Creative Advertising Design Combining CAD and Generating Adversarial Networks

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Abstract. The current advertising design market competition is extremely fierce, and traditional advertising market design methods can no longer meet the growing demand for creative efficiency. The level of automation in advertising design has enabled designers to focus more on creative expression. Therefore, by analyzing many advertising data elements, designers can creatively apply data learning in potential product designs. Advertising design creativity can, therefore, extract element features from the analysis of different creative works. This article fully utilizes the creative algorithms of CAD technology to develop diverse advertising design solutions. In the automated advertising application solution, simulation experiments have resulted in a brand new advertising design in the CAD precision technology model design. This article has developed a diversified model for the automatic generation of this model. The experimental results show that the model can perfectly reflect the creative scheme generation of advertising diversity. It can receive quantitative analysis and further verification of advertising evaluation in terms of innovative creativity. It has constructed a creative framework for CAD technology through innovative design solutions for the model.

Keywords: Computer-Aided Design; Generating Adversarial Networks; Generative Algorithms; Creative Advertising Design;
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1 INTRODUCTION

Under the wave of digitization, the advertising industry is undergoing an unprecedented transformation. Product color design is no longer just a simple combination and combination of different colors, but a profound and artistic discipline. In today's digital age, color has transcended simple visual elements and become a carrier of emotions, connecting products and consumers. The selection and application of colors should not only consider the characteristics and positioning of the product but also deeply study the psychological needs and cultural background of consumers in order to create color combinations that can touch people's hearts and resonate. The combination of CAD technology and advanced algorithms makes color design more precise and efficient. Through CAD technology, designers can present color effects more intuitively and make precise adjustments and optimizations. To address this challenge, Ding and Dong [1] proposed a novel solution - the MEPCD system based on Grey Theory (GT) and Non Explicit. The color design of products with diverse emotions not only has extremely high research value, but also is the key to promoting product design innovation. They utilized factor analysis and semantic difference techniques to conduct in-depth research on users' perceptions of color in different emotional dimensions. When users choose products, they are often deeply influenced by the emotional experience conveyed by colors. Next, we have constructed a multidimensional perception space for the color image of emotional products, providing strong support for subsequent design. In the field of advertising design, the choice of color is often directly related to the attractiveness of the product and user satisfaction. Fan [2] has developed an optimization objective function for intelligent color selection, which can comprehensively consider various factors, ensuring that the selected colors not only meet design requirements but also resonate with users. The core of this method is to accurately calculate color intelligent selection parameters based on color tone values through scientific calculation methods. Traditional advertising design color selection methods often suffer from issues such as low image to color matching and unsatisfactory user feedback. In addition to considering the matching of color tone values. To solve this objective function, we adopted the particle swarm optimization algorithm. This algorithm simulates the foraging behavior of bird flocks and finds the optimal solution through continuous iteration and optimization. This step ensures that the color selection not only matches the image, but also reflects the product's characteristics and brand culture.

Graphics, as an ancient and powerful form of information expression, are flourishing with rapid development. Fan and Li [3] have invested a lot of enthusiasm and effort in the research of computer graphics and image processing technology. They found that through carefully designed graphics, information can be conveyed more intuitively and vividly, enabling recipients to understand the content of information more quickly and accurately. These experiments not only cover traditional graphics processing techniques, but also involve the latest computer vision and deep learning technologies. As carriers of information, graphics and images have unique advantages in transmission and expression, so they have conducted in-depth research and exploration on this. It can intuitively and vividly convey information, and stimulate resonance and interest in the receiver. They also analyzed how computer graphics have become an efficient and economical way of information transmission. In the era of mobile media, the importance of interface design is becoming increasingly prominent. As an important carrier of visual information, graphics play a crucial role in information dissemination due to their intuitive, vivid, and easy to understand characteristics. At the same time, we also focus on the theoretical foundations of cognitive psychology, semiotics, and other fields closely related to computer graphic visual communication. The research mainly focuses on the field of graphic visual communication, aiming to explore the essential characteristics and evolutionary laws of graphic information. As a bridge between users and devices, interface design is not only related to the user experience, but also directly related to the effective transmission of information and the shaping of brand image. We have thoroughly analyzed the constituent elements and forms of graphic information, and Guan and Ko [4] have revealed their inherent logical relationships and evolutionary trends. However, in the field of visual communication design, traditional teaching methods are often limited by physical materials and manual operations, making it difficult to fully demonstrate the diversity and innovation of design. Ten students who are passionate about design participated in the experiment. Under the guidance of their teachers, they combined university design courses with digital learning to deeply learn the skills of using Illustrator and Photoshop. Through continuous practice, students have gradually mastered how to use software tools to express their design ideas, improving their design abilities and creativity. The research results indicate that digital drawing software such as Photoshop and Illustrator have significant application effects in visual communication design teaching.

Research on the optimization of advertising three color design is currently scarce, especially in exploring the subtle impact of color area ratio on user emotions. To verify the actual effectiveness of these design schemes, Guo et al. [5] conducted extensive questionnaire surveys and color image screening. It is committed to filling this research gap, deeply exploring and achieving multi-objective optimization of color design for tricolor products. Based on these two modes, they carefully designed 58 representative baby strollers with three color schemes using advanced three color scheme generation methods. In order to achieve multi-objective optimization. Aiming to achieve the best visual effect and emotional communication of colors in product design through scientific proportion allocation. This method can not only quickly find color combinations that meet multiple optimization objectives, but also ensure that these combinations have good performance in practical applications. Guo and Wang [6] paid special attention to the three-dimensional measurement method based on non-contact depth of field, which can accurately restore the three-dimensional shape of objects from focused images. Based on in-depth research on existing computer-aided modeling methods, they proposed a digital sculpture modeling method based on polygon modeling. In the process of creating digital sculptures, three-dimensional measurement technology plays a crucial role. By combining non-contact depth of field 3D measurement methods and polygonal modeling techniques, not only can efficient and accurate 3D reconstruction be achieved, but also the creativity of designers can be better presented. This method not only considers the practical needs of conceptual design, but also fully considers the uniqueness of artistic design, allowing digital sculpture works to more accurately reflect the designer's creativity and ideas. In order to verify the feasibility of this modeling method, we took the modeling implementation process of folk crafts as an example and demonstrated in detail the modeling steps and evaluation methods. The principle of innovation requires advertising design to have individuality and originality, demonstrating the originality of advertising work design. In terms of advertising design techniques, there are many ways to help designers create attractive advertising works. By using decorative design methods, enhance the visual impact of advertisements through text, painting, or product patterning [7].

This article is divided into six parts. Firstly, the introduction elaborates on the background, objectives, importance, main content, research methods, and structure of the article. The following is a literature review, which reviews the relevant research and development trends of CAD technology, generative algorithms, and creative advertising design. The third part provides a detailed description of how to construct and implement an advertising design model. The fourth part reports the results of the simulation experiment and provides an in-depth analysis and discussion of the data. The fifth part explores the application prospects of these technologies in advertising design education. Finally, the conclusion and outlook section summarizes the main achievements of the research and proposes prospects for future research directions.

2 RELATED WORK

Advertising creativity, as a core link in the field of computer-aided design (CAD), occupies an important position in the CAD workflow, accounting for up to one-third of it. In order to overcome this dilemma, Jones et al. [8] conducted in-depth research on the core mechanism of advertising creativity, defining it as a paired constraint system between parts, i.e. pairing. On this basis, an innovative SB-GCN scheme was proposed, which is a representation learning scheme on BREP. This scheme not only preserves the topological structure of element features, but also utilizes these learned representations to predict the pairing of CAD types. Constraints are not simply defined based on world coordinates, but are closely integrated with the BREP topology to more accurately describe the assembly relationships between images. The emergence of this plan provides new ideas and methods for the research of advertising creativity, which helps to promote the development of CAD systems. Ma and Hong [9] are committed to delving into a dynamic and game-driven supply chain scenario. How can manufacturers and retailers adjust their advertising innovation investment strategies in the context of channel encroachment, and how do these strategies affect their profits. The logic behind this strategic adjustment is that the increase in direct sales costs may weaken the competitiveness of manufacturers in direct sales channels, providing retailers with the opportunity to attract more consumers through advertising. In this complex supply chain, they found that the behavioral choices of all parties are closely related to the market conditions they face, especially the direct selling costs of manufacturers. Research has found that when manufacturers have higher direct sales costs, retailers may exhibit more aggressive encroachment behavior.

In today's booming development of new media, interactive advertising, as a new form of advertising creativity, is gradually being favored by a large number of advertisers and audiences. The success of interactive advertising creative design cannot be achieved without innovative thinking and methods. With the help of new media platforms such as the internet, mobile phones, and tablets, interactive advertising and achieve real-time interaction with the audience. Compared with traditional advertising, interactive advertising has stronger participation, experience, and innovation in the new media environment. Designers can use various advanced technological means, such as virtual reality, augmented reality, artificial intelligence, etc., to create rich and diverse interactive forms, allowing audiences to participate in the creation and dissemination of advertisements while enjoying them. By conducting in-depth research on the preferences, needs, and habits of the audience, designers can design interactive advertisements that are more in line with the audience's taste, improving their engagement and satisfaction [10]. Color, a unique element in visual language, can instantly touch the depths of people's emotions. Qiao et al. [11] invested a lot of effort in developing advertising algorithms. At the same time, delve deeper into the subtle connection. To achieve this goal, they first constructed a fuzzy Bayesian network prediction model for significant negative emotions in public advertising. When negative emotions spread in public, specific colors seem like a good medicine that can quickly dissipate or reduce the pressure of these emotions. This model is like an emotional detector that can keenly capture potential factors that may trigger negative emotions in advertisements. By using color cubes, we can more accurately select color combinations that can eliminate negative emotions and inject positive emotional elements into public advertising.

Wang [12] proposed a new form of advertising art - "intelligent visual art creation" - with his keen insight and forward-looking thinking. By combining computer-aided interaction technology, new media advertising can more accurately capture the audience's gaze, convey information more vividly and intuitively, and thus achieve maximum advertising effectiveness. By utilizing digital advertising technology, artists can break through the limitations of traditional creative materials and create in a more free and flexible way. Intelligent visual art creation, as a new form of advertising art, fully utilizes the advantages of new media technology and elevates the dissemination effect of advertising to a new height. The emergence of this new form not only injects new vitality into the field of advertising art, but also foreshadows the development direction of advertising art in the future intelligent era. Meanwhile, auditory expression, as an auxiliary means, complements visual elements and jointly constructs a multi-dimensional communication system for advertising. In addition, the role of digital advertising technology in promoting the practice of digital media advertising art cannot be ignored. Visual expression, as the core way of conveying information in advertising, presents unprecedented diversity and innovation through the support of digital technology. It not only promotes the digitization and intelligence of the advertising production process, but also expands the dissemination channels and audience range of advertising. In the advertising color coordination design system, we have deeply explored the application of the RGB model and Munsell color model. With the help of these two color science models, Yang and Fugen [13] have provided a solid theoretical foundation for the color design of advertisements. To ensure the accuracy and rationality of the optimization process, we set a fitness function based on the classical color coordination theory as a constraints. Furthermore, it adopts the particle swarm optimization algorithm, an efficient optimization tool, to finely optimize and adjust the color design scheme. Make the final color design conform to aesthetic principles and effectively convey advertising information. This function not only ensures the harmony and unity of color design, but also fully considers the dissemination effect of advertising and audience psychology. In this process, the group consensus decision results based on triangular fuzzy numbers are fully utilized to ensure that the generated color scheme can maximize the satisfaction of the consensus image preferences of the user group [14]. Zitouni et al. [15] explored an innovative texture image-supervised classification algorithm based on the principle of information fusion, aiming to improve the accuracy and efficiency of classification. In addition, wavelet features, with their ability to analyze at multiple scales, can represent textures of different scales, providing strong discrimination ability between textures with strong similarity. Gabor features perform well in finding class boundaries and accurately depict the edge information of textures. The grayscale co-occurrence matrix features are good at playing a role in the regions within the class, effectively capturing subtle changes within the texture. In the first step of the algorithm, they applied Gabor features, grayscale co-occurrence matrix features, and wavelet feature extraction strategies to texture images, thereby obtaining rich and diverse information.

3 CONSTRUCTION OF CREATIVE ADVERTISING DESIGN MODEL

3.1 Theoretical Basis

In the model construction stage of this study, particular emphasis was placed on applying the theoretical foundation of GAN. These two parts, through a competitive training process, enable the generator to gradually grasp and replicate the distribution of real data, ultimately producing results highly similar to real images. This adversarial training method ensures that the generator can create advertising visual effects with strong realism. In short, this process can be summarized as:

$$\min_{G}\max_{D}\ D,G\ = E_{x\sim p_{data}\ x}\left[\ \log D\ \ x\ \ \right] + E_{z\sim p_{g}\ z}\left[\ \log\ 1-D\ \ G\ \ z\ \ \ \right] \tag{1}$$

In the framework of GAN, the real sample set x follows the distribution $p_{data}\ x$, and the input noise z follows the distribution $p_{g}\ z$; G represents the generator, D represents the discriminator. During the training process, the goal is to maximize D, which requires maximizing the value of $D\ x$ while minimizing the value of $D\ D\ z$. In the application of advertising design, the effective use of GAN can create innovative and attractive advertising images.

3.2 The Construction Details of Creative Advertising Design Models

In the generation algorithm unit, the generator plays a crucial role. It is like an endless source of creativity, capable of continuously generating various unique and diverse design solutions based on preset parameters and rules. It can learn and extract the essence of design from massive design data through deep learning techniques and then generate design solutions that better meet the needs of designers. The discriminator ensures that the generated design scheme has not only aesthetic appeal but also practical application value by comparing the differences between the generated design scheme and real design data. Its function is similar to that of a picky art critic, able to judge the authenticity and innovation of each design proposal accurately. The model structure is shown in Figure 1.

$$L_{G} = -E_{z\sim p_{z}\ z}\left[\log\ 1-D\ \ G\ \ z\ \ \ \right] \tag{2}$$

In the operation process of the model, the advertising design concept generated by the generator can be represented as $G\ z$, and $D\ x$ is the output result of the discriminator, which evaluates the probability of x's authenticity. Meanwhile, z refers to random vectors extracted from the preset noise distribution $p_{z}\ z$, which are used as raw materials for the generator to create new concepts.

Within the framework of generative adversarial networks, the discriminator's responsibility is to accurately identify the advertising designs created by the generator and the real advertising designs in reality. To quantify the performance of the discriminator, a loss function is defined that reflects the degree of its judgment accuracy:

$$L_{D} = E_{x\sim p_{data}\ x}\left[\ \log D\ \ x\ \ \right] + E_{z\sim p_{g}\ z}\left[\ \log\ 1-D\ \ G\ \ z\ \ \ \right] \tag{3}$$

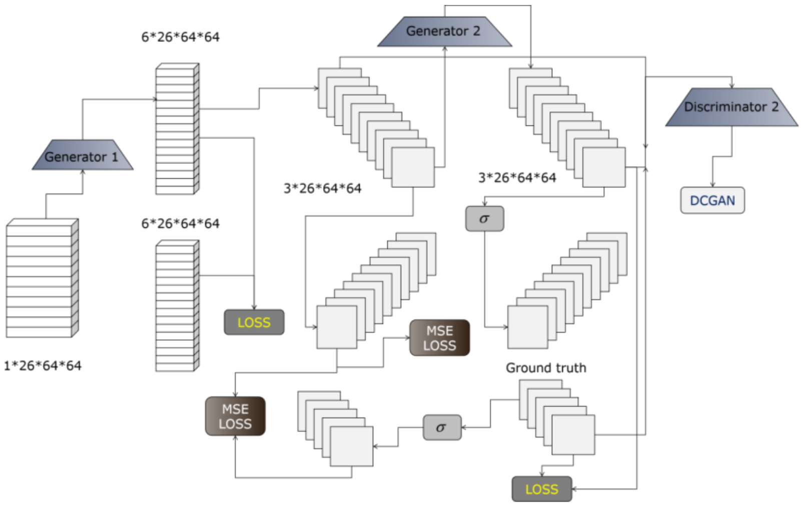

Figure 1: GAN structure.

The judgment result is not simply true or false, but a continuous value between 0 and 1. Therefore, the evaluation function of the discriminator is not only a simple judgment tool, but also a complex model that can quantify the authenticity of the design scheme.

$$D(x)=\frac{1}{2}\log\left(1+\frac{1}{1+e^{-E(x)}}\right) \tag{4}$$

Within this model framework, $E(x)$ represents the discriminator's discrimination results for a specific design scheme x. $D(x)$ evaluates the authenticity of another design sample x, and quantifies the true level of the design with a score of 0 to 1. x revealing the confidence level at which the design is judged to be true. In order to effectively train the generator and discriminator, this study adopted the widely recognized adversarial loss function in the industry to improve the overall performance of the model:

$$\min_G \max_D L_{adv}=E\left[\log D(\hat{y}^b)\right]+E\left[\log\left(1-D\left(G(V(E(p^a),a,b),c)\right)\right)\right] \tag{5}$$

In this structure, E serves as the encoder, V as the converter, G as the generator responsible for producing design sketches and D as the discriminator for performing authenticity verification tasks. p^a represents the original image observed under a specific perspective a, while $\hat{y}^b$ representing those actual, real images. The discrimination process in generative adversarial networks is shown in Figure 2.

Improving the evaluation system: By utilizing feedback from discriminators, the design scheme is carefully screened and further improved to ensure that the final produced advertisement not only has a novel design but also strictly meets the preset design standards.

In practical applications, the error distribution in the network weight space often presents extreme complexity, like a rugged terrain filled with numerous peaks and valleys, representing the existence of numerous local minimum points. In this regard, GAN gradually fine adjusts its weights through error gradients to correct errors. In order to achieve better correction results, an advanced optimization method was adopted, which takes into account the previous gradient information when calculating the weight correction amount, which is considered as the momentum term.

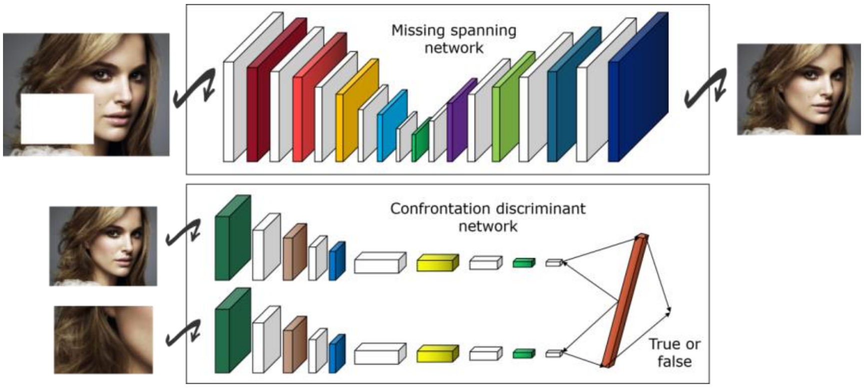

Figure 2: Discrimination process.

The specific calculation formula is as follows:

$$\Delta w_{ji}(n) = -\eta \sum_{t=0}^{n} \alpha^{\eta-t} \frac{\partial \varepsilon(t)}{\partial w_{ji}(t)} = -\eta \frac{\partial \varepsilon(n)}{\partial w_{ji}(n)} - \eta \sum_{t=1}^{n} \alpha^{\eta-t} \frac{\partial \varepsilon(t)}{\partial w_{ji}(t)}, \quad 0 < \alpha < 1 \tag{6}$$

The current gradient plays a crucial role $\Delta w_{ji}(n)$, with a constant coefficient of 1, demonstrating its unshakable position. Relatively speaking, the effect of previous gradients $\Delta w_{ji}(n)$ has shown completely different characteristics, as it will sharply weaken exponentially with the growth of $\alpha^{\eta-t}$, almost negligible. The error function formula used is detailed as follows:

$$E_p = \frac{\sum_t \left(t_{pi} - o_{pi}\right)^2}{2} \tag{7}$$

By doing so, it is possible to more clearly see the significant differences between the current gradient and the previous gradient in affecting $\Delta w_{ji}(n)$ and $\Delta w_{ji}(n)$, which helps to adjust and optimize the model more accurately.

t_{pi}, o_{pi} represents the expected output result of the network and the actual output result obtained after calculation. In order to determine the innovation of a design scheme, the discriminator will calculate the differences between it and existing design schemes. This measure of innovation can be achieved through a content-based measure of innovation, which compares the degree of difference between a design solution and a known solution, thereby obtaining quantitative indicators of innovation:

$$I(x) = \sum_{y \in Y} \left| E(x) - E(y) \right| \tag{8}$$

In this context, Y represents a collection of numerous existing design solutions. $E(x)$, on the other hand, refers to a specific design solution whose characteristics can be described in detail through the feature vector x. In other words, x is a mathematical expression that describes the unique properties of the $E(x)$ scheme.

The creative advertising design model integrates multiple practical functions: firstly, it can independently produce diverse creative advertising design drafts; Secondly, the model can intelligently screen and deeply optimize numerous design schemes based on the designer's instructions and requirements; Finally, it can also provide designers with immediate feedback so that they can make flexible adjustments and improvements to the design. Detailed information on these functional points can be found in Table 1.

Serial Number	*Function Overview*	*particulars*
1	Automatic generation of design drafts	Based on the design principles and characteristics mastered, the system can independently produce a variety of advertising design drafts with distinct styles and themes.
1.1	Diversified option supply	We are committed to ensuring that every design proposal produced is unique and innovative, thereby eliminating design homogenization and plagiarism.
1.2	Flexibility adaptation adjustment	Adjust the overall style and language of the design accordingly for different audience groups and brand characteristics to ensure a high degree of compatibility.
2	Scheme selection and refinement	We will carefully select and improve the produced design scheme based on the designer's guidance and requirements.
2.1	Designer guidance input	Designers can clarify their specific needs by inputting core vocabulary, specifying colors, and the desired layout.
2.2	Plan quality evaluation	We use advanced algorithms to conduct a comprehensive evaluation of the design scheme and select the high-quality solution that best meets the designer's expectations.
2.3	Iterative optimization process	After receiving feedback from the designer, further improvements and upgrades will be made to the selected solution.
3	Instant feedback system	We also provide designers with a real-time feedback system aimed at helping them better polish and improve their advertising designs.
3.1	Feedback and suggestions	This feedback will cover key aspects such as color selection, rationality of layout, and harmony of various design elements.
3.2	Function Overview	In addition, we will provide designers with targeted improvement suggestions and optimization paths based on the feedback.

Table 1: Functional details.

The following are the specific implementation steps of the model (see Table 2 for details):

Firstly, prepare the materials. This stage mainly involves collecting numerous excellent advertising design examples as raw materials for our training of generation algorithms.

Next, enter the algorithm training phase. We will use these carefully selected cases to train our generation algorithm and enable it to understand and master the core elements and style features of advertising design deeply.

Finally, engage in design creation and refinement. With the help of advanced CAD technology and fully trained generation algorithms, we can automate the production of diverse design solutions. Subsequently, we will screen and further improve these plans based on evaluation criteria.

Serial Number	*Process Overview*	*Practical process*
1	Information Preparation	To train generative algorithms and gather excellent advertising design examples from multiple sources
1.1	Resource collection	The data sources cover advertising magazines, various design websites, and different social media platforms, drawing the essence of various advertising designs from

		them
1.2	Data organization	Thoroughly screen and organize all collected data to eliminate non-compliant and low-quality data, ensuring the purity and uniformity of the dataset.
1.3	Data Annotations	Provide detailed annotations for each advertising design case, covering various aspects such as design style, thematic ideas, and color application.
2	Model building	Train our generative algorithm using the prepared dataset
2.1	Algorithm filtering	Among numerous generative algorithms, Generative Adversarial Networks (GANs) were chosen as the main tool for this study.
2.2	Training implementation	Train data to enable algorithms to deeply learn and understand the core elements and features of advertising design
2.3	Effect evaluation	After training, a comprehensive evaluation of the model is conducted to ensure that it has not only excellent generation ability but also good generalization performance.
3	Creative output and improvement	Integrating well-trained GAN with CAD technology to achieve automated generation and optimization of advertising design solutions
3.1	Design concept	Using this model, quickly generate a large number of diverse advertising design drafts.
3.2	Plan review and optimization	Designers will carefully evaluate and adjust the generated design scheme based on actual needs and aesthetic standards.
3.3	Output of achievements	Output carefully optimized advertising design solutions that provide valuable references for designers and can be directly used in actual projects

Table 2: Implementation steps.

4 EXPERIMENTAL EXPLORATION AND ANALYSIS OF INNOVATIVE ADVERTISING DESIGN MODELS

4.1 Exploring Design and Execution

The experimental process is summarized as follows: Firstly, organize, classify, and standardize the collected advertising design raw data to ensure its suitability for model training. Secondly, according to the specific objectives of the experiment, adjust and optimize the various parameters of the model. Next, the prepared training data will be used to train the model and test its performance on an independent validation dataset. Then, input the preliminary advertising design concept into a trained and mature model, generate a series of design proposals, and publicly display them. In addition, industry experts and ordinary consumers are invited to evaluate these design proposals to obtain broader feedback. Finally, the overall performance of the model will be comprehensively evaluated by combining quantitative data and qualitative analysis.

4.2 Experimental Results and In-Depth Analysis

This section will present the experimental results in detail and conduct an in-depth analysis of the obtained data.

Figure 3 clearly shows the efficiency performance of the proposed model in generating advertising design schemes.

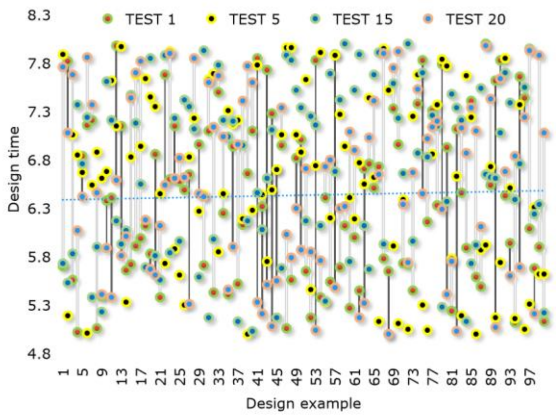

Figure 3: Design efficiency.

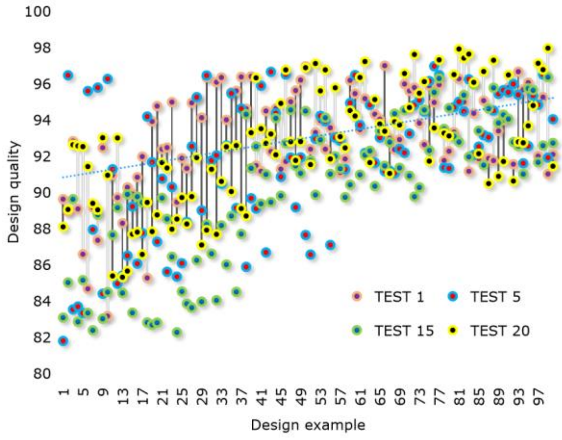

Figure 4: Design quality.

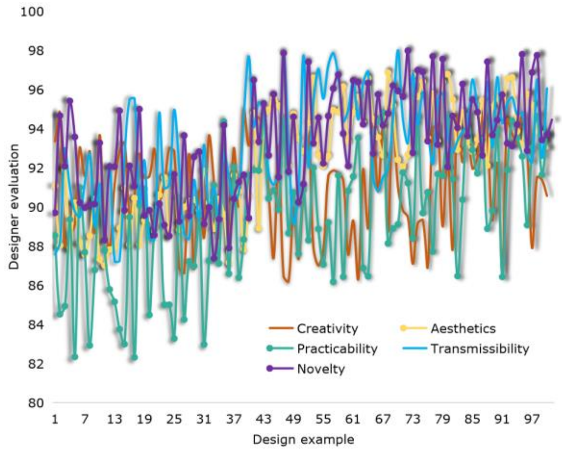

Figure 5: Designer evaluation.

Through the model proposed in this article, the quality distribution of advertising design schemes is obtained, as shown in Figure 4. Figure 5 shows the designer's evaluation of the advertising design proposal generated by the model. Figure 6 reflects the feedback from end users on these advertising designs.

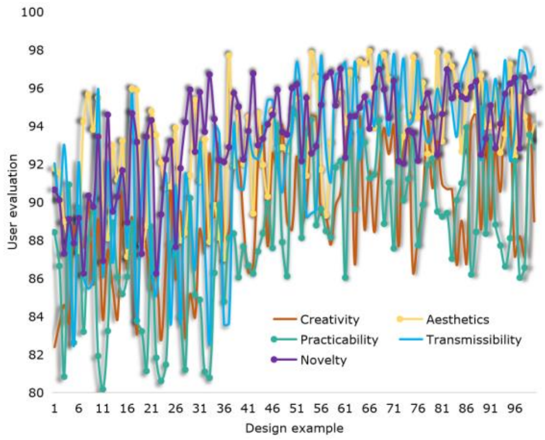

Figure 6: User reviews.

Based on the above experimental results, it is not difficult to see that this model not only efficiently generates numerous creative advertising designs but also achieves a high level of quality. Both professional designers and ordinary users have given positive evaluations of the design solutions generated by the model in terms of innovation, aesthetics, and practicality.

4.3 Experimental Summary and Outlook

The creative algorithms fully demonstrated their practical value in this experiment. This model can independently produce numerous unique advertising design drafts, and these designs have received unanimous praise from professionals and users in terms of aesthetics, practicality, and innovation.

Future exploration and optimization path:

Data Expansion and Diversity: In order to continuously enhance the model's creativity, we can expand the scope of data collection in the future, including more advertising design samples with diverse styles for the model to learn from.

User interaction and feedback: It is crucial to building a more refined user feedback system, which will help us more accurately capture user preferences and needs for design, and provide direction for continuous improvement of the model.

Model Adaptability and Expansion: In order to enhance the adaptability of the model to various advertising design styles, this study aims to collect richer training data and explore more advanced model architectures, in order to demonstrate stronger flexibility and adaptability in the ever-changing design field.

5 THE INNOVATIVE ROLE OF CAD TECHNOLOGY AND GENERATIVE ALGORITHMS IN ADVERTISING DESIGN EDUCATION

5.1 Stimulating the Creativity of Advertising Design

In the rapidly changing market, the creativity and practical ability of advertising design are particularly important. CAD technology and generative algorithms, as popular design aids today, have significantly improved these core abilities of students.

CAD technology, with its user-friendly graphical interface, enables students to easily and quickly convert their creativity into concrete visual designs. This fast feedback design process encourages students to be brave enough to try and constantly innovate, thereby cultivating their creative thinking. At the same time, the accuracy and flexibility of CAD also exercise students' observation and logical thinking abilities. On the other hand, the powerful creativity of generative algorithms presents students with infinite design possibilities. When students learn and apply these algorithms, they not only master the latest design skills but also integrate personal creativity into the algorithms, forming their own unique design language. This greatly enhances their ability to transform innovative thinking into practical operations.

5.2 Innovative Advertising Design Models

Traditional advertising design teaching mostly focuses on theory and hand drawing skills, while the addition of CAD technology and generative algorithms undoubtedly brings new changes to the teaching methods of advertising design.

Using CAD software, teachers can use examples to teach and lead students to fully experience the entire process from requirement analysis to design presentation. This immersive interactive teaching method not only enhances students' learning enthusiasm but also cultivates their self-learning ability and teamwork spirit. Meanwhile, as a novel design tool, generative algorithms enable students to explore and apply this innovative tool under the guidance of teachers. Through project-based learning, students can deepen their understanding of algorithms in practice and combine personal creativity to produce unique design works, which undoubtedly enhances their practical and innovative abilities.

5.3 Cases

In the case implementation, students proficiently applied CAD technology to achieve precise drawing and layout of advertisements, significantly improving the speed and accuracy of design work. With the assistance of the proposed model, the students successfully designed a series of advertising schemes (specific results can be found in Figure 7). This teaching method not only exercises students' practical abilities but also greatly expands their creative thinking.

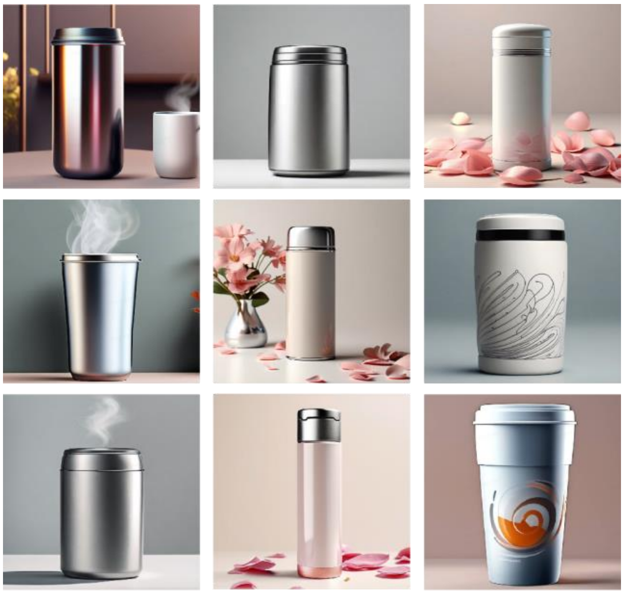

Figure 7: Design example.

At the end of the course, students not only gained basic knowledge of advertising design, but also honed their innovative thinking and teamwork skills through practical experience. Through practical project operations, they learned how to play their role in the team and how to integrate innovative thinking into design. In addition, Table 3 provides a detailed list of the application effects of CAD technology in advertising design courses, clearly demonstrating the enormous potential of these two technologies in enhancing students' design skills and creative thinking.

Serial Number	*group*	*Project cycle (days)*	*Design output*	*Efficiency gains brought by CAD technology (%)*	*Algorithms assist in creative output*	*Innovative thinking progress (1-10 points)*
1	Group A	10	5	60	3	8
2	Group B	12	4	50	2	7
3	Group C	11	6	70	4	9
4	Group D	9	5	65	3	8.5
5	Group E	10.5	5	55	3	7.5

Table 3: Application effect.

Remarks of the table 3:

"Project cycle" represents the total duration from project initiation to completion.

"Design output" reflects the number of advertising design works produced by each group of students.

The efficiency gain brought by CAD technology refers to the proportion of the increase in design efficiency of students compared to traditional methods after adopting CAD technology.

"Algorithm-assisted creative output" refers to the number of innovative advertising design solutions produced by students with the help of generative algorithms.

"Innovative thinking progress" is the self-evaluation score of students, ranging from 1 to 10 points. The higher the score, the greater the improvement.

Table 3 comprehensively records the project cycle, design output, efficiency improvement brought by CAD technology, and the number of algorithm-assisted creativity.

6 CONCLUSIONS

This study comprehensively analyzed the application of CAD technology and generative algorithms in creative advertising design and their impact on education and verified the actual effect of the advertising design model that integrates these two technologies through experiments. In the experimental design, high-quality advertising design works were selected as training data, and these data were systematically trained. Then, the trained model was used to input the initial advertising design concept and generate a unique creative advertising design scheme. Designers rely on their professional knowledge to analyze every detail of the model deeply and provide suggestions for professional improvement. This joint evaluation not only ensures the professionalism of the model but also ensures that it can truly meet the actual needs of users. We firmly believe that these advanced technologies and algorithms can not only improve the efficiency and quality of advertising design, but also become important tools for cultivating students' innovative thinking and practical abilities. In addition to conducting in-depth research in practical applications, we also pay special attention to the potential value of CAD technology and generation algorithms in advertising design education. Through practical operation, students can have a deeper understanding of the principles and methods of advertising design and also cultivate a new generation of advertising design talents with forward-looking thinking and technical strength. Therefore, we advocate for teachers to introduce CAD technology and generative algorithms into the classroom, guiding students to learn and master these advanced design tools. Secondly, by introducing CAD technology and generation algorithms, we have significantly improved the efficiency and quality of advertising design. This provides designers with a broader creative space and more efficient working methods.

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