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# An Effectiveness Assessment and Optimization Method for Artificial Intelligence-Assisted Visual Communication Design

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ABSTRACT

The emergence of artificial intelligence has changed the traditional visual communication design mode to a great extent. This study aims to conduct an in-depth theoretical discussion and empirical analysis of the intersection of artificial intelligence and visual communication design, for the generative design application of AI technology in visual communication design, based on the AttnGAN algorithm, designing the adaptive word attention module and feature alignment module, constructing the ACMA-GAN text image generation model, and evaluating its visual communication design by combining quantitative and qualitative experiments to assess its The effect of ACMA-GAN on visual communication design is evaluated by combining quantitative and qualitative experiments. Combined with OLS algorithm, the empirical analysis of the effect of AI technology on visual communication design is carried out, and the ACMA-GAN model achieves excellent performance in the evaluation of assisted visual communication design, with the BLEU-3 and CIDEr scores higher than the next highest scores by 7.48% and 7.35%, and the average scores of each qualitative index are over 4.5, which indicates the feasibility and good utility of AI technology in assisting visual communication design. AI technology can positively act on visual communication design through image recognition and analysis, image generation and creation assistance, personalized design and workflow optimization.

*Keywords:* artificial intelligence, AttnGAN, attention module, text image generation, OLS, visual communication design

## 1. Introduction

Artificial Intelligence (AI) is a new technological science that researches and develops theories, methods, technologies and application systems used to simulate, extend and expand human

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intelligence. In recent years, with the breakthrough of deep learning and other technologies, AI has been more and more widely applied in various fields [1-4]. Visual communication design refers to the design that expresses and conveys information through visual media. The history of this form of design can be traced back to ancient art forms such as murals and sculptures. With the development of technology, the application scope of visual communication design is expanding, including advertising, brand image design, digital media design and other fields [5-8]. In the field of visual communication design, the rapid development of artificial intelligence provides designers with more possibilities of creation and expression, and at the same time prompts them to keep learning and practicing to keep up with the times [9-12].

The application of artificial intelligence in visual communication design mainly includes the following aspects, automated design, i.e., artificial intelligence can automatically carry out graphic design, typography and color matching through machine learning and deep learning and other technologies to improve the design efficiency [13-16]. Data-driven design, that is, artificial intelligence can use a large amount of data for analysis and prediction, to provide more targeted design recommendations for industrial designers. Intelligent interaction design, i.e. AI can help designers realize more intelligent interaction design and improve user experience [17-20]. The positive impacts of AI on visual communication design mainly include: improving design efficiency, i.e., AI can help designers quickly complete repetitive tasks, allowing them more time for creative design [21-23]. Enhance the design effect, i.e., AI can provide designers with better design suggestions and improve the design effect through data analysis and prediction [24-26]. Broaden the design field, i.e., the application of AI makes the field of visual communication design further broadened, such as virtual reality, augmented reality and other fields. Of course with the existence of lack of innovation, data privacy and security, technology dependence and other problems [27-30].

The article discusses in detail the application of artificial intelligence in visual communication design from multi-dimensions, starting from one of the generative design and creation applications, and designing a text image generation model based on generative adversarial networks. Based on AttnGAN algorithm, adaptive word attention module and feature alignment module are designed, the former uses image features and sentence features to modify word information, and the latter utilizes an excellent image classification model to guide the discriminator to extract more image features, and constructs ACMA-GAN model. Ablation experiments and algorithm comparison experiments are conducted on the MSCOCO dataset to evaluate the image design effect of the model from a quantitative perspective. Then, the scores of each dimension of the model-generated images are obtained in the form of questionnaires to comprehensively evaluate the visual communication design effect with the assistance of artificial intelligence in both quantitative and qualitative dimensions. Subsequently, the research hypothesis is proposed, and the OLS algorithm is used to realize the model construction, and the path of the influence of the use of AI technology on visual communication design is explored through correlation analysis and model mechanism test. On this basis, optimization methods for AI-assisted visual communication design are further explored to boost the high-quality development of visual communication design.

## 2. Application of artificial intelligence in visual communication design

As an important medium for information communication, the application of AI technology provides new tools and possibilities for visual communication design, which not only affects the innovation and efficiency of design, but also changes the way of design thinking. The application of AI in visual communication design is analyzed.

### 2.1. *Intelligent image processing and material innovation*

The image recognition technology of artificial intelligence realizes a deep understanding of image content through deep learning and neural networks, making the selection of materials for graphic design and brand design more intelligent and efficient. Designers are able to quickly acquire, process and apply all kinds of image resources with the help of AI tools, promoting the improvement of design quality.

### 2.2. *Personalized User Experience and Emotion Analysis*

Artificial intelligence technology gives virtual reality and augmented reality smarter, more personalized features to create unique experiences for users. Through deep learning and sentiment analysis, VR and AR applications are able to understand users' behaviors, emotions, and preferences, enabling the shaping of personalized user experiences. Intelligent virtual environments are designed to be customized based on user interests, while intelligent avatars are able to sense and respond to user dynamics. In augmented reality, AI provides more accurate and real-time information for AR navigation and location services, while providing personalized, multilingual information overlays through visual recognition and real-time translation.

### 2.3. *Generative design and the creative process*

Artificial Intelligence's generative design capabilities are injecting new ways of creating visual design. Technologies such as Generative Adversarial Networks (GANs) enable computers to generate realistic artworks. Generative Adversarial Networks have a unique structure of generators and discriminators, providing designers with a whole new dimension of creativity. The generator is responsible for creating the image, while the discriminator evaluates the realism of the image. The two work against each other and progress together to make the generated images more realistic and creative. In the past, design required a lot of time to create virtual prototypes that simulated the actual form of the product. Nowadays, designers only need to fine-tune the parameters of the generator and discriminator to quickly generate virtual prototypes that simulate the appearance, texture and shape of the product. Technologies such as Generative Adversarial Networks provide richer and smarter design tools for visual design, driving innovation and development in the design field.

## 3. AI-assisted visual communication design and effect evaluation

Based on the generative design and creation application of AI in visual communication design in the previous chapter, this chapter utilizes GAN networks to construct a textual description generative image model for the intelligent design process of visual communication, and evaluates the effectiveness of AI-assisted visual communication design through experiments and surveys.

### 3.1. *Text Image Generation Model*

This section describes the Adaptive Cross-Modal Attention-based Text-to-Image Generative Model (ACMA-GAN), which uses AttnGAN as a baseline model.

3.1.1. AttnGAN. Attentional Generative Adversarial Network Model (AttnGAN), allows attention driven multi-stage processing to refine the details of different sub-regions of an image by generating word vectors and sentence vectors through text encoder, which ultimately produces a detail rich image with a resolution of 256×256.

The AttnGAN model is mainly divided into two parts which are Attentional Generative Network and DAMSM. Where the first part principle is as follows:

The attention generation adversarial network has $m$ generator $(G_0, G_1.....G_{m-1})$, which takes the hidden state $(h_0, h_1......h_{m-1})$ as the input and is divided into $F_0, F_1, F_2$ stages of generation, the $F_0$ th stage generates a target of a quarter resolution image (64×64×3) according to the global characteristics, the $F_1$th stage uses the Attention mechanism to generate a target of half resolution (128×128×3), and the $F_2$th stage uses the Attention mechanism to generate a target of the same resolution image (256×256×3). Where the $F_0$-stage text goes through a text encoder to extract sentence features $\tilde{e}$ and word features $e \in \Re^{D\times T}$. $\overline{e}$ converted to conditional vectors $c$ after dimensionality reduction by CA operations. Conditional vectors $c$ are collocated with random noise $z \sim N(0, I)$ conforming to Gaussian distribution, and after a series of up-sampling operations, the implied features $h_0$ are outputted, where $h_0$ have been primed with the position and object information of the image. Where the generation process of the first image features is shown in Equation (1):

$$G(h_0) = G(F_0(z, F^{ca}(\overline{e}))) \tag{1}$$

The subsequent image generation process is shown in Equation (2), where $F^{attn}$ is to generate the context vectors of all the sub-regions, and $F^{attn}$ works as shown in Equations (3) and (4):

$$\hat{x}_i = G_i(h_i) \tag{2}$$

$$h_i = F_i(h_{i-1}, F_i^{attn}(e, h_{i-1})) \quad for \quad i = 1, 2, ......m-1 \tag{3}$$

$$F^{attn}(e, h) = (c_0, c_1, ..., c_{N-1}) \in \Re^{D\times N} \tag{4}$$

The input of $F_i^{attn}$ is the word matrix vector $e$ and the implied features $h_{i-1}(h \in \Re^{\hat{D}\times T})$ obtained in the previous stage, and the word vectors are converted into $\hat{D}$ dimensions through a product transformation in the fully connected layer, at which time the word vectors $e$ satisfy $e' = Ue(U \in \Re^{\hat{D}\times D})$, which is consistent with the dimensions of the image features to facilitate the calculation of similarity by the inner-product operation in the later stage. Each column in $h$ represents a sub-region of the image, and for the $j$th sub-region, all the word vectors in the sentence are used to represent it, so that the relevant word vectors should have a larger weight, and the irrelevant word vectors have a very small weight, and the result of the weighted sum of word vectors for each sub-region is called the context vector. The process of calculating the weights of each sub-region with all the word vectors and finally the context vector is shown in equation (5):

$$c_j = \sum_{i=0}^{T-1} \beta_{j,i} e_i', \quad where \quad \beta_{j,i} = \frac{exp(s_{j,i}')}{\sum_{k=0}^{T-1} exp(s_{j,k}')} \tag{5}$$

where $\beta_{j,i}$ represents the level of attention that the $i$ rd word receives when the $j$ nd region of the image is generated. $c_j$ represents the context vector of the $j$ th sub-region.

The final objective function of this module is equation (6), where $\lambda$ is the hyperparameter that measures both ends of the equation:

$$\mathrm{L} = \mathrm{L}_G + \lambda \mathrm{L}_{DAMSM}, \; where \; \mathrm{L}_G = \sum_{i=0}^{m-1} \mathrm{L}_{G_i} \tag{6}$$

3.1.2. Overall network structure. ACMA-GAN uses AttnGAN as a baseline, which contains a text encoder, an image encoder, a three-stage generator and three discriminators. The text encoder and image encoder are pre-trained Bi-LSTM and Inception-v3 models, the three stages of the generator generate images with 64, 128, and 256 resolutions, and the three discriminators discriminate the authenticity of each of these three images. The generator has three inputs, the first is a noise vector conforming to a Gaussian distribution, the second is a sentence vector, and the third is a word vector.The three discriminators in ACMA-GAN consist of convolutional and activation operations, and all of them contain two discriminative branches, one is the unconditional discriminative branch, and the other is the conditional discriminative branch.

3.1.3. Adaptive Word Attention Module. The traditional methods AttnGAN and DM-GAN fail to reduce the granularity difference between words and local features of images while maintaining the contextual semantic information of words.In this paper, we propose an adaptive word attention module for optimization.Firstly, a global average pooling is performed on the image features to obtain an image feature vector, which is of the same dimensions as the word and sentence vectors, and then the word feature vector, sentence feature vector and image feature vector are spliced together and input into a self-attention module for learning, and the self-attention formula is as follows:

$$o_j = v(\sum_{i=1}^{N} \beta_{j,i} h(x_i)), h(x) = W_h x, v(x) = W_v x \tag{7}$$

where $x_i$ represents the content vector before using self-attention and $o_j$ represents the content vector after using self-attention. $\beta_{j,i}$ represents the attention score between the $j$ th content vector and the $i$ th content vector, $W_h$ and $W_v$ are the weights of the fully connected layer. The formula for $\beta_{ji}$ is as follows:

$$\beta_{j,i} = \frac{\exp(s_{i,j})}{\sum_{i=1}^{N} \exp(s_{i,j})}, \text{where } s_{i,j} = f(x_i)^T g(x_j), f(x) = W_f x, g(x) = W_g x \tag{8}$$

where $x_i$ and $x_j$ represent the $i$ rd and $j$ th content vectors, and $W_f$ and $W_g$ are the weights of the fully connected layer.

Then the obtained new word features along with the image features are fed into a word attention module to compute the word-content features and finally the original image features along with the word-content features are used as inputs for the next stage. The formula for calculating the word-content features is as follows:

$$c_j = \sum_{i=0}^{T-1} \beta_{j,i} e_i, \text{where} \beta_{j,i} = \frac{\exp(s_{j,i})}{\sum_{k=0}^{T-1} \exp(s_{j,k})}, s_{j,i} = v_j \cdot e_i \tag{9}$$

where $c_j$ represents the word-content feature vector at the $j$ nd pixel position, $\beta_{\mu t}$ represents the attention score between the local feature at the $j$ th pixel position and the $i$ th word, and $e_i$ represents the $i$ th word.

3.1.4. Feature alignment module. In order to improve the feature extraction capability of the discriminator and thus facilitate better performance of the discriminative network, a feature alignment module is proposed. This module aligns the local and global features in the pre-trained Inception-v3 model with the local and global features in the discriminator. Prior to feature alignment, the discriminator adjusts the dimensions of the local and global features using a 1×1 convolution operation, aiming to project the features in the discriminator into the feature space of the Inception-v3 model. During model training, the feature alignment module functions through a feature alignment loss, which is defined as follows:

$$L_{D_i}^{EA} = -\left[ \sum_{i=1}^{N} \log \frac{\exp(\gamma R(x_i^G, y_i^G))}{\sum_{j=1}^{N} \exp(\gamma R(x_i^G, y_j^G))} + \sum_{i=1}^{N} \log \frac{\exp(\gamma R(x_i^G, y_i^G))}{\sum_{j=1}^{N} \exp(\gamma R(x_j^G, y_i^G))} \right] - \left[ \sum_{i=1}^{N} \log \frac{\exp(\gamma R(x_i^R, y_i^R))}{\sum_{j=1}^{N} \exp(\gamma R(x_i^R, y_j^R))} + \sum_{i=1}^{N} \log \frac{\exp(\gamma R(x_i^R, y_i^R))}{\sum_{j=1}^{N} \exp(\gamma R(x_j^R, y_i^R))} \right] \tag{10}$$

where $x_i^G$ and $x_i^R$ denote the global and local features extracted in the discriminator, $y_i^G$ and $y_i^R$ denote the global and local features extracted in the Inception-v3 model, $N$ denotes the size of the batch, $R(\cdot)$ denotes the matching function between image features, and $\gamma$ is a smoothing factor.

3.1.5. Objective function:

1) Adversarial loss. Same as the baseline model AttnGAN, this chapter uses the cross-entropy loss as the adversarial loss. The adversarial loss of the discriminator is defined as follows:

$$\begin{aligned} L_{D_i}^{adv} = &-\frac{1}{2} \mathrm{E}_{I_i \sim P_{dua}} \left[ \log(D_i(I_i)) \right] \\ &-\frac{1}{2} \mathrm{E}_{I_i \sim P_{d_i}} \left[ \log(1 - D_i(I_i^{'})) \right] \\ &-\frac{1}{2} \mathrm{E}_{I_i \sim P_{dua}} \left[ \log(D_i(I_i, S)) \right] \\ &-\frac{1}{2} \mathrm{E}_{I_i \sim P_{d_i}} \left[ \log(1 - D_i(I_i^{'}, S)) \right] \end{aligned} \tag{11}$$

where $I_i$ and $I_i^{'}$ represent the real and generated images and $S$ represents the text condition. The adversarial loss of the generator is defined as follows:

$$\begin{aligned} L_{G_i}^{adv} = &-\frac{1}{2} E_{I_i^{'} \sim P_{G_i}} [\log(D_i(I_i^{'}))] \\ &-\frac{1}{2} E_{I_i^{'} \sim P_{G_i}} [\log(D_i(I_i^{'}, S))] \end{aligned} \tag{12}$$

The antagonistic loss of the discriminator and generator consists of unconditional and conditional loss, using unconditional antagonistic loss makes the synthesized image more realistic and using conditional antagonistic loss makes the generated image match the given text S better.

2) Cross-modal alignment loss. Cross-modal alignment loss motivates the generator to produce semantically consistent images by increasing the a priori and a posteriori probabilities between text and image. The cross-modal alignment loss used on the generator has the same function template as the feature alignment loss used on the discriminator, which is defined as follows:

$$L_{CMA} = -\left[ \sum_{i=1}^{N} \log \frac{\exp(\gamma R(x_i, y_i))}{\sum_{j=1}^{N} \exp(\gamma R(x_i, y_j))} + \sum_{i=1}^{N} \log \frac{\exp(\gamma R(x_i, y_i))}{\sum_{j=1}^{N} \exp(\gamma R(x_j, y_i))} \right] \tag{13}$$

where $\{x_i, y_i\}$ is the image-text pair, $R(\cdot)$ represents the matching function between image and text, and $\gamma$ is the smoothing factor. The cross-modal alignment loss consists of two parts: $x_i$ represents the global features of the image when $y_i$ represents the sentence features of the text, and $x_i$ represents the local features of the image when $y_i$ represents the word features of the text.

3) Total loss in the generator. The loss in the generator contains a cross-modal alignment loss $L_{CMA}$ in addition to the confrontation loss $L_{G_i}^{adv}$, so the total loss of the generator is defined as follows:

$$L_G = \sum_{i=1}^{N} L_{G_i}^{adv} + \lambda L_{CMA} \tag{14}$$

4) Total loss in the discriminator. The loss in the discriminator contains a feature alignment loss $L_{Di}^{FA}$ in addition to the confrontation loss $L_{D_i}^{adv}$, so the total loss of the discriminator is defined as follows:

$$L_D = \sum_{i=1}^{N} (L_{D_i}^{adv} + L_{D_i}^{FA}) \tag{15}$$

### *3.2. Effectiveness evaluation analysis*

In this section, the ACMA-GAN model is experimentally validated in two dimensions, quantitative and qualitative analysis, using the publicly available dataset provided by MSCOCO, in order to obtain better results.

3.2.1. Data sets. The MSCOCO dataset is a very useful image description dataset that collects more than 80,000 photos, which includes a training set, a validation set and a test set. In order to avoid overfitting and ensure the accuracy of the model, each utterance on the training set is truncated to ensure that the maximum width of each utterance does not exceed 16 characters. In addition, to further improve the accuracy of the model, some text preprocessing is performed, and each utterance is converted to lowercase letters and labeled in the margins to better simulate the actual situation.

3.2.2. Evaluation indicators. Image description is to describe the content and characteristics of an image in language, i.e., to utilize artificial intelligence technology for visual communication design through image description. In order to evaluate the quality of image description, BLEU, METEOR and CIDEr are selected as evaluation indexes.

BLEU (Bilingual Evaluation Understudy) is usually used to evaluate the quality of generated text for tasks such as machine translation or image description generation.METEOR (Metric for Evaluation of Translation with Explicit ORdering) is a metric used to Evaluation of automated metrics for tasks such as text generation, image description, machine translation, etc. CIDEr (Consensus-based Image Description Evaluation) measures the similarity between generated image descriptions and human-provided true descriptions to determine the quality of the generated descriptions.

3.2.3. Quantitative analysis:

1) Ablation experiments. For ease of representation, in this section, AttnGAN as the baseline algorithm is denoted as Baseline, the word attention module is denoted as AWAM, and the feature alignment module is denoted as FAM, and the four sets of experiments will be compared, in order of magnitude, Baseline, Baseline+AWAM, Baseline+FAM, Baseline+AWAM+FAM, in order to explore the differences between the different models.

The ablation experiment scoring results of the ACMA-GAN model are shown in Figure 1. With the increase of algorithm modules, the scores of all evaluation indices are improved, which indicates that all the three added modules can effectively improve the performance of the text-graphics generation algorithm. Among them, Baseline+FAM algorithm performs more prominently, with an increase of 4.20, 5.28, 2.68, 3.21, 3.68 and 7.14 points in the six evaluation indices of BLEU-1 BLEU-4, METEOR, and CIDEr relative to Baseline algorithm, which are 5.9%, 9.8%, 5.9%, 5.9%, respectively, 10.4%, 16.6% and 7.7%, which indicates that it plays an important role in improving the performance of the algorithm.Baseline+AWAM+FAM increases the scores by 5.65 to 10.99 points relative to Baseline algorithm by 9.6% to 29.1%, which indicates that the use of Adaptive Word Attention Module on AttnGAN baseline model and the use of features on its module for optimization to achieve the best image generation results.

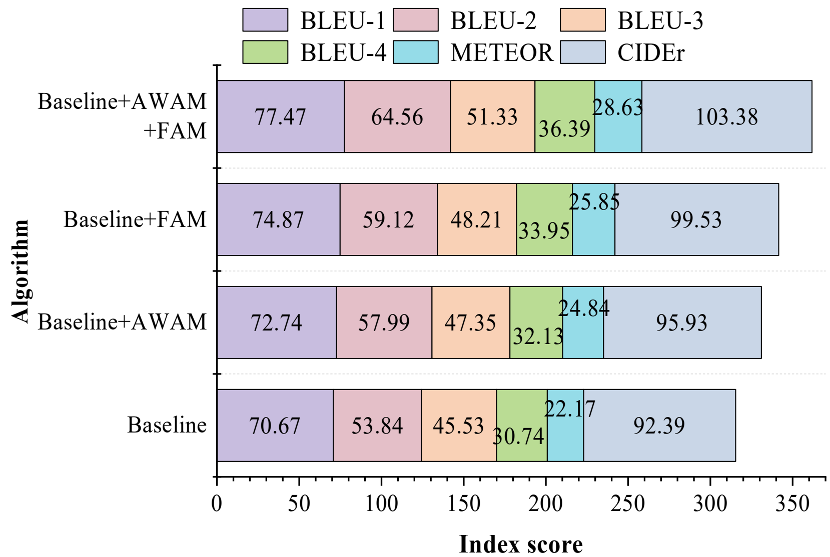



**Fig. 1.** The results of the ACMA-GAN algorithm ablation experiment

2) Quantitative comparison experiment of classical algorithms. The ACMA-GAN algorithm was evaluated for its role in the task of image description generation in AI-assisted visual communication design through ablation experiments, comparing it with other image description generation algorithms to determine the effectiveness of the algorithms. These algorithms include LRCN model, Hard-Attention model, ATT-FCN model, ERD model, MSM model, PG-BCMR model and Adaptive-Attention model.

The results of the metrics of different algorithms are shown in Fig. 2.The ACMA-GAN algorithm achieves the highest scores in all six evaluation metrics, especially in the BLEU-3 metric, the ACMA-GAN algorithm scores more than the next highest score by 7.48%, and in the CIDEr metric, it exceeds the next highest score by 7.35%, which gives this algorithm a clear advantage in generating image descriptions. These results indicate that the ACMA-GAN algorithm is an effective and promising algorithm for AI-assisted visual communication design tasks.

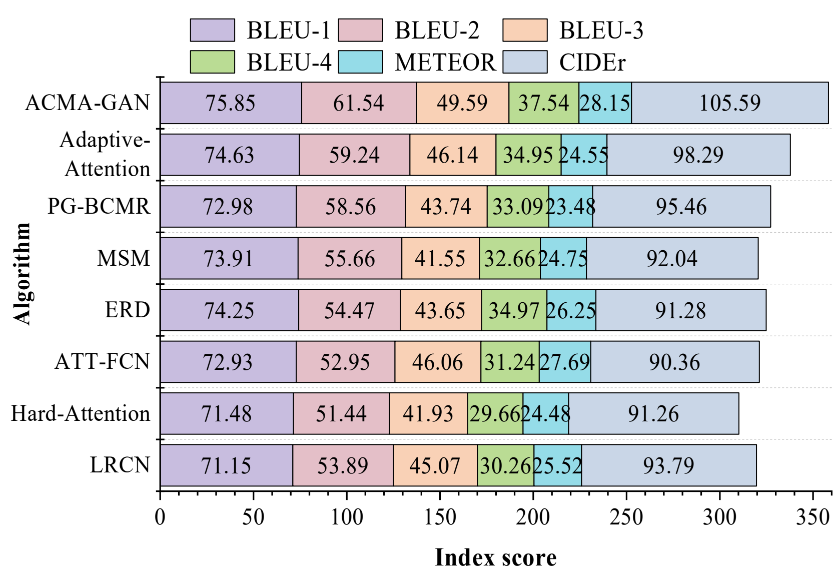
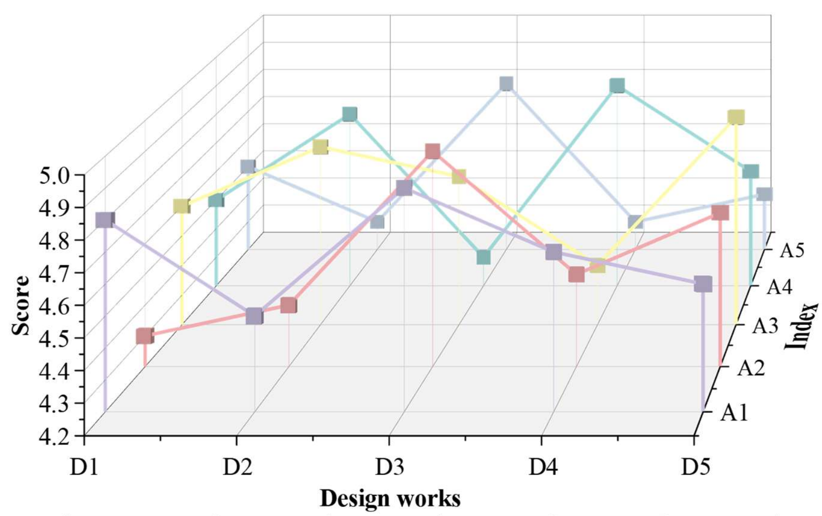


**Fig. 2.** The index results of different algorithms

3.2.4. Qualitative analysis. This section is based on the ACMA-GAN algorithm for visual communication work design, generating five visual communication design works (D1~D5), and adopting the questionnaire for data collection. The questionnaire design of this study is based on the theoretical foundations of art psychology and visual art assessment, and is quantified using a Likert scale. The Likert scale consists of a set of statements, and each statement has five kinds of responses: strongly agree, agree, not necessarily, disagree, and strongly disagree, which are scored as 5, 4, 3, 2, and 1, respectively, and the total score is obtained by summing up the scores of the respondents' responses to each question, and the total score can indicate the strength of their attitudes or their different statuses on this scale, and a total of 15 respondents were invited to rate the visual communication design works. The questionnaire aims to comprehensively assess the visual effect and audience experience of visual communication design works and evaluate the effectiveness of AI-assisted visual communication design.

Different audience groups were assessed for their feelings about the visual appeal A1, technical execution quality A2, innovativeness A3, emotional expression A4 and cultural relevance A5 of the AI-assisted visual communication design works, and the results of the audience assessment of different design works are shown in Figure 3. The five ACMA-GAN algorithm-assisted design works all scored greater than 4.2 on each index, and work D3 received high scores in terms of in visual appeal and quality of technical execution, both with a score of 4.9, indicating that the audience evaluates the displayed aesthetics and structural stability highly. The overall average scores of the designed works were 4.54, 4.56, 4.72, 4.56 and 4.64 respectively, all above 4.5, with a higher level of overall visual performance and design effect, indicating that AI technology is more than a good aid for the design of visual communication works.




| Design work | A1 | A2 | A3 | A4 | A5 |
|---|---|---|---|---|---|
| D1 | 4.8 | 4.3 | 4.6 | 4.5 | 4.5 |
| D2 | 4.5 | 4.4 | 4.8 | 4.8 | 4.3 |
| D3 | 4.9 | 4.9 | 4.7 | 4.3 | 4.8 |
| D4 | 4.7 | 4.5 | 4.4 | 4.9 | 4.3 |
| D5 | 4.6 | 4.7 | 4.9 | 4.6 | 4.4 |

**Fig. 3.** Audience assessment of different design works

## 4. Impact of AI use on visual communication design

The previous chapter evaluated the effectiveness of AI-assisted visual communication design by designing a textual image generation model, and this chapter constructs a mathematical model to explore the path of the impact of the use of AI technology on visual communication design.

### 4.1. Research hypotheses

Combined with the practical application of artificial intelligence in visual communication design (VCD), the following hypotheses are proposed:

H1: The use of AI technology can enhance visual communication design.

H2: AI technology enhances visual communication design through image recognition and analysis X1.

H3: AI technology enhances visual communication design through image generation and creation assistance X2.

H4: AI technology enhances visual communication design through personalized design X3.

H5: AI technology enhances visual communication design through workflow optimization X4.

### 4.2. Study design

4.2.1. Data sources. A questionnaire was used to design a questionnaire based on the research hypotheses, which was distributed to visual communication design industry personnel, visual communication design assignment students and teachers, and others. A total of 251 questionnaires were collected, of which 232 questionnaires were valid, with a valid recovery rate of 92.43%.

4.2.2. Modeling. Ordinary Least Squares (OLS) is a widely used parameter estimation method in practical applications. It is widely familiar as a basis for other estimation methods that take the principle of least squares as their starting point.

Where the sample observations $y_i, x_i (i=1,2,...n)$ have been determined, the linear equations $\hat{y}_i = \hat{\beta} + \hat{\beta}_1 x_i$, $i=1,2,\dots n$ should provide a better fit to the sample data if the parameter estimates of the model (16), for $\hat{\beta}$ and $\hat{\beta}$, can be obtained and they are the best parameter estimates. Where the observed values of the independent variables and the parameter estimates are known, where $\hat{y}_i$ as the estimate of the dependent variable can be obtained computationally. At this point, the estimate of the dependent variable is closest to the observed value overall, which is judged by minimizing the sum of the squares of the residuals between the two:

$$Q = \sum_{i=1}^{n} (y_i - \beta_i - \beta_i x_i)^2 = \sum u_i^2 = Q(\beta_i, \beta_i) \tag{16}$$

$$\begin{aligned} Q|_{\beta_0 =} \hat{\beta}_0, \beta_1 = \hat{\beta}_1 &= \sum \hat{u}_i^2 = \sum_{1}^{n} (y_i - \hat{y}_i)^2 \\ &= \sum_{1}^{n} (y_i - \hat{\beta}_i - \hat{\beta}_1 x_i)^2 = \min Q(\beta_i, \beta_i) \end{aligned} \tag{17}$$

Based on the principle of least squares and the sample observations, parameter estimates can be calculated. Then:

$$\begin{aligned} Q &= \sum_{1}^{n} (y_i - \hat{y}_i)^2 \\ &= \sum_{1}^{n} (y_i - (\hat{\beta} + \hat{\beta}_1 x_i))^2 \end{aligned} \tag{18}$$

Since equation (18) is a quadratic function of $\hat{\beta}$ and $\hat{\beta}_1$ and is nonnegative, its minima always exist. So the first order partial derivative of $Q$ with respect to $\hat{\beta}, \hat{\beta}_1$ is 0 when $Q$ reaches its minimum. i.e:

$$\frac{\partial Q}{\partial \beta} \mid \beta = \hat{\beta}, \beta = \hat{\beta}_1 = 0 \tag{19}$$

$$\frac{\partial Q}{\partial \beta_1} \mid \beta_1 = \hat{\beta}, \beta_1 = \hat{\beta}_1 = 0 \tag{20}$$

It is easy to derive the characteristic equation:

$$\sum_{i=1}^{n}(y_i - \hat{\beta}_i - \hat{\beta}_i x_i) = \sum(y_i - \hat{y}_i) = \sum e_i = 0 \tag{21}$$

$$\sum_{i=1}^{n} x_i(y_i - \hat{\beta}_i - \hat{\beta}_i x_i) = \sum x_i e_i = 0 \tag{22}$$

Solution:

$$\sum y_i = n\hat{\beta} + \hat{\beta}_1 \sum x_i \sum y_i x_i = \hat{\beta} \sum x_i + \hat{\beta}_1 \sum x_i^2 \tag{23}$$

So there:

$$\hat{\beta}_1 = \frac{n\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{24}$$

$$\hat{\beta} = \overline{y} - \hat{\beta}_1 \overline{x} \tag{25}$$

Thus the parameter estimates that conform to the principle of least squares are obtained.

In this paper, the study of the impact of the use of artificial intelligence technology on visual communication design is analyzed in depth using the OLS model as follows:

$$VCD_i = \alpha_0 + \alpha_1 AI_i + \alpha_2 Control_i + \varepsilon_i \tag{26}$$

where dependent variable $VCD_i$ represents the visual communication design effect, independent variable $AI_i$ represents the use of AI technology for design work $i$, $Control_i$ represents the control variables, $a_0, a_1, a_2$ represents the coefficients to be estimated, and $\varepsilon_1$ represents the random error term.

### *4.3. Correlation analysis*

Correlation analysis techniques are widely utilized to explore the intrinsic links between two and more variables, the core of which includes not only confirming the existence of some form of association between these variables, but also revealing the direction of the association and specific quantitative indicators of its strength. This study aims to provide insight into the structure of interdependence between specific pairs of variables and performs a Pearson correlation test using Stata version 17.0 software. In interpreting the test results, the first task is to scrutinize the statistical significance of the P-value. If the P-value reaches the level of significance, it indicates that the correlation test between the variables has been passed. Next, the resulting Pearson's correlation coefficient is scrutinized. As the absolute value of this coefficient gets closer to 1, it can be concluded that the strength of the correlation increases. In addition, by analyzing the positive and negative sign attributes of the coefficient, it is possible to accurately determine the positive and negative direction of the correlation, for example, if the coefficient is negative, it means that there is a negative correlation between the two.

The Pearson correlation analysis of the key variables is shown in Figure 4, with ***, **, and * indicating significant at the 1%, 5%, and 10% levels, respectively.A number of variables such as AI technology, image recognition and analysis X1, image generation and creation assistance X2, personalized design X3, and workflow optimization X4 all show significant correlations with visual communication design VCD at the 1% level. Preliminary evidence of the positive impact of AI technology on visual communication design.

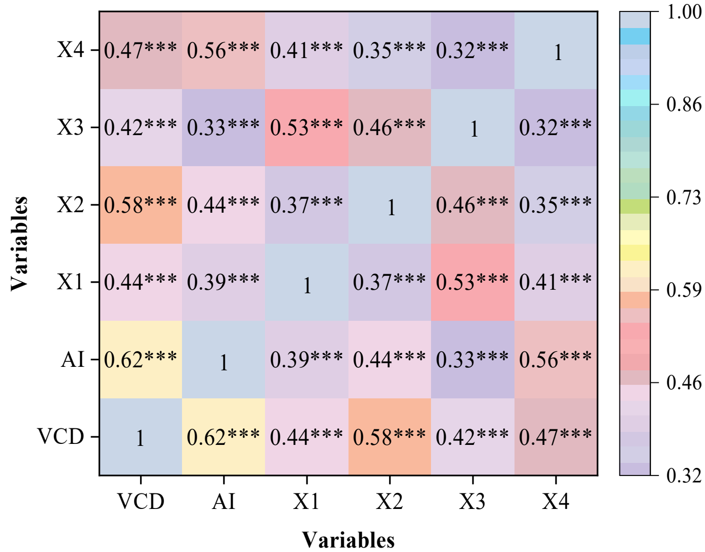



**Fig. 4.** Pearson correlation analysis of key variables

### *4.4. Mechanism test analysis*

How AI technology affects visual communication design through specific mechanisms is analyzed, and the mechanism test of AI technology on visual communication design is shown in Table 1, with standard errors in parentheses, and ***, **, and * denoting significance at the 1%, 5%, and 10% levels, respectively. Columns (1) to (4) in the table indicate the effects of AI technology on image recognition and analysis X1, image generation and creation assistance X2, personalized design X3, and workflow optimization X4, and column (5) indicates the effects of AI technology and the four variables on visual communication design VCD.

The use of AI technology has produced a significant positive effect on image recognition and analysis, image generation and creation assistance, personalized design and workflow optimization, and this effect has passed the 1% significance test. Among them, AI technology has the greatest positive effect on image generation and creation assistance with an impact coefficient of 0.527. Meanwhile, image recognition and analysis, image generation and creation assistance, personalized design and workflow optimization all have a significant positive effect on visual communication design ($p < 0.01$), validating hypotheses H2 to H5. The four variables X1~X4 play a mediating role in the effect of AI technology use on visual communication design. In addition, the coefficient of the influence of AI technology on visual communication design is 0.554 and passes the 1% significance test, which verifies the hypothesis H1, that is, the use of AI technology can promote the effect of visual communication design.

**Table 1.** The effect of AI technology to visual communication design

| Variable | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | X1 | X2 | X3 | X4 | VCD |
| AI | 0.424*** | 0.527*** | 0.409*** | 0.498*** | 0.554*** |
| | (0.029) | (0.036) | (0.019) | (0.046) | (0.052) |
| X1 | | | | | 0.413*** |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | (0.198) |
| X2 | | | | | 0.508***<br>(0.029) |
| X3 | | | | | 0.393***<br>(0.065) |
| X4 | | | | | 0.326***<br>(0.186) |
| Constant | 0.344***<br>(0.076) | 0.733***<br>(0.128) | 0.298***<br>(0.041) | 0.285***<br>(0.286) | 0.453***<br>(0.312) |
| Observations | 232 | 232 | 232 | 232 | 232 |
| R-squared | 0.483 | 0.461 | 0.438 | 0.469 | 0.501 |

## 5. AI-assisted visual communication design optimization methods

In order to promote the long-term development of AI technology in the visual communication design industry, it is of great significance to think about how to realize the efficient use of AI technology to promote the healthy and sustainable development of the industry. Combined with the previous analysis, the optimization method of AI-assisted visual communication design is discussed, and the optimization method of AI-assisted visual communication design is shown in Figure 5.

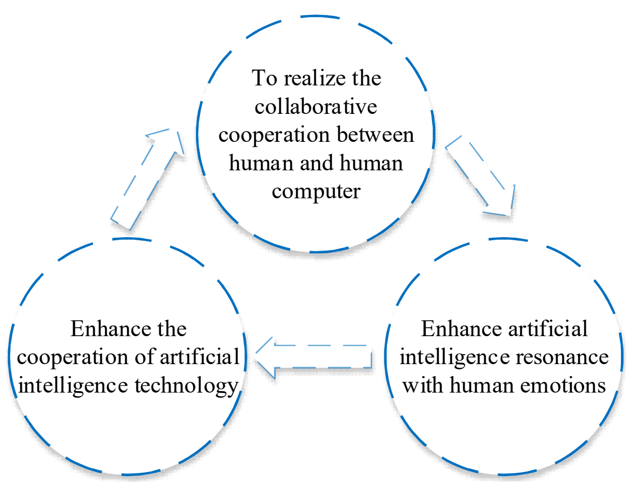



**Fig. 5.** Optimization method of artificial intelligent auxiliary visual communication design

### *5.1. Realization of human-computer interaction and cooperation*

Realizing in-depth human-machine collaboration is one of the keys to the application of AI technology. First, it is necessary to continuously improve the level of intelligence of AI technology, and through continuous research and development and optimization of AI technology, improve its level of intelligence in understanding and generating content, and through natural language processing, deep learning and other technologies, enable the AI system to more accurately understand the needs and intentions of the human user and generate content that more closely meets the user's expectations. Second, enhance the applicability of the human-computer interaction interface, and reduce the threshold and difficulty for users to use AI technology by designing an easy-to-use and intuitive human-computer interaction interface. Once again, establish a cooperative and effective collaboration mechanism, formulate clear human-computer collaboration processes and rules, and ensure that humans and AI can form effective cooperation in their work by establishing a collaboration platform and a task allocation system. Finally, designers are required to continuously learn and master AI technology to realize effective communication and cooperation between humans and machines, and always maintain the irreplaceable logical thinking ability and creative thinking of designers in the visual communication design process, and better utilize AI technology to achieve the purpose of improving the creative efficiency and quality of works by combining with their own creativity, judgment and professional knowledge, so as to formulate the optimal design solutions.

### *5.2. Enhancing AI empathy with human emotions*

When using AI technology for visual communication design, full attention should be paid to the emotional needs of users to realize the humanized consideration of design. Firstly, natural language processing (NLP) and emotion analysis technology can be used to enable AI systems to understand and recognize human emotional expressions, and through speech synthesis, facial expression recognition and other technologies, AI systems can express themselves in a more natural and emotional way, realizing AI's understanding and expression of emotions. Secondly, according to the user's emotional state, preference and historical data, it provides users with personalized interaction experience, and through user profiling and recommendation system, it provides users with content that meets their interests and emotional needs. Finally, the AI system is provided with emotional education and training so that it can better understand and respond to human emotional needs, and improve the AI system's ability in emotional communication through simulation and role-playing.

### *5.3. Enhancing cross-domain collaboration on AI technologies*

In order to promote the further development of AI technology and accelerate the updating and iteration of the technology, on the one hand, interdisciplinary exchanges and cooperation should be promoted, and researchers and enterprises in different disciplinary fields should be encouraged to work together to jointly promote the development and application of AI technology. On the other hand, the development of AI technology needs the support of interdisciplinary talents, colleges and universities, research institutes and enterprises should strengthen the cultivation and introduction of interdisciplinary talents, encourage students to study and practice in different fields, and cultivate talents with interdisciplinary knowledge and ability, which also cultivates professional talents for the continuous development of AI technology in the visual communication design industry.

## 6. Conclusion

The rapid development of artificial intelligence has led to a paradigm shift in artistic creative work. Based on the generative design application of AI in visual communication design, this study constructs an ACMA-GAN text image generation model based on AttnGAN and analyzes its image generation quality to assess the effect of AI-assisted visual communication design. Then explore the influence path of AI technology use on visual communication design, from which further optimization methods are proposed.

Tests were carried out on the MSCOCO dataset, and the design images generated by the ACMA-GAN algorithm were improved in BLEU, METEOR and CIDEr, especially in the BLEU-3 index and the CIDEr index, which were higher than the next highest scores by 7.48% and 7.35%, and the ACMA-GAN algorithm assisted the visual communication design with a better effect compared with other methods. . In the qualitative evaluation, the overall scores of the generated design works are above 4.5, indicating that the AI technology-assisted design works are highly recognized by the audience in terms of visual attractiveness, quality of technical execution, innovativeness, emotional expression and cultural relevance.

There is a certain positive effect of AI technology use on visual communication design, with an impact coefficient of 0.554. Specifically, AI technology promotes the visual communication design effect through four dimensions: image recognition and analysis, image generation and creation assistance, personalized design and workflow optimization. Among them, AI technology use has the most obvious positive impact on image generation and creation assistance, with an impact coefficient of 0.527.

Combining the above results, we propose three optimization development strategies from realizing the human-computer interaction synergy of AI technology, strengthening the resonance between AI technology and human emotion, and enhancing the cross-domain cooperation of AI technology, in order to realize a more efficient, vivid, automated, and creative production mode in the visual communication design industry with the help of AI technology.

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