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Analysis of Advertising Creativity Generation and User Response Mode Based on AIGC

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Abstract: Generative Artificial Intelligence is now used to generate all parts of advertising, such as concept ideation, copy creation, image generation, and revisions to these outputs. However, its effect on user clicks, conversions, emotional response and trust in a linear manner is not evident. This paper introduces an analytical system for investigating the impact of "AIGC advertising creative generation" on "user response patterns", and integrates creative quality evaluation scores, user response probability estimates, gain calculations, heterogeneity identification, and combination optimization within this framework. Three types of reproducible simulated delivery experiments are conducted to compare the three strategies: human creatives, human + AIGC collaborative creatives, and AIGC closed-loop creatives. According to the above results, AIGC closed-loop creatives have achieved higher click-through rates, interaction scores and creative costs compared with typical human creatives. However, the AI disclosure, privacy sensitivity and authenticity verification will likely have different conversion rates. Therefore, AIGC should not be treated as a cheap material production line; instead, a governance-oriented creative system that caters to the various needs of users and brands, allows for open disclosure, and responds promptly to real-time changes needs to be established.

1. Introduction

The competition in digital advertising has moved from the original "competition for media resources" to the present "competition for content understanding, creative generation and real-time feedback capabilities". In programmatic advertising and performance advertising systems, the advertising content also needs to attract users' attention, create a good image of the brand, and motivate conversions. AIGC tools can generate copies, images, short video scripts and multiple versions of landing pages based on product selling points, user profiles, scene semantics and historical feedback, so the frequency of creative production has shifted from low frequency and manual creation to high frequency and machine generation. Kshetri and others believe that generative AI is developing into a new platform for the creation of marketing content and generating sales leads and personalised communication at the same time. The reasons for this are an increase in efficiency and a better response to the needs of users [1].

Advertising creativity cannot achieve better market results by being numerous, quick and inexpensive. Grewal and others believe that as generative artificial intelligence continues to develop, the mode of communication between enterprises and consumers will be transformed; at the same time, a balance will need to be sought in using input data, the extent of human involvement, and the risk associated with the output [2]. AIGC models are also being used to reduce the duration of testing or maintain consistency in the creative concept for advertisements. However, the same training corpora and prompt templates will result in homogeneous materials. Moreover, if users believe that the content has been generated by AI, they will have doubts about its authenticity, feel that it is manipulated, and be concerned about their privacy. Therefore, research on AIGC advertising should present the generation tools and, at the same time, establish an analytical system for studying changes in user responses.

Therefore, this paper will address two main questions: Do AI-generated ad creatives have an advantage over human-created ads in terms of click-through rate, conversion rate and interaction effect? How do different groups of users respond to relevance, newness, emotion, trust signals and AI disclosure? A closed-loop model has been built around the two questions, and actual, feasible charts show the changes in these questions after three creative strategies.

2. Current Status Analysis of the Research Topic

2.1 Technological Evolution of AIGC Advertising Creative Production

There are three levels in the application of AIGC for advertising. The first stage is text-assisted generation, mainly for titles, selling points, short descriptions, search ad descriptions and email marketing content. The second stage is multimodal creative generation, and at this time, text, images, videos and sound are all used in the creative production process together. The third stage is data feedback-driven closed-loop generation; that is to say, instead of producing creatives once and done, prompts and creative structures are continuously adjusted based on exposure, clicks, dwell time, favourites, add-to-cart rates, conversions and comment sentiment.

Cillo and Rubera believe that, from the perspective of innovation and marketing processes, generative AI will not change the amount of content created by companies; rather, the role of consumers in the innovation process, how consumer preferences are expressed, and the standards companies set for assessing market value will all be altered. Therefore, AIGC advertising is not a standalone design problem but rather a series of problems across various links, including market research and understanding consumer needs, content creation, platform algorithm adjustments, etc. What advertisers want most is that AIGC capabilities should not replace designers but rather expand the scope of creative exploration and reduce the time cycle from creative concept to user response.

The seven links in the AIGC advertising technology process are: demand analysis, cue engineering, creative generation, quality screening, human review, platform delivery, and feedback learning. Demand analysis will adjust the characteristics, brand positioning and target groups of the products in line with the constraints of each generation; cue engineering will convert strategic objectives into practical generation instructions; creative generation will produce several creative works; quality screening will eliminate low-quality creations that do not meet requirements such as visual consistency, semantic relevance, compliance risk and brand tone; human review will ensure aesthetic quality, ethics and policy compliance; and delivery feedback will provide support for the next generation of creation.

2.2 Expanding User Response Measurement from Click Behavior to Psychological Mechanisms

The standard indicators of the effect of old-fashioned advertising are click-through rates, conversion rates, cost per thousand impressions and customer acquisition cost. With the rise of large-scale AIGC advertising generation, a single indicator such as click-through rate is no longer sufficient to explain why users click, why they do not purchase after clicking, and how they perceive the brand. Hermann and Puntoni think that the mode of impact on consumers' behaviours due to generative AI will move from prediction to generation. The model generates the content, suggestions and interfaces that consumers will see in real time [4] and, at the same time, makes modifications to the original data.

Thus, a user's response is a complex pattern that includes behaviour, cognition, emotions and trust. Clicks are immediate attention, conversions are willingness to act, interaction scores reflect content engagement, authenticity evaluations judge the source of creative content, and privacy concerns indicate whether personalised advertising has exceeded psychological boundaries. AIGC can improve content relevance, but it may also make people feel that they are being watched if it is too closely aligned with their own lives. Therefore, in terms of evaluating the effect of AIGC advertising, both behaviour and psychology need to be considered.

Table 1. AIGC Ad Creative Generation and User Response Variable Design

Module	Variable	Definition	Measurement
Creative Input	Product Attribute	Core selling points and category constraints	Text/image tags
Creative Input	Brand Constraint	Tone, compliance and visual identity	Rule checklist
Generation Output	Novelty	Degree of non-repetitive visual/textual expression	Embedding distance
Generation Output	Relevance	Fit between creative and user context	Semantic similarity
User Response	CTR	Click probability after exposure	Clicks / impressions
User Response	CVR	Conversion probability after click	Orders / clicks
Psychological Response	Trust Cue	Perceived credibility and authenticity	Survey score
Risk Control	Disclosure Risk	Negative effect of AI label and privacy concern	Moderation coefficient

Table 1 shows the four components of the AIGC advertising creative system: input variables, output variables, response variables and risk variables. Therefore, we aim to turn "generating creative materials" into an observable experimental subject. On the one hand, product attributes and brand constraints prevent the realisation of creative ideas in practice; on the other hand, different users' responses are motivated by various reasons such as novelty, relevance, trust signals and disclosure risk. This variable system will also provide a unified standard for the formula model and chart experiment.

2.3 Shortcomings of existing research

Studies have found that the Perception of consumers under AI-generated advertising varies. Arango and others have shown that artificial intelligence-generated advertising for charitable donation activities may alter people's choices in terms of what they wish to purchase, and the extent to which it affects people is not uniform [5]. However, most of the previous research has only taken a single advertising sample or a questionnaire scenario as its object of study and therefore cannot explain why there are multiple versions of creative changes, uneven platform distribution, and different user groups in the actual delivery process.

Research on AI disclosure has also published some serious alerts. Baek et al. found that disclosing AI-generated content in advertisements can change the public's evaluation of public service announcements by means such as advertising credibility, and the extent to which AI is humanised in users' perceptions will also play a moderating role [6]. Therefore, the speed of generation alone cannot be considered to indicate the value of AIGC advertisements; they should also be judged based on the form of disclosure, the fit with the environment, and user acceptance. In the absence of dynamic governance, although AIGC advertisements may have a relatively high click-through rate for a short period, their brand trust will eventually fall.

3. Problem Statement: Creative efficiency and response uncertainty in AIGC advertising

3.1 The tension between creative scaling and content homogenization

The first is that AIGC can be expanded easily. The marketing team can produce many hundreds of headlines, visuals and scene combinations in a short time and immediately delete the ineffective materials according to feedback from the platform. However, Scalability does not equal the best of all. If the prompt templates, visual styles and expressions for the selling points are too similar, then AIGC will generate a very thin material library of templates that look different on the surface but have the same meaning and converge in content. Users may be interested in a new campaign at first, but soon they lose interest as there are too many.

Uniform Content Reduces Brand Recognition. Brand advertising requires a uniform tone, visual symbols and values, and is less focused on rapid testing and localisation for performance advertising. AIGC continuously enhances high-click areas according to short-term click signals and loses brand consistency. Therefore, advertising has been limited by brand constraints and human review in terms of creativity, and has thus not been particularly innovative.

3.2 Uncertainty Regarding AI Disclosure, Authenticity, and User Trust

The second problem of AIGC advertising is the public's lack of trust in the content's origin. Kirk and Givi found that if consumers believe emotional marketing is AI-generated, positive word-of-mouth and loyalty decline, and the reasons include a lack of perceived authenticity and moral aversion. The creativity of advertising mainly involves emotions and brand personalities; if users perceive AIGC content as "mechanical persuasion", then the original advantage of advertising will be lost.

To show the general structure of user response, the probability that a user u will click or convert on creative i can be presented as a function of relevance, creative quality, emotional intensity, disclosure perception and individual characteristics.

$$P(y_{ui}=1)=\sigma(\beta_0+\beta_1 Rel_{ui}+\beta_2 AQS_i+\beta_3 Emo_i-\beta_4 Disc_{ui}+\beta_5 Seg_u+\varepsilon_{ui}) \quad (1)$$

As shown in Equation (1), $P(y_{ui}=1)$ is the probability that user u will click, convert or engage deeply with ad creative i; Rel_{ui} represents the relevance value of the user scenario to the creative content; AQS_i is the overall creative quality score; Emo_i is the strength of emotional expression; $Disc_{ui}$ is the user's sensitivity to AI disclosure and personalisation; and Seg_u is the user's segment demographic. The equation indicates that although enhanced relevance and quality of AIGC advertising are likely to have a positive effect, increased disclosure and privacy sensitivity will be negatively moderated.

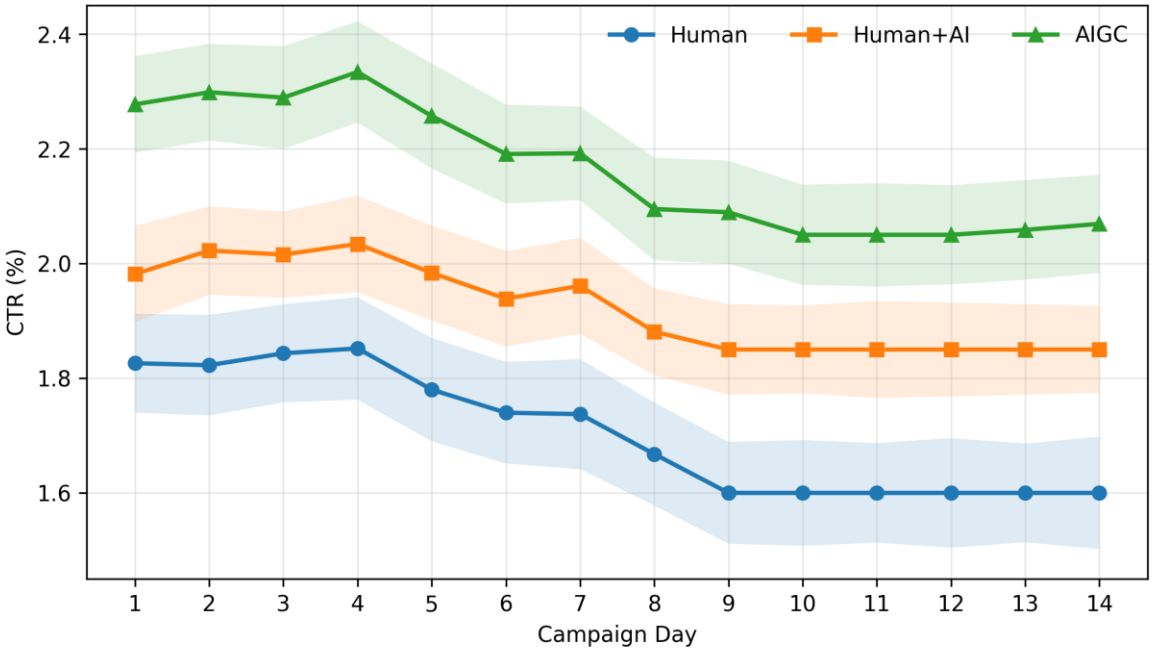

Figure 1. Changes in Daily Click-Through Rates under Different Creative Generation Strategies

Figure 1 is the CTR change over 14 days of a simulated campaign. AIGC closed-loop creatives consistently had the highest click-through rates on most days; thus, a cycle of creation and feedback could boost the initial attraction of the content. Human + AI creatives were still at a lower level and thus less popular. Human creatives showed a considerable decrease in click-through rates later on, indicating creative fatigue and outdated materials. It should be noted that the AIGC curve may also fall later; therefore, if we rely solely on automated generation, user fatigue will occur, and other ways such as new content creation, audience segmentation and brand consistency need to be employed.

Table 2 Comparison of Experimental Performance of the Three Types of Creative Strategies

Group	Impressions	CTR (%)	CVR (%)	Engagement Score	CPA Index	Creative Cost Index
Human	40,000	1.72	3.84	58.6	1.00	1.00
Human+AI	40,000	1.93	4.12	64.8	0.89	0.62
AIGC	40,000	2.17	4.05	67.9	0.82	0.38

As shown in Table 2, the AIGC group had higher CTR and engagement than the control group and had the lowest creative cost; therefore, it is more suitable for high-frequency testing and extended use of creative materials. However, the click advantage of the AIGC group did not lead to an increase in sales; thus, click advantage is not the same as purchase advantage. The conversion rates of human and AIGC collaboration were relatively even; it can be seen that the weaknesses in contextual understanding, brand tone and commitment boundaries of the AI-generated content were still somewhat offset by the human element.

3.3 User Response Heterogeneity and Platform Distribution Bias

The third issue of AIGC advertising is an unequal spread of user responses. Younger users are more open to new visual styles and AI-driven designs; privacy-aware users are more concerned about how their data will be used; long-time users are comfortable with the brand and price-conscious users will prefer clear-cut promotions. Madathil's research on generative AI video advertising shows that advertisements with human-AI collaborative characters have been received better by the public than those featuring only AI characters. Overall, click-through rate does not reflect the full impact of the creative, as a high rate in a small group of users may not be representative of the entire user base.

Platform Distribution aggravates the inequality. Advertising systems generally distribute high-performing early creatives to users with a higher likelihood of clicking, and thus different creatives are aimed at different groups. Braun and others believe that although the data on consumer research from digital advertising platforms is useful, it should be processed in light of the experimental distribution and delivery environment, as well as algorithmic modifications [9]. Therefore, in the experiment of this paper, the exposure scale, daily distribution and user segmentation were fixed to rule out the illusion caused by platform distribution advantages.

4. Problem Solving and Strategies: A Generative Framework for AI-Generated Advertising Creatives and Their Reactions

4.1 Establish a closed-loop system of "generation-evaluation-deployment-feedback".

To solve the problem of uneven results in AIGC advertisements, a closed-loop system that is traceable needs to be established. Creative creation should not be directly uploaded to the platform; rather, it needs to pass all-around tests on brands and semantic correctness, compliance with rules, visual standards, user safety limits, etc., before being released. Second, Optimising AIGC should not only focus on the short-term click-through rate but also consider conversion rate, quality of interaction, negative feedback rate, complaint rate, and brand trust level. Third, at key places in the system, human intervention needs to be possible; that is, the source of suggested keywords and the source of selected creative can be identified, the sensitivity of the content assessed, and any anomalies can be explained.

The four levels of the closed-loop system are: a data layer to collect product information, user context, historical materials and campaign logs; a generation layer that calls text models, image models and video models to generate candidate creatives; an evaluation layer to assess the quality of the creative, brand consistency and risk indicators; and an optimisation layer that conducts segmented delivery and material iteration based on user feedback. Compared with the traditional advertising model, the system will switch from "designing after delivery" to "continuous design during delivery".

4.2 Creative Quality Scoring Model

Given the substantial increase in the quantity of AIGC creative materials recently, to prevent quality control problems, the quality of the produced content should be evaluated before it is released. In addition to the visual attractiveness of a score, it should also be relevant, diverse, in line with the brand, and not misleading. The whole score is as follows:

$$AQS_i=\lambda_1 Sim(text_i,brand)+\lambda_2 Div_i+\lambda_3 Trust_i+\lambda_4 Read_i-\lambda_5 Risk_i \tag{2}$$

As shown in Equation (2), AQS_i is the general quality score of the i-th advertising creative;

$Sim(text_i, brand)$ represents the similarity between the text of the creative and brand semantics; Div_i is the degree of difference from the existing material library; $Trust_i$ is the strength of credible clues; $Read_i$ is readability and information clarity; $Risk_i$ includes the risk of violations, exaggerated promises, privacy issues, and visual misleading; and λ_1 to λ_5 are weights set by experts, historical campaign regressions, or multi-objective optimization.

4.3 Deployment Experiment and Gain Estimation

In the evaluation of the three new methods for performance assessment, the standards are the same: similar exposure, similar categories, the same target users and a consistent campaign period. The mean click-through rates in the sample will be relatively small, so a gain estimation formula will be used to standardise the relative improvements achieved by all strategies.

$$Lift_m=(Metric_m-MetricHuman)/MetricHuman\times 100\%,\ m\in\{Human+AI,AIGC\} \tag{3}$$

$Metric_m$ in formula (3) can be an index, such as CTR, CVR, interaction score or the reciprocal of CPA; Human refers to the baseline group for human-made creatives. The above formula can convert all types of dimension indicators into a relative improvement rate to conduct an all-encompassing assessment of the three attributes of AIGC: "attention attraction", "conversion promotion" and "cost reduction". If AIGC increases the number of clicks but fails to drive conversions, it is necessary to investigate further and determine whether there is a disconnect between what the creative presents and the landing-page experience.

4.4 User Response Pattern Recognition

User response patterns can be shown as user groups and creative attribute coefficient matrices. For each user group k, the strength of the response can be modelled as a composite result of attention, emotional relevance, trust cues and privacy pressure.

$$R_k=\alpha_1 Attn_k+\alpha_2 Aff_k+\alpha_3 Trust_k-\alpha_4 Privacy_k+\alpha_5 Habit_k \tag{4}$$

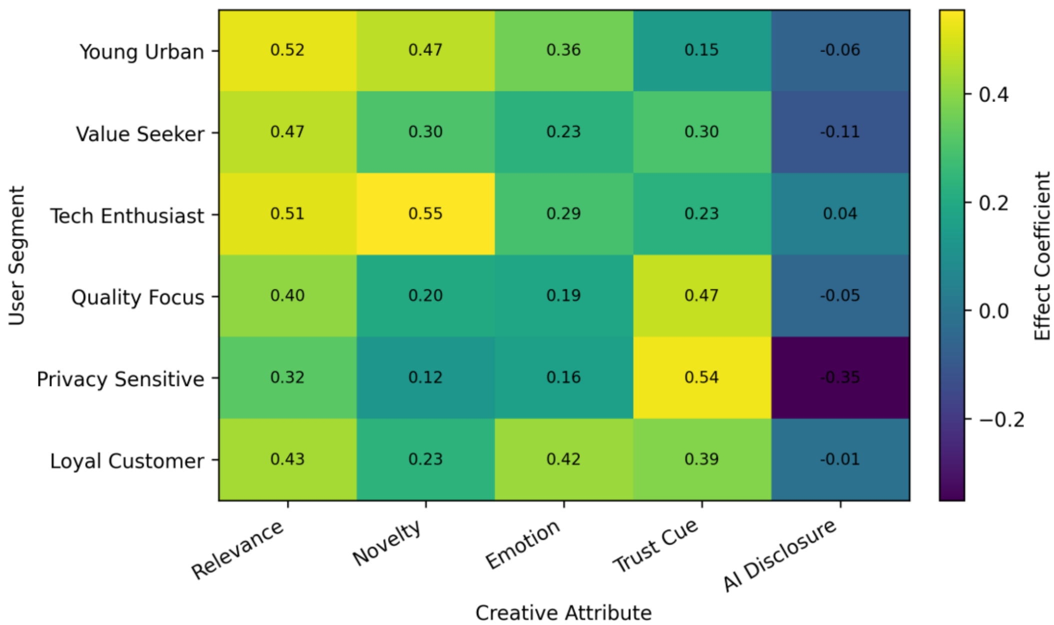

Figure 2. Response Coefficients of User Segments to Advertising Creative Attributes

The total response strength of the k-th user group in Equation (4) is denoted as R_k, and the attention-capture capacity by $Attn_k$, the emotional fit by Aff_k, the credible cue by $Trust_k$, the privacy pressure by $Privacy_k$, and the brand-or-category usage habit by $Habit_k$. The model believes that the best creative for AIGC advertising is not the same for all users, but rather an optimal creative that changes according to the characteristics of a certain user group, their situation and psychological boundaries, etc.

As shown in Figure 2, most of the user groups show a positive correlation with core factors; that is, the personalised advantages of AIGC have universal value, novelty has a greater impact on users with technical interests and young urban users, can be used as new products or trendy categories, trust clues are more important for quality-oriented users and privacy-sensitive users, AI disclosure has a significant negative coefficient for privacy-sensitive users, and transparent disclosure needs to be combined with data usage explanations, manual review explanations and brand endorsements to enhance advertising acceptance.

Table 3 User Response Patterns and Creative Optimization Strategies

Segment	Dominant Response	Preferred Creative Cue	Risk Trigger	Recommended Strategy
Young Urban	High click and fast fatigue	Novel visual and short slogan	Repeated style	Rotate variants weekly
Value Seeker	Price-driven conversion	Clear benefits and discounts	Ambiguous offer	Use explicit value proof
Tech Enthusiast	Positive AIGC acceptance	Interactive and futuristic cues	Low novelty	Expand multimodal formats
Quality Focus	Trust-based purchase	Review and certification cue	Over-promising claim	Add credible evidence
Privacy Sensitive	Cautious engagement	Data safety statement	Strong AI disclosure	Use minimal targeting copy
Loyal Customer	Stable repurchase	Brand memory and emotion	Inconsistent tone	Keep brand voice consistent

Table 3 is the reason for the user's response. AIGC ads cannot use a single "high-click template" for all users; therefore, different user groups will have diverse motivations and require various creative focuses. Younger users want new content, price-sensitive users seek value for money, quality-focused users demand evidence, and privacy-conscious users prefer reduced personalisation. Based on the above results, the advertiser will adjust the advertising plan.

4.5 Creative Combination Optimization and Risk Constraints

After the system receives many candidate creatives, an advertiser needs to choose a set for the campaign rather than selecting just the top-scoring or best one randomly. Portfolio optimisation's aim should be to achieve a good trade-off among expected return, risk and compliance requirements, and creativity.

$$\max \Pi=\Sigma_i x_i E(ROI_i)-\eta\Sigma_i x_i Var(ROI_i)-\rho\Sigma_i x_i Risk_i+\delta Div(X) \tag{5}$$

Xi is the value of the judgment variable for selecting creative i, $E(ROI_i)$ is the expected return on investment, $Var(ROI_i)$ is the performance variability, R(i) is the risk, Div(x) is the diversity of the selected creative set set according to the advertiser's own preferences, η is the advertiser's preference for stability, ρ is the advertiser's preference for risk, and δ is the advertiser's preference for diversity. The objective function does not aim to maximise click-through rate for AIGC creative optimisation but considers short-term impact, long-term user trust and the overall stability of the campaign.

5. Strategy Discussion: AIGC Governance Path for Advertising Practices

5.1 From Material Factory to Creative Operating System

The best application for AIGC in advertising is not to replace designers with models, but rather to introduce an operating system-level function for the creative process of advertising. That is to say, it can obtain product, user, scenario and feedback data, generate multiple expression paths, automatically filter experimental results, and write them back to the next round of creative production. Compared with traditional material outsourcing, this system of skills is more suitable for high-frequency updates, long-tail products and multi-channel promotion.

However, the creative operating system should still include people. Humans are not only the evaluators of brands but also the builders of brand language and value custodians who uncover the reasons for deviations. Relying only on models may result in exaggerated selling points and visual deception, lacking emotional connection, while relying solely on people cannot meet the high-demand requirements of personalisation. A stronger way is to have people set general goals, let AIGC be the creative tools, and have the platform test and improve how well it serves people.

5.2 Establish an AI disclosure and trust repair mechanism

The AI Disclosure requirement needs to specify how an artificial intelligence generates and uses creativity in one's works, not merely stating that it is AI-generated. Disclose that an advertisement uses only AI-generated visual backgrounds and is still under human supervision and brand responsibility. Provide the data source for personalised advertising, an exit plan, and privacy protection regulations. Duivenvoorde does not believe that the current laws provide adequate protection for consumers against potential harm from risks such as deepfakes, manipulation and chatbot control in AI-generated marketing. Therefore, in order to gain the public's trust, information may be released more readily rather than having to meet the legal requirements.

There are the following three ways. First, create a traceable record of the creative generation process and save prompts, model versions, material sources, review comments, etc. Second, build a blacklist of high-risk categories and rules for sensitive expressions to prevent misleading content in the areas of healthcare, finance and minors. Third, use layered disclosure to present a brief summary of the information in a small area near the ad, and provide more detailed details on AI and data usage on the landing page or in the information description. Fourth, periodically examine the effect of disclosure on click-through rates, conversion rates and brand trust, and do not use the same disclosure template in all situations.

5.3 Constructing a dynamic feedback system centered on user segmentation

According to the experimental results, although AIGC advertising has strengths such as relevance, newness and low-cost iteration, these advantages vary among different groups. Embed user segmentation in the creative-generation process to develop targeted advertising rather than running ads after the creative is finished. The system will generate several different prompt templates before generation, produce multiple creative versions by having the model generate these versions according to different reasons, and finally classify and collect the feedback on the campaign by industry instead of relying on a single overall click-through rate (CTR).

Dynamically adjust the display of information to reduce creative fatigue. As shown in Figure 1, the click rate of AIGC groups also dropped in the later period of the campaign; novelty is not eternal either. The system will set a life cycle for the creatives and update them based on frequency, click decay and negative feedback thresholds. Moreover, creative updates should not be trivial alterations to colours, fonts or titles; they need to be a new arrangement of scenarios, selling points, evidence and calls to action to prevent low-quality variations from being added to the creative pool.

5.4 Improve evaluation indicators and organizational coordination

Set up a multiple-tier indicator system for the implementation of the AIGC advertising system. The first level is the efficiency indicators: creation time of the work, cost per unit of work and test completion rate. The second level is behaviour indicators, such as CTR, CVR, add-to-cart rate, dwell time and response rate. The third level is psychological indicators; trustworthiness, authenticity, clarity of information and privacy are examples. The fourth is a risk of many complaints, false information, copyright infringement and platform failures. Only when all four kinds of indicators rise simultaneously can it be known that AIGC creatives have improved advertising effectiveness.

The organisation needs to change. The marketing team will set the vision and audience strategy for the brand; the data team will plan the design of response models and experiments; the legal and compliance team will control sensitive content; the design department will create a visual system and creative concepts; and the human-machine collaboration team will manage the storage of cue words and the evaluation of model output. If AIGC is only used by a single department, it will be at the tool level and fail to develop into a marketing asset.

6. Conclusion

Based on research on AIGC-based ad creative generation and user response patterns, a full-featured system has been constructed for creative generation, scoring and evaluation, campaign testing, user segmentation and portfolio optimisation. The three creative strategies were all performed on the same data for analysis. Based on the above results, AIGC closed-loop creatives can enhance click-through rates and engagement scores while reducing creative costs; collaborative creatives that integrate both human and AIGC have better stability in the transfer process; and purely manual creation is likely to lead to creative fatigue over time. Therefore, the benefits of AI-Genius are reduced cost and faster optimisation of ad materials by repeated experiments and improvements.

The AIGC ads are not effective in all situations. Users' Responses to Relevance, Novelty, Emotion Expression, Trust Signals, and AI Disclosure Differ Among Groups. Privacy-sensitive users are less likely to use the app's disclosure function, are more concerned about their own privacy, and thus judge the quality of the evidence they have obtained directly. Tech-savvy young people are also willing to learn new ways of expressing themselves. Therefore, the overall CTR of AIGC materials is not an appropriate measure of their effectiveness; instead, a model incorporating several metrics and different groups at different times must be built.

In practice, AIGC advertising needs to move beyond being a "materials factory" and become a "creative operating system". At the same time, all creation should consider brand constraints, compliance checks, transparent disclosure, data security, user segmentation, and dynamic feedback, and thus establish an auditable, explainable, and continuously improvable governance system for advertising creatives. Future studies will focus on A/B testing in a live environment, samples of all types of products, and a long-term system for evaluating brand value.

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