Frontiers in Computing and Intelligent Systems
ISSN: 2832-6024 | Vol. 17, No. 1, 2026

Generative AI Applications in Advertising

Yifei Wang *

College of Arts & Science, New York University, New York City, 10012, USA
*** Corresponding author Email:** yw7596@nyu.edu

Abstract: This paper aims to investigate the application of generative artificial intelligence (GenAI) models in advertising, particularly how their use affects the quality of advertising content and consumers' perceptions of AI-generated advertisements across different industries. In this paper, a curated AI-Generated Advertisement Dataset is used to conduct a content-level analysis, aiming to examine existing AI-generated advertisements based on their contents. Statistics and correlation analysis are applied to assess the quality AI-generated advertisements in four evaluation categories: Visual Quality, Style Consistency, Semantic Accuracy, and Creativity. The other, Xiaohongshu dataset, is used for user engagement and sentiment analysis. Two regression models are applied to the dataset to understand how people react and interact with AI-generated contents. This paper suggests a necessary improvement for the current development of GenAI models. That is, paying more attention to improving users' attitudes/perceptions toward AI-generated advertisements, leading to strengthened authenticity and reliability of advertisements. This suggestion is especially critical for industries where consumers value these qualities more, to enhance the overall effectiveness of AI applications in advertising. This paper addresses the real-world impact of GenAI model's application in advertising, offering new marketing lenses on how AI-generated ads can gain more consumers' attention and trust.

Keywords: Generative Artificial Intelligence; Artificial Intelligence Generated Content; Advertising; Marketing.

1. Introduction

The rapid development of Generative artificial intelligence (GenAI) marks the beginning of a new era for digital advertising [1]. Models such as text-to-image and text-to-video enable brands to generate high-quality visual content with shorter production times, lower costs, and greater creative freedom [2]. As a result, an increasing number of advertising campaigns are incorporating AI-generated elements [3], ranging from fully synthetic visuals to AI-assisted creation.

Although many brands have adopted GenAI in advertising, most lack knowledge of AI capabilities and characteristics, which affects their understanding of consumer perception of AI-generated advertisements (ads) [4]. Therefore, it is important to discuss how to highlight a brand's advantages in AI-generated ads in a more relevant, precise, and attractive way [5].

This study aims to analyze AI-generated ads from the perspectives of content production and public engagement&sentiment perspectives. First, a dataset of explicitly disclosed AI-generated ads from a variety of real-world marketing campaigns is created. The quality of each ad is assessed through four evaluation dimensions. Second, a large-scale social media dataset from the Xiaohongshu platform is incorporated, including user-generated posts and comments from different industries (later referred to as domains) about Artificial Intelligence Generated Content (AIGC).

This study will address the real-world impacts of GenAI tools, expanding on prior findings that focused on their creation capabilities, and provide insights not only for producing higher-quality AI-generated ads but also, more importantly, offer new marketing lenses on how AI-generated ads can gain more consumers' attention and trust.

2. Literature Review

Xiang et al. introduce the major technological capabilities and characteristics of generative GenAI. Unlike traditional machine learning models that aim to produce optimal solutions, GenAI is designed to generate creative outputs without predefined answers [6]. Particularly, two major functionalities of GenAI are text generation (e.g., copywriting, translation) and image generation (e.g., image and design creation, video generation, virtual avatars, 3D model generation), enabling companies across industries to improve both innovation and efficiency [6]. However, the accuracy and quality of AI-generated content remain questionable, a concern that is especially critical in advertising.

In the paper of Gao et al., how GenAI can be applied in the advertising context is discussed. AI applications in advertising often consist of three components: image/video production, copywriting, and content planning. Together, these functions provide a more data-driven, tailored advertising approach, improving efficiency and optimizing user targeting[4]. In addition, this paper addresses a few ethical challenges, such as algorithmic bias, privacy concerns, and lack of transparency, that AI applications in advertising face [3].

Beyond content generation, AI has profoundly reshaped the entire advertising process. In the Chinese market, AI advertising is built on a data-centric platform that uses algorithms to support every stage of the advertising workflow. Second, the process has become more tool-based, reducing the need for manual labor and enabling large-scale automation. Third, AI enables real-time synchronization of advertising activities, reducing the need for complex planning cycles and enabling dynamic changes based on user behavior. Finally, AI significantly improves efficiency, allowing for the creation of large volumes of personalized advertising content. This is especially important in rapidly growing markets like e-commerce, where demand for high-quality, personalized

advertising is rising [2].

3. Methodology

3.1. Research Design

This study combines two complementary data sources because generating a comprehensive dataset capturing both the visual characteristics of AI-generated ads and consumer responses is challenging.

The two datasets are the AI-Generated Advertisement Dataset and the Xiaohongshu AIGC Dataset. These two datasets generate two distinct but related perspectives, content-production and user engagement & sentiment, that could provide a more comprehensive understanding of AI-generated ads and their impacts on consumers.

3.2. Data Sources

3.2.1. AI-Generated Advertisement Dataset

This dataset consists of ads that are explicitly disclosed or clearly identifiable as AI-generated. For each ad, information including brand name, campaign name, year, industry, platform, region, AI modality, AI function, evidence type, and quality scores (visual quality, style consistency, semantic accuracy, creativity) is collected. This dataset is used to evaluate the visual quality of AI-generated ads.

Given the limited availability of publicly accessible datasets on AI-generated ads, this dataset is manually curated from verified sources. Therefore, this dataset is not large-scale.

3.2.2. Xiaohongshu AIGC Dataset

The second dataset is obtained from Kaggle and contains user-generated posts and comments related to AIGC on the Xiaohongshu social platform. This dataset includes post and comment subsets in specific domains (a total of 12), such as food and fashion. The subsets include variables such as likes, comments, shares, and comment content.

This Xiaohongshu dataset is used to analyze public engagement and sentiment toward AI-generated Ads, which are two key factors that experts use to evaluate the effectiveness of advertising campaigns on social media networks [7]. It provides large-scale evidence of how engagement and sentiment levels influence ad effectiveness [8].

3.3. Variable Construction

3.3.1. Content Evaluation Variables

The quality of AI-generated ads is evaluated across four dimensions. The name and definition of each variable are explained as follows:

- Visual Quality(VQ): The technical and aesthetic quality of visual output. This includes clarity, realism, and rendering quality [9].
- Style Consistency(SC): The degree of visual consistency among the various elements within an ad [10].
- Semantic Accuracy(SA): The extent to which the visual materials accurately reflect the intended message or concept [11,12].
- Creativity(CR): The originality and novelty of the ad's concept and execution [10].

Each variable is measured using a 5-point Likert scale, where 1 represents "very low quality" and 5 represents "very high quality" based on the definition of each variable.

3.3.2. Engagement Variables

The *posts.csv* subsets, such as *post-food.csv and post-fashion.csv*, are used in this study to examine consumers' engagement with AIGC across different domains. The following variables are analyzed:

- Like Count: Number of likes(the proxy for evaluating user engagement)
- Comment Count: Number of comments(interaction score)
- Share Count: Number of shares(interaction score)
- Collected Count: Number of collected(interaction score)

3.3.3. Sentiment Variables

The *comments.csv* subsets are used to study public sentiment toward AIGC across different domains. Specifically, each comment's like counts and sentiment are studied.

- Like Count: Number of likes for each comment.
- Sentiment: User's attitude depicted in each comment, evaluated as positive or negative.

These variables enable the study to examine how user responses to AIGC vary across content contexts.

3.4. Content Analysis of AI-Generated Advertisements

To examine the quality of AI-generated ads, a series of descriptive and comparative analyses is conducted using the first dataset.

First, an overall quality score is calculated as the average of the four variables for each campaign. Descriptive statistics are calculated for the overall quality scores of the four evaluation dimensions to provide a summary of content performance.

Second, a correlation analysis (e.g., $corr(VQ, SC)$, $corr(SA, CR)$) is done to examine the relationships among these variables.

Finally, conduct cross-group comparisons across categories such as industries or brand types to identify structural differences in the production methods of AI-generated ads.

3.5. Regression Analysis - User Engagement

A regression model is applied to the post subsets of the Xiaohongshu dataset. Since the engagement variables, such as like count, are highly skewed, a logarithmic transformation is applied.

The model is:

$$log(LikeCount_i + 1) = \beta_0 + \beta_1 CommentCount_i + \beta_2 ShareCount_i + \beta_3 CollectedCount_i + \beta_4 Domain_i$$

LikeCount is the dependent variable, representing user engagement. CommentCount, ShareCount, and CollectedCount track user interaction intensity. Domain represents different AIGC industries (e.g., food, fashion, cars, ...)

This model helps identify key factors associated with higher engagement and enables comparisons of engagement

patterns across different AIGC domains.

3.6. Regression Analysis - User Sentiment

To examine users' attitudes toward AIGC across different domains, comment subsets are used. Each subset includes the sentiment label, which categorizes attitudes toward AIGC as positive or negative. A logistic regression model is applied to these subsets:

$$P(Sentiment_i = k) = \beta_0 + \beta_1 Domain_i$$

Sentiment serves as the dependent variable. Domain is a categorical variable that represents different application areas, such as fashion, cars, food, literature, etc.

Specifically, this model can determine how users' attitudes vary across different AIGC domains.

3.7. Analytical Framework

This study combines two complementary levels of analysis in a parallel, comparative approach. Visual quality and user engagement&sentiment are analyzed separately but interpreted jointly.

4. Results & Analysis

4.1. Content Analysis of AI-Generated Advertisements

4.1.1. Descriptive Statistics

Table 1 shows the mean and standard deviation for the four evaluation dimensions of AI-generated ads.

Table 1. Mean and Standard Deviation for the four evaluation dimensions

	Visual Quality	Style Consistency	Semantic Accuracy	Creativity
Mean μ	4.286	4.810	4.714	4.619
Standard Deviation σ	0.717	0.512	0.902	0.669

Overall, the results indicate that AI-generated ads achieve relatively high scores in style consistency (**μ=4.810**) and semantic accuracy (**μ=4.714**), indicating that generative models are effective at producing visually coherent content and conveying the intended messages of the ads. However, the visual quality score (**μ= 4.286**) is the lowest, suggesting that AI-generated ads still have issues, such as a lack of realism or poor quality.

Semantic Accuracy shows the greatest variability (**σ=0.902**). This implies that the alignment with the intended message is not always consistent. Visual Quality also shows relatively high variability (**σ=0.717**), meaning that some brands can produce realistic AI-generated ads, while others cannot.

Creativity (**μ=4.619; σ0.669**) shows a moderate-to-high overall score and considerable variation across ads, suggesting differences in creativity levels among brands.

Thus, AI-generated ads tend to excel in visual coherence and semantic precision, but exhibit limitations in visual quality.

4.1.2. Correlation Analysis

To further investigate the relationship between the four dimensions, a correlation analysis is conducted.

The following is a pairwise summary table of Pearson correlation coefficient r and p-values (*Table 2*) as well as the correlation matrix (*Figure 1*) for n = 21.

Table 2. Pairwise Summary Table

Pair	r	p-value
VQ-SC	0.428	0.053
VQ-SA	0.364	0.104
VQ-CR	0.342	0.129
SC-SA	0.851	0.000
SC-CR	0.654	0.001
SA-CR	0.556	0.009

According to *Table 2 and Figure 1,* style consistency (SC) and semantic accuracy (SA) are strongly correlated (**r=0.851, p < 0.01**), indicating that AI-generated ads with more coherent visual styles tend to convey clearer, more accurate intended messages. Style consistency is also strongly correlated with creativity (CR), **r=0.654, p < 0.01**, suggesting that a consistent visual style helps maintain creativity.

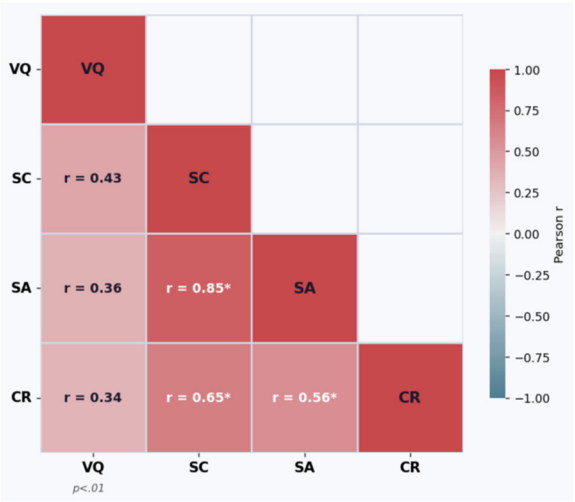

Figure 1. Correlation Matrix-AI Ad Quality Scores

A moderate positive relationship is observed between SA and CR (**r=0.556, p<0.01**), suggesting that more creative AI ads can still maintain the accuracy and clarity of the intended message.

In contrast, visual quality (VQ) has a statistically insignificant relationship with the other three variables.

Overall, this correlation analysis shows that style consistency plays a key role in AI ads and is closely related to both semantic accuracy and creativity. In contrast, visual quality has a relatively minor impact on variations in AI-ads performance across different industries.

4.1.3. Group Comparison

This paper also compares scores across four evaluation dimensions across industries (n =21).

Table 3. Means of different industry groups

Industry Group	VQ	SC	SA	CR
Fashion	4.600	4.800	4.400	4.800
Food&Drinks	4.430	4.860	5.000	4.710
Other	4.000	4.780	4.670	4.440

As shown in *Table 3 and Figure 2,* overall, fashion-related AI ads show a relatively higher quality score for VQ, SC, and

CR. However, its SA score is the lowest among the Food & Drinks and Other industries. In contrast, Food & Drinks-related AI ads have the highest SA score.

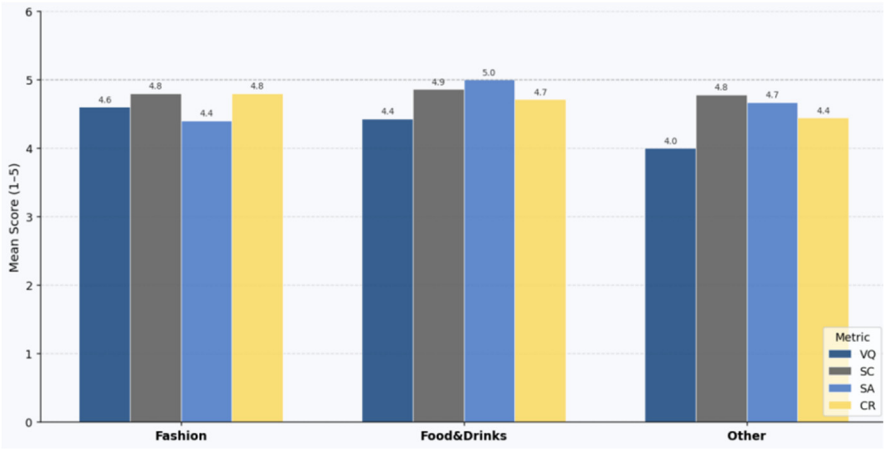

Figure 2. Group Mean Score Comparison

To investigate differences in overall evaluation scores across industries, a Kruskal-Wallis test is conducted.

Table 4. Kruskal-Wallis Test Results

VQ	H = 2.76, p = 0.2518 ns
SC	H = 0.12, p = 0.9411 ns
SA	H = 1.33, p = 0.5134 ns
CR	H = 0.53, p = 0.7667 ns

Table 4 shows no statistically significant differences across industries for any of the four evaluation dimensions. The p-values for VQ, SC, SA, and CR all fail to reach the statistical significance level (**p>0.05**).

In summary, the overall performance of AI-generated ads is relatively similar across industries, with no strong evidence that any one industry outperforms the others.

4.2. Engagement Analysis

Post subsets are used to analyze users' engagement on AIGC. To perform the analysis, all the post- CSV files are merged into a single dataframe.

4.2.1. Cross-Domain Comparison

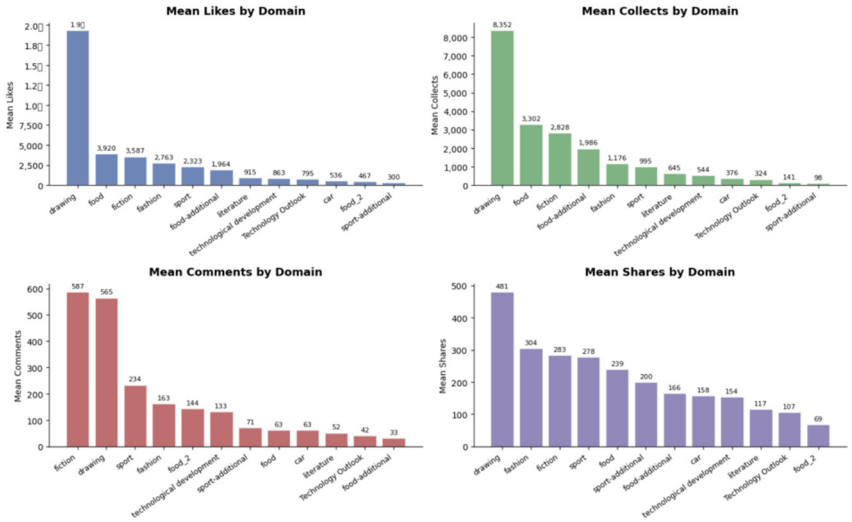

Figure 3. Mean Engagement Metrics Across AIGC Domains

The results shown in *Figure 3* indicate that the Drawing domain tends to generate the highest engagement, as its mean likes, collects, and shares are the highest across all domains. Food, Fashion, and Friction domains also tend to generate higher engagement levels. The Car and Sport domains tend to generate relatively lower engagement levels.

This result suggests that consumers may respond differently to AIGC depending on the domains associated with it.

4.2.2. Regression Results

Table 5 represents the results of the OLS regression model examining factors influencing user engagement, measured as the logarithm of like counts.

Overall, the model can explain different factors' impact on user engagement well, with an R^2 of **0.413**, suggesting that approximately **41.3%** of the variation in engagement levels can be explained by the included variables. The model is statistically significant, with an F-statistic of **73.47** and **p< 0.01**, indicating a strong overall fit.

OLS Summary:

$$R^2 = 0.4130 \; Adj.R^2 = 0.4074$$
$$F-statistic = 73.47, p = 0.0000$$
$$N = 1,477$$

Table 5. OLS Regression Results

	Coefficient	Standard Error	t-value	p-value	Significant
const	2.8796	0.1742	16.5298	0.0000	significant
comment_count	0.0005	0.0001	6.0039	0.0000	significant
share_count	0.0007	0.0001	9.8480	0.0000	significant
collected_count	0.0001	0.0000	8.4201	0.0000	significant
Domain: car	0.3375	0.2062	1.6372	0.1018	Non-sig
Domain: drawing	5.1090	0.3669	13.9231	0.0000	significant
Domain: fashion	1.7911	0.2080	8.6118	0.0000	significant
Domain: fiction	3.8029	0.3987	9.5386	0.0000	significant
Domain: food	0.7434	0.2693	2.7598	0.0059	significant
Domain: food-additional	-0.8619	0.3188	-2.7034	0.0069	significant
Domain: food_2	1.7043	0.3759	4.5340	0.0000	significant
Domain: literature	1.2191	0.3297	3.6977	0.0002	significant
Domain: sport	0.3744	0.2605	1.4373	0.1508	non
Domain: sport-additional	1.0250	0.3167	3.2363	0.0012	significant
Domain: technological development	1.5446	0.3362	4.5946	0.0000	significant

Interaction-Based Variables

The results show that all interaction-based variables have positive and statistically significant effects on user engagement level. The β value and p-value for each variable are:

- CommentCount: β**=0.0005, p< 0.01**
- ShareCount: β**=0.0007, p< 0.01**
- CollectedCount: β**=0.0001, p<0.01**

These results indicate that posts with higher interaction scores tend to receive more likes, suggesting greater user engagement. Among these three variables, content sharing plays a critical role in increasing engagement as its β is the largest.

Domain Effects

Table 5 also shows variation in engagement across each AIGC domain. Several domains show strong positive and statistically significant effects on user engagement level compared to the baseline category:

Drawing: β**=5.109, p<0.01**
Friction: β**=3.803, p<0.01**
Fashion: β**=1.791, p<0.01**
Technological development: β**=1.543, p<0.01**
Food: has multiple values, but is generally significant
Literature: β**=1.219, p<0.01**

The Drawing and Friction show especially higher levels of user engagement. A possible implication of this finding is that users are more likely to engage with visually appealing or creativity-driven AI-generated content.

However, some domains do not show statistically significant effects: Car (**p=0.102**) and Sport (**p=0.151**).

In addition, the food_additional category has a statistically significant negative effect (**β= -0.862, p< 0.01**), indicating a decreasing impact on engagement

In summary, user engagement with AIGC posts is influenced not only by interaction-based variables but also by certain domains, with content-sharing variables and visually appealing domains generating higher user engagement.

4.3. Sentiment Regression Analysis

4.3.1. Descriptive Statistics

Table 6. Descriptive Statistics of Comments' Like Count by Domain

source_file	Mean	Standard Deviation	Minimum	Maximum
Technology Outlook	2.97	51.91	0.0	2122.0
car	2.69	69.77	0.0	5508.0
drawing	39.01	510.66	0.0	15000.0
fashion	11.87	433.68	0.0	34000.0
fiction	6.29	98.39	0.0	5087.0
food	3.34	42.55	0.0	1958.0
food-additional	2.62	37.68	0.0	1443.0
food_2	39.54	530.26	0.0	22000.0
literature	9.54	156.32	0.0	7966.0
sport	16.70	521.95	0.0	38000.0
sport-additional	0.33	1.62	0.0	18.0
technological development	94.48	1334.56	0.0	28000.0

According to *Table 6*, comments related to the Technological development domain generate the highest counts of likes. Comments associated with the Drawing domain also generate higher counts of likes, while comments related to the Car domain generate relatively lower counts of likes.

The standard deviation for each domain is relatively high, suggesting that like counts vary widely across comments.

4.3.2. Cross-Domain Comparison

Figure 4 displays the distribution of sentiment labels (negative or positive) across domains.

The results show that the Car domain generates the most negative sentiment labels, while the Technological Development domain generates the fewest. The Car and Sport domains also generate a relatively higher number of positive labels.

These results suggest that consumers' attitudes toward AIGC may vary depending on its domains.

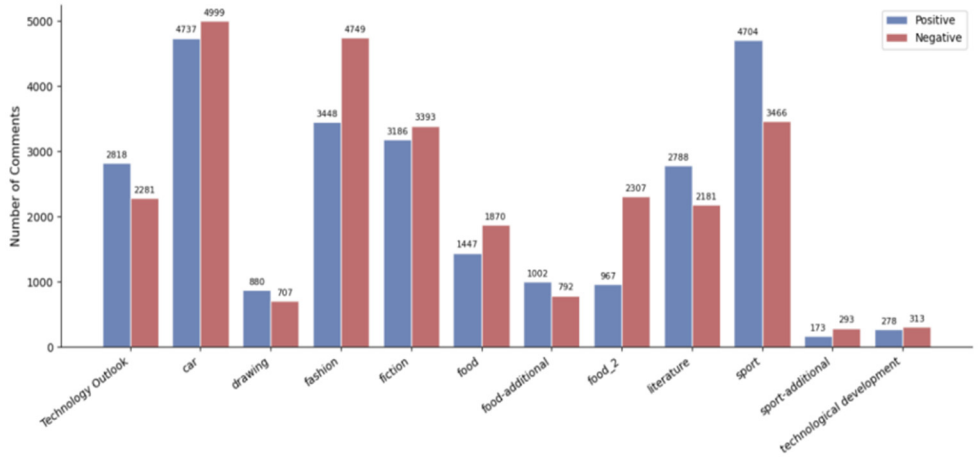

Figure 4. Sentiment Distribution Across AIGC Domains

4.3.3. Regression Results

Table 7 demonstrates the relationship between AIGC domains and user sentiment using a logistic regression model. The model includes a large sample size (**N=53,779**) and is statistically significant overall. However, the pseudo R^2 of **0.0164** suggests that the application domain explains only a small portion of the overall variation in user sentiment. Other factors can also influence users' sentiment toward AIGC.

Domain Effects on Sentiment

Several domains, including Food, Fashion, Technological Development, Car, and Fiction, show significant negative effects on sentiment (as indicated by negative coefficients and odds ratios < 1), suggesting a lower likelihood of positive sentiment towards content in these domains.

In contrast, the domain Sport shows a significant positive effect, indicating that positive emotions are slightly more likely to appear in sports-related AIGC content.

Additionally, the Drawing and Literature domains show no statistically significant effects, indicating that sentiment in these domains does not differ significantly from the baseline.

Table 7. Logistic Regression Result

	Coefficient	Standard Error	z-value	p-value	Odds Ratio	Significant
const	0.2114	0.0282	7.5063	0.0000	1.2354	significant
Domain: car	-0.2652	0.0347	-7.6430	0.0000	0.7670	significant
Domain: drawing	0.0075	0.0578	0.1293	0.8971	1.0075	Non-significant
Domain: fashion	-0.5316	0.0360	-14.7776	0.0000	0.5877	significant
Domain: fiction	-0.2744	0.0374	-7.3278	0.0000	0.7601	significant
Domain: food	-0.4679	0.0449	-10.4120	0.0000	0.6263	significant
Domain: food-additional	0.0238	0.0553	0.4303	0.6670	1.0241	Non-significant
Domain: food_2	-1.0809	0.0475	-22.7330	0.0000	0.3393	significant
Domain: literature	0.0341	0.0401	0.8504	0.3951	1.0347	Non-significant
Domain: sport	0.0940	0.0360	2.6127	0.0090	1.0986	significant
Domain: sport-additional	-0.7383	0.0999	-7.3879	0.0000	0.4779	significant
Domain: technological development	-0.3300	0.0871	-3.7890	0.0002	0.7189	significant

Overall, public sentiment of AIGC is subject to more consistent constraints. In most application domains, users are less likely to stay positive about AIGC.

5. Integrated Discussion: Content Production vs Public Engagement& Sentiment

The findings of this study indicate a significant contrast between the capabilities of generative AI in content creation and consumers' engagement with and attitudes toward such content.

From a content-production perspective, AI-generated ads can perform well in style consistency and semantic accuracy. Most companies can produce visually consistent ads and deliver their messages to consumers. However, visual quality tends to vary. Some brands may own more advanced generative models capable of producing more realistic, visually appealing ads. Additionally, there are differences in the level of creativity among different brands. This might be

because some brands might use their own teams to develop frameworks or write scripts. Moreover, style consistency & semantic accuracy, and style consistency & creativity, exhibit a strong positive correlation, suggesting that stylistic coherence is critical in shaping the overall quality of AI ads. Additionally, the group comparison results highlight that brands generate ads with specific design priorities. Some prioritize aesthetic appeal, while others emphasize clarity and functionality.

Overall, the analysis of content-production perspectives indicates that the overall performance is strong.

However, the overall quality score of AI-generated ads does not guarantee universal consumer satisfaction. The user engagement analysis shows that only domains associated with creative or visually appealing content are more likely to make consumers willing to engage.

The sentiment regression model demonstrates distinct patterns in user attitudes across domains. In fields such as food, fashion, and technology, users tend to have a negative attitude towards AI-generated ads, possibly because they expect these areas to be trustworthy and authentic, and AIGC might not meet those expectations. Meanwhile, the model suggests that the domain alone does not decide how people feel about AIGC. Consumers' attitudes are influenced by factors such as how good the content looks, what they like, what they have experienced with AI before, and how much they trust the AIGC. Therefore, attitudes toward AIGC are influenced by multiple contexts, rather than determined solely by domains.

Furthermore, the findings reveal that consumers' behaviors might not align exactly with their attitudes. Some domains, such as Fashion, generate high engagement levels but receive more negative comments, comparing the two regression models. This suggests that consumers may feel unsure or conflicted, yet still engage with AIGC content out of curiosity or for entertainment.

In summary, while generative AI excels at producing visually satisfying ads, it does not necessarily foster positive attitudes among consumers. This result serves as a reminder to marketers that future use of GenAI in advertising should not only improve the quality of visual content, especially realistic images, but also needs to prioritize consumers' feelings about and willingness to engage with AI-generated ads. One potential method to enhance this is to boost AIGC's authenticity and credibility.

6. Conclusion

This study builds on existing research on AI in advertising and provides comprehensive insights into the evaluation of AIGC and how it is received across different industries.

The content-production analysis shows that AI-generated ads can achieve high style consistency and semantic accuracy, with a strong correlation among style consistency, semantic accuracy, and creativity. These findings indicate that companies can use current GenAI models to produce visually coherent and compelling advertising content. However, variations occur across industries due to companies' intentions and needs.

The consumer engagement&sentiment analysis shows a relatively conflicted picture of how consumers engage with AIGC and how they feel about it. While consumers are more likely to engage with AIGC, particularly in domains related to creative or visually appealing content, their sentiment toward it remains relatively cautious across many areas. However, user sentiment is only weakly explained by domain differences and may also be influenced by other factors, such as user demographics and prior AIGC experience.

In conclusion, this study reveals a critical problem in the current development of GenAI models. That is, enhancing models' technical capabilities does not necessarily guarantee consumers' positive attitudes toward AIGC. It is necessary to pay greater attention to improving the authenticity and reliability of AIGC, especially in industries where consumers value these qualities more, to enhance the overall effectiveness of AI applications in advertising.

7. Limitations & Future Research Directions

7.1. Limitations

From the perspective of content-production analysis, a significant limitation is the small sample size (n=21). Such a small sample size reduces statistical power and may lead to less reliable results. Moreover, the scores for the four evaluation dimensions are assessed subjectively, which may cause measurement bias. The results cannot be generalized perfectly to the broader population of AI ads.

For the engagement&sentiment analysis, the biggest limitation is the uneven distribution of observations across domain subsets, leading to biased estimates and unreliable comparisons across industries. In particular, subsets with larger sample sizes may have a disproportionate impact on results.

Another potential limitation is that the analysis relies solely on data from the Xiaohongshu platform, and distinct consumer behaviors, preferences, and demographics that can also influence engagement and sentiment are not included. Thus, the results may not represent the entire population of consumers.

7.2. Future Research Directions

Future studies can explore more objective evaluation methods using deep learning and other applications. For instance, by incorporating a computer vision model alongside human Likert-scale ratings, the consistency of the advertisement evaluation would improve.

Furthermore, future research could examine ethical issues in AI applications in advertising by integrating theoretical frameworks on consumer trust and AI transparency from prior studies. For instance, by comparing users' reactions to content explicitly labeled as AI-generated versus content without such labeling, the findings could gain deeper insights into how transparency influences trust, engagement, and user sentiment.

References

[1] Li, H. (2019). Special section introduction: Artificial intelligence and advertising. *Journal of Advertising*, 48(4), 333–337. https://doi.org/10.1080/00913367.2019.1654947.

[2] Qin, X., & Jiang, Z. (2019). The impact of AI on the advertising process: The Chinese experience. *Journal of Advertising*, 48(4), 338–346. https://doi.org/10.1080/00913367.2019.1652122.

[3] Gao, B., Wang, Y., Xie, H., & Hu, Y. (2023). Artificial intelligence in advertising: Advancements, challenges, and ethical considerations in targeting, personalization, content creation, and ad optimization. *SAGE Open*, 13(4). https://doi.org/10. 1177/21582440231210759.

[4] Beyari, H., & Hashem, T. (2025). The role of artificial intelligence in personalizing social media marketing strategies for enhanced customer experience. *Behavioral Sciences*, 15(5), 700. https://doi.org/10.3390/bs15050700.

[5] Sharakhina, L. V., Ilyina, I., Kaplun, D., Teor, T. R., & Kulibanova, V. (2023). AI technologies in the analysis of visual advertising messages. *Journal of Marketing Analytics*. https://doi.org/10.1057/s41270-023-00255-1.

[6] Xiang, Y., Wu, Y., Song, J., Gong, Y., & Liang, P. (2024). Generative AI in industrial revolution: A comprehensive research on transformations, challenges, and future directions. *Journal of Knowledge Learning and Science Technology*, 3(2), 11–20. https://doi.org/10.60087/jklst.vol.3n2.p20.

[7] Raudeliūnienė, J., Davidavičienė, V., Tvaronavičienė, M., & Jonuška, L. (2018). Evaluation of advertising campaigns on social media networks. *Sustainability*, 10(4), 973. https://doi. org/ 10.3390/su10040973.

[8] Achar, C., So, J., Agrawal, N., & Duhachek, A. (2016). What we feel and why we buy. *Current Opinion in Psychology*, 10, 166–170. https://doi.org/10.1016/j.copsyc.2016.01.009.

[9] Sheng, X., Li, L., Chen, P., Wu, J., Xu, L., Yang, Y., & Li, Y. (2023). Technical quality-assisted image aesthetics quality assessment. In *Lecture Notes in Computer Science* (pp. 50–62). https://doi.org/10.1007/978-981-99-8552-4_5.

[10] Zheng, J. (2025). Generative AI-driven visual advertising creativity generation and style consistency modeling. *Advances in Computer and Communication*, 6(5), 262–267. https://doi. org/ 10.26855/acc.2025.12.001.

[11] Ganmote, D. P., & Bapuso, S. S. (2025). Artificial intelligence and the future of English semantics. In *Global Dimensions of Multidisciplinary Research* (p. 47). https://doi.org/ 10. 25215/ 9371837764.07.

[12] Yang, Y., Guo, C., Liu, F., Sun, L., Liu, C., & Sun, Q. (2022). Semantic communications with artificial intelligence tasks: Reducing bandwidth requirements and improving artificial intelligence task performance. *IEEE Industrial Electronics Magazine*, 17(3), 4–13. https://doi. org/10. 1109/ mie. 2022. 317433.