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Applications of Generative Artificial Intelligence in Marketing: A Research Review and Future Prospects

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Abstract

Generative artificial intelligence (GenAI) is turning marketing content into an abundant resource with near-zero marginal cost, but related research is highly fragmented. This paper thematically integrates Chinese- and English-language literature published from 2019 to 2026. The findings show that gains from GenAI marketing are "stratified along the funnel": evidence of improvements at the attention and interaction stages is sufficient, whereas the effect on final conversion is weak; consumers' evaluations of content are decoupled from evaluations of the "artificial intelligence (AI) source" label, and disclosure of the AI source significantly suppresses transactions; only 13% of the literature examines moderating variables. Accordingly, this paper proposes a five-stage integrated framework of "technical characteristics → marketing applications → psychological mechanisms → consumer responses → moderating boundaries" and a future research agenda.

Keywords

generative artificial intelligence, marketing, consumer response, disclosure paradox, human-AI collaboration

1. Introduction

1.1 Research Background and Motivation

Generative artificial intelligence (GenAI), represented by large language models (LLMs) and multimodal generative models, is reshaping the technological foundation of marketing. GenAI can produce copy, images, videos, and conversational content at scale, turning them into abundant resources with near-zero marginal cost [1]: 62% of market researchers already use AI in their work, an increase of about 23 percentage points from 2024 [2]. However, counterintuitive consumer responses have emerged: disclosing that content is produced by AI reduces trust and purchase intention even when its quality is not inferior [3]; luxury brands receive more negative evaluations after disclosing the use of AI-generated images [4]. The core question has therefore shifted from "Can AI produce good marketing content?" to "How do consumers respond to a marketing world in which AI participates?"

Related research has grown explosively but remains highly dispersed. Early reviews used bibliometric methods to depict the broad landscape of "AI marketing" [5,6]. Reviews devoted to GenAI either followed the Theory-Context-Characteristics-Methodology (TCCM) framework [7] or focused on customer engagement under the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) procedure [8]. Existing literature shows "three abundances and three shortages": many conceptual papers but few rigorous

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empirical studies; many scenario experiments but few field experiments and longitudinal follow-ups [9]; and many fragmented theoretical borrowings but few integrated constructions, making cross-context patterns difficult to identify.

1.2 Research Gaps and Research Questions

Existing reviews have three limitations: narrow coverage or a single organizational dimension, with no integrated analysis connecting "application scenarios-psychological mechanisms-boundary conditions" [8]; insufficient direct treatment of conflicting evidence on whether disclosure reduces or increases trust; and inadequate integration of systemic risks and methodological implications [10]. Accordingly, this paper addresses three progressive questions: Research Question 1 (RQ1): What is the current status of GenAI marketing applications, and how does the evidence of effects differ across funnel stages? Research Question 2 (RQ2): How do consumers respond to AI-generated content and marketing contacts involving AI, and what are the mechanisms and boundary conditions? Research Question 3 (RQ3): What structural gaps exist in the literature, and how should future research proceed?

1.3 Research Contributions

The first contribution is the proposal of a five-stage integrated framework of "technical characteristics → marketing applications → psychological mechanisms → consumer responses → moderating boundaries," which addresses the weakness in "moderating boundaries": only 13% of the sampled literature examines moderating variables [8]. The second contribution is the identification of six cross-context patterns: (1) quality-source decoupling-AI content performs no worse than, and may outperform, human content in blind evaluations [11]; (2) the disclosure paradox-disclosure of AI use reduces trust and advertising effectiveness in most contexts [3]; (3) task-source matching-AI has an advantage in objective and utilitarian tasks, whereas humans have an advantage in subjective and affective tasks; (4) the efficiency-authenticity trade-off-human-in-the-loop (HITL) is the consistently validated solution [12]; (5) the funnel-stratification effect-evidence of improved attention and interaction is sufficient, whereas final conversion is weak; and (6) the homogenization dilemma-GenAI increases individual creativity but reduces collective content diversity [10,13]. The final two constitute the distinctive contributions of this paper.

2. Concept Definition, Literature Overview, and Theoretical Foundations

2.1 Concept Definition and Review Scope

In the marketing context, "artificial intelligence" has long referred mainly to predictive AI, namely systems that classify, predict, and match consumer behavior [5,6]. GenAI, by contrast, refers to technologies based on large language models and multimodal generative models that autonomously produce new content such as text, images, audio, and video. Hermann and Puntoni [14] summarized the distinction between the two generations of technology as "judgment and prediction" versus "creation and dialogue." This paper defines GenAI marketing as the application of generative artificial intelligence in scenarios such as content production, conversational customer service, virtual endorsers, and human-AI collaborative creativity, together with its consumer consequences.

The review window of this paper is 2019-2026. Foundational empirical studies appeared intensively in marketing journals in 2019 [15,16], and research grew explosively after the release of ChatGPT. The literature was drawn from peer-reviewed Chinese- and English-language journals. A thematic review method was adopted, and screening referred to the PRISMA process and the TCCM quality-control framework [7,8].

2.2 Literature Overview and Research Landscape

Existing reviews have formed three progressively narrowing paths. The first is broad-field bibliometrics: Verma et al. [5] first mapped the knowledge structure of AI marketing on a large scale through bibliometric analysis and Louvain clustering of 1,580 papers, while Mustak et al. [6] combined topic modeling with scientometrics to outline the topic map. The second is topic-specific bibliometrics, covering contexts such as business-to-business (B2B) marketing and service marketing [17]. The third is GenAI-specific systematic reviews, which either follow the TCCM framework [7], select 33 papers from 528 records through the

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PRISMA process [8], or introduce the Antecedents-Decisions-Outcomes (ADO) framework [18]. Reviews are supplied intensively, but their contribution to theoretical integration is insufficient.

In terms of methodological structure, the field is dominated by quantitative research. A TCCM review of AI and tourism marketing showed that, among 177 core studies, 134 were quantitative and only 16 were qualitative [19]. A review of green consumption showed a similar questionnaire-dominated structure [20]. The absence of longitudinal research leaves the long-term effects of AI unknown, while field experiments and neurophysiological measurements are scarce [9].

2.3 Core Theoretical Perspectives

The theories borrowed in GenAI marketing research can be grouped into four families: adoption, social response, persuasion and processing, and decision making (see Table 1). First, in adoption theories, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Stimulus-Organism-Response (SOR) framework are the theories most frequently integrated in research on the adoption of chatbots and GenAI tools, and several meta-analyses provide support [21]. However, Mogaji et al. [22] asked whether TAM has ended in the era of generative AI, criticizing its individual-centered and static nature and its difficulty in capturing dynamic generative interactions (see Section 5.1 for details).

Second are social-response theories. The Computers Are Social Actors (CASA) paradigm shows that people make automatic, mindless social responses to computers [23]. Anthropomorphism is driven by elicited agent knowledge, effectance motivation, and sociality motivation [24,25]. Mind-perception theory characterizes mind attribution along two dimensions, agency and experience: AI is commonly perceived as having "high competence and low warmth," which is the psychological root of insufficient trust in AI [26]; attribution of an "experiential mind" is also associated with uncanny-valley discomfort [27]. The "automated social presence" of van Doorn et al. [28] connects this mechanism to service contexts. Marketing evidence converges into a chain of "anthropomorphism → social presence → trust → intention" [29], while anger, uncanniness, and a lack of direct experience all reverse its benefits [30,31,32].

Third are persuasion and processing theories. The Elaboration Likelihood Model (ELM) separates the dual-route structure of AI persuasion: interaction quality and expertise serve as central cues, while anthropomorphic design, brand awareness, and social proof serve as peripheral cues [33]. The Persuasion Knowledge Model (PKM) provides the leading explanation for the "AI disclosure effect": disclosing that content was generated by AI activates persuasion knowledge, raises doubts about corporate motives, and reduces attitudes toward advertising and purchase intention [3,8,34]. The machine heuristic further suggests that when consumers evaluate an information source as "machine-objective and unbiased," an AI source may instead increase reliance in utilitarian judgments [35].

Fourth are decision-making theories. Algorithm aversion and algorithm appreciation form the central tension. Dietvorst et al. [36,37] demonstrated that people abandon an algorithm after seeing it make an error even when it still outperforms humans overall, whereas allowing users to modify algorithmic output can overcome aversion. In contrast, Logg et al. [38] found the opposite "algorithm appreciation" across six experiments. There are two reconciliation paths: trust in algorithms is lower for subjective tasks but equivalent or higher for objective tasks [16]; Morewedge [39] argued that most "algorithm aversion" is actually a positive preference for humans [11]. In addition, privacy-calculus theory describes the trade-off between personalization benefits and privacy disclosure [40], while service-dominant logic conceptualizes AI as a "quasi-actor" participating in value co-creation [41].

Table 1: Comparison of Major Theoretical Perspectives

Theory Family	Theory Name	Core Proposition	Typical Application in GenAI Marketing	Representative Literature
Adoption	Technology Acceptance Model (TAM)/UTAUT	Perceived usefulness and ease of use determine adoption intention	Adoption of chatbots and GenAI tools	Latulippe and Ladhari [21]; Mogaji et al. [22]
Adoption	Stimulus-Organism-Response (SOR)	Environmental stimuli affect behavioral responses through internal psychological states	Path modeling of "anthropomorphic cues → presence/trust → purchase intention"	Latulippe and Ladhari [21]

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Theory Family	Theory Name	Core Proposition	Typical Application in GenAI Marketing	Representative Literature
Social response	Computers Are Social Actors (CASA) paradigm	People make automatic, mindless social responses to computers	Consumers regard AI agents as social actors	Nass and Moon [23]; Kim and Sundar [25]
Social response	Anthropomorphism theory	Knowledge, effectance, and sociality motivations drive anthropomorphism	Anthropomorphic design; excessive anthropomorphism triggers the uncanny valley	Epley et al. [24]; Blut et al. [29]; Crolic et al. [30]
Social response	Mind-perception theory	Mind is perceived along the two dimensions of agency and experience	The trust gap arising from AI's "high competence and low warmth"	Gray et al. [26]; Gray and Wegner [27]; Li et al. [32]
Social response	Social presence theory	Technological media convey a sense that "another is present"	Automated social presence mediates anthropomorphism and relationship quality	van Doorn et al. [28]
Persuasion processing	Elaboration Likelihood Model (ELM)	Persuasion occurs through central and peripheral routes	Distinguishing central cues from peripheral cues	Keng et al. [33]
Persuasion processing	Persuasion Knowledge Model (PKM)	Recognition of persuasive intent activates cognitive defenses	Explaining suspicion and reduced trust caused by AI disclosure	Schilke and Reimann [3]; Pokhrel and Somasiri [8]
Persuasion processing	Machine heuristic	The heuristic cue that "machines are objective and unbiased"	Intuitive trust in AI recommendations for utilitarian tasks	Ziyun Lin et al. [35]
Decision making	Algorithm aversion/algorithm appreciation	Avoidance of or preference for algorithmic judgment depends on task and experience	Explaining trust penalties and the task-matching principle	Dietvorst et al. [36]; Logg et al. [38]; Castelo et al. [16]
Decision making	Privacy-calculus theory	Trade-off between privacy disclosure and personalization benefits	Willingness to disclose data in AI marketing	Zhou et al. [40]
Decision making	Service-Dominant Logic (S-D Logic)	Value is co-created through interaction among resource integrators	AI participates in value co-creation and co-destruction as a quasi-actor	Coelho and Farias [41]

2.4 Theoretical Analytical Framework for GenAI Marketing

Based on the preceding review, this paper constructs the theoretical analytical framework for GenAI marketing shown in Figure 1, linking the five-stage causal chain of "technical characteristics → marketing applications → psychological mechanisms → consumer responses → moderating boundaries."

As shown in Figure 1, the framework takes a five-stage causal chain as its main line. The left side presents the technical characteristics of GenAI (generative capability, multimodal interaction, scalable efficiency, and dynamic learning). The upper middle analyzes consumers' psychological processes through three paths: cognitive, affective, and social responses. The right side presents four categories of outcomes-content efficiency, consumer engagement, brand effects, and business-model innovation-and highlights the two major tensions of the "funnel-stratification effect" and the "homogenization dilemma." The lower middle defines boundary conditions at the consumer, firm, and environmental levels, and the bottom provides support through four families of theories.

3. Application Scenarios of Generative AI Marketing

This section turns to the firm side. Integrating existing reviews [1,42] with the distribution of empirical literature, this paper divides GenAI marketing applications into five major scenarios: content generation and advertising creativity, personalized recommendation and precision marketing, intelligent customer service and conversational interaction, virtual influencers and digital humans, and market insight and decision support. Representative studies are shown in Table 2.

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Figure 1: Theoretical Analytical Framework for GenAI Marketing

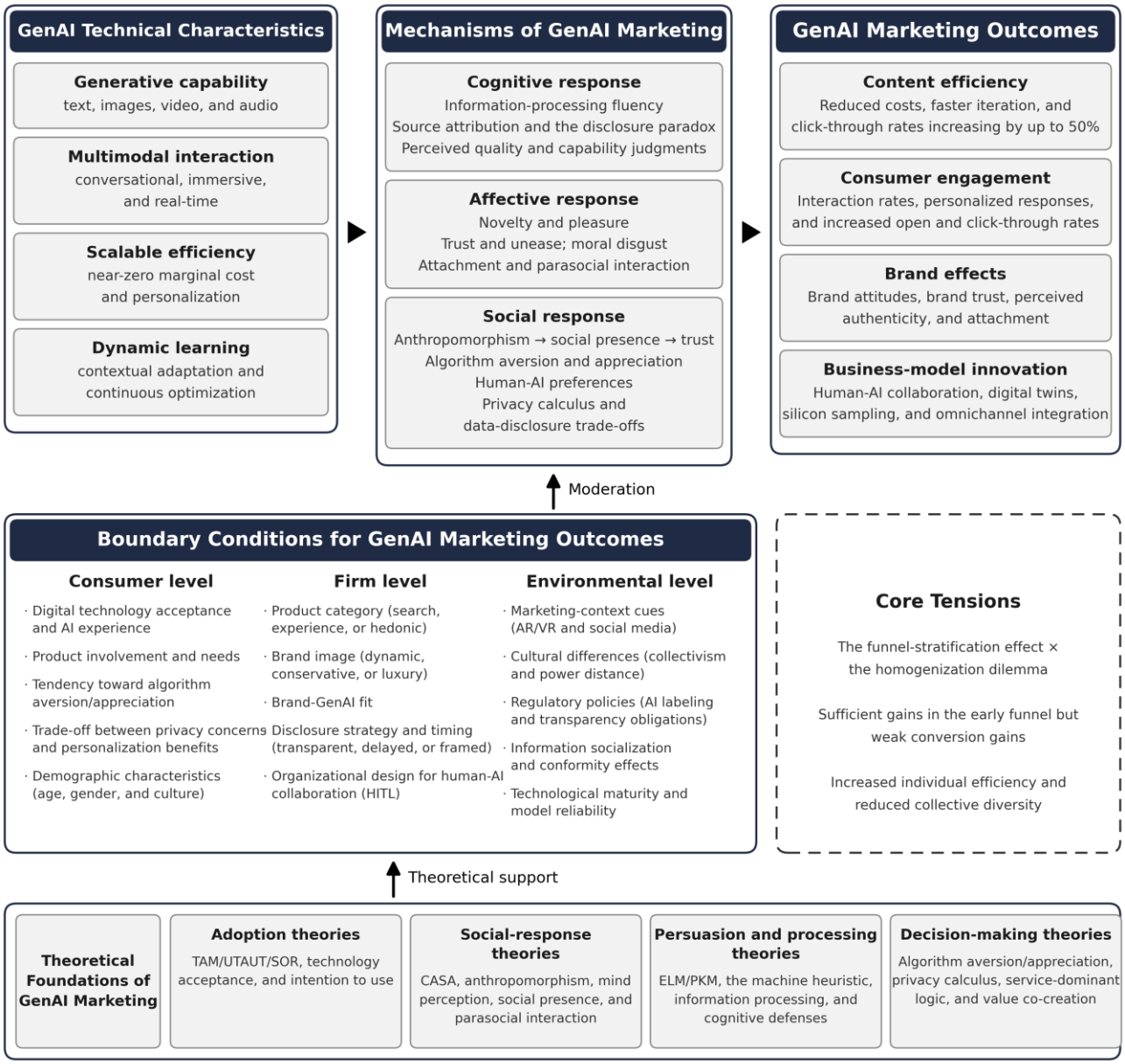


Table 2: Comparison of Representative Studies on Five Major Application Scenarios of Generative AI Marketing

Application Scenario	Representative Literature	Research Method	Core Finding	Main Limitation
Content generation and advertising creativity	Hartmann et al. [43]	Evaluation of 10,320 AI images + a field experiment with 173,000 impressions	The quality of AI marketing images can surpass human work; the click-through rate of the best AI banner ads increased by about 50% at most	Single-exposure design; long-term performance not tested
Personalized recommendation and precision marketing	Matz et al. [44]	A series of experiments: ChatGPT generated targeted copy based on the Big Five personality traits	Personality-matched AI copy was significantly more persuasive, realizing "scaled" personalized persuasion for the first time	Focused mainly on attitudes and click intention, with no evidence of actual purchases
Intelligent customer service and	Brynjolfsson et al. [45]	Natural experiment with staggered rollout among	AI assistants increased agent productivity by about	Supply-side evidence; satisfaction and

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Application Scenario	Representative Literature	Research Method	Core Finding	Main Limitation
conversational interaction		5,172 customer-service agents	15% on average, with novices benefiting most	loyalty not measured
Virtual influencers and digital humans	Barari et al. [46]	Meta-analysis of 110 papers and 210 experiments (N=91,058)	Virtual influencers had an advantage in novelty and matched humans in engagement, but were significantly weaker in credibility and behavioral intention	High heterogeneity; insufficient coverage of Chinese livestreaming contexts
Market insight and decision support	Toubia et al. [47]	Four-wave survey of 2,058 people × 500 questions (Twin-2K-500)	Digital twins achieved 72% predictive accuracy on held-out questions (88% of the upper bound of human test-retest reliability)	Synthetic samples have systematic bias

3.1 Marketing Content Generation and Advertising Creativity

Content production is the scenario in which GenAI penetrated earliest and for which evidence is most sufficient. For copywriting, advertising copy generated by Chinese large language models is generally equivalent to human work in interaction effects [48]. Based on two field experiments on Autohome (each lasting 188 days and involving 1.455 million consumers), Guo and Jiang [49] found that human-AI coupled copy outperformed traditional copy in cognitive, behavioral, and affective dimensions. For images, Hartmann et al. [43] found that AI marketing images reached or even exceeded the level of human freelancers across 254,400 person-evaluations, and the click-through rate of the best AI banner ads increased by up to about 50%. For video, the field experiment of Kapoor and Kumar [50] found that GenAI-personalized video advertisements had engagement rates 6-9 percentage points higher than image advertisements.

Evidence across media yields a regular finding: the human-AI gap in content quality is narrowing or even reversing, and the main source of differences in effect has shifted from the "content itself" to the "source label" and "task matching." Consumers can no longer distinguish whether copy was produced by AI or humans [51]; AI advertising has an advantage for agentic appeals, whereas human advertising has an advantage for communal appeals [52]. The "authenticity discount" caused by disclosure [53] is discussed in detail in Section 4. This scenario has reached a consensus of "no quality difference, an efficiency advantage, and matching that determines success," but long-term brand effects remain to be tested.

3.2 Personalized Recommendation and Precision Marketing

In recommendation systems, existing reviews have summarized three technical paths: discriminative direct recommendation [54], generative retrieval [55], and LLM-agent conversational recommendation [56]. The more substantive contribution of GenAI is to move personalized persuasion toward "scaled production." Matz et al. [44] demonstrated that ChatGPT can generate highly matched advertising copy according to consumers' Big Five personality traits. Teeny and Matz [57] then noted that the question had shifted from "whether it can enhance" to "when it enhances." However, field evidence converges on "funnel stratification." The field email-marketing experiment of Jobson et al. [58] found no significant increase in subject-line open rates, a 23.63% increase in recommendation click-through rates within emails, and no significant change in purchase conversion (-0.42%). Agent simulations also indicate an ecological cost: recommendations mainly reduce diversity across users [59]. Overall, personalization shows a pattern of "stratified effects and uncertain increments."

3.3 Intelligent Customer Service and Conversational Interaction

Intelligent customer service is the scenario with the strongest evidence of GenAI productivity effects. Brynjolfsson et al. [45] used the staggered rollout of AI assistants among 5,172 customer-service agents to construct a natural experiment. They found that AI increased the average number of problems resolved per hour by about 15%, with the greatest improvement among low-skilled and novice employees. Based on a randomized field experiment involving 138 agents and 256,934 conversations, Zhang and Narayandas [60]

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found that real-time AI script suggestions reduced response time by 22% and increased customer-sentiment scores by 0.45 points on a five-point scale. Both studies point to the deployment logic of "AI-augmented labor": compressing the learning curve of novices and flattening the distribution of service quality.

Demand-side evidence diverges from supply-side optimism: 64% of customers do not want firms to use AI in customer service [61]. Task matching is the first boundary: satisfaction is higher when AI serves utilitarian products, whereas humans have an advantage for experiential products [62]. Service failure is the second boundary. Three experiments by Fan et al. [63] (N=1,875) found that human recovery better promotes forgiveness under symbolic loss; the human-AI difference disappears under utilitarian loss; and humans have a comprehensive advantage in high-severity failures. Jinrui Wei et al. [64] likewise found that complementary human-AI collaboration is the most effective immediate recovery strategy. AI empathy also has an "expression-reception" gap: responses make people feel more "heard," but disclosing an AI source immediately produces a negative bias [65].

3.4 Virtual Influencers, Digital Humans, and Livestreaming E-Commerce

Virtual-influencer and digital-human livestreaming centrally embodies the multimodal capabilities of GenAI. A meta-analysis covering 110 papers and 210 experiments [46] provides the most integrative conclusion to date: virtual influencers significantly outperform human influencers in novelty and match them in consumer engagement, but are significantly weaker in credibility, advertising/brand attitudes, and behavioral intention-they win "attention" but have not yet won "trust." The mediating effect of credibility has strengthened significantly in recent studies, indicating a shift from a "novelty gimmick" to a conventional endorsement format.

The disadvantage of virtual influencers is concentrated in an "authenticity deficit." A between-subjects experiment by Liu and Lee [66] found that virtual influencers are perceived as less authentic across product categories, thereby harming brand attitude and purchase intention. Matching patterns have been refined: virtual influencers are more effective for utilitarian products, whereas human influencers are more effective for hedonic products [67]; endorsements emphasizing proximal sensory experience produce lower purchase intention [68]; and the degree of anthropomorphism forms a nonlinear boundary [46]. Chinese evidence also provides support: Haixia Yuan et al. [69] tested the uncanny-valley mechanism, finding that the interaction between streamer appearance and driving type significantly affects livestream engagement; Xiaoxiao Gong et al. [70] found that purchase intention is highest when assistant-type virtual streamers recommend search products and friend-type virtual streamers recommend experience products. The pattern of "equal engagement and a trust deficit" is clear, but longitudinal tracking of livestreaming contexts and trust remains a gap.

3.5 Market Insight and Marketing Decision Support

This scenario concerns the internal marketing function. Industry surveys show that adoption has entered the mainstream but remains limited in depth. In a survey of 426 researchers worldwide by the Market Research Institute International (MRII) [2], time savings (85%) and data-processing efficiency (76%) were widely recognized, but fewer than half believed that AI improved insight quality, indicating that GenAI is currently more of an "efficiency tool." Academic evidence echoes this judgment: the randomized experiment of Noy and Zhang [71] showed that GenAI accelerated professional writing by about 0.8 standard deviations; Doshi et al. [72] found that a single LLM evaluation is often inconsistent and biased, while aggregation across models approaches human experts. "A single evaluation is unreliable; aggregation is usable" has become a design principle.

The most controversial contribution of GenAI in market research is the "synthetic consumer" ("silicon sampling"). This path was established by Argyle et al. [73]: under the demographic backgrounds of actual respondents, the distribution of views generated by Generative Pre-trained Transformer 3 (GPT-3) closely matched that of real subgroups, leading to the concept of "algorithmic fidelity." Benchmarks have further raised replication accuracy: the agents of Park et al. [74] reproduced social-survey responses at 85% of individuals' test-retest consistency; the Twin-2K-500 dataset of Toubia et al. [47] reached an average accuracy of 72% on held-out questions. The doubts are equally strong: LLMs exhibit systematic bias in capturing preferences [75]; synthetic data show "matching means but unnaturally low variances" [76]; and identity-conditioned LLMs "misrepresent and flatten" identity groups [77]. "Calibration rather than replacement" has

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become the consensus: synthetic consumers are suitable as exploratory tools for concept screening and hypothesis generation [78].

4. Consumer Responses and Underlying Mechanisms

This section turns to the demand side and focuses on the link of "psychological mechanisms → consumer responses": consumers' negative responses mainly target the "AI source" label rather than content quality.

4.1 Consumer Acceptance, Trust, and Adoption

Trust is the central mediator of the behavioral consequences of GenAI marketing. The randomized field experiment of Luo et al. [15] with more than 6,200 customers is the most persuasive. When identity was not disclosed, AI chatbots were as effective as skilled human agents in generating purchases and four times as effective as novice human agents. After disclosing "I am a bot," the transaction rate fell by more than 79.7%. This effect did not arise from the objective capability of the chatbot, but from consumers' subjective inference that it had "less knowledge and weaker empathy." Delayed disclosure and prior AI experience both mitigate the effect, and Chinese research also confirms the mediating role of trust [33,79]. Research on trust repair indicates three paths: allowing users to modify algorithmic output [37], explaining algorithmic principles in plain language [80], and reframing the nature of the task (the most effective in the meta-analysis, g=0.55) [81].

Consumer attitudes toward algorithms show the classic dual effects. Dietvorst et al. [36] demonstrated "algorithm aversion": people abandon an algorithm after observing it make an error, even when it still outperforms humans overall. By contrast, Logg et al. [38] found the opposite "algorithm appreciation" across six experiments. Morewedge [39] reinterpreted most "algorithm aversion" as a positive preference for humans. Recent research has turned to mapping boundary conditions, as shown in Table 3.

Table 3: Comparison of Boundary Conditions for Algorithm Aversion and Algorithm Appreciation

Boundary Dimension	Context Favoring Aversion	Context Favoring Appreciation	Representative Literature
Task nature	Subjective tasks (intuition, taste, affect)	Objective, quantifiable tasks	Castelo et al. [16]
Decision objective	Hedonic consumption decisions	Utilitarian consumption decisions	Longoni and Cian [82]
Product type	Experience products	Search products	Xie et al. [83]
Brand positioning	Luxury and highly symbolic positioning	Mass-market and functional positioning	Xu and Mehta [84]
Decision valence	Favorable decisions (credit is difficult to internalize)	Unfavorable decisions (human-AI differences are reduced)	Yalcin et al. [85]
Failure attribution	Failure transfers to other AI systems ("algorithmic transference")	Algorithm errors harm brands less than human errors	Srinivasan and Sarial-Abi [86]; Longoni et al. [87]

Table 3 reveals a unified logic: the divide between aversion and appreciation depends on "task-source matching" and attribution structure. Appreciation predominates in objective, utilitarian, low-symbolism tasks, whereas consumers insist on human sources in domains involving affect, taste, and self-uniqueness. Two apparently opposite failure effects merit attention: algorithmic errors harm brands less than human errors because algorithms are perceived as lacking intentionality [86]; "algorithmic transference" causes the failure of one AI system to be overgeneralized to other AI systems [87]. The two can coexist in similar paradigms, with direction depending on how the human-AI framing is presented [88].

4.2 Decoupling Quality from Source: The Disclosure Paradox

The "disclosure paradox" is the organizing core of this section: evidence from blind evaluations shows that consumers have difficulty distinguishing GenAI content from human content, yet trust and behavioral responses generally decline once the AI source is disclosed. The structural tension between regulatory requirements for transparency and consumers' punishment of transparency constitutes the most active area of dispute in this field.

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After source information is removed, evaluations of GenAI content are strong. Zhang and Gosline [11] found that consumers even prefer AI copy when they do not know the source. After the source becomes known, evaluations of human content rise, while evaluations of AI content do not decline. On this basis, the authors proposed "human favoritism rather than algorithm aversion." Adjacent contexts reproduce this pattern: people devalue assessments of GenAI's "competence" but do not discount its advice [89]; users adopt ChatGPT's moral advice to the same extent as human advice [90]; and informed individuals have no inherent prejudice against the accuracy of AI output [91].

Disclosure of an AI source triggers a consistent trust penalty across multiple contexts. Longoni et al. [92] found that the same news is perceived as significantly less credible when labeled as written by GenAI. Across 13 preregistered experiments with more than 5,000 participants, Schilke and Reimann [3] found that those who disclosed using GenAI consistently received less trust. The mechanism was reduced perceived legitimacy rather than quality inference, and none of six disclosure wordings eliminated the effect. In marketing communication, disclosure harms attitudes toward advertising and donation intention by reducing brand/advertising credibility [34,93]. Kirk and Givi [53] established the "AI authorship effect": when emotional marketing communication was attributed to AI, word of mouth fell from 5.45 to 4.11, sequentially mediated by perceived authenticity and moral disgust. Altay and Gilardi [94] found an "AI discount": headlines labeled as AI-generated aroused suspicion even when true.

Contrary evidence makes this issue a genuine academic divide. An industry study by Yahoo and Publicis Media [95] involving 1,200 U.S. consumers found that noticed AI disclosure instead increased advertising appeal (47%), credibility (73%), and trust in the company (96%), although only about one-quarter noticed the disclosure. Koning and Voorveld [96] also observed a two-way mechanism. There are four moderators. First, content type: the penalty is concentrated in affective content [53]. Second, disclosure wording: "how to disclose" is more important than "whether to disclose" [97], and a systematic review also recommends "framed transparency" [8]. Third, consumer characteristics: the penalty is weaker, though not necessarily eliminated, among consumers with positive attitudes toward AI [3]. Fourth, disclosure timing: delayed disclosure and emphasis on anthropomorphic features of AI can buffer the negative effect [15,93]. Moreover, the loss of trust when concealment is exposed by a third party is greater than that caused by proactive disclosure [3].

4.3 Anthropomorphism and Mind-Perception Mechanisms

Anthropomorphism is a mainstream strategy for alleviating algorithm aversion and building trust. Its theoretical foundations are the three-factor theory of Epley et al. [24] and the two-dimensional mind-perception framework of Gray et al. [26]. The evidence chain is stable: anthropomorphism increases purchase intention through the mediating effects of social presence and telepresence [98]; a meta-analysis confirms its overall positive effect, which is stronger in collectivist cultures [29]. However, it does not hold unconditionally. A field experiment by Schanke et al. [99] found that although a humanized chatbot increased transaction conversion, it also increased sensitivity to quoted prices. Anthropomorphism shifted consumers into a "fairness evaluation/bargaining" mode of thought. The mediating effect of social presence is also not completely robust [100].

The two-dimensional mind-perception framework reveals that the benefits and costs of anthropomorphism are asymmetric across the warmth and competence dimensions. Anthropomorphism operates mainly through the warmth (experience) dimension. Li et al. [32] found that, without direct experience, anthropomorphism reduces algorithm aversion through the mediation of perceived warmth, but the effect disappears after direct experience. Kim et al. [31] found that anthropomorphism increases perceived warmth but reduces overall liking because of uncanniness. Negative boundaries include the uncanny valley-humanoid robots can evoke eeriness and identity threat [101]; emotional mismatch-angry customers are more dissatisfied when facing anthropomorphic robots [30]; amplified responsibility-anthropomorphic brands are punished more severely for product failures [102]; and erosion of autonomy-anthropomorphic assistants weaken users' sense of autonomy and enjoyment in gaming contexts.

4.4 Negative Effects and Ethical Risks

The concentrated brand-level manifestation of the disclosure paradox is an authenticity crisis. To et al. [4] demonstrated that consumers respond significantly more negatively when luxury-brand advertisements

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disclose the use of AI-generated images, because they infer that "less human effort was invested." A deeper feature is the divergence between behavioral and attitudinal indicators. Hanson et al. [103] found that making AI involvement explicit can increase online interaction while provoking fear, anxiety, and psychological reactance and harming brand attitudes-short-term performance may conceal erosion of long-term brand equity. AI-written marketing narratives can match professional copy but fabricate details in product reviews [104]; deepfake advertising further magnifies trust risks [105].

Hyper-personalization is premised on large-scale personal data, bringing the privacy-calculus mechanism back into focus. A synthesis of 42 studies by Duggal et al. [106] estimated an average correlation of about $r \approx 0.38$ between personalization and trust and about $r \approx -0.41$ between privacy concerns and trust. High privacy concerns significantly weaken or even reverse the trust-building function of personalization. McKee et al. [107] extended this framework to Generation Z and identified the dual paradoxes of "privacy-benefit" and "avoidance-fatigue." Nusir et al. [108] found that transparency disclosure failed to reduce privacy concerns and only strengthened the conversion of personalization value into algorithmic trust.

The scaled application of GenAI also brings systemic risks: gains in individual creativity accompany losses in collective diversity. The online writing experiment of Doshi and Hauser [10] demonstrated that GenAI increases individual creativity but reduces collective content diversity; using large language models for ideation or collaborative writing likewise narrows diversity [109]. Homogenization also has a technical origin: when models are recursively trained on their own generated data, "model collapse" occurs, and the rare tails of the distribution disappear first [13]. Industry-wide dependence on a small number of foundation models to mass-produce content may lead to collective degradation of the marketing-content ecosystem. Human-in-the-loop is the only solution currently validated consistently [8].

5. Research Review and Critical Analysis

This section mainly draws on secondary evidence such as systematic reviews and bibliometric studies [5,7,8] to evaluate, at a meta level, "how well the research itself has been conducted."

5.1 Review of Theoretical Applications

The primary problem with theoretical application in this field is the coexistence of fragmentation and "atheoretical" research. On the one hand, theoretical lenses are highly dispersed: a Chinese review identified 12 theories and stated directly that "the theoretical foundation needs to be broadened and deepened" [35]. A bibliometric study of 492 MarTech papers likewise noted that "theoretical fragmentation persists" [110]. On the other hand, as many as 39 papers in the corpus of a TCCM review had "no guiding theory," while the remainder mainly borrowed scattered theories such as psychological reactance, SOR, privacy calculus, and TAM [40]. Theoretical fragmentation leads to confused naming of effects and vague construct boundaries, hindering knowledge accumulation. A recent PRISMA review introduced the ADO framework into this field for the first time (134 papers) [18].

An open "abolish-or-retain debate" has emerged around the Technology Acceptance Model (TAM). Critics, represented by Mogaji et al. [22], question TAM's individual-centered, static, and self-report-dependent nature and its difficulty in capturing the dynamic generation and continuous interaction of GenAI. Supporters respond through empirical extensions: a systematic review synthesizing four meta-analyses shows that the TAM family still has strong explanatory resilience [21]. The essence of the debate is the tension between a "static adoption paradigm" and a "dynamic interaction paradigm." GenAI use is not a one-time adoption decision but a continuous process of human-AI collaboration; replacing fragmented borrowing with an integrated framework is a feasible path [7,8].

5.2 Review of Research Methods

The imbalance revealed by Table 4 has cumulative consequences. First, the evidence base depends excessively on measurements of attitudes and intentions in one-time hypothetical scenarios, while actual purchasing behavior and long-term brand relationships are almost unobserved [9]. Second, the marginalization of qualitative research leaves process knowledge about "how human-AI collaboration actually occurs" at the conceptual level. Third, most bibliometric papers are descriptive maps with limited theoretical contribution.

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Aoran Hong et al. [115] demonstrated the feasibility of a mixed design of "computation + experiment + field," but such methodological awareness remains uncommon.

Table 4: Comparison of the Distribution and Gaps of GenAI Marketing Research Methods

Method Type	Current Application	Representative Evidence	Main Gap
Scenario-based online experiments	Most mainstream; dependent on online convenience samples	van Berlo et al. [111] proposed and validated the Mapping, Assembling, Demonstrating, and Executing (MADE) framework	High internal validity but limited external validity
Questionnaire surveys and structural equation modeling	Widely used; mostly cross-sectional self-reports	Quantitative studies accounted for 134 of 177 core papers [19]	Self-report and common-method bias make causality difficult to support
Qualitative and mixed methods	Low proportions (16 qualitative papers and 27 mixed-method papers)	In-depth interviews with advertising firms by Cui et al. [112] proposed a co-creative process model	Insufficient exploration of process mechanisms and internal organizational practices
Field experiments	Generally scarce; concentrated in content-effect and customer-service-efficiency scenarios	Randomized field experiment in e-commerce customer service by Liao et al. [12] (N=1,090)	Severe lack of evidence on long-term effects in real contexts
Longitudinal research	Almost absent	Long-term effects remain unknown because longitudinal research is absent [9]	Long-term effects such as brand equity and habit formation cannot be assessed
Neurophysiological measurement	Very rare, with small samples and poor generalizability	Neuromarketing review [113]; Nogueira et al. [9]	Differences in neural responses to GenAI and human content have not been measured
Bibliometrics/reviews	Intensive output	Verma et al. [5]; Mustak et al. [6]	Criticized as "descriptive, single-database, and limited by the time window" [114]

GenAI is not only an object of research but is also becoming a research method itself. At the experimental-stimulus end, van Berlo et al. [111] proposed the MADE framework to standardize the production of GenAI advertising stimuli; validation showed no significant difference from professional advertising and a substantial cost reduction. At the participant end, since Argyle et al. [73] established "algorithmic fidelity" through "silicon sampling," distributional replication accuracy has continued to increase [47,74]. However, validity disputes are equally sharp: unnaturally low variance [76], systematic preference bias [75], and the "flattened portrayal" of identity groups [77] collectively show that synthetic samples have structural distortions. Methodologists also warn of ethical and generalizability risks in replacing human participants with models [116]. "Calibration rather than replacement" should become the methodological norm [78].

5.3 Review of Contexts and Samples

The external validity of evidence in this field is constrained by the geographic structure of the samples. Research output is concentrated in China, the United States, and India and depends on online platforms and single-country samples [9,19]. This creates two risks: consumer responses to AI disclosure and authenticity are likely moderated by cultural values, so existing "average effects" may be only local conclusions for particular cultures; moreover, China and the United States are precisely the markets with the most aggressive adoption of GenAI, leaving extrapolation without a basis. Compared with the prosperity of consumer-to-consumer (C2C) and business-to-consumer (B2C) contexts, B2B research is clearly scarce, and current understanding comes mainly from bibliometric reviews [17] rather than first-hand empirical evidence.

The final, and perhaps most critical, structural defect is the scarcity of research on moderating mechanisms. Pokhrel and Somasiri [8] found that only 13% of the sampled literature examined moderating variables, in sharp contrast to the high context dependence of effects in this field. The strength of the disclosure penalty depends on disclosure wording, brand type, and consumer trust in AI; the drivers of resistance to AI also vary

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by market, method, and time [117]. When the overwhelming majority of studies report only main effects, many "contradictory" findings in the literature may simply be unmodeled moderating effects, directly constraining the specification of theoretical boundaries and the accumulation of knowledge.

6. Future Research Directions

6.1 Theoretical Level

To respond to theoretical fragmentation, the first task is to develop constructs native to the GenAI context. First, "AI authenticity" should be conceptualized independently: the disclosure penalty is mediated by perceived authenticity [53], and "perceived low effort" is its upstream mechanism [4]. Future research can develop a scale along this structure. Second, the psychology of algorithm disclosure should go beyond the single path of persuasion-knowledge activation: trust-penalty and trust-enhancement paths coexist [3], indicating an unmodeled dual-process mechanism. Third, a theory of human-AI co-creation urgently needs to take shape. The four-stage co-creation model of Cui et al. [112] remains a qualitative exploration and urgently requires operationalization and quantitative testing [1].

The essence of the debate over retaining or abandoning TAM is the tension between the static adoption paradigm and the dynamic interaction paradigm [22]. Future research should shift the unit of analysis toward the life cycle of human-AI relationships by tracking trajectories of trust evolution, mechanisms for repairing trust after AI errors [104], and preference drift during long-term use [118]. Long-term brand loyalty and the boundary conditions of AI aversion are also priority directions [8].

6.2 Methodological Level

The methodological agenda should directly correct the structural imbalances identified in Section 5. First, longitudinal designs should be prioritized: the long-term effects of AI on consumers are "unknown because longitudinal research is absent" [9], and panel tracking is key to testing whether "short-term interaction comes at the expense of long-term brand equity." Second, field experiments should be expanded: field research examining long-term brand equity is nearly a single point [12]. Third, neurophysiological measurement should fill the gap: differences in consumers' neural responses to AI and human content are essentially unmeasured. Fourth, mixed methods should be integrated: the "computation + experiment + field" design of Aoran Hong et al. [115] provides a replicable model.

Standards for the use of synthetic consumers should be established as soon as possible in response to validity disputes. Evidence has outlined a division of labor: digital twins have considerable distributional replication accuracy [47,74], but systematic distortions remain [75,76,77]. Future research should do three things: first, establish a "calibration-first" procedure [78]; second, establish a benchmark-testing system across model versions and cultural contexts to fill the validity gap for digital twins of Chinese consumers; and third, test the applicable boundaries of "AI-human hybrid" designs to provide standards for journal review and ethical review [116,119].

6.3 Practical and Governance Levels

Disclosure is shifting from an academic issue to a mandatory compliance need. Article 50 of the European Union (EU) Artificial Intelligence Act requires machine-readable labeling of AI-generated content (applicable from August 2026). China's Measures for Labeling Artificial Intelligence-Generated and Synthesized Content, implemented in September 2025, established a dual-track system of explicit and implicit labels. The U.S. Federal Trade Commission (FTC) has formed a "dual disclosure" enforcement practice. However, there is tension between mandatory labeling and empirical evidence: disclosure generally triggers a trust penalty [3], creating the risk of an "honesty tax." Future research should: first, test whether "framed transparency" [8] can balance compliance and effectiveness; second, test the external validity of the distinction between technical and relational disclosure [97]; and third, use differences among European, U.S., and Chinese regulatory paths to conduct quasi-natural experiments [120].

At the organizational and governance levels, there are two related agendas. The first is the organizational design of human-AI collaboration. Benefits from AI augmentation are highly uneven (inexperienced customer-

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service agents benefit about six times as much as experienced agents) [12], but empirical answers are absent for issues of "institutionalized oversight," such as review checkpoints, attribution of responsibility, and allocation of creative decision rights [112]. The second is capability erosion and ethical governance. Firms are concerned that repeated GenAI use will make marketing capabilities obsolete [118]. Combined with content homogenization [10], this risk may evolve into degradation of the industry ecosystem. The ASSURANCE principles-Autonomy, Security, Sustainability, Representativeness, Accountability, Nonbiasedness and Nondiscrimination, Crediting, and Empowerment [121]-provide a normative starting point; governance frameworks must also consider the compliance capabilities of small and medium-sized enterprises [42].

7. Conclusion

7.1 Main Conclusions and Contributions

This paper thematically integrates Chinese- and English-language literature from 2019 to 2026 around three research questions. For RQ1, GenAI marketing applications can be grouped into five major scenarios, and evidence of effects shows systematic "funnel stratification": evidence of improvements at the attention and interaction stages is sufficient [43], while gains in final conversion and purchasing are weak or insignificant [58]. For RQ2, this paper identifies six cross-context patterns, including quality-source decoupling and the disclosure paradox, which jointly point to a fundamental tension: the erosion of authenticity and uniqueness by scalable efficiency. For RQ3, this paper identifies four major gaps-theoretical fragmentation, methodological imbalance, sample concentration, and scarce moderation research (only 13% of the literature examines moderating variables) [8]-and proposes a research agenda.

7.2 Research Limitations

This paper has four limitations. First, it is a thematic narrative review rather than a PRISMA systematic review. Literature selection depends on existing review lineages and judgments of representativeness and may therefore contain selection bias. Second, no bibliometric mapping analysis was conducted, and the knowledge structure is characterized mainly through qualitative integration. Third, the evidence comes mainly from English-language journals, so the conclusions should be extrapolated cautiously. Fourth, both GenAI technology and related research are evolving rapidly, and the conclusions in this paper should be regarded as a stage-specific synthesis within a particular time window.

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Conflicts of Interest

The authors declare no conflict of interest.

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