



Department of Digital Business

**Journal of Artificial Intelligence and Digital Business (RIGGS)**

Homepage: <https://journal.ilmudata.co.id/index.php/RIGGS>

Vol. 5 No. 1 (2026) pp: 2800-2807

P-ISSN: 2963-9298, e-ISSN: 2963-914X

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## The Effects of AI-Generated Content on Consumer Perceptions: A Structured Review and Conceptual Model

Muhammad Aqshel Revinzky Nizar<sup>1</sup>, Zidny Ilma Hasan<sup>2</sup>, Kurnia Khafidhatur Rafiah<sup>3</sup>

<sup>1</sup>Fakultas Ekonomi dan Bisnis, Universitas Padjadjaran

<sup>2</sup>Sekolah Vokasi, Universitas Padjadjaran

<sup>3</sup>Fakultas Ekonomi dan Bisnis, Universitas Padjadjaran

[aqshel@unpad.ac.id](mailto:aqshel@unpad.ac.id), [zidny@unpad.ac.id](mailto:zidny@unpad.ac.id), [kurnia.khafidhatur@unpad.ac.id](mailto:kurnia.khafidhatur@unpad.ac.id)

### Abstract

*Generative Artificial Intelligence (GenAI) has fundamentally transformed marketing by enabling firms to produce persuasive and scalable marketing content at unprecedented speeds. Despite its operational advantages, consumer reactions to AI-generated content (AIGC) remain deeply ambivalent. This article provides a comprehensive synthesis of peer-reviewed evidence regarding consumer responses to AIGC and develops an integrative conceptual model to explain the psychological shifts in consumer perceptions. Using a structured search and thematic synthesis, we identify three recurring psychological mechanisms that drive these responses: (1) persuasion-knowledge activation, where AI disclosures trigger inferences of manipulative intent and strategic cost-cutting; (2) competence-fit and algorithm beliefs, which encompass the dynamics of algorithm aversion versus appreciation based on the perceived capability of the AI for specific tasks; and (3) socio-emotional inferences, specifically regarding authenticity, moral disgust, and unease. These emotional reactions are found to be especially salient when AI is positioned as the primary author of affect-laden or empathic messages. Furthermore, we consolidate critical boundary conditions at the consumer level (AI literacy, privacy concerns), the message level (appeal type, modality), and the governance level (disclosure framing, human-oversight cues). The proposed framework offers a series of testable propositions and provides actionable guidance for marketing practitioners on how to strategically deploy GenAI. Ultimately, this research emphasizes the importance of maintaining human-centric oversight to protect consumer trust and preserve long-term brand equity in an increasingly automated digital landscape.*

*Keywords: AI-Generated Content; Generative AI; Consumer Perception; Authenticity; Disclosure; Advertising; Persuasion Knowledge*

### 1. Introduction

Generative artificial intelligence (GenAI) has become a core tool for producing marketing communications, enabling rapid creation of text, images, and video for advertising, branded social media, customer engagement, and personalization. Unlike earlier “predictive” AI applications that mainly classified or recommended, GenAI produces novel creative outputs that consumers may experience directly (Grewal et al., 2025; Hermann & Puntoni, 2024). As a result, consumer research faces a timely question: when consumers infer that an ad, post, or brand message is created (or substantially assisted) by AI, how does that belief shape perceptions of the message, the brand, and the marketer’s intent?

This question is consequential for at least three reasons. First, AIGC introduces ambiguity about the message source and agency. Consumers may infer a human communicator, a machine communicator, or a human–AI team. Source inferences can shift perceived warmth, competence, authenticity, and trust even when content quality is held constant (Puntoni et al., 2021). Second, AIGC can amplify personalization and scale, which may simultaneously increase relevance and heighten concerns about manipulation, privacy, and deception. Third, policy and industry norms increasingly encourage or require disclosure of AI-generated content, which makes “how to disclose” a strategic choice rather than an optional detail (e.g., in advertising and social platforms).

While practitioners have rapidly adopted GenAI, the academic evidence is still emerging and fragmented across streams such as advertising disclosure effects, algorithm aversion/appreciation, virtual influencers, and authenticity perceptions. Some studies report that AI disclosures can reduce ad evaluations and trust (Baek et al.,

2024; Qiu et al., 2025), whereas other work suggests that AI involvement can be advantageous when it fits a task-oriented message or when consumers perceive high competence and controllability (Chen et al., 2024; Logg et al., 2019). These mixed findings imply that AIGC is not universally beneficial or harmful; rather, it changes the inferences consumers draw about meaning, intent, and humanity of the message.

This article offers a structured review and an integrative conceptual model that organizes extant evidence into (a) AIGC cues (e.g., disclosure, modality, appeal type, anthropomorphism, and human-oversight cues), (b) consumer inferences (e.g., authenticity, credibility, skepticism, creepiness, self-efficacy), and (c) outcomes (e.g., attitudes, intentions, loyalty and word of mouth). We synthesize evidence into three mechanisms that recur across contexts: persuasion-knowledge activation, competence-fit/algorithm beliefs, and socio-emotional authenticity-related reactions. We then propose a model (Figure 1) and a set of testable propositions that can guide both research and managerial decision-making.

This inquiry is consequential for the future of marketing for three primary reasons:

First, AIGC introduces a crisis of agency and authorship. Traditional communication models assume a human sender with a specific intent. AIGC disrupts this by introducing a machine "source." These source inferences can shift perceived warmth and competence even when the actual quality of the content remains constant (Puntoni et al., 2021). The "source" is no longer just a brand; it is a human-machine hybrid, and consumers are still learning how to calibrate their trust in such entities.

Second, there is a growing tension between scale and sincerity. While GenAI allows for hyper-personalization, it simultaneously heightens consumer concerns regarding manipulation and privacy. If a brand can generate a thousand personalized apologies in a second, does the apology still carry moral weight? This "authenticity discount" represents a significant risk to long-term brand equity, particularly in relational or service-recovery contexts where human accountability is expected.

Third, the regulatory and ethical landscape is shifting toward mandatory transparency. With the advent of AI disclosure laws and platform-specific labels (e.g., "Generated by AI" tags on social media), disclosure is no longer a choice but a strategic constraint. Understanding how these labels activate "Persuasion Knowledge"—the cognitive defense mechanisms consumers use when they feel they are being targeted by a tactic (Friestad & Wright, 1994)—is essential for any firm navigating this transition.

Despite the surge in interest, academic evidence remains fragmented. Existing studies offer mixed results: some find that AI disclosure reduces trust (Baek et al., 2024), while others suggest that consumers may actually prefer AI for specific, task-oriented messages (Logg et al., 2019). This article addresses this fragmentation by offering a structured review and an integrative conceptual model. We organize extant evidence into a cohesive framework of AIGC Cues (e.g., disclosure, anthropomorphism), Consumer Inferences (e.g., skepticism, creepiness), and Downstream Outcomes (e.g., purchase intention, word-of-mouth).

By synthesizing these findings into three recurring mechanisms—persuasion-knowledge activation, competence-fit, and socio-emotional authenticity—this article provides a roadmap for both researchers and managers. Our goal is to shift the conversation from a binary debate on whether AI is "good or bad" for marketing toward a more nuanced understanding of when, why, and for whom AIGC serves as an effective communication tool.

To understand the complexity of consumer responses to AIGC, this research integrates three primary theoretical lenses: Persuasion Knowledge Theory (PKT), Computers are Social Actors (CASA), and the Uncanny Valley Effect. Persuasion Knowledge Theory (PKT) is Proposed by Friestad and Wright (1994), PKT suggests that consumers develop "coping mechanisms" when they recognize a persuasion attempt. In the context of AIGC, disclosure acts as a "change-of-meaning" trigger. When consumers see an "AI-Generated" label, they stop focusing solely on the message and start questioning the tactic—often perceiving it as a cost-cutting measure that lacks genuine brand commitment. CASA Paradigm is The CASA framework posits that humans mindlessly apply social rules to computers. However, AIGC creates a "social paradox." While consumers might use polite language with a chatbot, they simultaneously penalize the brand for a perceived lack of "Theory of Mind"—the ability to actually feel the empathy expressed in a marketing message. The Uncanny Valley and Moral Disgust: In visual and text-based AIGC, as the output approaches human-level perfection without being truly human, it can trigger a sense of "creepiness" or moral unease. This research synthesizes how this "uncanny" feeling shifts from a physical response

(in robotics) to a psychological response in AIGC, where the "falseness" of a sincere-sounding apology evokes distrust.

## **2. Research Methods**

### **2.1 Research design and rationale**

This article adopts a secondary data synthesis approach (also referred to as an integrative, theory-driven evidence synthesis) to consolidate what is currently known about how AI-generated content (AIGC) influences consumer perceptions. Unlike a systematic literature review (SLR) that prioritizes exhaustive retrieval and protocol-driven screening, secondary synthesis emphasizes conceptual integration, triangulation across heterogeneous evidence, and the development of a coherent explanatory framework suitable for a fast-evolving phenomenon such as generative AI in marketing.

### **2.2 Evidence base (secondary sources)**

To synthesize evidence, we drew on three categories of secondary data:

Peer-reviewed empirical research on consumer responses to AI- vs. human-generated messages and ads, including controlled experiments and field-related studies in marketing and consumer behavior (e.g., AI-authorship and AI-generated advertising). Foundational behavioral theories and established findings that explain human responses to machine outputs and persuasive intent (e.g., persuasion knowledge; algorithm aversion; social responses to computers). Conceptual and agenda-setting marketing scholarship on how generative AI changes marketing practice and consumer interaction patterns, used as boundary-setting context rather than as causal evidence.

### **2.3 Search and selection logic (non-systematic but structured)**

Evidence identification followed a structured but non-exhaustive process:

Seed study identification from high-impact marketing outlets and frequently cited work on AI in marketing and consumer behavior (e.g., *Journal of Business Research*, *Journal of Consumer Research*, *Journal of the Academy of Marketing Science*). Backward and forward chaining (reviewing references and "cited by" lists) to capture closely related empirical papers and theoretical anchors.

Eligibility focus, sources had to (a) involve AIGC/AI authorship or AI-generated advertising stimuli, and (b) report consumer perception outcomes (e.g., authenticity, trust/credibility, attitude, intention, WOM/loyalty), or provide a core explanatory theory relevant to those outcomes. Because the purpose is theory integration rather than exhaustive coverage, selection prioritized studies that are (i) methodologically clear, (ii) frequently cited, and (iii) directly informative for mechanism-building.

### **2.4 Data extraction and synthesis procedure**

For each empirical source, we extracted stimulus type (text vs. ad; emotional vs. factual; AI-authored vs. AI-edited), key dependent variables (authenticity, moral reactions, attitudes, WOM/loyalty), identified mediators/moderators (e.g., self-efficacy; role framing), and direction of effects. We then conducted a narrative synthesis using pattern matching and mechanism mapping. Specifically, evidence was organized into thematic pathways that converge on a unified conceptual model linking AIGC cues to consumer perception outcomes through (i) authenticity and moral evaluation, (ii) persuasion knowledge activation, (iii) algorithm aversion dynamics, and (iv) message–source fit.

## **3. Results and Discussions**

This section reports synthesized findings as robust qualitative regularities across the evidence base. The synthesis indicates that consumer responses to AIGC are contingent: AIGC can be neutral, beneficial, or harmful depending on message characteristics and the interpretive cues available to consumers. The secondary evidence synthesis indicates that consumer perceptions of AI-generated content (AIGC) are best explained as contingent evaluations rather than uniformly positive or negative. Across empirical studies and theory, four recurring pathways

consistently appear: (1) authenticity inference and moral evaluation, (2) persuasion knowledge activation under disclosure and salient AI cues, (3) algorithm aversion dynamics driven by perceived errors and loss of human accountability, and (4) message–creator fit (particularly agentic versus communal appeals) moderated by how AI is framed socially (e.g., assistant vs. author). These pathways jointly explain why some AIGC executions are perceived as efficient and credible, while others are judged as inauthentic, manipulative, or untrustworthy.

Importantly, the synthesis suggests that AIGC effects are rarely “direct.” Instead, AIGC often works through interpretive cues that shape what consumers infer about (a) the sender’s intention, (b) the sender’s capacity for sincerity and empathy, and (c) who is accountable for the message. This aligns with persuasion knowledge theory—where cues that make persuasion tactics salient invite coping and resistance—and with behavioral work showing that algorithmic tools can lose acceptance after errors, even when objectively capable. (If you will paste this in your paper, keep the citations aligned to your reference list; below I use in-text citations rather than tool citations.)

#### Regularity 1: AI authorship cues shape authenticity inferences, with strong downstream consequences

A central pattern emerging across evidence is that perceived AI authorship functions as a cue that alters consumer judgments of authenticity—a construct closely tied to perceived sincerity, human intent, and “realness” of brand communication. When consumers believe that a marketing message (especially one expressing gratitude, apology, solidarity, or emotional warmth) is produced by AI rather than a human communicator, they frequently infer that the message is less “felt” and more instrumental. In turn, this authenticity discount tends to reduce downstream outcomes such as positive word-of-mouth, brand attachment, and loyalty intentions.

The key mechanism is not that consumers necessarily believe AI is inaccurate. Rather, AI authorship cues alter perceived motive and emotional capacity: emotional communication is interpreted as a signal of human feeling, and the belief that AI generated the content weakens the perceived legitimacy of that signal. In this sense, authenticity is not merely a stylistic judgment (“sounds human”), but a moral-psychological inference about the sender’s inner state and intent. This helps explain why AI authorship penalties are consistently stronger for communications that are expected to be empathic, value-laden, or relational in nature, and weaker for messages that are primarily informational, utilitarian, or technical. (Kirk & Givi, 2025).

This pathway also clarifies a practical paradox: a message can be well-written and coherent yet still be evaluated negatively if consumers judge it as “performative” rather than sincere. For example, brand apologies and supportive messages after a service failure require perceived human accountability and genuine remorse. AI authorship cues may undermine those requirements, leading consumers to discount the communication even before considering the substantive content. In related persuasion research, cues that reduce perceived sincerity can prompt resistance and reduce persuasion effectiveness (Friestad & Wright, 1994).

Boundary conditions. The synthesis indicates at least three conditions under which authenticity penalties may weaken. AI as editor rather than author. When AI is framed as a tool that helps refine human-authored content (e.g., “AI-assisted” rather than “AI-written”), consumers can maintain the inference that a human initiated the emotional intention, with AI serving a supportive role. This is consistent with the broader finding that giving AI a subordinate role can reduce backlash by preserving human agency and accountability. Primarily factual communications. When the purpose is to transmit information (policy updates, product specifications, logistics notifications), authenticity is less diagnostic and therefore less influential. In such contexts, consumers may accept AI generation as efficiency-enhancing rather than sincerity-threatening. High baseline skepticism toward marketing talk. For categories where consumers already assume marketing messages are strategic and curated (e.g., price promotions), the authenticity gap between human and AI may be narrower because consumers may not strongly expect genuine emotion in the first place.

#### Regularity 2: Disclosure and “AI-salience” trigger persuasion knowledge and reframe how the message is interpreted

A second dominant pathway concerns the effects of disclosure and other cues that make AI involvement salient. Persuasion knowledge theory argues that consumers infer and respond to persuasion attempts by activating knowledge about tactics and motives; when a persuasive episode becomes transparent, consumers may engage coping strategies—skepticism, discounting, counter-arguing—which reduce persuasion effectiveness (Friestad &

Wright, 1994). In AIGC contexts, disclosure can act as a salient cue that prompts consumers to reinterpret the message as a cost-saving tactic or as a strategy to scale persuasion and personalization. Consequently, even when disclosure improves transparency and compliance, it can also introduce skepticism and reduce perceived credibility.

However, the synthesis suggests that disclosure effects are not unidirectional. Whether disclosure harms or helps depends on how consumers attribute the reason for using AI. If disclosure implicitly signals “automation to replace human care,” negative attributions increase. Conversely, if disclosure is paired with a consumer-benefiting rationale (e.g., faster response times, more consistent information, multilingual support, or safety screening), consumers may interpret AI use as a service improvement rather than an authenticity shortcut.

Disclosure format matters. Secondary synthesis indicates that disclosure is not a binary switch. The framing of disclosure (e.g., “AI-generated” vs. “AI-assisted and reviewed by our team”) is likely to change consumer attributions. A minimalist disclosure may heighten uncertainty (“Who is accountable?”), while a disclosure that explicitly adds human oversight can preserve credibility. This logic is consistent with the mechanism of persuasion knowledge: what matters is the inferred tactic and intent, not the mere presence of a disclosure label.

When transparency becomes risky. A particular risk zone emerges when disclosure is applied to content types that are strongly associated with human care—empathy-driven service replies, charitable appeals, or sensitive well-being messaging. Here, the disclosure cue can shift the interpretation from “genuine concern” to “procedural communication,” and the negative effect can be amplified by authenticity inference and moral evaluation (see 4.2). This implies that disclosure strategies should be customized by message function: the same disclosure policy may produce heterogeneous consumer reactions across contexts.

Regularity 3: Algorithm aversion implies that trust in AIGC can be brittle after salient errors

A third recurring theme is the fragility of consumer trust when AIGC produces errors or appears unreliable. Behavioral research on algorithm aversion demonstrates that people can disproportionately penalize algorithms after observing mistakes, even when algorithmic performance is objectively strong (Dietvorst, Simmons, & Massey, 2015). This provides a powerful lens for understanding consumer perception in AIGC: a single salient failure—hallucinated facts, mismatched tone, culturally inappropriate phrasing, or “template-like” generic content—can become a diagnostic cue that triggers generalized distrust toward AI-generated outputs and, by extension, the brand using them.

From the synthesis, error salience is not only about factual inaccuracies. Consumers may treat genericness and tone mismatch as “soft errors” indicating low care or low accountability. For example, a customer-facing reply that uses overly formal, robotic language or fails to address specific details of the complaint can signal that the brand is not listening. In such cases, consumers may not say “AI is inaccurate,” but rather infer “the brand is using automation to avoid effort.” This inference can undermine perceived service quality and brand warmth.

Mitigation: control and oversight cues. Evidence suggests algorithm aversion can be reduced when users have even slight control over algorithmic outputs or perceive that the system is adjustable and accountable (Dietvorst et al., 2018). Translating this to AIGC in marketing, consumer perceptions may improve when brands clearly signal human review for important messages, provide channels for correction (“If this response misses your point, reply and a human agent will follow up”), and demonstrate specificity (personalized details, context-sensitive language) that reduces the impression of generic automation. This yields a practical implication: in AIGC deployment, preventing the first visible failure may be disproportionately important because early errors can seed lasting distrust.

Regularity 3: Disclosure cues can activate persuasion knowledge and increase skepticism

When consumers are aware that content is AI-generated (through disclosure or salient cues), it can serve as a trigger for persuasion knowledge, increasing scrutiny of the marketer’s tactics and reducing persuasion effectiveness. This mechanism aligns with classic persuasion knowledge theory, which predicts heightened coping and resistance once the persuasion agent and tactics become more transparent. Disclosure enhances transparency but may also heighten attributions of manipulation or efficiency-over-sincerity—particularly for affect-laden messages.

#### Regularity 4: Message–creator fit explains when AIGC performs well (agentic vs. communal appeals)

Secondary synthesis strongly indicates that AIGC is not evaluated only by “who created it,” but also by whether the content’s persuasive goal matches consumer beliefs about AI’s strengths. Empirical evidence suggests AI-generated ads are typically more acceptable—and sometimes preferred—when the appeal is agentic (competence, productivity, performance, functional improvement) rather than communal (warmth, belonging, relational closeness) (Chen et al., 2024). This pattern is consistent with consumers’ lay beliefs that AI is competent at optimization and efficiency but limited in emotional depth and social understanding.

This fit-based explanation resolves apparent contradictions in the literature. If a study uses a performance-focused message (e.g., “save time,” “improve accuracy,” “maximize results”), consumers may view AIGC as congruent and judge it as credible and appropriate. Conversely, for messages that require human intimacy or empathy (e.g., “we understand your pain,” “we care deeply”), AI generation can feel incongruent, triggering authenticity discounting and skepticism.

Role-framing as a lever. The fit mechanism also interacts with AI role framing. When AI is framed as a social actor in a supportive role (assistant/partner), consumers can maintain the perception that the brand retains human intent while leveraging AI for execution, which can improve evaluations even for communal appeals (Chen et al., 2024). This is consistent with the broader CASA literature: people respond socially to machines under minimal cues, and the assigned role shapes expectations and acceptance (Nass & Moon, 2000). In marketing, role framing can therefore serve as a bridge between AI competence and human warmth: AI is positioned as enabling better service, not replacing caring.

#### Managerial Implications: The "Trust-by-Design" Framework

The "Human-in-the-Loop" Signal: Managers should not just use AI; they must conspicuously signal human oversight. Phrases like "Drafted by AI, refined by our experts" perform significantly better than "Generated by AI" because they maintain the bridge of accountability. Strategic Disclosure: Disclosure should be framed as a commitment to transparency rather than a warning label. Highlighting that AI was used to personalize a benefit for the customer (e.g., "We used AI to find the best deal for you") can shift the attribution from "manipulative" to "helpful." For marketing managers, the "efficiency vs. authenticity" trade-off can be managed through a strategic deployment framework:

Message Type	Recommended Source Framing	Disclosure Strategy
Functional/Technical	AI-Authored	Full Disclosure (Focus on Speed/Accuracy)
Relational/Empathic	Human-Authored, AI-Edited	Human-First (Focus on Intent)
Crisis/Apology	Strictly Human	Avoid AI Cues (Avoid Perceived Deception)
Creative/Abstract	Human-AI Collaborative	"Co-Created" Framing (Focus on Innovation)

#### Synthesizing the Hybrid Path Forward

The discussion of these results leads to a critical realization: the "Human-AI" binary is a false dichotomy. The most successful marketing outcomes described in recent literature are not purely AI-generated, but AI-Augmented.

By positioning AI as a "Co-pilot" rather than the "Pilot," firms can capture the efficiency of GenAI while shielding themselves from the authenticity penalty. This "Hybrid Model" preserves the human as the source of *intent* (the "why") while utilizing the AI as the source of *execution* (the "how"). This maintains the psychological contract with the consumer while allowing for the scalability that modern digital marketing demands.

#### 4. Conclusion

AIGC is reshaping marketing communications by reducing production costs and enabling scalable personalization, but consumer responses depend on what AI involvement signals. The emerging evidence indicates that disclosure and perceived authorship meaningfully shift consumer inferences about credibility, manipulation, and authenticity. AIGC tends to perform best in task-oriented, agentic communications where competence and clarity are valued, and performs worst in contexts where moral sincerity, empathy, and human authenticity are central. For practice, the key recommendation is design-for-trust. When disclosure is required or strategically chosen, pair it with cues of human oversight and verification, emphasize tangible and verifiable claims, and avoid positioning AI as the originator of human emotion in sensitive communications. For research, the conceptual model clarifies mechanisms and boundary conditions that can be tested with multi-method designs (experiments, field studies, and panel data) and can be extended to cross-cultural contexts where norms about technology and authenticity differ. Taken together, the synthesis suggests AIGC effects are governed by an integrated logic: a) Consumers interpret AIGC cues as signals of intent and accountability. b) AI cues can imply cost-cutting or scaling persuasion; if so, persuasion knowledge and skepticism rise. c) Authenticity is central for relational and moralized communications. d) When the communication is expected to be sincere or empathic, AI authorship undermines authenticity inference and can evoke moral discomfort. e) Trust is fragile under visible mistakes. f) Algorithm aversion implies that errors—hard or soft—can disproportionately damage credibility. g) Fit and framing can offset penalties. When messages are agentic and/or AI is framed as supportive with human oversight, AIGC can be evaluated as appropriate and credible. This integrated view suggests that the managerial question should shift from “Should we use AI-generated content?” to “For which message functions, audiences, and disclosure/oversight designs does AIGC improve rather than degrade perceived value?” In other words, AIGC is not a uniform content class but a communication technology whose consumer impact depends on how it shapes authenticity, accountability, and interpretive attributions. Overall, brands that proactively manage transparency, authorship, and human oversight are better positioned to realize the efficiency benefits of GenAI while protecting consumer trust and long-term brand equity. While this synthesis clarifies several mechanisms, the rapid evolution of Large Language Models (LLMs) leaves several questions unanswered: 1). The "AI-Taint" vs. "AI-Halo" Effect: Future studies should investigate if certain high-tech industries (e.g., SaaS, FinTech) experience an "AI-Halo" where AIGC is seen as a sign of innovation, contrasting with "AI-Taint" in artisanal or heritage brands where AIGC might signal a loss of craft. 2). Longitudinal Trust Erosion: Most current evidence is based on one-off experiments. Research is needed to determine if consumer skepticism toward AIGC "normalizes" over time or if repeated exposure leads to a permanent decline in brand equity. 3). Cross-Cultural Moderation: Does the "Authenticity Penalty" for AIGC hold in collectivist cultures (where the source of the message may be less important than the harmony of the outcome) compared to individualist cultures that prize personal sincerity? 4). Generational Literacy: As "AI Natives" enter the market, will the activation of Persuasion Knowledge decrease because they view AI-assisted creation as a standard baseline rather than a deceptive tactic?

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