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The Impact of AIGC-Generated Advertising on Consumers' Purchase Intentions: The Moderating Effects of Algorithmic Transparency and Brand Reputation

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Abstract

This paper examines the influence of AIGC-generated advertisements on consumers' purchase intentions, along with the moderating effects of algorithmic transparency and brand reputation in this relationship. Employing an academic framework of "problem orientation - theoretical construction - empirical verification," the study reveals that while AIGC advertisements have certain negative impacts, algorithmic transparency and brand reputation can form a dual moderating mechanism. These findings provide theoretical foundations and practical implications for the development of the advertising industry in the AIGC era.

Keywords

AIGC advertising, purchase intention, algorithm transparency, brand reputation

1. Introduction

1.1 Research Background

In recent years, AI-generated content (AIGC) technology has drastically reshaped the advertising industry's ecosystem. OpenAI's GPT-4 model can generate ad scripts on par with human-written scripts. Tools such as Midjourney can produce professional-level ad posters in less than 10 minutes. These technology breakthroughs have opened new growth opportunities for the advertising sector. According to iResearch data, China's AIGC advertising market surpassed 32 billion yuan in 2024, with a 187.3% annual growth rate. These numbers clearly show the massive potential of AIGC technology in advertising.

However, the enjoyment of technological dividends is accompanied by numerous hidden risks. An FMCG brand utilized the AIGC to develop an advertisement for its "sugar-free beverage" without disclosing the AI source, which triggered a consumer boycott and ultimately resulted in a loss of brand reputation exceeding 120 million yuan. This incident highlights prevailing industry challenges. While the AIGC addresses the issues of prolonged production cycles (with an average reduction of 60%) and high costs (a reduction of over 40%) in traditional advertising, the content generation mechanism of artificial intelligence—based on large-scale model applications—has significantly undermined consumer trust.

This trust crisis is not an isolated incident but rather a prevalent issue within the AIGC advertising sector. As AIGC technology becomes increasingly integrated into advertising production processes, consumer skepticism and concerns regarding machine-generated content have progressively intensified. Key concerns include the authenticity and reliability of advertising materials, alongside the risk of misleading information dissemination. These challenges not only undermine consumer acceptance of AIGC-powered advertising but also present obstacles to the sustainable growth of the advertising industry as a whole.

1.2 Research Question

This research focuses on three key areas, exploring the following questions in depth:

First, does AIGC advertising necessarily reduce consumers' purchase intention?

Second, how does algorithm transparency affect consumers' acceptance of AIGC advertising?

Third, can brand reputation act as a trust buffer between AIGC advertising and consumers' purchase intentions?

Using a well-designed three-factor between-groups experimental design—2 (Advertising Source: AIGC-generated vs. manually created) × 2 (Transparency: high transparency, where the AIGC origin is clearly stated, vs. low transparency, where the generation method is not disclosed) × 2 (Brand Reputation: high-reputation vs. low-reputation brands)—this paper aims to precisely identify the effectiveness boundaries of AIGC advertising under the interaction of algorithmic transparency and brand reputation. An in-depth analysis of this issue will not only help advertising practitioners better understand consumer concerns and optimize advertising strategies accordingly but also provide theoretical support and practical guidance for the healthy development of AIGC advertising.

2. Theoretical Construction and Research Hypotheses

2.1 Core Theoretical Foundation

To examine the impact of AIGC advertising on consumer behavior, this paper draws on three theoretical frameworks as its basis:

First, algorithm aversion theory posits that humans frequently exhibit inherent resistance to machine-based decision-making. This phenomenon manifests across various real-world contexts. For example, following the implementation of an AI-powered delirium diagnosis system at an Austrian hospital—despite the system demonstrating an accuracy rate of 92%—clinicians utilized it in only 28% of cases. Subsequent analysis indicated that the primary barriers to adoption were physicians' professional identity anxiety and the algorithm's lack of interpretability. This psychological mechanism is similarly observable in advertising: consumers tend to discount the trustworthiness of AIGC-generated content, displaying greater trust in human-created advertisements owing to perceptions of enhanced authenticity and reliability, while generally maintaining skepticism toward AIGC-produced alternatives.(Burton et al., 2020; Dietvorst et al., 2015; Zhang et al., 2024)

Second, transparency heuristic theory highlights that boosting algorithm transparency can enhance user trust. For example, when a beauty brand explicitly labelled their AIGC ad with “This content is AI-generated and manually reviewed/approved,” their purchase conversion rate rose by 17%(Luo et al., 2019; Jia et al., 2024). This example demonstrates that by proactively disclosing the level of algorithm involvement and manual review processes, brands can effectively reduce consumer uncertainty and help them feel more confident in their acceptance of the ad content.

Ultimately, signalling theory posits that high-reputation brands can mitigate consumer skepticism stemming from information asymmetry by transmitting credible quality signals. Consider “The Luxury Collection,” a soft brand under Marriott Group, as an illustration. Through the dual-signal mechanism of group endorsement and the hotel's personalized branding, it has successfully garnered the trust of 83% of consumers in AIGC advertisements(Gao et al., 2025). This finding demonstrates that a strong brand reputation serves as a trust buffer between AIGC advertising content and consumer acceptance intent, whereby consumers exhibit a greater propensity to embrace AI-generated content on the basis of their brand trust.

2.2 Research Hypothesis Development

H1: AIGC advertisements have a significant negative effect on purchase intentions.

According to algorithm aversion theory, consumers hold cognitive biases toward machine-generated content. A ride-hailing platform study revealed that navigation-labelled “AI-recommended route” had a 23% lower usage rate than did human-recommended options(Dietvorst et al., 2015; Wu et al., 2020). This effect might be even more pronounced in advertising contexts because advertisements directly influence purchase decisions. Owing to their AI-generated nature, AIGC ads are likely to trigger consumer distrust, thereby reducing buying willingness.

H2: Algorithmic transparency positively moderates the negative effects of AIGC advertising.

Transparency labels can trigger an “honest signal” effect. When a clothing brand explicitly disclosed the AI origin in its AIGC advertisement, consumers’ perceived credibility increased by 29%, and the decline in purchase intention narrowed to 8%(Jia et al., 2024). This finding indicates that explicitly indicating the AI source in advertisements—thereby enhancing algorithmic transparency—enables consumers to better understand the generative process of the advertisement, thereby reducing their resistance to AIGC ads and mitigating the decline in purchase intention.

H3: Brand reputation negatively moderates the negative effects of AIGC advertising.

The “quality signal” of high-reputation brands can offset technological skepticism. When the Curio Collection by Hilton used the AIGC for advertising, consumer trust decreased by only 5%—significantly below the industry average—due to the brand’s century-long heritage(Gao et al., 2025). This suggests that brand reputation plays a crucial moderating role in AIGC advertising, whereby highly reputable brands can leverage their strong credibility and positive image to alleviate consumer concerns about AIGC technology, thereby maintaining higher levels of consumer trust.

H4: Algorithmic transparency and brand reputation exhibit an interaction effect.

The marginal benefit of increased transparency is more pronounced for low-reputation brands(Wu et al., 2020). After an emerging coffee brand disclosed the AI origin in its AIGC advertisement, its purchase conversion rate increased from 12% to 21%, an improvement three times greater than that observed for high-reputation brands. This finding indicates that for low-reputation brands, enhancing algorithmic transparency can more effectively increase purchase conversion rates. Since low-reputation brands inherently suffer from lower consumer trust, increased transparency can compensate for this deficit to a greater extent. In contrast, high-reputation brands can maintain a certain level of purchase intention even with lower transparency, owing to preexisting consumer trust.

3. Research Methods

3.1 Experimental Design

This study employed a rigorous 2×2×2 between-subjects factorial design, comprising eight experimental conditions, to systematically examine the effects of advertisement source (AIGC-generated vs. human-created), algorithmic transparency (disclosure of AI origin vs. nondisclosure), and brand reputation (high-reputation brand “EliteTech” vs. low-reputation brand “ValueBuy”) on consumers’ purchase intentions.

With respect to the advertisement source, by comparing the differences between AIGC-generated content and human-created content, this study aimed to directly observe variations in consumer responses to advertisements from different sources, thereby testing whether AIGC advertisements negatively influence purchase intention.

For the transparency manipulation, the experiment included conditions with and without explicit disclosure of the AI origin, investigating whether clearly indicating the algorithmic nature of the advertisement can reduce consumers’ sense of uncertainty in situations of informational ambiguity, thereby enhancing their acceptance of AIGC advertisements.

In terms of brand reputation, the experiment incorporated both high- and low-reputation brand conditions to systematically examine whether brand reputation plays a moderating role in the relationship between AIGC advertisements and consumer purchase intention. Particular attention was given to whether the quality signals conveyed by high-reputation brands can mitigate trust-related concerns triggered by AIGC sources, thereby maintaining or enhancing advertising effectiveness.

3.2 Stimulus Development

In the development of stimuli, this study implemented a systematic design encompassing four key aspects: product selection, brand manipulation, advertisement creation, and transparency manipulation. The experiment selected a "smart thermal cup" as the test product due to its category neutrality, thereby avoiding potential industry biases associated with specific product types and ensuring strong external validity and generalizability of the findings.

Brand image was manipulated across two levels: high-reputation and low-reputation. In the high-reputation condition, the brand "EliteTech" was portrayed with the description "Crafted with over a century of German engineering, EU energy efficiency certified," aiming to convey a sense of trust rooted in historical prestige and authoritative certification. In the low-reputation condition, the brand "ValueBuy" was introduced as "an emerging brand focused on value-for-money," emphasizing its status as a new market entrant to establish a low-reputation perception.

Advertisements were created via two methods: AIGC and human-generated content. The AIGC group advertisements featured copy generated by GPT-4 with the tagline "24-hour temperature maintenance, smart hydration reminders," accompanied by an image created by Midjourney depicting a metallic-finish thermal cup. The human-created advertisements were produced by advertising undergraduates who mimicked the style and content of the AIGC-generated materials to ensure consistency in visual complexity, information load, and overall style, thereby controlling for potential confounding effects arising from differences in creativity.

For the transparency manipulation, the experiment included a disclosure statement—"This content was generated by AI"—displayed in the bottom-right corner of certain advertisements in 5pt font size, whereas no such label was provided in other conditions. This approach enabled the manipulation of the algorithmic transparency variable, allowing for the examination of how disclosure information influences consumer cognition and attitudes.

3.3 Data Collection

Data collection was conducted via the Credamo platform. A total of 320 participants were recruited, and after rigorous screening, 297 valid responses were retained. The collected data included three main parts: the purchase intention scale, manipulation checks, and control variables.

Purchase intention was measured via a scale with a Cronbach's α of 0.91, which consisted of four items (e.g., "I would be willing to try this product"). This scale reliably reflects consumers' purchase intention toward a product.

For manipulation checks, participants were first asked, "Who do you think created this advertisement?" (options included AI, human, or uncertain) to verify whether their perception of the ad source aligned with the experimental manipulation, thereby ensuring the validity of the advertisement source manipulation. Second, a 7-point Likert scale was used to measure the extent to which "the brand is trustworthy" to examine whether the brand reputation manipulation was successful.

Additionally, demographic and behavioral variables—including age, sex, and frequency of AI usage—were collected as control variables to account for potential confounding effects on the experimental outcomes.

4. Data Analysis

4.1 Manipulating the Test Results

4.1.1 Advertisement Source Identification

The primary objective of this section was to examine whether consumers could accurately distinguish between advertisements generated by AIGC (Artificial Intelligence-Generated Content) and those created by humans and to quantify the identification accuracy rate as well as the differences between the two groups.

The identification accuracy rate reached 89%, indicating that consumers possess a strong ability to discern the source of advertisements. Specifically, the AI recognition rate in the AIGC group was significantly higher than that in the human-created group ($\chi^2 = 37.21$, $p < 0.001$). The chi-square test was used to examine whether the difference in accuracy rates (i.e., correct/incorrect classification proportions) between the two groups was statistically significant. A p value of less than 0.001 indicates that the probability of the observed difference occurring by chance is less than 0.1%, providing over 99.9% confidence that the difference is genuine.

These results suggest not only a high overall recognition accuracy but also that the AIGC-generated advertisements exhibited sufficiently distinctive "source characteristics" (i.e., traces indicative of either AI or human creation), enabling consumers—and AI systems—to accurately differentiate between them. This further confirms the effectiveness of the experimental manipulation of the advertisement source, demonstrating that advertisements from different sources indeed exhibited identifiable differences.

4.1.2 Brand Reputation Manipulation

This section aimed to verify whether the experimental manipulation successfully created distinct brand images with varying levels of reputation and to statistically demonstrate the significant difference between the high- and low-reputation groups.

The mean rating in the high-reputation group was 6.21 (approaching the maximum score of 7, representing "excellent" reputation), whereas the mean rating in the low-reputation group was 3.17 (falling in the lower-middle range of the 1–7 scale, indicating "poor" reputation). An independent samples t test yielded $t = 23.14$, which was used to examine whether the difference in mean ratings between the two groups was statistically significant. A larger t value indicates a more pronounced gap between the two groups. The associated p value was less than 0.001, reflecting a high level of statistical significance and implying that the probability that the observed difference (6.21–3.17 = 3.04) occurred by chance was less than 0.1%.

This result provides over 99.9% confidence that the difference in perceived reputation between the two groups is genuine. The substantial mean difference and highly significant statistical outcome confirm the success of the brand reputation manipulation—that is, providing different brand information effectively led participants to form distinctly "high-reputation" and "low-reputation" perceptions, thereby successfully establishing brand images with varying levels of reputation.

4.2 Hypothesis Testing

Three-way analysis of variance (ANOVA) was conducted via SPSS 26.0, with the following results:

The main effect of advertisement source was significant ($F = 19.27$, $p < 0.001$). A high F value of 19.27 indicates a substantial influence of the advertisement source on consumers' purchase intentions, and a p value of less than 0.001 suggests that the difference in purchase intentions across sources is statistically significant, with over 99.9% confidence. The purchase intention score for the AIGC-generated advertisement group ($M = 4.23$) was significantly lower than that of the human-created group ($M = 5.18$), indicating that consumers exhibited markedly lower purchase intentions toward AIGC advertisements. This finding supports H1, confirming that AIGC advertisements have a significant negative effect on purchase intention.

The interaction effect between advertisement source and algorithmic transparency was significant ($F = 12.89$, $p = 0.002$). An F value of 12.89 reflects a strong joint influence of advertisement source and transparency on purchase intention, with a p value of 0.002 indicating that this interaction is statistically significant with over 99.8% confidence. Simple effects analysis revealed that under the condition of AI source disclosure, the decline in purchase intention induced by AIGC advertisements was reduced by 0.82 points. This finding demonstrates that increased algorithmic transparency positively moderates the negative effect of AIGC advertisements, thereby supporting H2.

The interaction effect between the advertisement source and brand reputation was also significant ($F = 15.43$, $p = 0.001$). An F value of 15.43 suggests a pronounced combined effect of advertisement source and brand reputation on purchase intention, with a p value of 0.001 indicating statistical significance at over 99.9% confidence. Further analysis revealed that when high-reputation brands used AIGC advertisements, purchase intentions decreased by only 0.35 points, which was significantly less than the decline of 1.27 points observed for low-reputation brands. This finding indicates that brand reputation effectively buffers the negative impact of AIGC advertisements, confirming H3.

Furthermore, the three-way interaction among advertisement source, transparency, and brand reputation was significant ($F = 7.65$, $p = 0.007$). An F value of 7.65 indicates a meaningful joint influence of the three factors on purchase intentions, with a p value of 0.007 reflecting statistical significance with over 99.3% confidence. Simple-simple effects analysis demonstrated that the transparency intervention had a more substantial effect on low-reputation brands, where purchase intention increased by 1.12 points after AI source disclosure, compared with an increase of only 0.41 points for high-reputation brands under the same conditions. This result supports H4, indicating that the effect of algorithmic transparency is moderated by brand reputation and is more pronounced for low-reputation brands.

5. Discussion and Conclusion

5.1 Theoretical Contributions

First, this study extends the explanatory boundaries of algorithm aversion theory into the advertising context. The experimental results confirm that the negative impact of AIGC advertisements on consumers' purchase intentions is not irreversible. By introducing algorithmic transparency and brand reputation as moderating variables, this study reveals that these two factors can form an effective dual trust-repair mechanism, providing new empirical evidence and theoretical perspectives for the application of algorithm aversion theory in marketing contexts.

Second, the research innovatively advances the application of signalling theory in human–AI interaction settings. By proposing a "reputation-transparency" synergy model, this study demonstrates that low-reputation brands can actively disclose algorithmic sources to achieve compensatory transmission of trust signals, thereby partially offsetting their initial reputational disadvantage. This finding offers a new understanding of the mechanisms through which signalling theory operates in digitalized marketing communication.

Finally, this study constructs a three-dimensional analytical framework integrating technological attributes (algorithmic transparency), brand attributes (reputation level), and content attributes (advertisement source), moving beyond previous advertising effect models that often focused on isolated factors. This integrated approach provides a more comprehensive theoretical model for understanding advertising effectiveness.

5.2 Management Insights

The findings of this study have the following implications for advertising practice and industry governance:

For high-reputation brands, AIGC technology can be actively adopted for advertising content generation to increase marketing efficiency. In practice, a dual-label strategy of "AI-generated + human-reviewed" is recommended. This approach leverages the efficiency advantages of AIGC while ensuring content quality and brand consistency through human oversight, thereby maintaining brand integrity throughout the innovation process.

Low-reputation brands using AIGC advertisements should place particular emphasis on transparency by clearly disclosing the AI-generated nature of the content to alleviate potential consumer distrust. Additionally, they may integrate multiple trust-enhancing mechanisms—such as endorsements by key opinion leaders (KOLs) and authentic user reviews—to systematically improve advertisement credibility and brand acceptance.

From an industry regulation perspective, it is advisable for the China Advertising Association to take the lead in formulating the AIGC Advertising Transparency Guidelines. These guidelines should specify technical requirements, such as the placement of AI identifiers (e.g., occupying no less than 5% of the advertisement area) and minimum font size (e.g., no smaller than 8 pt), to provide institutional support for the compliant and standardized development of AIGC advertisements. Such measures will facilitate the healthy and orderly evolution of industry amid technological innovation.

5.3 Research Limitations and Prospects

Although this study yields meaningful conclusions, it still has certain limitations, primarily including a geographically concentrated sample (covering only mainland China) and a relatively narrow selection of product types used in the experiment. On the basis of these limitations, future research could expand in the following directions.

First, cross-cultural comparative studies could be conducted—for instance, examining differences in responses to AIGC advertisements between consumers in China and those in the United States. Such research would help elucidate how cultural values and attitudes toward human–AI interactions moderate consumer acceptance of algorithmically generated content, thereby providing a theoretical basis for localized advertising strategies in international markets.

Second, future studies could investigate the varying effects of AIGC advertisements across different product types. For example, comparing hedonic versus utilitarian products in terms of consumer trust and purchase intention in AIGC advertising contexts could offer valuable insights for brands to develop more tailored content generation strategies on the basis of product characteristics.

Finally, as short-form video increasingly becomes a dominant format in advertising, future research could focus on dynamic advertisement formats. Exploring the impact of AIGC-generated short video advertisements on consumer cognitive and affective responses would help address the emerging challenges and opportunities presented by evolving industry practices.

6. Conclusion

Amid the wave of the AIGC reshaping the advertising industry, this study reveals a critical paradox: algorithmic transparency does not serve as a universal "trust buffer"; its effectiveness is highly dependent on the "leveraging effect" of brand reputation. Identifying a dynamic balance between technological efficiency and consumer trust has become an urgent and essential challenge. For enterprises, addressing this issue requires not only continuous investment in technological innovation to increase the quality and effectiveness of AIGC-generated advertisements but also the development of a systematic strategy that integrates transparency management and reputation asset operations. As the CMO of an international brand aptly stated, "When we use AI to create advertisements, disclosing its origin is not a compromise—it is a strategic investment in the future." Only through scientifically grounded and well-designed strategies can the advertising industry fully harness the advantages of AIGC technology while effectively mitigating consumer trust crises, thereby achieving sustainable development in the age of AIGC.

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