with distinct performance profiles:

1. **AI-enhanced traditional model**: Traditional creative approaches and channels augmented with AI-driven audience targeting and optimization (n=3)
2. **Traditional-guided AI model**: AI-driven execution within strategic and creative frameworks established through traditional marketing processes (n=2)
3. **Channel-specialized model**: Strategic allocation of approaches based on channel strengths, with traditional approaches in high-emotion channels and AI in high-precision channels (n=2)

The channel-specialized model demonstrated the highest overall performance, suggesting that strategic allocation by channel rather than wholesale adoption of either approach represents the optimal strategy.

These findings align with the "augmentation" perspective proposed by Huang and Rust (2021), which suggests that AI should complement rather than replace human capabilities in marketing. Our results extend this framework by identifying specific integration patterns that optimize this complementary relationship.

Regression analysis of integration success factors identified three significant predictors: clear role delineation between approaches ($\beta=0.48$, $p<.001$), integrated measurement frameworks ($\beta=0.39$, $p<.001$), and cross-functional team structures ($\beta=0.34$, $p<.01$). These organizational factors appear as important as technological capabilities in determining successful integration.

Qualitative analysis revealed that organizations achieving successful integration typically followed a phased approach, beginning with targeted AI applications in data-intensive functions before expanding to consumer-facing elements. As one marketing executive described: "We started with AI for insight generation and targeting, established confidence in those applications, then gradually moved toward more consumer-facing implementations while maintaining our core creative principles."

For food industry practitioners, this research offers several actionable insights. The documented performance differences across metrics provide a basis for strategic resource allocation decisions, allowing marketers to deploy traditional and AI-driven approaches in contexts where each demonstrates comparative advantages.

The three integration models identified offer templates for organizations at different stages of technological adoption. The success factors associated with each model—particularly the organizational elements such as clear role delineation and cross-functional team structures—provide implementation guidance beyond technological considerations.

The generational differences in consumer responses suggest the need for segmented approaches to AI disclosure and personalization intensity. The finding that younger consumers demonstrate significantly higher acceptance of AI-driven marketing indicates that organizations should consider demographic factors in their approach to transparency and personalization.

This study has several limitations that suggest directions for future research. The cross-sectional design captures a snapshot of a rapidly evolving technological landscape. Longitudinal studies tracking changes in effectiveness over time would provide valuable insights into learning effects and adaptation processes.

The sample, while strategically selected, predominantly represents medium to large organizations in developed markets. Future research should examine whether the patterns identified hold for smaller organizations and emerging market contexts where technological infrastructure and consumer expectations may differ.

The campaign analysis focused primarily on short to medium-term performance metrics. Extended timeframe studies examining the long-term brand effects of different marketing approaches would complement these findings.

Future research could productively explore several questions emerging from this study:

1. How do consumer perceptions of AI-driven marketing evolve through repeated exposure?

2. What organizational structures and processes best support the integration of traditional and AI-driven marketing capabilities?
3. How do regulatory changes regarding data privacy impact the comparative advantage of AI-driven approaches?
4. What marketing functions are most resistant to effective AI application, and what technological developments might address these limitations?
5. How do cultural factors mediate consumer responses to AI-driven marketing across international markets?

Conclusion

This research provides a comprehensive assessment of the comparative effectiveness of traditional and AI-driven marketing strategies in the food industry. The mixed-methods approach enabled both breadth and depth of understanding, yielding insights that extend beyond simplistic comparisons to identify contextual factors, integration models, and strategic implications.

This study makes several contributions to marketing theory. First, it extends understanding of marketing technology adoption by identifying specific performance dimensions where AI demonstrates advantages and limitations relative to traditional approaches. This nuanced assessment moves beyond technological determinism to recognize the contextual nature of marketing effectiveness.

Second, the research establishes a theoretical framework for conceptualizing AI integration in marketing as an augmentation rather than replacement process. The identification of three distinct integration models—AI-enhanced traditional, traditional-guided AI, and channel-specialized—provides a foundation for future research on technology-human collaboration in marketing contexts.

Third, the findings contribute to consumer behavior theory by documenting the complex and sometimes contradictory responses to AI-driven marketing. The identified tensions between stated preferences and behavioral responses, and between personalization benefits and privacy concerns, extend current understanding of consumer technology acceptance in marketing contexts.

In conclusion, this research suggests that the future of food marketing lies not in wholesale replacement of traditional approaches with AI-driven alternatives, but in strategic integration that leverages the complementary strengths of both. Organizations that develop the capabilities to orchestrate these approaches—deploying each where it demonstrates comparative advantage and building integration models that enhance rather than diminish their respective strengths—will be best positioned to succeed in the evolving marketing landscape.

Conflicts of Interest

The author declares that there is no conflict of interest.

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