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Algorithmic Trust in Interactive Marketing: A Conceptual Framework for Consumer Responses to AI-Generated Persuasion

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ABSTRACT

The rapid diffusion of generative artificial intelligence (AI) in marketing has transformed how firms design, personalize, and disseminate persuasive messages across global markets. However, limited research has theorized how consumers develop trust in AI as an active source of marketing communication rather than as a background analytical infrastructure. This study introduces algorithmic trust in interactive marketing as a multidimensional construct that captures cognitive, emotional, ethical, and institutional confidence in AI-generated marketing messages and the socio-technical systems that produce and govern them. Drawing on trust theory, technology acceptance research, source credibility theory, and cross-cultural institutional frameworks, we developed a conceptual model explaining how cultural values, regulatory environments, and transparency strategies shape the psychological mechanisms underlying trust formation and its behavioral outcomes. The framework advances interactive marketing theory by repositioning AI as a relational actor in consumer–brand communication. We derive six theoretically grounded propositions and outline a research agenda to guide empirical investigations into transparency, governance, and human–AI interaction in marketing contexts.

Keywords: algorithmic trust; interactive marketing; artificial intelligence; AI governance; algorithmic persuasion; transparency; cross-cultural consumer behavior

1. INTRODUCTION

Generative artificial intelligence (AI) reshapes marketing by enabling algorithms to curate, generate, and personalize persuasive communication at an unprecedented scale and sophistication. Conversational AI agents now serve as frontline communicators between brands and consumers, recommendation algorithms shape purchase decisions in real time, and generative models produce advertising copies, product descriptions, and personalized offers with minimal human oversight (Huang & Rust, 2021; Davenport et al., 2020). In these environments, AI systems increasingly function not only as decision-support tools for marketers, but also as interactive agents that participate directly in persuasion and relationship building with consumers.

This transformation introduced a form of distributed agency in which persuasive intent and accountability are shared across human marketers, algorithmic systems, and institutional governance structures. Consumer responses to marketing communication are consequently shaped not only by perceptions of the brand or platform, but also by evaluations of the algorithmic systems that generate and mediate these interactions. As AI becomes more visible and consequential in consumer-facing touchpoints, understanding how consumers develop, sustain, and withdraw trust in algorithmic marketing agents is central to both theory and practice.

While prior research on interactive and digital marketing has examined trust in online platforms (Gefen et al., 2003), personalization technologies (Aguirre et al., 2015), and automated decision systems (Lee & See, 2004), limited attention has been paid to how consumers develop trust in AI as a message source embedded in persuasive marketing encounters. This gap is theoretically consequential because AI-mediated communication introduces layered credibility judgments in which consumers must simultaneously evaluate brands, platforms, and algorithmic agents. This is also practically significant, as firms increasingly deploy AI systems that interact directly with consumers while navigating evolving regulatory landscapes that demand transparency and accountability.

This study addresses this gap by introducing the construct of algorithmic trust in interactive marketing and developing a global sociotechnical framework to explain how such trust is formed across diverse cultural and institutional contexts. We argue that algorithmic trust extends beyond the assessments of message accuracy or brand reliability to encompass emotional comfort, ethical legitimacy, and institutional confidence in the governance of AI-enabled persuasion.

This study makes three primary contributions to the literature: First, it reconceptualizes trust in marketing by positioning AI as a relational and persuasive actor rather than a passive technological infrastructure. Second, it integrates trust theory, source credibility research, technology acceptance, and institutional theory into a unified framework to explain how psychological mechanisms shape consumers' responses to AI-generated marketing communication. Third, it advances the research agenda by identifying pathways for empirical investigation of transparency, explainability, and ethical governance in interactive AI marketing systems.

2. THEORETICAL FOUNDATIONS

The conceptualization of algorithmic trust in interactive marketing draws on four interrelated theoretical traditions: trust theory, technology acceptance and algorithmic decision-making research, source credibility theory, and cross-cultural and institutional frameworks. Together, these perspectives provide the foundation for understanding how consumers evaluate AI-generated marketing messages and the socio-technical systems that produce and govern them.

2.1 Trust Theory and Its Extension to Algorithmic Contexts

Trust theory in marketing and organizational research has traditionally conceptualized trust as the willingness to accept vulnerability based on the positive expectations of another party's intentions or behavior (Mayer et al., 1995; Morgan & Hunt, 1994). The integrative model proposed by Mayer et al. identifies ability, benevolence, and integrity as core antecedents of trust formation: ability reflects competence to perform as expected; benevolence captures perceived goodwill toward the trusting party; and integrity refers to adherence to acceptable principles. In relationship marketing, trust has been linked to commitment, loyalty, and long-term engagement (Palmatier et al., 2006).

However, these models presuppose human or organizational trustees. When the trustee is partially technological, as in AI-mediated marketing contexts, the traditional framework requires an extension. Consumers may evaluate not only whether a firm is competent and benevolent but also whether the algorithmic systems governing message creation are transparent, fair, and aligned with social norms. McKnight et al. (2011) introduced the concept of trust in technology, distinguishing between functionality (reliable performance), helpfulness (adequate support), and reliability (consistent operation). Lankton et al. (2015) further demonstrate that trust in technology operates through both human- and system-like dimensions, with the relative weight of each depending on perceived anthropomorphism.

In AI-mediated marketing, trust is distributed across brands, technologies, and institutional safeguards. This introduces the ethical and institutional dimensions that transcend traditional ability–benevolence–integrity assessments. Consumers must judge not only whether the AI performs accurately but also whether its use is morally appropriate, whether the firm deploying it is acting in good faith, and whether regulatory structures provide adequate protection against algorithmic harm.

2.2 Technology Acceptance and Algorithmic Decision-Making

Research on technology acceptance has examined how perceived usefulness, ease of use, and control shape individuals' willingness to adopt new technologies (Davis, 1989; Venkatesh et al., 2003). The Technology Acceptance Model (TAM) and its extensions have been widely applied to understand consumer adoption of e-commerce, mobile applications, and digital services (Gefen et al., 2003). These models emphasize instrumental evaluations, and technologies are adopted when they provide functional values with acceptable effort.

Recent studies on algorithmic decision systems have complicated this picture. Dietvorst et al. (2015) documented algorithm aversion, showing that individuals often prefer human judgment even when algorithms demonstrably outperform humans, particularly after observing algorithmic errors. This aversion is driven by expectations of perfection and discomfort with algorithmic opacity. Conversely, Logg et al. (2019) identified algorithm appreciation in contexts where individuals view algorithms as more objective than potentially biased human judges. These seemingly contradictory findings suggest that consumer responses to algorithmic systems are shaped by context, framing, and perceived stakes.

In interactive marketing contexts, generative AI systems have moved beyond supporting human decisions to actively participate in persuasive communications. This shift expands the relevance of technology acceptance research by introducing symbolic and relational concerns: whether AI-generated messages feel authentic, reflect genuine brand values, and respect consumer autonomy (Longoni et al., 2019). Consumers may experience discomfort when AI systems mimic human interaction without disclosure, when personalization feels intrusive rather than helpful, or when algorithmic recommendations seem to prioritize firm interests over consumer welfare (Aguirre et al., 2015). Trust formation in this context is shaped by both performance-based evaluations and affective responses to perceived manipulation, opacity, or loss of control.

2.3 Source Credibility in Algorithmic Environments

Source credibility theory posits that the persuasiveness of a message depends on the perceptions of the source's expertise, trustworthiness, and attractiveness (Hovland et al., 1953; Ohanian, 1990). In traditional marketing contexts, source credibility assessments focus on identifiable spokespersons, brand representatives, and the firm. In digital environments, the notion of "source" becomes ambiguous as messages may be produced, curated, or mediated by algorithmic systems rather than identifiable individuals (Sundar & Nass, 2001).

Sundar's (2008) MAIN model extends source credibility to account for technological affordances, identifying modality, agency, interactivity, and navigability as cues that shape credibility perceptions in digital environments. When AI functions as a marketing message source, credibility judgments are layered at multiple levels. Consumers may evaluate the brand commissioning the message, platform delivering it, and algorithmic system that generates it. Each layer introduces distinct credibility considerations: brand reputation signals benevolence and integrity; platform design signals reliability and fairness; and algorithmic transparency signals competence and ethical appropriateness.

This distributed evaluation process suggests that traditional source credibility models must be extended to account for institutional signals such as transparency disclosures, explainability features, and regulatory compliance mechanisms that communicate the legitimacy of algorithmic persuasion. Consumers increasingly encounter disclosure labels indicating AI involvement in content creation. Research suggests that these disclosures can enhance trust through transparency and potentially undermine it through authenticity concerns (Jago, 2019; Kim & Duhachek, 2020).

2.4 Cross-Cultural and Institutional Frameworks

Cross-cultural research emphasizes that consumer perceptions and decision-making processes are shaped by cultural values such as individualism–collectivism, uncertainty avoidance, and power distance (Hofstede, 2001; Schwartz, 2006). These values influence how individuals interpret authority, risk, and technological change. Cultures characterized by high uncertainty avoidance tend to prefer explicit rules and predictable outcomes, suggesting heightened sensitivity to algorithmic opacity and a stronger demand for transparency mechanisms. High-power-distance cultures may be more accepting of algorithmic authority when endorsed by legitimate institutions, whereas individualistic cultures may place greater weight on personal control and autonomy in algorithmic interactions.

Institutional theory further highlights the role of formal regulations, normative expectations, and cultural-cognitive structures in shaping organizational legitimacy and consumer confidence (Scott, 2014). Regulatory frameworks such as the European Union's AI Act and GDPR establish disclosure requirements and accountability mechanisms that signal institutional commitment to protecting consumers from algorithmic harm. These institutional signals may substitute or complement firm-level transparency strategies in building consumer trust.

In AI-enabled marketing environments, cultural and institutional contexts shape not only trust in brands, but also expectations regarding algorithmic governance, ethical standards, and regulatory oversight. Markets with strong regulatory frameworks and high institutional trust may enable faster consumer adoption of AI-mediated marketing, whereas markets characterized by regulatory uncertainty or institutional distrust may experience greater resistance. As a result, algorithmic trust formation is embedded within broader socio-political systems rather than being solely determined by firm-level strategies or technological performance.

3. DEFINING ALGORITHMIC TRUST IN INTERACTIVE MARKETING

Algorithmic trust in interactive marketing is defined as the multidimensional confidence that consumers place in AI-generated marketing messages and the sociotechnical systems that produce, govern, and regulate them. This construct positions AI as an active relational actor in consumer–brand communication rather than as a passive technological infrastructure. It comprises four interrelated dimensions.

Cognitive trust reflects consumers' beliefs about the accuracy, competence, and informational quality of AI-generated marketing messages. This corresponds to the "ability" dimension in traditional trust models, and is shaped by perceptions of algorithmic performance, relevance of recommendations, and quality of generated content. Consumers with high cognitive trust believe that AI systems can reliably deliver accurate, useful, and contextually appropriate marketing communications.

Emotional trust captures affective responses, such as comfort, reassurance, anxiety, or unease, associated with interactions with AI-driven marketing systems. This reflects the humanness and warmth dimensions identified in technology trust research (Lankton et al., 2015). Consumers may feel emotionally comfortable when AI interactions are natural and personalized, or emotionally uneasy when they are mechanical, intrusive, or manipulative. Emotional trust is particularly significant in hedonic consumption contexts and in relationship-oriented marketing.

Ethical trust refers to the perceptions of fairness, transparency, and moral appropriateness in the use of AI for marketing purposes. It encompasses concerns about data privacy, algorithmic bias, manipulative design, and broader social implications of AI-mediated persuasion. Consumers with high ethical trust believe that AI systems are deployed responsibly, their data are used appropriately, and algorithmic decisions do not unfairly disadvantage or exploit their vulnerabilities.

Institutional trust represents confidence in the legal, regulatory, and organizational systems that oversee and govern AI deployment in marketing contexts. This reflects the belief that adequate safeguards exist to hold firms accountable for algorithmic harms, regulatory bodies effectively monitor AI marketing practices, and industry standards promote responsible AI use. Institutional trust may compensate for the limited cognitive or ethical trust at the firm level when consumers believe that external oversight provides adequate protection.

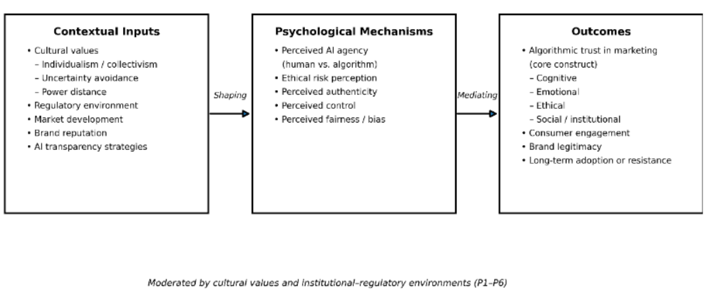
These four dimensions operate configurationally rather than additively. Under certain conditions, high trust in one dimension may not compensate for deficiencies in the other. For example, consumers may cognitively trust an AI recommendation system's accuracy while harboring deep ethical concerns about its data practices, resulting in avoidance, despite functional appreciation. Conversely, strong institutional trust in regulatory oversight may enable engagement with AI marketing systems even when firm-level transparency is limited. This configurational logic suggests multiple pathways for trust-based engagement and resistance, which have important implications for both measurement and managerial strategies.

Algorithmic trust in interactive marketing is conceptually distinct from the related constructs. Brand trust focuses on confidence in a firm's intentions and capabilities without specifically referring to AI systems (Delgado-Ballester & Munuera-Alemán, 2005). Platform trust concerns confidence in the reliability and fairness of digital intermediaries (Pavlou & Gefen, 2004). Trust in automation addresses reliance on automated systems in operational contexts such as aviation or manufacturing (Lee & See, 2004). Algorithmic trust in interactive marketing uniquely centers on the intersection of persuasive intent, algorithmic agency, and institutional governance within consumer-facing communication environments.

4. A Conceptual Framework of Algorithmic Trust Formation

The proposed framework conceptualizes algorithmic trust as a dynamic process that emerges from the interaction between contextual inputs, psychological mechanisms, and behavioral outcomes within AI-mediated marketing environments. Figure 1 presents the conceptual model, which adopts configurational logic that suggests multiple trust pathways to similar behavioral outcomes.

Figure 1. Conceptual Framework of Algorithmic Trust in Global Marketing



[Figure 1: Process Model of Distributed Algorithmic Trust Formation]

4.1 Contextual Inputs

Contextual inputs shape the conditions under which consumers encounter AI-generated marketing messages, and form their initial expectations. Five input categories are identified.

Cultural values, including uncertainty avoidance, power distance, and individualism–collectivism, shape baseline expectations of algorithmic authority, transparency requirements, and acceptable risk (Hofstede, 2001). These values condition how consumers interpret AI marketing encounters and what they require to feel comfortable engaging with.

Regulatory environment refers to the strength, clarity, and enforcement of legal frameworks governing AI use in marketing. Strong regulatory environments signal institutional commitment to consumer protection and establish accountability mechanisms that may enhance trust even when firm-level practices are opaque.

Market digital maturity captures the prevalence and sophistication of digital and AI technologies in a given market. Consumers in digitally mature markets may have greater familiarity with AI systems, potentially reducing novelty-based anxiety, while raising expectations for performance and transparency.

Brand reputation reflects pre-existing perceptions of a firm's competence, benevolence, and integrity. Established brand trust may be transferred to AI systems deployed by the brand, providing a heuristic that reduces the cognitive burden of evaluating algorithmic trustworthiness.

Transparency strategies encompass firm decisions about disclosing AI involvement, explaining algorithmic processes, and providing consumer-control mechanisms. These strategies directly signal firm intentions and shape consumers' expectations of algorithmic behavior.

4.2 Psychological Mechanisms

Contextual inputs activate mediating psychological mechanisms that shape trust formation:

Perceived algorithmic agency refers to the degree to which consumers attribute autonomous decision-making capabilities to an AI system. Higher perceived agency may enhance impressions of competence, while simultaneously raising concerns about control and predictability (Waytz et al., 2014). In high-power-distance cultures, perceived agency may be more readily accepted when legitimized by institutional authority.

Ethical risk perception captures consumer assessments of the potential harms from AI marketing, including privacy violations, manipulation, discrimination, and exploitation of vulnerabilities. Ethical risk perception is shaped by both firm transparency and regulatory signals, and mediates the relationship between the institutional environment and behavioral responses.

Perceived authenticity refers to judgments about whether AI-generated messages genuinely reflect brand values and intent or represent artificial, inauthentic communication. Brand reputation influences perceived authenticity by establishing expectations regarding what constitutes genuine brand communications.

Perceived control captures consumers' sense of agency in AI marketing interactions, including their ability to modify their preferences, opt out of personalization, and understand why they receive particular messages. Perceived control moderates the relationship between trust and engagement by enabling consumers to manage their vulnerability.

Perceived fairness reflects assessments of whether AI systems treat consumers equitably, whether personalization advantages some consumers at others' expenses, and whether algorithmic decisions can be contested. Fairness perceptions are particularly salient in contexts involving pricing, access, or resource allocation.

4.3 Trust Dimensions and Behavioral Outcomes

These psychological mechanisms jointly influence the four dimensions of algorithmic trust (cognitive, emotional, ethical, and institutional), which in turn drive behavioral outcomes.

Consumer engagement includes attention to AI-generated messages, interaction with AI-powered features, and the willingness to provide data that enables personalization. High algorithmic trust facilitates engagement by reducing the perceived risk and increasing the expected value.

Acceptance or resistance reflects consumers' responses to AI involvement in marketing, ranging from enthusiastic adoption to active avoidance. Resistance may manifest as ad-blocking, preference falsification, or platform switching.

Brand legitimacy perceptions capture how AI deployment affects the broader assessments of brand appropriateness and social acceptability. Irresponsible AI use can generate legitimacy deficits that extend beyond specific marketing encounters.

Long-term adoption refers to the sustained use of AI-enabled marketing services over time, reflecting durable trust relationships that survive occasional failures or negative experiences.

4.4 Comparative Analysis: High-Trust vs. Low-Trust Configurations

The configurational nature of algorithmic trust produces distinct consumer response patterns depending on how the four trust dimensions combine. Understanding these configurations provides deeper insight into the pathways through which trust influences behavioral outcomes.

High-trust configurations emerge when consumers exhibit elevated levels across multiple trust dimensions simultaneously. In the most favorable scenario, consumers demonstrate high cognitive trust (confidence in AI accuracy), high emotional trust (comfort with AI interactions), high ethical trust (belief in responsible AI use), and high institutional trust (confidence in regulatory oversight). These consumers typically exhibit enthusiastic engagement with AI-generated marketing, willingly share personal data for enhanced personalization, and demonstrate brand loyalty that withstands occasional algorithmic errors. They may even become advocates for AI-enabled services, recommending them to peers and defending them against criticism. High-trust configurations are most likely to emerge in markets with strong regulatory frameworks, among digitally mature consumers, and when brands have established reputations for responsible technology deployment.

Low-trust configurations manifest when consumers exhibit deficits across multiple trust dimensions. In severe cases, consumers may simultaneously distrust AI accuracy, feel uncomfortable with algorithmic interactions, question the ethics of AI marketing, and lack confidence in regulatory protections. These consumers actively resist AI-mediated marketing through behaviors including ad-blocking, preference falsification (providing inaccurate data), platform switching, and negative word-of-mouth. Low-trust configurations may trigger what we term "algorithmic alienation"—a comprehensive rejection of AI-mediated brand relationships that extends beyond specific encounters to encompass broader skepticism toward digital marketing ecosystems. Such configurations are more prevalent in markets with weak regulatory environments, among consumers who have experienced algorithmic harms, and when brands have histories of data misuse or privacy violations.

Asymmetric trust configurations present particularly interesting theoretical and managerial challenges. For instance, consumers may exhibit high cognitive trust paired with low ethical trust—they believe AI systems work effectively but distrust how their data are being used. This combination produces cautious engagement characterized by limited data sharing and heightened privacy-protective behaviors. Alternatively, consumers with high institutional trust but low firm-level trust may engage with AI marketing primarily because they believe external oversight constrains potential harms, even when they harbor reservations about specific brands' AI practices. These asymmetric configurations highlight that algorithmic trust cannot be meaningfully captured by a single aggregate measure and that managerial interventions must address specific trust deficits rather than pursuing undifferentiated trust-building strategies.

The existence of multiple trust pathways to engagement—and multiple pathways to resistance—suggests that firms cannot rely on a one-size-fits-all approach to building algorithmic trust. A brand targeting consumers in high uncertainty-avoidance cultures may need to prioritize transparency and process explanations to build cognitive and ethical trust, while a brand targeting consumers in high power-distance cultures may benefit more from institutional endorsements and authority signals. This configurational perspective underscores the importance of diagnosing specific trust profiles within target segments before designing AI marketing strategies and trust-building interventions.

5. RESEARCH PROPOSITIONS

Building on this conceptual framework, we derive six theoretically grounded propositions that identify the key relationships for empirical investigation.

Proposition 1: The positive relationship between AI transparency strategies and ethical and institutional trust is stronger in cultures characterized by high uncertainty avoidance.

Theoretical rationale: Uncertainty avoidance reflects cultural preferences for predictability, explicit rules, and risk reduction (Hofstede, 2001). In cultures with high uncertainty avoidance, consumers experience greater discomfort owing to ambiguity and opacity. Transparency strategies that explain AI involvement and decision processes directly address this discomfort by reducing the perceived unpredictability. Conversely, in low uncertainty-avoidance cultures, consumers may be more comfortable with algorithmic opacity and less responsive to transparency intervention.

Proposition 2: In high-power-distance cultures, perceived algorithmic agency is more strongly associated with institutional trust than with cognitive trust.

Theoretical rationale: Power distance reflects the cultural acceptance of hierarchical authority and unequal power distribution (Hofstede, 2001). In high-power-distance cultures, authority is more readily accepted when legitimized by institutional endorsement rather than demonstrated competence alone. Algorithmic agency may be perceived as an extension of institutional or corporate authority, such that trust derives primarily from the legitimacy of the institutions deploying AI rather than from the direct assessment of algorithmic performance.

Proposition 3: Regulatory environment strength increases long-term adoption of AI-mediated marketing communication through reduced ethical risk perceptions.

Theoretical rationale: Strong regulatory environments establish accountability mechanisms, disclosure requirements, and enforcement procedures that signal institutional commitment to protect consumers from algorithmic harm (Scott, 2014). These institutional safeguards reduce consumers' perceptions of ethical risks by providing external assurance that AI systems operate within acceptable boundaries.

Proposition 4: Perceived authenticity mediates the relationship between brand reputation and emotional trust in AI-generated marketing messages.

Theoretical rationale: Brand reputation establishes expectations about what constitutes genuine brand communication (Delgado-Ballester & Munuera-Alemán, 2005). When consumers encounter AI-generated messages from reputable brands, they assess whether the messages align with established brand identity and values. Consistency between AI-generated content and brand expectations enhances perceived authenticity, which in turn generates emotional comfort and reduces unease about artificial communication.

Proposition 5: Perceived control moderates the relationship between algorithmic trust and consumer engagement such that the relationship is stronger when perceived control is high.

Theoretical rationale: Trust involves willingness to accept vulnerability based on positive expectations (Mayer et al., 1995). Perceived control reduces vulnerability by enabling consumers to manage exposure, modify algorithmic inputs, and disengage if expectations are violated (Aguirre et al., 2015). When perceived control is high, trust translates more readily into engagement, because consumers feel protected against potential harm.

Proposition 6: The negative relationship between perceived algorithmic bias and algorithmic trust is attenuated in markets characterized by strong institutional oversight.

Theoretical rationale: Perceived algorithmic bias undermines trust by signaling unfairness and potential discrimination (Dietvorst et al., 2015). However, strong institutional oversight provides an external assurance that biased systems are identified, corrected, and sanctioned. When consumers believe that regulatory bodies effectively monitor AI marketing practices, the trust-damaging effects of perceived bias may be partially offset by their confidence that institutional safeguards limit harm.

6. MANAGERIAL AND POLICY IMPLICATIONS

The conceptual framework and research propositions offer actionable guidance to marketing managers and policymakers in navigating the deployment of AI in consumer-facing communication.

6.1 Implications for Marketing Managers

Treat AI as a relational actor, not technical infrastructure. This framework highlights that consumers evaluate AI systems as communicative agents based on perceived intentions, competencies, and ethical standing. Managers should design AI marketing systems that focus on relationship building rather than purely optimizing functional performance.

Differentiate between process transparency and outcome transparency. Process transparency involves explaining how artificial intelligence (AI) systems make decisions. Outcome transparency involves disclosing the involvement of AI without explaining its mechanisms. Process transparency can enhance cognitive and ethical trust by reducing opacity, while outcome transparency can support institutional legitimacy through disclosure compliance. However, outcome transparency without process transparency may trigger skepticism by highlighting AI involvement without addressing underlying concerns.

Provide meaningful control mechanisms. Given the moderating role of perceived control, managers should design AI marketing systems that offer genuine consumer agency. This includes easy-to-use preference settings, clear opt-out mechanisms, and explanations of how consumer choices affect algorithmic behavior.

Calibrate strategy to cultural context. Cultural moderation effects suggest that global firms should adapt AI marketing strategies to suit local cultural values. Markets characterized by high uncertainty avoidance may require more extensive transparency investments, whereas markets with a high power distance may benefit from institutional endorsements and authority signals.

6.2 Implications for Policymakers

Recognize the trust-building function of regulation. This framework positions the regulatory environment as a contextual input that shapes algorithmic trust through ethical risk perceptions and institutional confidence. Policymakers should recognize that clear, well-enforced AI marketing regulations can serve a market-enabling function by building consumer trust and facilitating adoption.

Develop disclosure standards that balance transparency and usability. Mandatory AI disclosure requirements should be designed to provide meaningful information without overwhelming consumers or triggering reflexive avoidance behaviors. Research on disclosure effectiveness suggests that simple, standardized formats outperform lengthy legalistic notices (Loewenstein et al., 2014).

Establish accountability mechanisms for algorithmic harms. Policymakers should establish clear accountability mechanisms, including audit requirements, complaint procedures, and enforcement sanctions, that signal commitment to protecting consumers from algorithmic harm.

7. FUTURE RESEARCH AGENDA

This conceptual framework opens multiple avenues for empirical investigation. We highlight five priority areas for future research:

Scale development and validation. A critical step in interactive marketing is the development and validation of multidimensional measurement scales for algorithmic trust. Such scales should capture the four dimensions while demonstrating discriminant validity from the related constructs. Cross-cultural validation is essential given the proposed moderating role of cultural values.

Experimental studies of transparency effects. Controlled experiments can examine how different transparency interventions affect trust dimensions and behavioral outcomes. Research should compare process transparency with outcome transparency, test the effects of timing, and examine how transparency affects algorithmic performance quality.

Cross-cultural comparative research. Testing the cultural moderation effects proposed in P1 and P2 requires cross-national studies spanning diverse cultural contexts. Multilevel modeling approaches can partition the variance between individual- and country-level factors, enabling rigorous tests of cultural moderation.

Longitudinal trust trajectories. Cross-sectional research cannot capture how algorithmic trust develops, evolves, or erodes over time. Longitudinal studies that track consumer trust across multiple AI marketing encounters can reveal how initial expectations are updated based on experiences.

Configurational analysis of trust pathways. The framework's configurational logic suggests that multiple combinations of trust dimensions may lead to similar behavioral outcomes. Qualitative comparative analysis (QCA) and fuzzy set methods can identify equifinal pathways for engagement.

8. LIMITATIONS AND BOUNDARY CONDITIONS

Several limitations and boundary conditions must be acknowledged. First, this conceptual framework focuses specifically on consumer-facing AI-mediated marketing communications, and may not be generalizable to non-promotional contexts or business-to-business marketing, where trust dynamics may differ substantially.

Second, the framework assumes that transparency generally enhances trust. However, emerging evidence suggests that transparency can backfire under certain conditions. Excessive transparency may overwhelm consumers, reduce usability, or highlight limitations that would otherwise go unnoticed (Buell & Norton, 2011).

Third, the framework does not explicitly address competitive dynamics. Consumer trust in a firm's AI marketing may be affected by experiences with competitors or industry-level scandals that shape general attitudes toward AI in marketing.

Fourth, the focus on AI-generated marketing communication may require updating, as AI capabilities evolve. The current distinctions between AI-generated and human-generated content may become increasingly blurred.

Fifth, an extremely poor algorithmic performance likely overwhelms all trust-building efforts. The framework implicitly assumes that AI systems perform adequately on functional dimensions.

Finally, the framework does not explicitly compare AI-generated marketing to human-generated alternatives. Consumer trust responses may be relative rather than absolute and shaped by comparisons with available alternatives.

9. CONCLUSION

This study advances interactive marketing theory by conceptualizing algorithmic trust as a layered, multidimensional, and socio-technical construct embedded within cultural and institutional contexts. By repositioning AI as a relational actor in consumer–brand communication rather than background technological infrastructure, the framework highlights the psychological and ethical mechanisms that shape consumer responses to AI-generated persuasion.

The four dimensions of algorithmic trust—cognitive, emotional, ethical, and institutional—provide a comprehensive vocabulary for analyzing consumer relationships with AI marketing systems. The proposed mechanisms, perceived agency, ethical risk perception, authenticity, control, and fairness, identify the psychological processes through which contextual inputs translate into trust judgments. These six research propositions offer testable predictions that can guide empirical investigations while informing managerial strategies.

As generative AI continues to transform marketing practices, understanding how consumers develop, sustain, and withdraw trust in algorithmic systems has become increasingly central to both scholarly inquiry and industry success. Firms and policymakers who successfully navigate algorithmic trust are positioned to realize the substantial benefits of AI-mediated marketing while maintaining consumer relationships that underpin long-term value creation.

We call upon scholars to prioritize empirical validation of this framework across diverse cultural and regulatory contexts, with particular attention to developing standardized measurement instruments that capture the configurational nature of algorithmic trust. Practitioners must move beyond viewing AI transparency as a compliance checkbox toward recognizing it as a strategic investment in consumer relationships. The window for establishing ethical norms and governance structures for AI marketing is narrowing rapidly; researchers and industry leaders must collaborate now to shape these emerging standards before consumer trust deficits become entrenched and irreversible.

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