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AIGC Personalized Ad Generation Strategy and Communication Effect Optimization for Generation Z

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SUMMARY: *This paper carries out a research on AIGC personalized advertisement generation strategy and optimization of dissemination effect. In the embedding network design, AIGC personalized advertisement images and attributes are taken as inputs and put into the pre-trained VGG16 model to generate 128-dimensional feature vectors y. In order to make the AIGC personalized advertisement generation strategy more suitable for generation Z, the 128-dimensional vectors* y *in the embedding network are used as the conditional information into the layout generative network (GAN), thus designing a VGG16-GAN-based AIGC personalized ad generation strategy model. Subsequently, on the basis of the neural graph cooperative model, the Adam algorithm is introduced, aiming to further improve the dissemination effect of its AIGC personalized advertisements, and in this way, the AIGC personalized advertisement recommendation graph neural network model (GNN-Adam) is constructed. The addition of VGG16 to the GAN model improves the PSNR and SSIM values of the generated AIGC personalized advertisement images, which range from 27.11 to 34.594 and 0.674 to 0.935, demonstrating the role of VGG16 in optimizing the generation strategy of AIGC personalized advertisements based on GAN. In addition, the MAE, Recall, and Precision results of AIGC personalized advertisement recommendation graph neural network model (GNN-Adam) are distributed as 0.011~0.048, 0.900~0.939, and 0.901~0.938, which reflects that Adam algorithm can enhance the dissemination effect of AIGC personalized advertisement. The research in this paper can provide valuable references for the theoretical research and design practice of AIGC personalized advertisement design under Generation Z, and prompt AIGC personalized advertisement to produce higher communication benefits.*

KEYWORDS: *VGG16-GAN; GNN-Adam; Generation Z; AIGC personalized advertisement; generation strategy; dissemination effect*

1 Introduction

Generation Z is the aborigine of the real digital era, shifting the focus of life to online, coupled with the continued impact of the epidemic, they are fully Internetized from entertainment and socialization to shopping and learning [1]. Generation Z audiences present personalized demands for the design and dissemination of advertisements, which is due to the fact that Generation Z audiences are highly fragmented for advertisement viewing, their attention is dispersed, and they require advertisements to attract the users, while traditional advertisements are seriously homogenized and the click rate of advertisements decreases rapidly [2-5]. In addition, in advertising, reference groups have always had an important influence on consumer

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decision-making, and for Generation Z audiences, their reference groups are more influenced by key opinion leaders such as Internet celebrities and celebrities, as well as interest circles such as the rice circle, the shoe circle, and the Chinese dress circle, in addition to celebrities [6-9]. Single hard advertisements, which are no longer able to persuade Gen Z consumers, also need to be accurately disseminated through content, especially consumer word-of-mouth, objective recommendations from third parties, and actively searched by them or even jumped directly to the purchase interface to satisfy the current consumption needs [10-14]. Saha et al [15] reported that the clicking intention of personalized social media advertisements of Gen Z consumers is influenced by the consumer's personality traits such as extroversion, responsibility, and neuroticism positively influence as a way to increase the perceived value of the communication and further increase the click intention. Therefore, it is necessary to design personalized ads for Gen Z consumers.

Meanwhile, under the background of artificial intelligence (AI), artificial intelligence-generated content (AIGC) has improved, optimized, and sublimated the production of advertisements by leaps and bounds, and intuitively brought us an unprecedentedly stunning visual effect.AIGC relies on machine learning, especially deep learning algorithms, and simulates human thinking and creativity through the in-depth learning and parsing of massive amounts of data, in order to produce high-quality and diverse content [16]. In the specific application of advertising design and production, AIGC technology can efficiently create advertising copy and poster design and other marketing materials for enterprises and brands, effectively reducing the cost of the industry and improving work efficiency.

Jiang et al [17] stated that relevant AIGC advertisements promote users' consumption by deepening their perceived usefulness of the product, while divergent AIGC advertisements increase users' positive response to the advertisements by reinforcing perceived entertainment. Huang and Shen [18] showed that consumers have higher behavioral intention towards products designed by AIGC advertisements compared to traditional advertisement designs, which is due to the mediating role of consumer affective attitudes. Mohammadi and Jafari [19] found that AIGC is able to shape customer engagement in advertising situations, and that factors such as product type and customer attributes affect AIGC's interaction with customers in advertising. Tian et al [20] used Pix2Pix Conditional Generative Adversarial Network (GAN) to generate personalized poster content and generated posters with style transfer mechanism and detail enhancement to obtain high quality image quality to satisfy personalized poster campaigns. Ramagundam and Karne [21] used GAN to generate advertisements for ad-supported TV programs that are highly relevant to consumer preferences based on information such as viewer or consumer behavior, enterprise data, and customized content, which not only saves time and cost, but also improves the quality of advertisements. Lei et al [22] used a dynamic gesture recognition model supported by the Transformer architecture to capture user semantic signals, combined with conditional GAN to generate advertisements matching the user, and realized interactive control of movie advertisements with a high user satisfaction score of 4.6 (on a 5-point scale). Tsvetanova et al [23] study emphasized that AI tools in AIGC video advertisements provide more advertisement material, which helps marketing designers to customize their campaigns with increased effectiveness, thus improving the competitiveness of their products and services. Huang et al. [24] proposed a thought chain called “AdGPT”, which automatically understands the category, content, and sentiment of meaningful advertisements with the help of visual expert analytics and large-scale linguistic modeling, which is more helpful for creating and distributing advertisements. Jin et al [25] showed that AIGC image ads based on a large-scale visual language base model improved image quality and cue control, increased the click rate of image ads by 29%, and increased revenue for the application of Baidu search ads. These studies show that the advertising field is making innovative attempts with the help of AIGC. Whether it is to improve production efficiency, innovate the expression form, expand the imagination boundary, or help brands in digital transformation, enhance consumer interaction, and explore the new connection between people and technology, AIGC shows a unique value.

Zeng [26] analyzed the perceptions of AIGC-generated content by Gen Z groups on several new media platforms, which were mainly classified into entertainment-driven engagement and pragmatic skepticism, and the dissemination patterns of AIGC-generated content are changing due to the unique behaviors of Gen Z groups on the platforms. Wang et al [27] analyzed the effect of the application of AIGC advertising, AIGC increased the efficiency of advertising content production by 4.2 times, but 56% of users have concerns about the credibility and ethical risks of AIGC, and copyright disputes and operational thresholds are also challenges in the application of AIGC technology. Under the structure of "problem orientation-theoretical construction-empirical validation", Yang [28] reveals that consumers' negativity towards AIGC advertisements can be improved through the dual regulation mechanism of algorithmic transparency and brand reputation. Gu et al [29] focused on consumer acceptance of AIGC ads, where consumers' perceived weirdness reduces the acceptance of AIGC ads, but more realistic and imaginative AIGC ads reduce this weirdness. However, Chen and Lv [30] pointed out that AIGC is efficient and quality for e-commerce copywriting and ad generation, but may lead to problems such as homogenization and lack of emotion in the generated copy, which requires manual review and intervention to improve the overall quality.

In order to generate high-quality AIGC personalized advertisements in the context of Generation Z, a generative adversarial network-based AIGC personalized advertisement generation strategy model (VGG16-GAN) is proposed, which consists of an embedding network (VGG16), and a layout generation network (GAN), where the embedding network is responsible for the extraction of features and the layout generation network is responsible for the generation of AIGC personalized advertisements. On this basis, in order to realize the optimization of the dissemination effect of AIGC personalized ads, a recommendation graph neural network model (GNN-Adam) is designed for this purpose, and with the help of the Mean of Error (MAE) method, checking the whole rate, and checking the accurate rate, the practical effectiveness of this research content is verified, aiming at the comprehensive realization of the generation strategy and dissemination effect optimization of AIGC personalized ads for generation Z.

2 AIGC Personalized Ad Generation and Communication Effect Optimization

2.1 AIGC Personalized Ad Generation Model

2.1.1 Embedded network design (VGG16)

The embedding network is intended to train on visual and attribute representations of AIGC personalized advertisement images and their corresponding attributes, which will guide the creation of personalized AIGC advertisements. Personalized advertisement images along with attribute information are considered to be input data in this research, out of which visual and attribute feature embeddings are obtained using specific image and attribute encoders respectively. These two representations are then combined through two fully connected layers to create a 128 dimensional latent vector y that will be used to control the behavior of the generative network.

To encode an AIGC personalized advertisement image, the visual representation of a given advertisement image is initially encoded using a pre-trained VGG16 network. The output of the last convolutional layer, i.e., 8×8×256, is used as the feature map of the personalized advertisement image. This representation is then subjected to spatial global average pooling to produce a 256-dimensional vector, which is then input into three fully connected layers to produce a 256-dimensional visual embedding of the AIGC personalized advertisement image.

The encoding of attributes related to AIGC personalized advertisements: Four design-related attributes are included in this study: advertisement style, target audience, product category, location of the advertisement subject, and position of the primary and secondary slogan text in the entire advertisement image. The ad style is an important factor in personalized AIGC advertisement creation since it defines how the advertisement will be portrayed. Target audience refers to the set of people that the advertisement subject is aimed at. Product category is the kind of commodity that the advertising subject represents. The spatial data of the advertisement subject, as well as the position of the main and secondary banners, depict the location of these visual and textual elements in the advertisement image.

2.1.2 Layout Generative Network Design (GAN)

In order to make the AIGC personalized advertisement generation strategy more suitable for Generation Z, this paper inputs the 128-dimensional vector y embedded in the network as conditional information into the layout network and sends it to the encoder, generator, and discriminator so that (1) the encoder E can induce the distribution $p(\hat{z} \mid x, y)$ to map the layout example x from the actual layout distribution $p(x)$ to the feature space conditional on y, (2) Generator G can induce the distribution $q(\hat{x} \mid z, y)$ to map examples from the previous distribution $q(z)$ to the layout space conditional on y, and discriminator D learns to recognize input joint pairs conditional on y. Connecting y directly to the generator G as an input to G is applied to the encoder E and the discriminator D, while replicating y along the spatial dimensions to form a $60 \times 45 \times 128$ feature map. Then, this paper connects this function graph with x or $\hat{x}$ as input to D and connects it to the fourth layer of E.

2.1.3 Overall framework of the model

In order to create high-quality AIGC customized ads within the Generation Z environment, this research will attempt to come up with a model that has high learning capability to accommodate more sophisticated design variations. Under this consideration, a generative adversarial network approach to AIGC personalized advertisement creation, specifically VGG16-GAN, is suggested. The model trains the conditional distribution of a particular visual layout along with design variables including advertising style, target audience, and other related variables and subsequently samples to synthesize several layout outputs under these conditions. As shown in Figure 1, the framework consists of two modules: an embedding module that uses VGG16 and a layout generation module that uses GAN. The embedding module receives visual data in the form of images and textual data in the form of attribute data and passes them through the layout generation module. The latter can capture the pattern of distribution of layouts that indicate significant variation patterns and extract higher-level representations to fulfill the requirements of generating AIGC personalized advertisements.

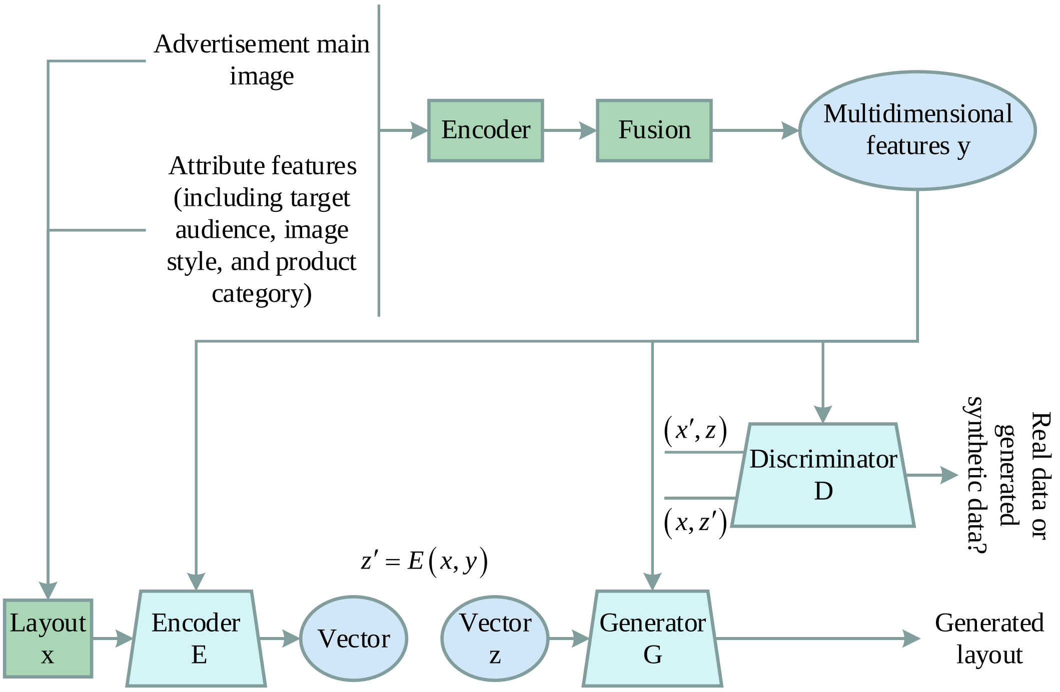

Figure 1: Model structure

2.1.4 Loss function

The loss terms of the generator G and discriminator D used in this study are given by:

$$L_{GAN}^{D} = \frac{1}{2}(D(x, E(x, y), y) - 1)^2 + \frac{1}{2}(D(G(z, y), z, y))^2 \tag{1}$$

$$L_{GAN}^{G} = \frac{1}{2}(D(G(z, y), z, y) - 1)^2 \tag{2}$$

In order to enhance the quality of the images two additional elements are added to the objective, which are the reconstruction loss L_{rec} and the KL divergence term L_{KL}:

$$L_{rec} = \left\| x - G(E(x, y), y) \right\|^2 \tag{3}$$

$$L_{KL} = D_{KL}\left(p\left(\hat{z}^{*} \mid x, y\right) \| q(z) \right) \tag{4}$$

where D_{KL} is the KL variance. Also, to produce diversity in layout and add loss $L_{variety}$ to the loss function to represent the diversity:

$$L_{variety} = \min_{k \in 1,2,\ldots,K} \left\| x - G\left(z^{k}, y\right) \right\|^2 \tag{5}$$

where k is a hyperparameter. Then, the loss expressions of the generator and encoder have the form:

$$L_G = L_{GAN}^{G} + L_{rec} + L_{variety} \tag{6}$$

$$L_E = L_{rec} + L_{KL} \tag{7}$$

2.1.5 Model realization

In order to improve the AIGC personalized advertisement generator plan to meet the needs of Generation Z, the generator output is transformed into a starting design (60×45×3) by eliminating the filler pieces and converting every value to 0 or 1. A post-processing step is then added to smooth element boundaries and address small positioning errors in elements. Namely, individual elements are initially isolated based on the initial layout by combining connected-component indicators. In order to minimize irregular image edges, a series of morphological image processing operations is employed to approximate the boundaries with higher accuracy. Small misalignment of some elements is subsequently fixed by using top, bottom, left and right alignment processes. If the difference between the top boundary coordinates of element boxes is less than two cells, the elements are grouped accordingly in order to align them at the top. The lowest top boundary of each box is set to the top boundary of all boxes within the group to provide enough space between the elements. Bottom, left and right alignment work similarly.

The proposed method of generating a matching layout using the attribute information of the input image with the advertisement image itself is also introduced in the study. Depending on the style of the input advertisement, the sample of the position of the advertising subject and of the descriptor in the full image is performed using the data set. On every attribute combination sample, 32 layouts are randomly created. They are filtered by examining whether the aspect ratio of the advertising subject in the created layout can be matched to that of the input image; if the difference between them is too large, i.e., greater than 1.34 or less than 0.65, they are eliminated. In order to enhance diversity amongst the remaining candidates, the Maximum Marginal Relevance (MMR) criterion is employed to select layouts. To be more precise, the discriminator output is considered as the quality score of every generated layout, and the L2 distance is calculated in the feature space to measure the similarity between layouts. First, the layout with the highest quality score is chosen and included into the ranked list L. For each other's layouts t, this paper calculates the ranking score: $r_t = Q_t - \max_{e \in L} S(t,e)$, where Q_t is the quality score of t and $S(t,e)$ is the similarity score between t and e. The layouts that have the highest ranking values are then inserted into L, one by one. This iterative method is used to rank all the candidate layouts by both quality and diversity and return the final three best layouts as the generated results.

2.2 AIGC personalized ad recommendation graph neural network model

AIGC ad recommendation scenario and graph neural network model for users in the same area in the context of Generation Z. This paper argues that the consumption level of people in some small cities is different from that existing in large and medium-sized cities. According to the user's resident city information and city level to recommend AIGC advertisements, this paper proposes an AIGC personalized advertisement recommendation graph neural network model (GNN-Adam). That is, on the basis of the base neural graph cooperative model, the location information dimension of the user is added. This information dimension is represented in the dataset as the user's city and the level of the user's city. By further fusing the user information, the items are recommended. In order to further improve its AIGC personalized advertisement dissemination effect, Adam's algorithm optimizes the prediction model and updates the model parameters.

2.2.1 Embedding layer

AIGC personalized advertisement recommendation graph neural network model embedding layer is usually used as the first layer in natural language processing to convert discrete, high dimensional data into dense, low dimensional data to simplify the data, which can achieve a reasonable fitting effect with fewer parameters and avoid fitting unimportant information. In AIGC personalized ad recommendation, embedding techniques usually include matrix decomposition based embedding, Word2Vec based embedding, directed graph based embedding and embedding using deep neural networks.

Firstly, the interaction data of users and items are received at the layer and the parameter matrix is built. For user u or item i, first use one-hot coding for vector representation to obtain embedding representation $e_u \in R^d$ and $e_i \in R^d$ of size d, which is used to construct the parameter matrix for embedding lookup, the matrix is as follows:

$$E = \left[e_{u1}, e_{u2}, \dots, e_{uN}, e_{i1}, e_{i2}, \dots, e_{iM}\right] \tag{8}$$

After processing by the embedding layer, the total number of users, the total number of items, and this matrix can be counted; in subsequent processing of the model, the matrix is used again to learn the interaction between users and items.

2.2.2 Message Embedding Layer

For defining the interaction between a user and an AIGC personalized advertisement recommendation item and the corresponding attenuation coefficient to define the message encoding function for describing a message $m_{u\leftarrow i}$ transmitted by an AIGC personalized advertisement recommendation item i to a user u. Namely:

$$m_{u\leftarrow i} = ff\left(e_i, e_u, p_{ui}\right) \tag{9}$$

$$f\left(e_i, e_u, p_{ui}\right) = \frac{1}{\sqrt{|N_u||N_i|}}\left(W_1 e_i + W_2\left(e_i \odot e_u\right)\right) \tag{10}$$

$$p_{ui} = \frac{1}{\sqrt{|N_u||N_i|}} \tag{11}$$

where the encoding function of the message is f, e_i, e_u are used as inputs to the encoding function and p_{ui} is used to control the decay coefficients of each edge in each AIGC personalized advertisement propagation; in p_{ui} N_u, N_i are the nodes of the next hop for the user u and AIGC personalized advertisement recommendation item i, respectively, W_1, W_2 are the learnable weight matrices. In addition, the symbol $\odot$ denotes the same-or operation, i.e., $F=1$ when two input variables have the same value. In order to make the training easier and more efficient, the messages are normalized when they are constructed.

In addition, the message $m_{i\leftarrow u}$ flowing from user u to item i can be defined according to the above rule. Namely:

$$m_{i \leftarrow u} = f\left(e_u, e_i, p_{iu}\right) = \frac{1}{\sqrt{|N_i||N_u|}}\left(W_1 e_u + W\left(e_u \odot e_i\right)\right) \tag{12}$$

Message aggregation is targeted at individual users or AIGC personalized advertisement recommendation items, using message construction to enable messages to propagate among users and AIGC personalized advertisement recommendation items related to them, and to update the corresponding embedding representations by combining their own characteristics. Then, after message construction, user u or item i needs to aggregate the messages $m_{u \leftarrow i}$ or $m_{i \leftarrow u}$ propagated from the neighboring nodes for updating its own embedding representation. The aggregation function of Eq. (12) is used to obtain the embedding representation for updating user u. i.e:

$$e_u^{(1)} = Leak\,\mathrm{Re}\,LU\left(m_{u \leftarrow u} + \sum_{i \in N_u} m_{u \leftarrow i}\right) \tag{13}$$

where $e_u^{(1)}$ denotes the meaning of the embedding representation of user u obtained by updating after the first message embedding layer; $m_{u \leftarrow u}$ denotes the meaning of the self-connection of user u, which preserves the information of the original feature; and N_u denotes the meaning of the neighboring nodes of user u node. In addition, the embedding representation of the updated AIGC personalized advertisement recommendation item i can be obtained according to the above rule:

$$e_i^{(1)} = Leak\,\mathrm{Re}\,LU\left(m_{i \leftarrow i} + \sum_{i \in N_i} m_{i \leftarrow u}\right) \tag{14}$$

After completing one AIGC personalized advertisement recommendation propagation, the first-order interaction relationship between the nodes can be obtained. In addition, multiple message embedding layers can be stacked to obtain higher-order interactions between nodes. By stacking k message embedding layers, a user or an AIGC personalized advertisement recommendation item can obtain the messages propagated from its k hop neighbors. Then at the k th step, the embedding of user u is represented as:

$$e_u^{(k)} = Leak\,\mathrm{Re}\,LU\left(m_{u \leftarrow u}^{(k)} + \sum_{i \in N_u} m_{u \leftarrow i}^{k}\right) \tag{15}$$

$$m_{u \leftarrow i}^{(k)} = p_{ui}\left(W_1^{(k)} e_i^{(k-1)} + W_2^{(k-1)}\left(e_i^{(k-1)} \odot e_u^{(k-1)}\right)\right) \tag{16}$$

$$m_{u \leftarrow u}^{(k)} = W_1^{k} e_u^{(k-1)} \tag{17}$$

where $m_{u \leftarrow i}^{(k)}$ is the message propagated to the user by the k th hop neighbor, and p_{ui} is as in equation (10). W_1, W_2 are the learnable weight matrices.

In addition, the embedding representation of item i at the k th step can be obtained according to the above rule as:

$$e_i^{(k)} = Leak\,\mathrm{Re}\,LU\left(m_{i\leftarrow i}^{(k)} + \sum_{i\in N_i} m_{i\leftarrow u}^{k}\right) \tag{18}$$

Then, the matrix representation of the above equation is:

$$E^l = Leak\,\mathrm{Re}\,LU\left\{\left(\mathcal{L}+I\right)E^{(l-1)}W_1^{(l-1)} + \mathcal{L}E^{(l-1)} \odot E^{(l-1)}W_2^{(l-1)}\right\} \tag{19}$$

$$\mathcal{L} = \begin{bmatrix} 0 & R \\ R^T & 0 \end{bmatrix} \tag{20}$$

where R is the matrix of user interactions with AIGC's personalized ad recommendation items. I is the unit matrix.

2.2.3 Forecasting layer

After K layers of message embedding layers, K vectors about user u or item i can be obtained, and since these K vectors are all obtained in different layers, representing messages propagated from different nodes, they have different contributions in responding to user preferences. By concatenating these K vectors, the final representation of user u and AIGC personalized advertisement recommendation item i is obtained. I.e:

$$e_u^* = concat\left(e_u^{(0)}, e_u^{(1)}, e_u^{(2)}, \cdots, e_u^{(K)}\right) \tag{21}$$

$$e_i^* = concat\left(e_i^{(0)}, e_i^{(1)}, e_i^{(2)}, \cdots, e_i^{(K)}\right) \tag{22}$$

The vectors of users u and items i are multiplied using dot product operations to obtain the final predicted values. It is used to estimate the user's preference for items.

$$\hat{y}(u,i) = e_u^{*T} e_i^* \tag{23}$$

2.2.4 Model optimization

After completing the higher-order propagation of messages to obtain the user's preferences for the recommended items of AIGC personalized advertisements, the need to obtain reasonable predictions requires appropriate adjustment of the model by using a loss function commonly used in recommendation models paired with the BPR. using this loss function is able to take into account the relative order of the interactions with the observed and unobserved user items. In addition, the Adam function is used to optimize the prediction model and update the model parameters. Namely:

$$Loss = \sum_{(u,i,j)\in O} -\ln\sigma\left(\hat{y}(u,i) - \hat{y}(u,j)\right) + \lambda\left\|\Theta\right\|_2^2 \tag{24}$$

$$O = \left\{(u,i,j) \middle| (u,i) \in R^+, (u,j) \in R^-\right\} \tag{25}$$

$$\Theta = \left\{E, \left\{W_1^k, W_2^k\right\}_{k=1}^K\right\} \tag{26}$$

where R^{+} denotes observed interactions; R^{-} denotes unobserved interactions; and σ denotes the sigmoid function.

3 Analysis of empirical studies

3.1 AIGC Personalized Ad Generation Effectiveness Analysis

3.1.1 Subjective evaluation

(1) Questionnaire Setting

The questionnaire that was utilized in the study has two sections. The first section is an assessment of the performance of GAN-based image generation in respect to AIGC personalized advertising products. Three questions are included, and every question covers four image evaluation conditions, including category diversity, style diversity, silhouette completeness of clothes, and image clarity. The evaluators are required to evaluate, using the Fashion-MNIST dataset, how important it is to have these four indicators when generating images to be used in subsequent experiments in Question 1. Topic 2 requires the evaluator to score the effect of personalized advertising product images generated by the GAN model based on the above indicators, and topic 3 requires the evaluator to score the effect of personalized advertising product images generated by the model VGG16-GAN by comparing the images generated by the VGG16-GAN model. The second part scores the layout effect of personalized advertising product images based on VGG16-GAN, there are 4 questions and 3 evaluation indexes are set up, which are layout reasonableness, layout beauty, and layout neatness, and the evaluators must assess the quality of the layout by looking through the images.

(2) Data Analysis

a) Evaluation of advertising image quality

Table 1 shows the advertising image effect scores given by the GAN model. The scoring scale is 1-10 and is based on the decreasing quality of performance with five levels of scoring, with 1-2 points indicating very poor performance, 3-4 points indicating poor performance, 5-6 points indicating average performance, 7-8 points indicating good performance, and 9-10 points indicating very good performance. As per the questionnaire findings, the average scores of the four indicators, sorted in descending order, are 7.625 on category diversity, 7.545 on silhouette completeness, 7.533 on style diversity, and 6.905 on image clarity. It can be seen that the images of the products that were obtained by the GAN model have quite clear category differences but their visual clarity is not so good. The proportions of scored images rated 7 or higher on each of the four measures are 79.56 percent, 76.64 percent, 76.64 percent, and 56.09 percent respectively indicating that the aggregate quality of the advertising images created using the model is fairly good.

Table 1: The effect score of the advertising image generated by the GAN model

Indicators	Rating level (%)					Average score
	1-2	3-4	5-6	7-8	9-10	
Category diversity	0	2.87	17.57	47.12	32.44	7.625
Diversity of styles	0	2.87	20.49	52.87	23.77	7.533
Contour completeness	0	5.79	17.57	44.06	32.58	7.545
Image clarity	2.87	2.87	38.17	35.15	20.94	6.905

Table 2 presents the effect scores of advertisement images produced by the CT-GAN model. The average values of the four assessment items in descending order are 7.845 (contour completeness), 7.705 (style diversity), 7.611 (category diversity) and 7.508 (image clarity). The percentages of samples with scores greater than 7 on these indicators are 76.59,88.42,82.43 and 76.64 respectively. Such results point to the fact that the CT-GAN model is quite effective in the generation of advertising images. As compared to the mean scores of every criterion by the GAN model, CT-GAN enhances the scores in all the indicators apart from category diversity. To be more precise, the increase in style diversity is 5.79 percent, contour completeness 11.78 percent and image clarity 20.5 percent which means that the quality of the produced images has been improved.

Table 2: Advertising images generated by the VGG16-GAN model

Indicators	Rating level (%)					Average score
	1-2	3-4	5-6	7-8	9-10	
Category diversity	0	5.79	17.57	49.52	27.12	7.611
Diversity of styles	0	0	17.57	49.52	32.91	7.705
Contour completeness	0	5.79	5.79	52.87	35.55	7.845
Image clarity	0	8.76	14.65	44.06	32.53	7.508

b) Evaluation of advertisement layout effect

The evaluators evaluated the advertisements by considering three different perspectives of visual presentation, i.e., rationality of the layout, aesthetics of the layout, and neatness of typography. These dimensions were scored using the same criteria as in the first part of the questionnaire, where 1-2 points meant a very bad effect on the layout, 3-4 points indicated a bad effect on the layout, 5-6 points suggested an average effect on the layout, 7-8 points represented a good effect on the layout and 9-10 points stood for a very good effect on the layout. The results of the evaluations of GAN-generated layouts are given in Table 3, and the results of the evaluations of VGG16-GAN layouts are given in Table 4. As per the tabulated information, GAN is inferior to VGG16-GAN in terms of layout rationality, visual aesthetics, and typographic neatness, with mean scores of 7.844, 7.547 and 8.346, respectively. These results clearly indicate that the suggested model is highly effective in enhancing the layout behavior of AIGC personalized advertisement generation.

Table 3: Evaluation of GAN layout image effects

Indicators	Rating level (%)					Average score
	1-2	3-4	5-6	7-8	9-10	
Layout rationality	0	2.47	11.68	55.79	30.06	7.537
Aesthetic layout	0	5.79	20.49	41.09	32.63	7.317
Layout neatness	0	2.47	20.54	35.24	41.75	7.537

Table 4: Evaluation of VGG16-GAN layout image effects

Indicators	Rating level (%)					Average score
	1-2	3-4	5-6	7-8	9-10	
Layout rationality	0	0	14.35	52.47	33.18	7.844
Aesthetic layout	0	0	32.17	35.24	32.59	7.547
Layout neatness	0	0	11.38	35.24	53.38	8.346

3.1.2 Objective evaluation

PSNR is an effective tool that can be used to compare the grayscale disparities on the pixel level between a produced image and its corresponding ground-truth image, thus being an adequate measure of generation quality. SSIM builds on the limitations of PSNR by incorporating structural sensitivity similar to human visual perception and measures image quality based on the correlation of the pixel distribution between two image sets, which helps alleviate the shortcoming of PSNR in ignoring visual structure. As PSNR and SSIM are complementary in quality measurement and have both been extensively used in image evaluation studies, the present study chooses these two objective measures to evaluate the effectiveness of the AIGC personalized advertisement generation strategy. In the implementation based on Python, the image processing libraries that are used include Pillow and scikit-image. The reference image in the dataset and the generated output are supplied to the evaluation model to get PSNR and SSIM values. PSNR represents the difference between the generated outcome and the original image and the size of this number means the amount of distortion: the more distorted the image, the smaller the PSNR, and therefore the poorer the image quality. The results of the PSNR comparison are given in Fig. 2 and the SSIM comparison is given in Fig. 3. Compared with GAN, the VGG16-GAN performs significantly better on PSNR and SSIM, with PSNR values falling within the range of 27.11-34.594 and SSIM values within the range of 0.674-0.935, indicating that VGG16-GAN is superior to GAN in terms of AIGC personalized advertisement generation to Generation Z.

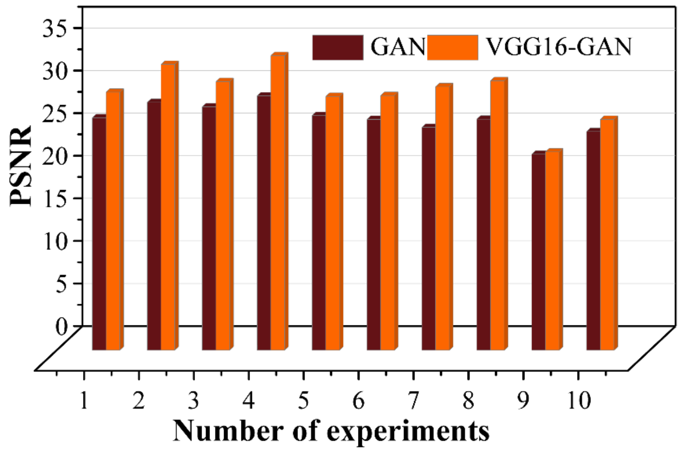

Figure 2: Comparative analysis of PSNR values

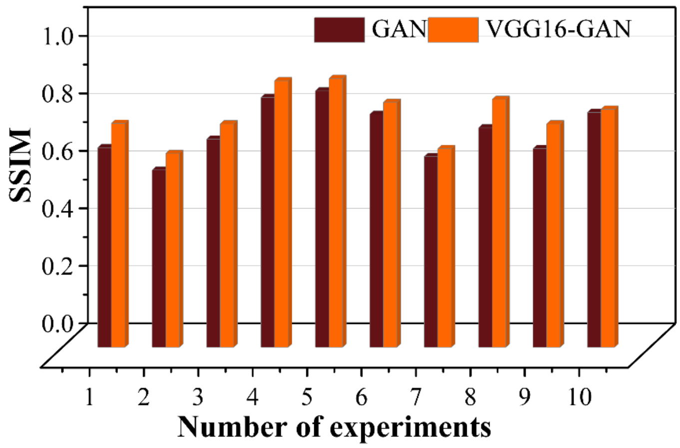

Figure 3: Comparative analysis of SSIM values

3.2 Optimization analysis of communication effectiveness

A model that is able to optimize the effect of AIGC personalized advertisement dissemination is most important to be able to create a model that meets the user's interest and uses an accurate recommendation algorithm to combine the user's interest with the advertisement topic, and at the same time is able to change as the user's interest is shifted. In this paper we propose a personalized advertisement recommendation graph neural network model that can improve the precision and accuracy of AIGC personalized advertisement dissemination, which will be verified by the experiments in this section.

3.2.1 Introduction to the experimental data set

The dataset was collected for a total of 12 months from 2014 to 2015, and we found that each record includes the user ID, the item ID, the rating value, and the time of the user's rating. The user's basic information records are accompanied by a user ID as a unique identifier of the user in the data set. Then there are some basic information about the user, mainly including the user's occupation and age information.

3.2.2 Division of the data set

In this section of the experiment, as we need to use the training set and test set. Therefore it is necessary to divide our data set into two parts, one part is used for the training of the model called the training set and the other part is used as a validation result called the test set to verify the performance of the experiment. The dataset is divided into 8 parts using the script tool for slicing the dataset, and the sliced dataset is divided into 8 pairs of training and test sets, each pair of training and test sets represents a single slice, which splits the original dataset into two according to the 80%/20% principle. One cut can only guarantee that the test set obtained is 20% of the original scoring dataset, so it is necessary to cut a total of 8 times, and to ensure that the test set obtained from each cut is a subset of the original scoring dataset that does not intersect. After slicing the set, when doing experiments in order to be able to produce balanced results on the entire training set, you should run on all 8 pairs of sets after slicing once, and take the average of the 8 results.

3.2.3 Evaluation methodology

After the completion of any recommendation model, it is necessary to evaluate its recommendation quality, which is an essential part. And in different environments, different recommendation models or different recommendation contents, the evaluation criteria and methods of the model recommendation quality are also different. The following introduces several methods commonly used in recommender systems.

(1) Mean error method (MAE)

The recommendation model scores the unscored AIGC personalized ads to derive the scoring value, and there is a certain difference between this predicted value and the real value.MAE is to calculate the difference between the two, and then take the absolute value.The absolute value of MAE is small, indicating that the predicted scoring value is close to the real value, and the accuracy of the recommendation model is relatively high.The calculation method of MAE is as follows:

$$MAE = \frac{\sum_{i \in U, j \in I} \left| P_{ij} - r_{ij} \right|}{n} \tag{27}$$

where p_{ij} represents the predicted rating value of user i on $Item_j$ through the recommendation model, and r_{ij} is the real rating of user i on AIGC personalized advertisement j. U is the set of users, I is the set of AIGC personalized advertisements to be recommended, and n is the total number of ratings of AIGC personalized advertisements.

(2) Finding rate

The check rate, also known as the recall rate, is the ratio of the number of correctly recommended AIGC personalized ads to the total number of test sets. We assume that the test set of users i is T_i, the set of correctly recommended items is P_i, and n is the total number of users. Then the formula for checking the full rate is:

$$recall = \frac{1}{n}\sum_{i=1}^{n}\frac{|T_i \cap P_i|}{|T_i|} \tag{28}$$

(3) Accuracy rate

Check rate, also known as the accuracy rate, is the ratio of the number of correctly recommended items in the Top-N when the Top-N is recommended. The way to calculate the check rate is as follows:

$$precision = \frac{1}{n}\sum_{i=1}^{n}\frac{|T_i \cap P_i|}{N} \tag{29}$$

In the formula, N denotes the number of AIGC personalized advertisement items recommended by the model, and n is the total number of users.

3.2.4 Analysis of results

In this subsection, based on the AIGC personalized advertisement recommendation graph neural network model (GNN-Adam) proposed in the previous article section, in the experiment, we use the top-N recommendation and the number of AIGC personalized ads recommended to the user each time is 8. The MAE result is shown in Fig. 4, the Recall result is shown in Fig. 5, and the Precision result is shown in Fig. 6. Based on the values of MAE, Recall, and Precision results, it can be seen that compared with the traditional graph neural network recommendation model, the AIGC personalized advertisement recommendation graph neural network model (GNN-Adam) has a better priority, and the MAE, Recall, and Precision results are distributed as 0.011~0.048, 0.900~0.939, 0.901~0.938, i.e., it shows that the introduction of Adam algorithm can improve the practical application effectiveness of AIGC personalized advertisement recommendation model, which also reflects the optimization effect of Adam algorithm. Overall, the model in this paper is able to better understand the interests and needs of users and provide them with personalized advertisement recommendations. Selecting the Adam algorithm and training and optimizing the model makes the ad recommendation more accurate and effective. By implementing this technology, advertisers can accurately deliver advertising messages to target users, improving the accuracy and click-through rate of advertisement dissemination. At the same time, consumers are able to access advertising content that better matches their personal interests and needs, providing a more valuable advertising experience. Personalized advertisement dissemination technology based on GNN-Adam has a broad application prospect in providing accurate advertisement recommendation and satisfying consumers' needs.

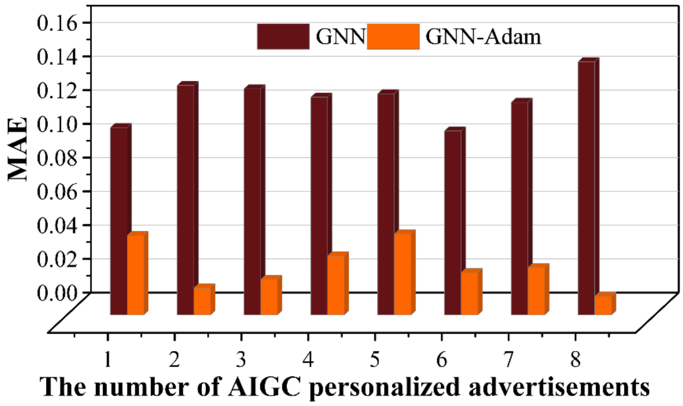

Figure 4: MAE results

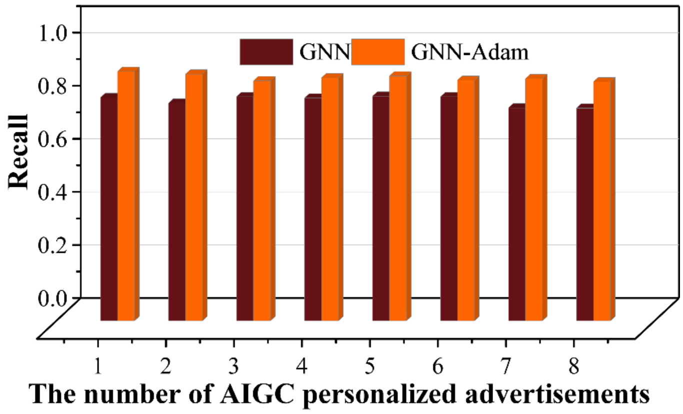

Figure 5: Recall results

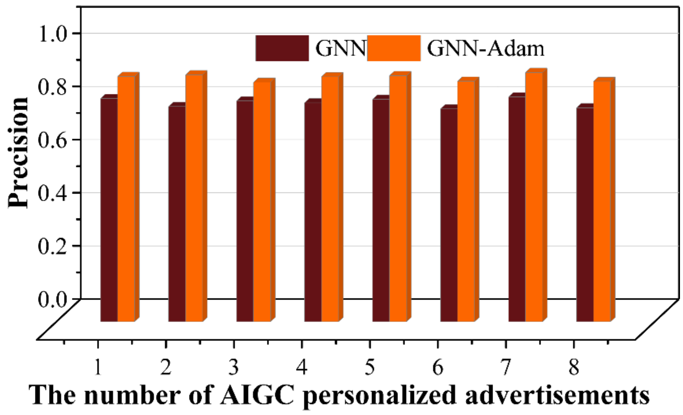

Figure 6: Precision results

4 Conclusion

Generation Z is called “Net Generation”, “Internet Generation”, “Second Yuan Generation”, “Digital Media Natives” and so on. In this context, it is found that the traditional AICC personalized ad generation strategy and communication effect are not satisfactory. In this regard, this paper realizes the optimization of AICC personalized advertisement generation strategy and dissemination effect by constructing AICC personalized advertisement generation model (VGG-GAN) and AICC personalized advertisement recommendation graph neural network model (GNN-Adam).

(1) Compared with GAN, VGG16-GAN performs better in terms of layout reasonableness, layout aesthetics, and typographic neatness, with values of 7.844, 7.547, and 8.346, which well demonstrates the effect of VGG16 on the optimization of AIGC personalized advertisement generation strategy based on GAN.

(2) Compared with GNN, GNN-Adam has a higher priority in the dissemination effect of AIGC personalized advertisements, and its values are distributed as 0.011-0.048, 0.900-0.939, and 0.901-0.938, which shows the optimization effect of Adam algorithm on the dissemination effect of AIGC personalized advertisements.

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Mengting Guan was born in Henan, China, in 1989. She received her Bachelor's degree from Tianjin Foreign Studies University in 2011, her Master's degree from Pusan National University (South Korea) in 2013, and her Doctorate from Cheongju University (South Korea) in 2021. She has published seven academic papers to date. Her current research interests focus on the application of intelligent media technology and network communication.

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