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A Style-Oriented Approach to Intelligent Generation of Product Creative Concepts

Jianning Su [1,2], Baoyin Yu [1], Xiong Li[2,3] and Zhipeng Zhang[2]

[1]School of Design Art, Lanzhou University of Technology, 212130500001@lut.edu.cn
[2]School of Mechanical & Electrical Engineering, Lanzhou University of Technology, zhangzhipeng@lut.edu.cn
[3]School of Bailie Mechanical Engineering, Lanzhou City University, leanodesign@163.com

Corresponding author: Jianning Su, sujn@lut.edu.cn

Abstract. Traditional product concept innovation design relies on designers' design experience and is hindered by integrating tacit knowledge such as work experience, time, and ideas. Rapidly iterating design solutions and meeting diverse market needs has become one of the challenges for designers. Intuitive and varied visual stimulation can quickly inspire designers' creative thinking, effectively improve their efficiency, and assist them in creating various styles of products, breaking the product innovation and design process of design thinking curing. In this paper, we propose a style-oriented approach for the intelligent generation of creative product concepts to help designers quickly obtain creative inspiration and improve design efficiency. First, we build a high-quality hairdryer dataset and generate multiple styles of hairdryer images by training the StyleGAN3 generative adversarial network to solve the hairdryer creative concept image generation problem. Second, a stable diffusion model is introduced to optimise and innovatively generate the obtained images so that they can innovatively generate various details to maintain the original styles and thus improve the image quality. Third, a 3D hairdryer model is generated based on the Shap·E model and parametric design using the images as input conditions. Finally, the effectiveness of product conceptual design generation is assessed using three indicators: novelty, variety, and timeliness. The intelligent product creative concept generation methodology system we constructed provides designers with a dedicated, fast, and effective source of conceptual creative inspiration, helping to advance product conceptual design solutions efficiently.

Keywords: Innovative design of product concepts; generative adversarial networks; stable diffusion model; product styles; intelligent generation; design creativity.
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1 INTRODUCTION

The product style is a collection of similar features constructed by reorganising, retransforming and recalling different styling elements by various modelling means[1-3]. As the most intuitive external manifestation of the product form, product style plays a crucial role in the product's sales tendency and the user's emotional preference. Successful product style design can fully reflect the concept of the designer and is an essential bridge between the designer and the user to establish communication, but it is also a necessary means for the designer to grasp the future development direction of the product design style. The user's perceptions of preference play a decisive role[4].

Creativity is recognised as a critical factor for success in all fields, especially in design. Effectively generating new and innovative ideas through design conceptualisation remains a key research issue for designers[5]. Design conception is used in the early design stage and is the source of creative design and creativity. Eighty percent of human information is acquired visually, and a user's first impression of a product's style also comes from visual information[6]. One of the attributes of vision is visual perception. Visual perception in receiving information input has the characteristics of positive and active, holistic and simplified tendencies, consistent with designers' output design solutions and the process of users identifying the product style. Therefore, visualising the research object can improve designers' information input efficiency and generate creativity. Traditional design relies on the experience of designers, who usually obtain design inspiration from design websites, books, journals and magazines to generate conceptual designs. This design requires designers to accumulate long-term experience, which is time-consuming, labour-intensive and inefficient in specific design tasks. Acquiring inspiration that comprehensively, conveniently, and efficiently ignites creativity is crucial for enhancing designers' efficiency in tackling specific design tasks and crafting suitable product solutions.

Images are widely used for idea generation because they contain rich and different information. Several scholars have researched the generation of design inspiration and creativity from sketches and images. Earlier research has shown that the advantages of intuitive and effective pictorial representations far outweigh detailed representations of textual information[7, 8]. Casakin[9] found that using extensive collections of visual displays (pictures, sketches, diagrams) in the ideation phase of design effectively improves the quality of design solutions for designers and novices in solving ill-defined problems. The results of Cardoso et al.[10] showed that using different types of visual stimuli and more abstract samples supported the generation of new ideas. Borgianni et al.[11] experimented with stimulus idea generation through three dimensions, text, image, and text-plus-image, and showed that the image dimension led to a significant increase in rarity and saliency. The above research shows that image-based forms of visual stimulation can obtain an efficient source of design inspiration for designers, significantly help generate creativity, effectively improve design efficiency, increase the design space, and positively influences design workflows.

There are many methods by which designers can represent information (textual descriptions, sketches, line drawings, photographs, models, etc.). Due to the development of computer technology, more groups are moving away from using sketches in favour of computer-aided design-generated renderings and images for the early idea conceptualization [12, 13]. Artificial intelligence has made significant breakthroughs in creative design generation in recent years. Artificial intelligence-generated content (AI-generated content, AIGC) has demonstrated extraordinary creative potential based on extensive data learning and strong potential in image generation and creatively generated content. Advances in technology have led to a diversification of conceptual innovations. From generative adversarial networks (GANs)[14], where unsupervised learning is dominant, to the current diffusion model, which performs better, updating strategies and optimising details during the process of divergence of ideas to the generation of conceptual solutions are achieved. For example, Li et al.[15] proposed a product concept generation design framework, PCGA-DLKE, by training a GAN model and constructing a fast neural style migration model to create new design styles. Creation tools based on stable diffusion, Midjourney, etc., Focused etc., focused enhancements in user interaction, generation of guidance, more personalised, support user-defined style input. In the 3D domain, implicit neural representation (INR) has become a popular method for encoding 3D assets, e.g., the conditional generation model proposed by OpenAI for Shap·E[16] representation of 3D assets exhibits high flexibility, short time and high quality, which can effectively overcome the shortcomings of traditional 3D generation , improve the efficiency of creative design and speed up the iteration of different styles of products. The above studies and applications show that AI-generated content based on deep learning technology has great potential and advantages in assisting the creative design of product designers in generating inspiration and new product styles. However, most of the current research focuses on the study of individual "points", and a complete design process is rarely formed in the creative design of intelligent concepts. Therefore, it is an important and meaningful task to use deep learning technology and parametric design to construct a design process applied to product concept innovation design.

2 OVERVIEW OF RELATED WORK AND RESEARCH

2.1 Generative Design Based on Design Creativity

Diverse approaches at the conceptual design stage effectively stimulate creativity and provide as many options as possible for solving design problems[17]. As Gero et al.[18] suggest that generating processes incorporating multiple solutions is considered a form of creative exploration. In product design, design features are used to reflect a certain design style[19], distinguish between different solutions and are indicators characterising the richness of a designer's creativity. Chan et al.[19] demonstrated through several experiments that the degree of style is directly proportional to the number of identical features. Additionally, experiments have shown that the hallmark of independent style is the presence of three identical features in a product originating from the same designer. The creativity of the designer shows a relevant linear relationship with the creation of the characteristics of that product.

However, the ultimate goal of creativity is to generate innovative products[20], and quickly putting the generation of creativity into the product concept design process has become an urgent problem for designers. Currently, competitive relationships and changes in the marketplace have led to the need for designers to ensure high quality and efficiency in their product design output while being highly innovative. In recent years, artificial intelligence represented by deep learning has achieved stunning results in idea generation. It has been widely used in generating and presenting ideas in the conceptual design stage. For example, Lin et al.[21] constructed a shape-generation model for automobile taillights through DCGAN and PGGAN and innovatively generated many automobile taillight images. Wu et al.[22] combined a convolutional neural network and generative adversarial network to generate a series of classic oil-paper umbrellas using oil-paper umbrellas as the research object in the cultural and creative design field, inspiring the design of oil-paper umbrellas. AIGC has realised the leap of AI from perception and understanding of the world to generating and creating the world, and models such as stable diffusion, DALL-E 2, and Midjourney have achieved "human-like" performances in many fields, such as writing, painting, and composing. Because of the breakthrough and innovation of basic generation models, the 2D image generation method, based on the diffusion model and neural radiance field (NeRF), has been applied in many 3D generation fields and has shown high accuracy and quality. Therefore, this study concludes that combining deep learning and AIGC in product conceptual innovation design can assist designers in continuously generating, iterating and validating ideas, effectively improving the efficiency of creatively generated designs.

2.2 StyleGAN3 Network Model

The StyleGAN3[23] network is based on the GAN network and improved on the foundations of its predecessors, StyleGAN[24] and StyleGAN2[25]. StyleGAN3 series networks introduce style vectors while increasing the resolution of the generator and the discriminator, changing the input and input mode of the generator. By separating image content and style, different aspects of image generation can be carefully controlled, which can significantly improve the quality, relevance, diversity and stability of the generated data. Designers can utilize its advantages to create various design solutions, expanding design possibilities and enhancing design innovation. The model can be converged more easily because of the architecture change, allowing for quicker image generation and iteration of the design scheme. Designers can evaluate and adjust design options in time to find a more satisfactory solution. In computer vision and creative design, StyleGAN3 is widely used due to its excellent stability in image creation, style, and feature control. Therefore, we chose StyleGAN3 as the initial image generation model.

Figure 1 shows the StyleGAN3 generator structure. The whole network structure consists of two parts: the mapping network and the synthesized network. The mapping network converts the serving input random noise Z (potential vectors) into the potential spatial representation w. The input of the synthetic network is the Fourier feature, that is, the learned affine A output, and then the feature map is converted into the RGB colour space image by a total of 14 operation levels L0 to L13 and ToRGB layer. Since each of the 14 operational levels is encapsulated as a separate CUDA core, it effectively increases training speed and reduces memory usage.

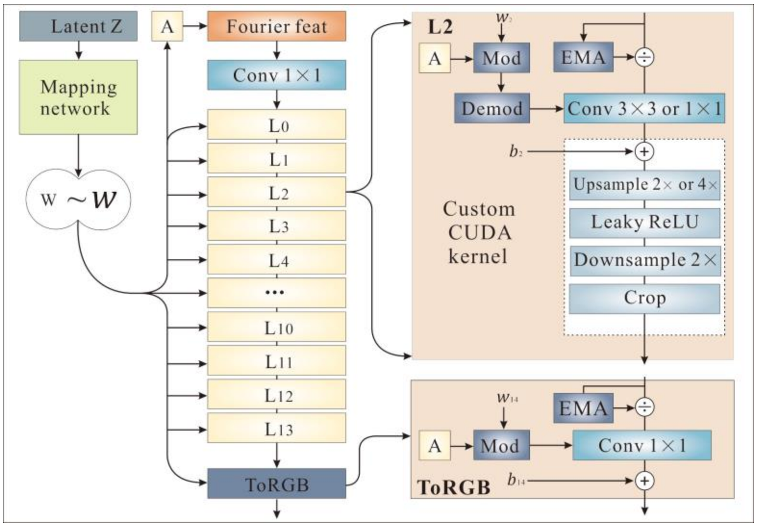

Figure 1: Architecture of StyleGAN3 generator.

Based on the excellent image generation capability of StyleGAN3, some scholars have made extensive applications in product idea generation, style migration, and rendering generation. For example, Deng et al.[26] proposed a StyleGAN-based method for generating effect drawings from product sketches, using the deformation technique of the StyleGAN model to achieve the conversion from sketches to the target style effect drawings and selecting the appropriate style migration scheme to achieve the optimal scheme design. Ou et al.[27] generated a large number of ceramic defect samples with StyleGAN3 and, on this basis, improved the detection accuracy of defect samples and effectively improved work efficiency. The StyleGAN3 network can generate diverse and novel images and unidirectional delivery of product innovation visually, with rapid generation, which provides positive ideas for this study.

2.3 Stable Diffusion Model

The rise of diffusion models[28, 29] is a significant factor in recent breakthroughs in AI generative art. Due to its outstanding performance in image generation, it has formed one of the crucial directions in the generation filed. The stable diffusion model[30] is a potential text-to-image diffusion model derived from the diffusion model, one of its variants. The stable diffusion model includes text generation and text plus image generation (text generation image and image generation image). In

This paper, we use the stable diffusion model to optimize and improve the generated image, so the second mode is the research focus.

Figure 2 shows the image generation image structure for the stable diffusion model. It consists of four steps: the first step is to encode the input textual information to obtain textual features; the second step is to encode the input image and obtain the information array of the image (also known as Latent) through the VAE encoder; the third step is to carry out the diffusion, which is a step-by-step processing of the input shallow spatial information processing through the UNet and Scheduler, and the output of the processed information array (Latent); and the last step is to decode the processed information array into an image through the VAE decoder. Since the stable diffusion model compresses the data into low-dimensional latent data, much smaller than the original data, it is more efficient than the diffusion model in the inverse denoising process. In addition, modifications to the backpropagation model allow it to accept multiple types of data inputs and support a rich set of downstream tasks.

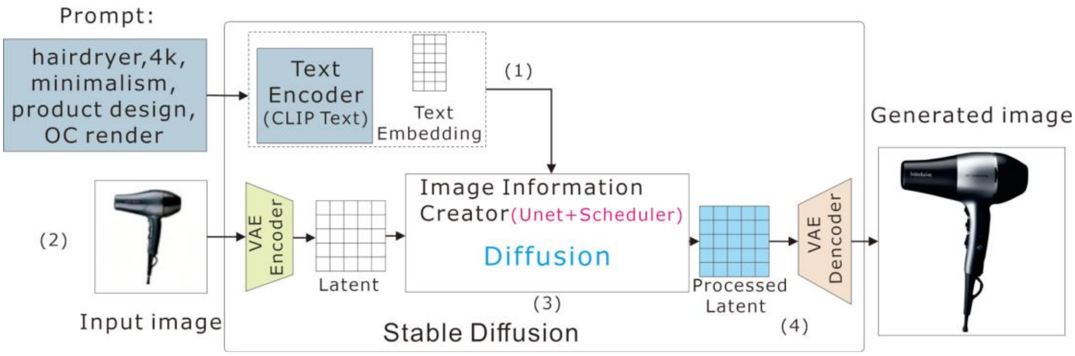

Figure 2: Stable diffusion model.

Compared with the GAN network, which requires a more significant quantity of data to generate higher-quality images (including resolution size, clarity, completeness, diversity of images), the stable diffusion model can be used to generate images creatively through text encoding and inputting a single image, and the results can be generated by adding additional network controls such as ControlNet[31]. Therefore, in this section, through the data exchange and fusion of the GAN network and stable diffusion model, we can generate high-quality, creatively generated images and obtain image datasets that are rich in detail and high quality and guide designers to diverge their thoughts, which will, in turn, improve the fluency of the whole design process.

2.4 3D Generation Related Research

3D models are widely used in various industries as the most basic form of product expression. In product design, the 3D model of a product is not only a representation of the design but also an indispensable step for design feasibility verification. Unlike 2D representations, 3D shapes can be represented in various forms, and the effects of generating 3D shapes under different demands also have enormous differences[32]. Therefore, high-quality and accurate 3D shape generation is becoming increasingly important. Building 3D models manually can achieve high quality and fine detail, but it is time-consuming and requires the designer to have the appropriate technical support. Generating flexible 3D models that can be interactively used and further refined by designers or users can effectively improve design work efficiency and meet different design needs.

With the increase in data size, computational power has been significantly improved, and deep learning-based 3D shape generation representation has achieved remarkable research results. Existing 3D shape representations generally fall into two categories: "hard (solid)" representations dominated by point clouds[33, 34], voxels[35, 36] , meshes[37, 38], etc., and "soft" representations dominated by neural radiation fields[39]. However, although the above 3D shape representations have been explored in different aspects with good results, such as single-view reconstruction[40], adversarial generation[41], and self-coding[42], they still have their shortcomings, such as the lack of connectivity of the underlying network in the point cloud, the cubic increase in voxel memory footprint and the poor data output topology of the mesh. Compared to "hard (solid)" representations, NeRF-based "soft body" representations, i.e., INRs, are a new approach to parametric signal representations. The method is easy to combine with grid structures, can quickly learn a priori, fit learning objects, is easy to learn, and has been used in many applications in 3D shape representation. For example, Mescheder L et al.[43] proposed a 3D reconstruction method based on direct learning of the 3D occupancy function using a neural network to predict the complete occupancy function, reducing memory usage during training and representing the output 3D model at infinite resolution. Peng S et al.[44] proposed a more flexible implicit representation-convolutional occupancy network by combining a convolutional encoder with an implicit booth encoder to achieve 3D structured spatial reasoning, which enables large-scale reconstruction of complex indoor scenes while preserving model details.

Based on INR's excellent 3D model representation, Jun et al.[16] proposed a potential diffusion model Shap-E on a 3D implicit function space. The model is a 3D representation with NeRF and the 3D conditional generative model DMTet[45] and its extended 3D mesh generative model GET3D[46] as primary 3D representations. The Shap·E model architecture consists of two parts: one generates the implicit representation by the encoder, and the other trains a diffusion model on the shallow representation generated by the encoder as the model generator. The input to the encoder is a rendered view of the point cloud and 3D assets. The input to the encoder is a rendered view of the point cloud and 3D assets, while the decoder output is the 3D model rendered via NeRF and STF. The above study shows that NeRF-based "soft body" representation has better applicability in a 3D generation, can effectively connect the information flow between 2D representation and 3D model, and can be used in conceptual, innovative product design.

By analysing the above research methods and related technologies, we believe that in the product creative concept design process, the new generation of technology based on deep learning and AIGC can help to change designers' method of creation, improve design efficiency, and play an essential role in solving problems from 2D concept design to 3D generation. Therefore, to explore the coherence, flow, and realisability from 2D to 3D in product conceptual creative design, we propose a style-oriented method for intelligently generating creative concepts conducive to computer-aided design and innovative applications.

3 METHODS

3.1 Research Framework

To use artificial intelligence to assist designers in design thinking, design processing, and product style generation for product creative concept generation design, we propose a style-oriented product creative concept intelligence generation method, as shown in Figure 3. The research framework contains four parts. The first part obtains hairdryer pictures from relevant websites and channels through crawler technology and manual search. After the preprocessing stage, we can obtain the high-quality hairdryer dataset I. In the second part, we use the StyleGAN3 network, a derivative of the generative adversarial network, to generate many hairdryer pictures with diverse styles and innovative features. The hairdryer pictures are used as the dataset of the third part. The third part optimises the experimental dataset provided in the second part with a stable diffusion model to obtain a high-quality correlation dataset. It uses it as the 3D model generation dataset for the final part. The last part applies the Shap·E network to generate the 3D model based on the optimised dataset of the stable diffusion model, mesh transformation, reorganisation and compression of parametric quantities of the acquired 3D model by constructing the Grasshopper parametric design program, and finally, refinement of the model by SubD based on the Rhino platform. We finally obtained various new style hairdryer innovation solutions through the data exchange and articulation of the four parts.

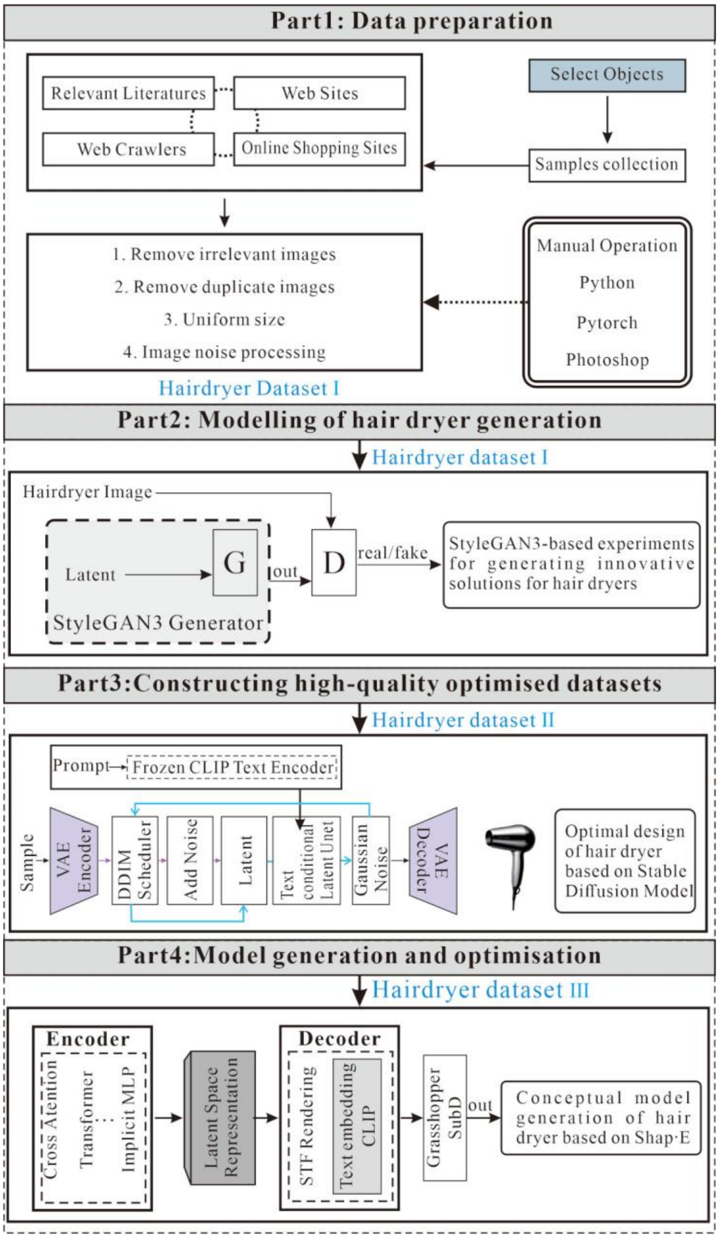

Figure 3: A Style-oriented framework for intelligent generation of product creative concepts.

3.2 Test Environment and Equipment

All experiments were run on 64-bit Windows 10 operating system and GPU (GeForce RTX 3090/32GB) devices, using Python language and Pytorch deep learning framework as the experiment environment. The Python and Pytorch versions are 3.8.13 and 2.0.0, respectively.

3.3 StyleGAN3-Based Hairdryer Innovation Concept Generation Experiment

This experiment aims to study the conceptual innovation design of a hairdryer through the styleGAN3 network model and provide a data set for the next experiment. Firstly, we built a high-quality hairdryer dataset1, then trained the model based on the dataset. Finally, we constructed the hairdryer conceptual innovation generation model and generated dataset II.

3.3.1 Hairdryer dataset I

High-quality image data are one of the primary screening conditions in acquiring the initial hairdryer dataset to provide a positive impact on the subsequent hairdryer optimisation test and 3D model generation. Establishing the hairdryer dataset is based on Part 1 of the method framework, as shown in Figure 4. First, some hairdryer images were crawled from pages provided by Bing and Google search engines using web crawler tools, and other products were crawled from Amazon.com, JD.com and Taobao.com. Figure 4 shows the results of a Bing search. Next, we manually checked and removed inappropriate images (based on previous experience, we chose images with appropriate angles to show more detailed features, as shown in the angles below). Then, Brime was used for image filtering, format conversion (*.jpg), and standard sizing (resolution: 256×256). Photoshop and Topaz DeNoise AI were used to process the image backgrounds, noise reduction, and other processing to improve the pixel quality of the data. Finally, we collected 4000 high-quality hairdryer images (hairdryer dataset I). The final dataset is shown in Figure 5.

Figure 4: Example of a Bing Search Web page search for hairdryers.

Figure 5: Partial hairdryer dataset I.

3.3.2 Network structure

A generation model of a hairdryer was constructed by the StyleGAN3 network experiment, which consists of two parts: generator and discriminator. The structure of the generator is shown in the upper left part of Figure. 6. The input data is a 512-dimensional latent vector, and ToRGB is the hairdryer image output layer (size is 3×256×256). The structure of the discriminator is shown in the right part of Figure 6. The input consists of two parts: the real hairdryer image input and the hairdryer image generated by the generator the activation function uses the LeakyReLU, and the output layer consists of the sigmoid function that performs the discriminatory function by discriminating the probability of 0 or 1 to determine if the output image is real. Through the mutual game between the generator and the discriminator, the equilibrium state is reached and then stopped. Figure 6 shows the overall architecture of this experiment's innovative concept generation of the hairdryer.

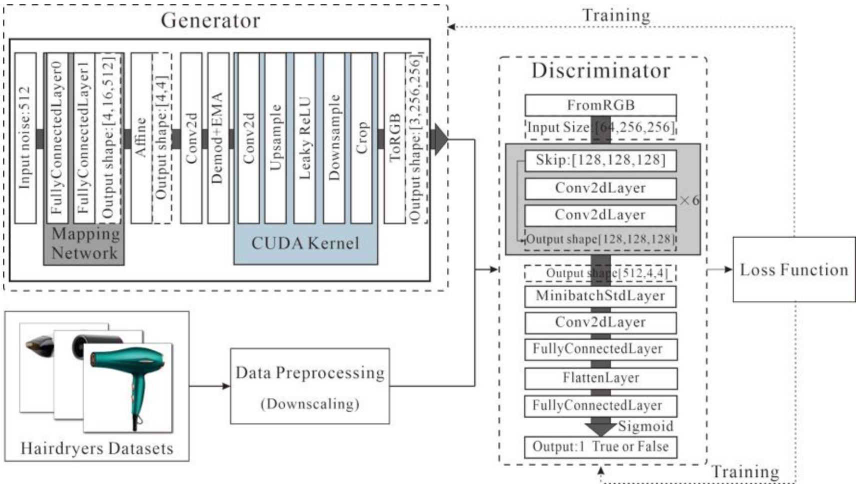

Figure 6: Structure of the hairdryer generation algorithm.

3.3.3 Network training and results

The noise input dimension is 512, the learning rate is set to 0.01, the number of inputs per batch is 4, the parameter gamma is set to 2, gamma is the R1 regularisation weight, the parameter mirroring is set to true to increase the training data given the volume of the dataset, and the total training Kimg is set to 700.

The adjustment of the parameters through many trials successfully trained a better generation effect: when the training Kimg is 516, the quality of the experimentally generated images is better. Additionally, the loss curves of the generator and the discriminator show that our training has reached a state of convergence, and the results are shown in Figure 7.

The total training time for StyleGAN3 network training was two days, 4 hours and 38 minutes, and the total number of training iterations Kimg was 676.

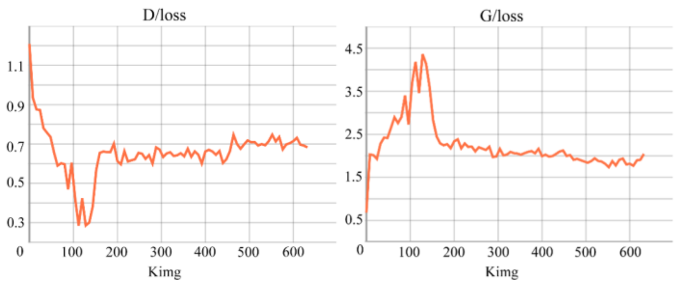

Figure 7: Generator and discriminator training loss curves.

Figure 8 shows the results of the images generated by stylegan3 at different moments, which are the initialized image, 200 Kimg, 400 Kimg, and 600 Kimg. As the training time grows, the resolution of the generated hairdryer increases, and finally, the final number of Kimg iterations end at 676 according to the training results and the adjustment of the parameters.

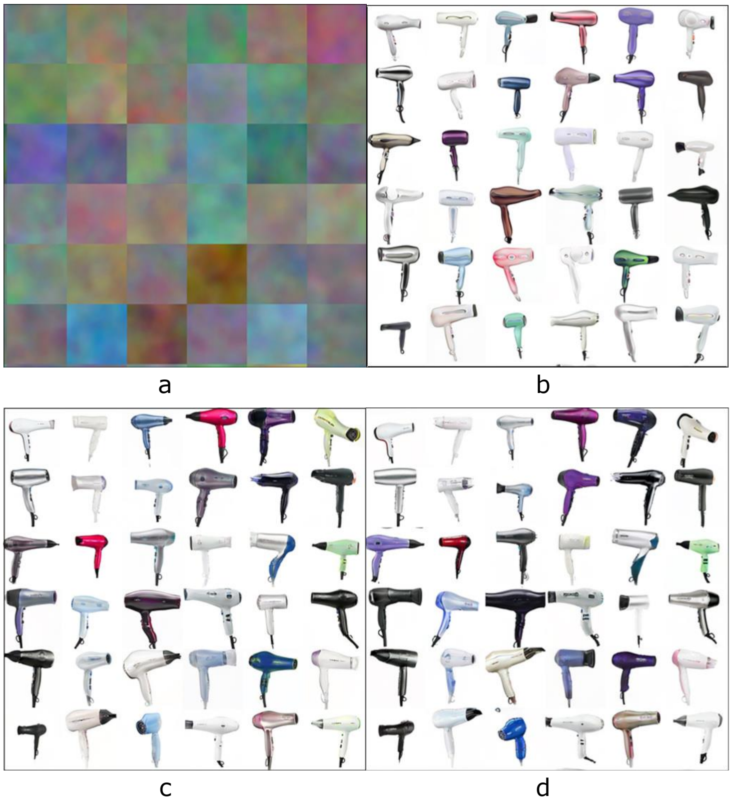

Figure 8: Hairdryer-generated images at different moments (a, 0 Kimg; b, 200 Kimg; c, 400 Kimg; d, 600 Kimg).

In order to assess the quality of the generative model more accurately and objectively, we introduced the Fréchet Inception Distance (FID) [47] to assess the difference between the generative model and the real data distribution. In generative adversarial networks, the FID value is used to assess the quality of the generated images, with lower scores indicating higher quality.

For two identical images, the extracted vectors obey the same distribution, and the corresponding high-dimensional vector features of the images generated by the GAN also obey this distribution, so the distance between two univariate gaussian distributions can be computed from the variance and the mean. Since the images generated by the GAN for this experiment belong to a multi-dimensional distribution, the correlation between multiple dimensions is measured using the covariance matrix, and the distance between two high-dimensional distributions is calculated using the covariance matrix and the mean value with the following formula:

$$\mathrm{FID}(\mathrm{x},\mathrm{g}) = \| \mu_{\mathrm{x}} - \mu_{\mathrm{g}} \|_2^2 + \mathrm{Tr}\left(\Sigma_{\mathrm{x}} + \Sigma_{\mathrm{g}} - 2\left(\Sigma_{\mathrm{x}}\Sigma_{\mathrm{g}}\right)^{0.5}\right) \tag{1}$$

Where, μ_x and μ_g denote the eigenvalues of the real and generated images, respectively, and Σ_x and Σ_g denote the covariance matrices of the real and generated images, respectively.

In this experiment, the total number of iterations was 676, and the FID values for each stage were summarized as shown in Figure 9. From the Figure 9, we can find that the FID value of the entire training process shows a gradual decline in the trend, when to 200 after the decline in the trend gradually becomes smaller and stabilized and a small range of fluctuations, indicating that our training process is gradually reaching a convergence state. So, in this range, choosing a smaller FID value to determine the better generative model and ultimately choosing the FID value is 10.48.

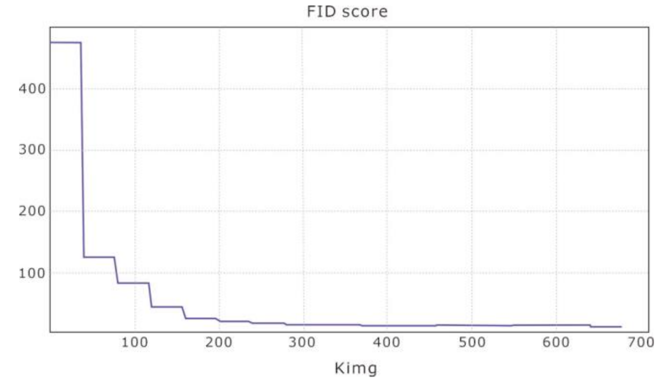

Figure 9: Value of FID change.

The selected model weights are applied to generate the hairdryer images, and Table 1 shows some of the generated hairdryer images. From the comparison between the results and actual samples, the StyleGAN3-based hairdryer generation model can generate images of hairdryers in a variety of innovative styles (e.g., No. 1 and 9, which favour professional hairdryers, No. 5 and 14, which favour cute style hairdryers, while No. 4 favours minimalist styles and No. 8's style tends to be more mellow). By comparing the dataset I, we found that some generated samples are high degree of similarity with the training samples (No. 16, 18). In the generated image samples and training samples, we find that the number of different kinds of styles is also very different (e.g., No. 4, 5). The main reason for this phenomenon is the relatively small dataset and the difference in the number of training samples containing different styles of hairdryers.

							
1	2	3	4	5	6	7	8
							
9	10	11	12	13	14	15	16
							
17	18	19	20	21	22	23	24

Table 1: Generated hairdryer with random noise (pixel size 256×256).

Further analyzing the details of the generated hairdryer images, we find that although StyleGAN3 can generate samples of hairdryers of different kinds of styles, the resolution is not high and it is rough in terms of reflecting the design features of the styles, such as the parts marked by the blue boxes in Figure 10 (the tail air inlet, the positions and shapes of the buttons, and the segmentation of the styling, etc.).

Figure 10: Detail of hairdryer image generated by StyleGAN3.

3.4 Optimal Design of Hairdryer Based on the Stable Diffusion Model

Combining the shortcomings of the generated images in Section 3.3 and the advantages of the stable diffusion model in terms of fine control and improved image resolution. In this experiment, we focus on optimising and improving the quality of the samples generated by the GAN network to generate controllable hairdryer samples.

3.4.1 Hairdryer dataset II

The test dataset of this part is generated by the experiment in Section 3.3, which removes the samples with apparent defects and cannot be used by manual screening to obtain the hairdryer dataset that can be optimised for design. The final partial test dataset is shown in Figure 11.

Figure 11: Partial hairdryer dataset II.

3.4.2 Network training and results

Since the purpose of this experiment is to enhance the experimental results in subsection 3.3 optimally and to explore the commonalities and differences between the stable diffusion model and the StyleGAN3 generative adversarial network, the experimental inputs for this section are the hairdryer dataset II and the cue words of the corresponding hairdryer style. To control the shape of the hairdryer image accurately, we use the edge detection tool of the ControlNet model for control. The structure of the framework for generating the optimal design of the hairdryer based on the stable diffusion model is shown in Figure 12. The data size for the image condition input is a 3-channel 512 × 512 resolution image of a hairdryer, and the text input condition is the information necessary to characterize the features associated with the hairdryer (upper left corner of the figure). Since the UNet of the stable diffusion model accepts latent features (64×64) instead of the original image, the image is converted to a 64×64 feature space using the network ε to match the size of the corresponding input when using ControlNet. The final output is the same size as the input (3 × 512 × 512), producing a hairdryer-optimised image that meets the objectives.

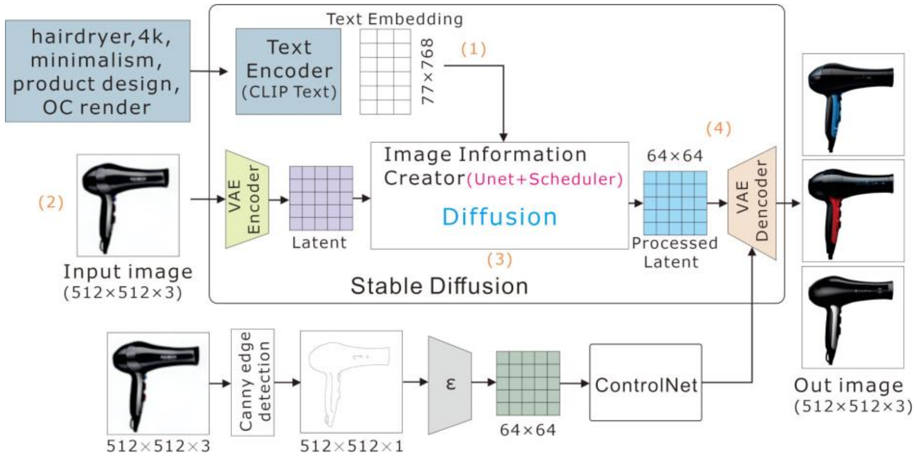

Figure 12: Optimal design framework of hairdryer based on stable diffusion model.

The default settings for the stable diffusion model are 512 × 512 pixels, 20 inference steps, a guidance scale of 7.5, and the Euler sampling method. The ControlNet network input image size is 512×512, and the preprocessor uses edge detection. Some of the hairdryer optimisation images are shown in Figure 13.

Figure 13: Part of the hairdryer optimization picture.

Comparing and analyzing the results of hairdryer generation with StyleGAN3 in Table 2, we find that the problem of rough design features can be effectively solved, the resolution has been significantly improved, and the detail parts are more precise. While keeping the original shape unchanged, the consistency of the style can be effectively inherited and innovated to a certain extent. Therefore, it meets our expected goal.

StyleGAN3 generated	Stable Diffusion generated

Table 2: Comparison of stylegan3 and stable diffusion model results.

3.5 Generation of a Hairdryer Conceptual Model Based on Shap·E

The complete product design process includes the design concept in the early stage, model generation in the latter stage, and the testing of various indicators. Different difficulties in each stage hinder the traditional design process, and the 3D model generation stage is an inevitable key technical node that designers must overcome, which is crucial to design efficiency. Therefore, in this experiment, through the deep learning method, Shap·E network model architecture and parametric design, a three-dimensional conceptual model was generated for the test results in Section 3.4 to explore the feasibility of this method.

3.5.1 Hairdryer dataset III

The experimental dataset for this section was generated in Section 3.4. Optimisation design, where the optimisation samples of different styles of hairdryers were used as inputs to the conceptual models to generate conceptual models corresponding to the different styles.

3.5.2 Test procedure and results

The architecture of the Shap·E-based 3D conceptual model generation is shown in Figure 14, which is the same as the overall architecture of the stable diffusion model in Section 3.4 and consists of an encoder and a decoder. In the encoder section, the inputs are point cloud information or 3D-rendered views. Since we need to generate a conceptual model of a hairdryer and a large number of high-quality 3D-rendered views of the conceptual hairdryer were obtained in Section 3.4.2, the inputs are conceptual drawings of a hairdryer. The input 3D-rendered view is represented as an implicit function, and the generator section uses a conditional diffusion model to generate the parameters of the implicit function output by the encoder. In the decoder section, a hairdryer 3D model with triangular mesh is decoded using a renderer based on NeRF and STF.

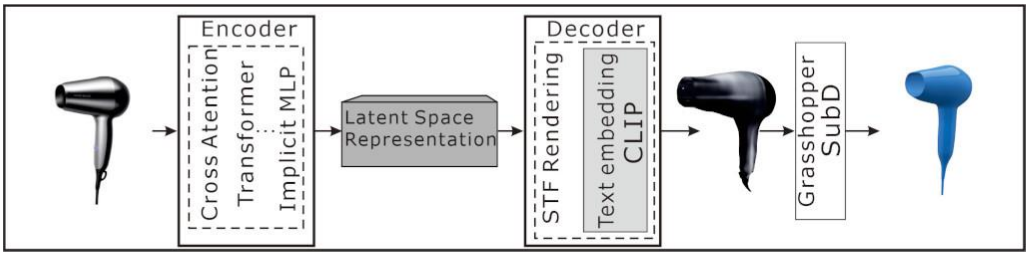

Figure 14: Architecture diagram generated based on Shap·E conceptual model of hairdryer.

Since the 3D model output in Section 3.5.2 is composed of a triangular mesh, it cannot be edited, and the quality of the model cannot achieve pleasing effects to a certain extent, significantly impacting the subsequent detail adjustment. Therefore, we performed further editable manipulation and optimized the design of the triangle mesh by writing a parametric design program using a visual programming language (Grasshopper) based on the Rhino platform and SubD (Subdivision Surface, a new type of geometry that creates editable, high-precision geometries) modelling. The parametric design program is shown in Figure 15.

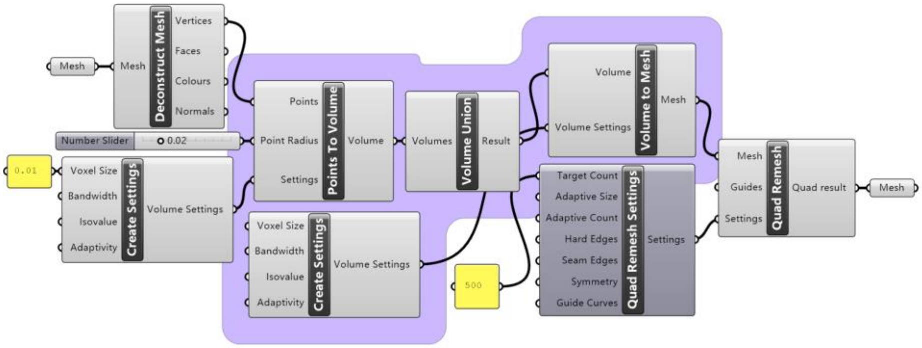

Figure 15: Parametric design procedure.

The input to the program is the 3D hairdryer mesh model generated in subsection 3.5.2, and the mesh is decomposed into points and surfaces using the deconstruct mesh component. Since our goal is to achieve fast and controllable model editing, the points obtained by decomposing the original mesh are converted and reduced in data format using the Grasshopper volumetric modelling plug-in based on the OpenVDB library, which yields data formatted in the volumetric data type. Then, it is merged and converted into a small volume mesh, the quad remesh algorithm is used to divide the four-sided surface mesh, and the regular four-sided surface mesh is obtained. Based on obtaining the four-sided surface mesh model with a complete restoration degree, the SubD is used for fine optimisation of the model. Finally, the optimised hairdryer model is obtained. Part of the hairdryer optimisation model is shown in Figure 16.

Figure 16: Hairdryer optimisation model.

3.6 A/B Test Analyses

This study aims to explore the feasibility and value of the above research methods and processes in the conceptual design stage of assisting designers in design innovation, improving design efficiency, and creative generation. To further understand the application innovation of deep learning technology and AI-generated content in product design, two sets of experiments were conducted to compare and evaluate the effectiveness of the proposed method as a conceptual design aid to verify the reliability of the proposed method. Through this study, we aim to describe further and initially solve whether artificial intelligence's deep learning and intelligent generation can help designers create better methods and conceptual design-related issues in actual design research.

3.6.1 Test preparation

Based on the abovementioned experimental methodology, this experiment was divided into two groups: the traditional design process group (Group A) and the research methodology process group of this paper, i.e., the "intelligent tool-assisted group" (Group B).

The participants were all interns, PhD students and product designers in industrial and product design, and the design researchers all had several years of design experience and a good level of competence. The trial was conducted in a fixed-variable manner. There were six designers in each group, and the designers in the intelligent-assisted group were trained before the trial to master and apply the design methodology process.

The trial evaluation metrics were based on four measures of validity proposed by Shah et al.[48] based on judging the value of conceptual design methods: quantity, quality, novelty and variety. In this study, we used two of these four indicators (novelty and diversity), and secondly we added a new metric (timeliness). All indicators are described below:

Novelty: Novelty is a measure of how unusual or unexpected an idea is compared to other ideas. In this paper, we focus on the metrics of design features such as the morphology of the hairdryers, chamfers, parting lines, etc.

Diversity: Diversity measures the solution space explored in the idea generation process. The generation of similar ideas indicates low diversity. This article refers to measuring the design features of all the hairdryer images in each group.

Timeliness: Time in this test is used to measure the time spent by each group in each period to measure the efficiency of the test.

Considering the differences in each individual's knowledge background and the different metrics for novelty and diversity thresholds, in order to average out such differences and improve the recognition of diversity, we trained participants before the start of the experiment (viewing images of more hairdryers in the market, focusing on different design features of the hairdryer, details of the components).

3.6.2 Test process

To meet the needs of our trials, the two groups differed somewhat in their trial processes. The trials were aimed at the innovative design of the hairdryer concept, and the conditions and objectives of the designers are summarised as shown in Table 3.

	conditions	purpose
Traditional Design Process Group	Arbitrary references	Design a concept hairdryer
Intelligent Tools Assistance Group	Stable Diffusion and 3D out puts	Design a concept hairdryer

Table 3: Test conditions and purpose.

For the traditional design process group, we observed and analysed how designers design a product. According to Prats[49] and McGown et al.[50], the time variable needs to range from 10 to 15 minutes or even weeks of observation. Given the purpose and nature of our research, 30 minutes was set as the time for the traditional group to obtain inspiration for the conceptual design of the hairdryer. The time for the whole design process was set to 1 hour, with no limitations on the sources of inspiration, which could be obtained from the internet, books, icons, nearby products, etc. For the intelligent tool-assisted group, created by the proposed research methodology, the hairdryer conceptual design sample is provided by subsection 3.4, and the final model is provided by the experimental part of subsection 3.5, again with the innovative design by the six designers. The structural flow of the two groups of tests is shown in Figure 17, where part of the hairdryer test samples of the intelligent tool auxiliary group is obtained from Section 3.5.1

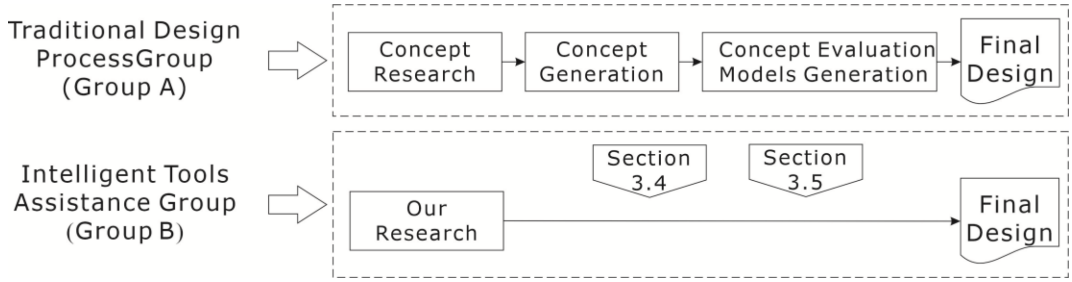

Figure 17: A/B test flowchart.

Before the start of the experiment, it was determined that the designer did not know the design task in advance. Additionally, the designer needed to conceive as many innovative design schemes as possible within the prescribed 1 hour and design in full accordance with the actual requirements of each group. To accurately record the time used in each stage of the process, the designer must record the time using a stopwatch during the design process. The groups were allocated to different workplaces with similar layouts to achieve a relaxed psychological environment to ensure that the test of each group can be carried out reasonably and orderly.

For the evaluation process of the trial, we invited 15 designers (seven men and eight women) with at least five years of experience in industrial and product design to evaluate relevant indicators. The timeliness indicators were not researched and evaluated at this stage because we asked for the timing of the stages before we started the trial with the designers, and only the diversity and novelty indicators were evaluated separately. For the evaluation of diversity and novelty, we used an ordinal scale of 1 (low) to 5 (high), and the evaluation samples were provided by the traditional group and the intelligent-assisted group, in which novelty was evaluated individually for each sample and diversity was evaluated in groups.

3.6.3 Result statistics and analysis

The experimental results were as follows: the traditional design process group produced six sketches using pen and paper and a digital sketching tool, each of which proposed one innovative solution for the hairdryer; the intelligent tool-assisted group produced ten solutions. Figure 18 shows some results obtained for the traditional group's sketched solutions.

Figure 18: Traditional design process group sketch scheme.

The statistical results of the time spent in each stage and the novelty and diversity recorded using the stopwatch are shown in Table 4. The statistical results for each sample of novelty and the average statistical score for diversity are shown in Figure 19. For the accuracy and readability of the data, we retained two decimal places. Thirty evaluation questionnaires were distributed, and 28 valid questionnaires were obtained through analysis and assessment. According to the number of design solutions in the traditional design process group, six samples were randomly selected from the intelligent tool-assisted group for evaluation to effectively compare the two groups of trials.

			Scheme 1	Scheme 2	Scheme 3	Scheme 4	Scheme 5	Scheme 6
Time (minutes)	Idea Acquisition	A	16.74	18.43	12.28	9.87	15.72	13.47
		B						
	Scheme determination	A	14.65	13.79	14.76	6.98	13.57	14.41
		B	6.39	2.72	5.57	4.90	6.62	2.90
	Final design	A	28.61	27.78	—	43.15	30.71	—
		B	29.98	22.76	27.56	32.93	26.80	31.08
Scheme samples		A	 a	b	—	 c	 d	—
		B	 e	 f	 g	 h	 i	 j
Novelty		A	3.11	2.79		3.46	3.36	
		B	3.71	2.82	3.14	3.14	2.79	3.46
Variety		A	Average Score (3.30)					
		B	Average Score (3.56)					

Table 4: Statistical results (Note: A "—" in the table indicates that the final design was not completed within the specified time.).

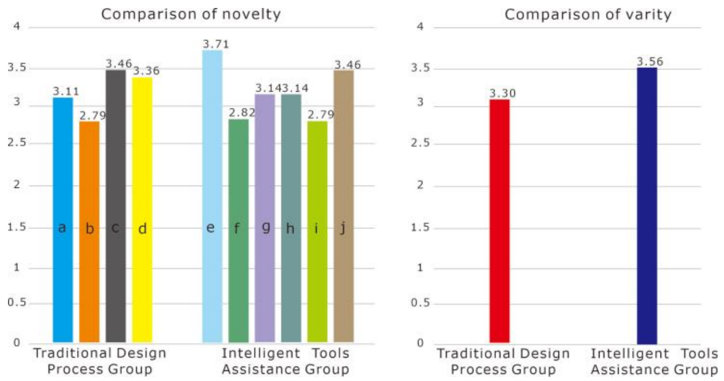

Figure 19: Results of novelty and diversity statistics.

The results of this part of the experiment showed that the intelligent tool-assisted group produced more solutions than the traditional design process group in the same amount of time and that the traditional design process group had a more cumbersome process for completing the task, took more time, and some designers did not complete the final design. The results of the timeliness segmentation showed that the traditional design process group spent the most time on inspiration and the final design process. In contrast, the intelligent tool-assisted group had to focus on only the final design stage after deciding which option to pursue and, therefore, spent significantly less time on each stage. By analysing the results of the evaluation of the novelty of the two groups, the traditional design process group is slightly better than the intelligent aid group. Additionally, the comparative analysis of the statistical results and the design solutions reveals that the solutions with more shape features have higher novelty. The diversity of the intelligent tool-assisted group is significantly greater than that of the traditional design process group.

4 DISCUSSIONS

Product concept innovation design usually requires designers to integrate their accumulated experience, the design environment, design resources and other sources of design inspiration. Forming a conceptual framework for a specific product from scratch is a difficult requirement in terms of time and effort. Additionally, due to designers’ "varying levels", it is often difficult to make quick decisions when faced with specific design tasks. With the continuous innovation of artificial intelligence technologies such as deep learning and AIGC, innovative design has become a new generation of driving force to assist designers in their creation by showing unprecedented design forms from the perspective of combining scientific rigour and artistic diffusion. The article initially tries a new artificial intelligence-assisted product conceptual innovation design process, proposes a relatively complete product conceptual innovation design generation framework, and explores the realisation form of a new generation of artificial intelligence-assisted design innovation.

Analysing and extrapolating from the results generated by StyleGAN3, we found that some of the generated samples have a high deviation from the original dataset because hairdryer sample styles are diversified during the training process. The difference in the number of samples for each style is relatively apparent, so the generated results become relatively worse for samples with a small variety of styles. For such samples that do not morphologically collapse, we cannot rule out that they result from innovation in the model. However, this fusion of multiple style characteristics of sample outputs is also what we would like to see. In fact, StyleGAN3 is an innovation based on traditional GAN networks and has excellent advantages in detail generation, as shown in Figure 9. In addition, for the trademark logos on the samples, we find that StyleGAN3 does not learn such features, and comparisons to previous GAN network models have relatively few applications in this area. Therefore, how such features are identified and adapted has a more significant impact on the creation of a high-quality, diverse style dataset.

The stable diffusion model focuses on optimising the outcome to improve and perform some degree of divergent innovation. This paper focuses on the connection and control between models. Since the input of the model contains text and cannot change the style type of the result we generate, during the process from StyleGAN3 to the stable diffusion model, we controlled the hairdryer style type through the former. Additionally, the latter focused on the overall optimisation, stability and partial divergence innovation in detail. From the experimental results in subsection 3.4.2, it can be seen that the hairdryer dataset II and the hairdryer dataset III remain identical in terms of the overall modelling profile, inheriting the stylistic diversity of dataset II. In terms of quality, resolution and detail, the stable diffusion model has better results, which depend on the fine control of both text and input images. Compared to designers who need to master only the primary light and shadow relationship, colour matching and scene layout, the model can complete the rendering design drawings of all kinds of products. Regarding single-product generation, the stable diffusion model has dramatically decreased the gap between designers. Even from the picture, we can observe that in the expression of light and shadow, the fineness of the picture can reach the level of human designers. Therefore, the process of AI assisting designers in carrying out innovative designs, combined with designers' professional design knowledge and experience, can improve the model's expression ability and the effect of presentation.

Shap·E-based Conceptual Model Generation for Hairdryers with Emphasis on 2D to 3D Data Transformation. Figure 16 shows that, in the generated 3D model, although the detailed features of the model cannot be well reflected, the block ratio of colour can be used as a reference for model optimisation, and the model's overall shape is consistent with the two-dimensional image. In addition, we found that different viewpoints affect the generation of 3D models to some extent, e.g., the quality of the perspective angle is higher than that of the orthographic angle (The hairdryer image numbered 4 in Table 1 has fewer design features). This discrepancy produces incomplete data, which affects subsequent optimization and the output of 3D generation. In the future, it is hoped that further optimisation and adjustments will be made in the collection and processing of the dataset, and better 3D generation models will be explored.

The results of Experiment 3.6 show that AI-assisted design improves designers' overall efficiency and ability in the idea acquisition stage. The powerful computing capabilities of the new generation of AI-assisted design help to focus attention, improve understanding and control of design tasks, and produce better results. In addition, generating diversified hairdryers is more helpful in inspiring designers to quickly discriminate and adjust the use of different product styles in the design process to enhance the design function and visual expression further. The results also showed that the traditional design process group was slightly higher in novelty than the intelligent tool-assisted group (rated 3.18 versus 3.14, respectively), consistent with previous studies. As Zboinska et al.[51] indicated, computers can compensate for human deficiencies in computational power and memorability; they are not a substitute for humans for aesthetic reasoning, creative reasoning, intuitive thinking, and other abilities at present.

From the analysis of the three statistical time periods (idea acquisition, scheme determination, and final design), the traditional design process group spends more time on idea acquisition and final scheme presentation. It can be found from Table 2 that the time spent in the first stage is different because the scheme is relatively less detailed, the idea time is short, and the novelty evaluation of this scheme is lower than other schemes overall. In addition, it is found from the table that two design schemes had yet to be completed within the specified time. In addition to the complexity of schemes, the mastery of model generation and rendering tools is also an important influencing factor. The intelligent tool assist group selected the appropriate object in a given hairdryer-generated image to connect directly to the generation and rendering, so it took less time. However, interestingly, it can be found in the sketches drawn by the traditional design process group, in the inspiration acquisition stage, the designer not only considered the hairdryers as the search target but also considered other products similar to the shape of the hairdryer. From the reference drawing of one of the designers, we find that many details, such as the hole, texture and parting line of the hairdryer, were also collected. This shows that the traditional design process group considered broader content in designing a product and demonstrated divergent solid thinking, which is also a step that AI assistance cannot do and explain well. The diversity results in Table 2 show that the intelligent tool-assisted group was higher than the traditional design process group (scores of 3.56 and 3.3) because the intelligent tool-assisted group created a wider variety of design solutions in the allotted time. In contrast, the traditional design process group failed to complete the given task within the allotted time. In addition, the generation of conceptual images of hairdryers for the intelligent tool assistance group was based on existing datasets, the merit and diversity of which were directly related to the type, quantity, and quality of styles of the generated hairdryers and the performance of the model likewise affected the final result. In contrast, the traditional design process group depended on the individual capabilities of the designers and required long-term accumulation.

In the time statistics phase, we did not consider the time to prepare dataset I. It takes a lot of knowledge and time for designers to go from novice to professional to create new designs. Our model simulates the same process, which also requires learning. However, the time spent using computers to acquire and assimilate these datasets and train to generate such specialized neural networks is more targeted and specialized than the former, and the ability to innovate quickly is significantly higher than human accumulation. Therefore, we need designers with professional backgrounds and already prepared data sets at this stage.

From designers and AI-assisted design creation, it can be found that in creative design, designers always use abstract concepts in their minds to solve a given design task. Abstract and concrete design representations play a crucial role in creative design. As mentioned in the literature[7], [52] ,[11] ,[53] , a large number of visual stimuli, such as sketches, ICONS, pictures and diagrams, can improve design efficiency and overall design quality. Thus, creative design is constantly influenced by intrinsic and extrinsic phenomenal representations.

Finally, unlike the traditional conceptual innovation design process, innovation design in the context of AI-assisted design produces new changes. The application of artificial intelligence technology breaks the traditional design process of relying on human experience and intuition so that it can meet changing user needs. Intelligent design with AIGC as its core has rapid data processing and pattern recognition capabilities. It can discover deep-seated trends and patterns in the design process, which can help designers make accurate and efficient decisions. Moreover, it has already surpassed traditional design methods regarding product style identification[2], intelligent decision-making[54], and product concepts[55, 56] and fully embodies the new capabilities of AI-assisted design. Looking to the future, proficiency in new methods of intelligent design, combined with the advantages of AI-assisted design in data collection and processing, will fully liberate designers and create more opportunities and value.

Overall, we propose a new method to express design quickly and optimise the creative design process, which can effectively improve design efficiency and provide an effective solution for designers in innovative design.

4.1 Other Survey Results

Since this study was designed to explore deep learning and AIGC to assist designers in creative product design, to better understand the effectiveness of the method proposed in this paper, four of the designers were probed through a questionnaire about their feelings about the results generated by the method. Table 5 summarises the results of the survey, according to which the majority of designers' choices are in line with our expected results.

Results of a survey on the conceptual generation of hairdryers. (29 participants)

Question1	No help	Not very helpful	usual	useful	Very useful
Would the above picture of a hairdryer be helpful to you in innovatively designing a hairdryer?	0.00%	0.00%	31.03%	51.72%	17.24%
Question2	Score 1	Score 2	Score 3	Score 4	Score 5
Please rate the innovativeness of the above hairdryers according to your perception.	0.00%	10.34%	27.59%	51.72%	10.34%
Question3	Experiment 3.3	Experime nt 3.4			
Which of the above sets of test results inspire d you more to come up with an	42.31%	57.69%			

innovative design for a hairdryer?					
Question4	One type	Two types	Three types	Four types	More
In your opinion, how many styles do you think you can categorise the above 12 hairdryers into?	0.00%	6.90%	37.93%	44.83%	10.34%

Table 5: Survey results.

According to the results in Table 5, 51.72% of the designers found the research methodology of this paper useful for the innovative design of hairdryers (31.03% average and 17.24% very useful). This implies that design references with high relevance and quantity are more helpful in inspiring designers' concept generation in the product design process. In addition, 51.72% of designers said that the generated concept hairdryer was relatively innovative, and the high score accounted for more than 89% (10.34% judged 2 points, 27.59% judged 3 points, 51.72% judged 4 points, 10.34% judged 5 points). Additionally, we compared the results of Sections 3.3 and 3.4 on inspiring designers to innovate their designs. We found that the results of Section 3.4, namely, the optimised conceptual hairdryer, were relatively superior (42.31% and 57.69%). According to the analysis of the results, the latter has better results in terms of resolution, product details, lighting shadows, etc. However, the difference between the two is slight, showing that the two experiments achieved good results in creative stimulation, roughly the same as our expected ideas. Finally, we verified through the survey that some of the selected hairdryer concept generation samples had multiple styles (6.90% with 2, 37.93% with 3, 44.83% with 4, and 10.34% thought there were more styles). In summary, the findings suggest that designers maintain a positive attitude towards using AI-assisted design tools and favour creative design assistance.

5 CONCLUSIONS

In the context of technological development and the formation of the global economy, innovation has become a significant factor in the development and competitiveness of various industries. It is considered to be the embodiment of human exclusivity and intelligence. Today, AI-assisted design is reaching human-like performance in several areas, demonstrating extraordinary potential based on extensive data learning, which presents a new challenge and opportunity for designers. In this study, we propose a style-oriented approach for the intelligent generation of product creative concepts. First, we obtained the product image data through web crawling and preprocessing. The StyleGAN3 generative adversarial network was used to generate creative conceptual designs of multiple styles of hairdryers. A high-quality hairdryer dataset II was established to provide a direct source of inspiration for designers. Second, we introduced a stable diffusion model to control the shape of the hairdryer dataset II while completing the optimisation design. We innovatively generated a new hairdryer dataset III based on the original style. Third, we completed the corresponding hairdryer conceptual model generation through a conditional generation model representing 3D assets and parametric design. Finally, we validated the effectiveness and advantages of the proposed method by setting up a trial group and a control group. We evaluated the generated solution using three novelty, diversity, and timeliness indicators. Experimental data prove that integrating AI-assisted design tools in product concept creative design can improve idea generation efficiency, and design diversity and novelty can be more effective.

The workflow developed based on StyleGAN3, Stable Diffusion, Shap·E model and Grasshopper to assist designers in creative design can effectively improve the efficiency of designers' creative design. However, the realisation of individual points still needs to be improved. For example, some details are lost in the conversion process from 2D image to 3D model, but this step is crucial to improve design efficiency. Therefore, in the following research step, we will focus on the detailed generation of 3D models. Through the analysis and understanding of existing literature and large models, in the future, we will start with small sample data sets and proprietary data sets and finetune the relevant visual large models to realize the generation of specific styles of hairdryers. During the stable diffusion modelling phase, we used a small number of textual cues to assist in controlling the output, which was positive in terms of results. Therefore, in future work, we will study the impact of stylization from semantic dimensions in conjunction with proprietary datasets to investigate the underlying logic and mechanisms.

The style-oriented intelligent generation method of the product creative concept has the following advantages:

(1) A new conceptual design method for the automatic generation of hairdryers is provided. The conceptual hairdryer dataset generated by the experiment can stimulate the creative inspiration of designers, locate the design goal and solve the space faster, improve the efficiency of the designer's design process, and explore more design possibilities.

(2) It provides a dedicated product inspiration, a creative stimulation tool, and a dedicated system for producing product concept form, forming an end-to-end concept generation framework, which can be applied to the innovative generation of other concept product designs.

Although the proposed method can provide designers with different product styles, some disadvantages remain. For example, 1. we do not identify and categorise the product styles generated; 2. in the stage from model generation to optimisation, partial manual operation is still needed, and complete automation is not achieved, and 3. the model used in this study mainly explores the application in product conceptual creative design and focuses less on the innovation of algorithm structure. In the future, the existing StyleGAN3 network structure can be improved and innovated to a certain extent to adapt to our tasks. We train a large model suitable for a stable diffusion model. Regarding 3D model generation, we will continue to address and study the latest generation algorithms.

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Jianning Su, https://orcid.org/0000-0002-2409-9207
Baoyin Yu, https://orcid.org/0009-0002-6237-8132
Xiong Li, https://orcid.org/0000-0002-4961-7920
Zhipeng Zhang, https://orcid.org/0000-0001-7400-116X

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