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Article

Combining AIGC and Virtual Simulation Technology to Enhance the Personalization of Apparel Designs

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Abstract: With the increasing demand of consumers for personalized experience and fast response, the design and production model of traditional apparel companies is facing serious challenges. In order to adapt to market changes and maintain competitive advantages, the industry urgently needs to adopt emerging technologies. In this paper, based on CycleGAN, we make the generated images more natural by improving the network model and adding background optimization loss to achieve clothing image style migration and fusion. Based on the LoRA-DAE framework, the method of LoRA integration into the stable diffusion model is proposed, which enhances the model adaptation ability. A fashion clothing model dataset is established to provide data support for the model. Through comparative experiments to evaluate the viewing experience of the method proposed in this paper, the model of this paper scores 27.1585, 14.4955, 17.6485, and 13.8486 on overall, shape, shadow, and detail texture, respectively.Meanwhile, it is also superior to other algorithms on subjective scores, and the average score of users' subjective evaluations is 27.9588.The model of this paper is mounted on the apparel personalization applet, and the experimenter's evaluation of this paper's apparel personalization apparel is conducted. When the model of this paper is installed on the apparel personalized customization app, the “gaze duration” of the experimenters on the apparel customization app is 1834.6985ms, which is 41.7156% higher than that of the control group, and the mean value of the subjective experience rating is 4.2663, which is higher than that of the control group, and based on the model of this paper, the model provides a higher psychological experience.

Keywords: CycleGAN; LoRA-DAE; stable diffusion model; clothing personalization

1. Introduction

In recent years, with the rapid development of the economy and the continuous improvement of people's living standards, the apparel industry has shifted from a traditional “product-centric” model to a “consumer-centric” service model, with new consumption patterns such as fast fashion and personalized customization becoming the mainstream in the market [1-3]. Consumers' demand for apparel has gradually shifted from single-style selection to diversified personalized customization, with a greater emphasis on comfort and personalized experiences, driving apparel product design toward personalized, small-batch customization, and flexible production [4-6]. The market for personalized apparel customization is gradually emerging, with consumers' pursuit of personalized and high-quality apparel driving industry transformation [7-8]. However, development in this field remains in its exploratory phase, and the development model for personalized customization has yet to mature. Since 2012, the global community has placed high priority on the development of digital technology, leveraging the advantages of massive data and diverse application scenarios to promote the deep integration of digital technology with the real economy. This has empowered traditional industries to upgrade and transform, spawned new industries, business models, and modes of operation, and strengthened new engines for economic growth [9-11]. To address the increasingly diverse and rapidly changing consumer demands, as well as the continuous advancement of technology, the apparel design and production sector is entering an unprecedented era of innovation. Over 68% of consumers are willing to pay a 10%-30%

premium for personalized apparel, with the customized apparel market size expected to exceed 300 billion USD by 2025 [12-13]. However, traditional customization models are constrained by significant measurement errors, long production cycles, and high costs, making it difficult to meet consumer market demands [14]. Meanwhile, the maturation of digital technologies such as AI-generated content (AIGC) and virtual simulation technology has opened new pathways for the industry to break through these challenges.

AIGC is a technology that uses artificial intelligence to automatically generate various types of content, including text, images, audio, and video, through algorithmic learning and inference [15]. It analyzes data and language models to intelligently, automatically, and mass-produce the required content. In the field of fashion design, literature [16] describes how AIGC saves production and time costs in the fashion design process through market trend analysis, rapid design generation, virtual try-on, and sales forecasting. Virtual simulation technology, as an emerging digital technology, is applied in personalized clothing customization models. Through its encompassing technologies such as 3D human body data collection, 3D style design, virtual sewing, virtual sample garment production, virtual runway shows, and rendering, it can provide consumers with quick and accurate body measurement data collection, participatory style design, realistic virtual try-on effects, and efficient access to finished garments, thereby greatly satisfying consumers' demand for personalized clothing customization [17-20]. The apparel industry is poised to achieve breakthroughs in the field of personalized customization, transitioning from high-end customization to mass-market personalized customization, and driving the entire apparel industry toward higher quality and greater personalization [21].

In personalized custom clothing design, image style design is a crucial component. Literature [22] employs attention mechanisms and improved residual networks to develop a local style transfer method and local artifact correction model for clothing image style transfer, enhancing the style design of personalized custom clothing images. Literature [23] employs multi-level dilated convolutional semantic networks, trunk parameter extraction networks, and principal component analysis to extract human body contours, multi-view human body segmentation parameters, and three-dimensional human body model latent space semantic features, thereby reconstructing precise three-dimensional human body models. Meanwhile, [24] combines 3D human body scanning systems, descriptive analysis, principal component analysis, hierarchical clustering, and fast clustering methods to analyze human body features and shapes, obtain human body parameters, and integrate them with digital human body modeling system algorithms to improve various indicators in human body modeling for the apparel industry. These studies provide human body data support for personalized clothing customization, making customization more aligned with customer needs. Literature [25] utilizes evolutionary algorithms and fuzzy theory to provide an electronic customization collaborative design system for clothing design, enabling collaboration among customers, designers, manufacturers, and experts to meet customers' personalized needs. Literature [26] combines a clothing customization system with participatory customization services, fully considering customer involvement to enhance clothing personalization, and connects with factory production to improve the management of the entire production line. Literature [27] collaborates with well-known clothing companies to design an in-store knitted custom wool sweater production system under the support of Industry 4.0 technology, achieving urbanization, automation, flexibility, and customer personalized demand, and has achieved good economic benefits.

Literature [28] considers typical clothing design styles, applies an interactive genetic algorithm, and establishes a personalized custom clothing intelligent design model, which has evolved into an automatic suit jacket design system. The design style aligns with customers' personalized needs and alleviates customer fatigue. Literature [29] develops a clothing customization application where users can customize clothing to meet their personalized needs in a virtual studio. The clothing is displayed using augmented reality technology with 3D model support, and users can purchase it after confirmation. Literature [30] proposes personalized clothing customization using radial basis function convolutional neural networks for customer body modeling to ensure a snug fit; genetic algorithms for custom design based on customer attributes and needs; probabilistic neural networks to assess the snugness; and support vector regression based on user feedback to adjust the customized clothing.

In this paper, with the help of CycleGAN model as the baseline model, segmentation mask is introduced to constrain the target region to realize stylization and complete the clothing style migration. For regular texture patterns, a high-resolution network is added to improve the resolution of the image, and the VGG-19 model is used to complete the style migration of the texture pattern to realize the natural integration of the pattern style and the clothing. LoRA is integrated into the stable diffusion model to generate the LoRA-DAE framework, which further optimizes the texture and material detail issues in garment image generation and improves the material finesse. Construct a fashion clothing model dataset to provide sufficient data support for the training of the intelligent model. Introduce the adaptive enhancement module, using ControlNet network for clothing images, combining different modal information, multimodal generation and conversion. Combine AIGC and virtual simulation technology to extract the clothing data from the massive features to enhance the clothing design effect. Through the combination of simulation and empirical evidence, the quality of the garments generated in this paper is evaluated.

2. GAN-Based Style and Style Migration Model for Apparel Images

2.1. Style Migration Methods and Improvements

2.1.1. Improvement of the Structure of the Style Switching Network

For clothing images in complex backgrounds, realizing style migration of clothing styles not only requires the transformation of clothing geometry, but also needs to avoid the background being affected by style migration and maintain the realism of the image. In this chapter, by taking the advantage of CycleGAN that does not require paired training datasets and cyclic consistency to improve the effect of style migration, CycleGAN is used as the baseline model, and a segmentation mask is introduced to constrain the target region to achieve stylization [31]. In addition, the generated images are made more natural by improving the network model and adding background optimization loss.

The Resnet generator in this paper includes three parts: downsampling block, residual block and upsampling block, and the specific network structure is shown in Fig. 1. k represents the size of the convolutional kernel, s represents the step size, and ch represents the number of channels. Since the mean and variance of each channel in the feature vector [C × H × W] in the generative model affects the style of the generated image, normalization is done along the channel level in the Resnet generator, i.e., using the Instance Normalization (IN) method, which calculates the mean variance of the height in the image with respect to the width, i.e., H × W, if the image pixel value is x. This method effectively maintains the independence of the image instances and speeds up the convergence of the model as in equation (1):

$$IN(x) = \gamma(\frac{x-u(x)}{\sigma(x)}) + \beta \tag{1}$$

where β is a constant, which is set to 0.00001 in this paper, and the mean $u(x)$ and variance $\sigma(x)$ are Eqs. (2) and (3), respectively:

$$u_{nc}(x) = \frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W} x_{nchw} \tag{2}$$

$$\sigma_{nc}(x) = \sqrt{\frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W}(x_{nchw} - u_{nc}(x))^2 + \in} \tag{3}$$

where $\in$ is a constant, which is set to 0.00001 in this paper.

Meanwhile, ReLU is used as the activation function, which is conducive to reducing the complexity of the calculation and speeding up the calculation. In order to achieve a better training effect, the ResNet residual block is set with 9 layers, retaining the convolutional layer, instance normalization and activation layer. Thereafter, the image size is enlarged by reducing the number of channels through the inverse convolutional layer in the upsampling block for generating the target (e.g., skirt) image. Finally, to make the training more stable and to map the image in the range [-1, 1], Tanh is used as the final activation function of the generator.

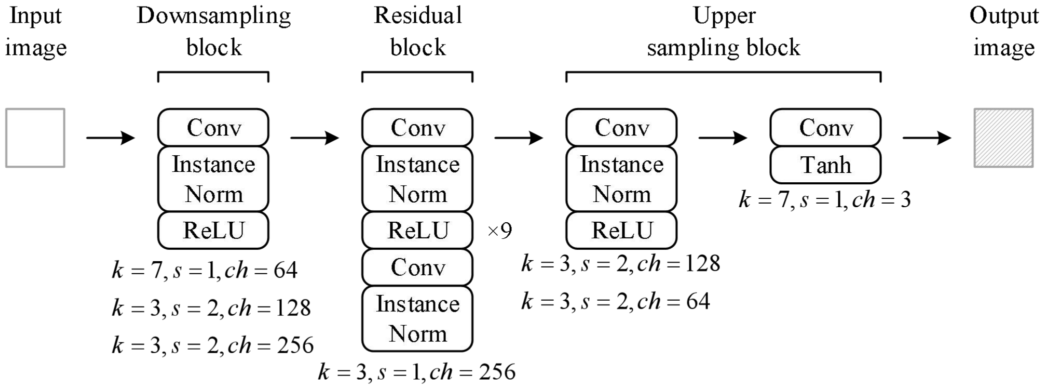

Figure 1. The network structure of the generator.

2.1.2. Design of Model Conversion Network Structure

Although the above network structure can improve the problem of difficult geometry conversion, the generated image is still rough and unnatural in terms of the displayed detail texture. In order to enhance the detail texture information after style conversion and improve the quality of the generated images, this section focuses on the contextualization during the style conversion process, i.e., the problem of the background character limbs and boundary residuals after the geometric shape (style) of the garment is changed. The content domain A image and Mask image can be denoted as (x,a), and the style style domain image and mask image can be denoted as (y,b), and the samples (y',b'), (x',a') are obtained after style migration. In order to enhance the realism of the generated image, the background optimization loss $\mathcal{L}_{back}$ is added in this paper as in equation (4):

$$\mathcal{L}_{back} = \| \omega_2 f(a,b') \odot (x - y') \|_1 + \frac{\omega_3}{N} \sum_{n=1}^{N} \sum_{c=1}^{3} \| (G(x) - x) - (y - F(y)) \|_1 \tag{4}$$

where: a is the content domain mask selected region, and b' represents the region after a is transformed. In the corresponding style domain, b can be set as the style domain mask selected region, and a' represents the region after b is transformed. ω_2 and ω_3 are the weights for adjusting the content retention and skin color display, respectively, N represents the number of pixels in the converted region, and c is the number of channels. When the instance is set to 0 and the background is set to 1, $f = \overline{a \cup b}$ is the convertible state, which realizes the conversion of the instance and the preservation of the background. Since the details of the edge region are more complex than the center region, the weight value of ω_2 is gradually increased from the center to the edge. In addition, in order to compensate for the differential changes that will occur in the shape texture of the transformed region during the transformation process, such as the presence of legs that still retain some of the texture of long pants after they are converted to shorts. In this study, the difference value between the image generated by generator G (e.g., shorts style image) and the content domain x (e.g., long pants style image) is differed from that of the style domain (e.g., shorts style image) and generator F (e.g., generated long pants style image), and the gap is continuously narrowed through training, so as to make the details of character's legs more realistic. Where ω_3 is a hyperparameter.

Therefore, the total loss of the proposed method in this paper is is the sum of generative adversarial loss, cyclic consistency loss and background optimization loss, as in equation (5):

$$\mathcal{L}_{total} = \gamma_1 \mathcal{L}_{LSGAN} + \gamma_2 \mathcal{L}_{cyc} + \gamma_3 \mathcal{L}_{back} \tag{5}$$

where: $\gamma_i (i = 1 \sim 3)$ is the hyperparameter.

2.2. Style Migration and Fusion of Images

Clothing pattern as one of the elements of clothing design, the update speed is relatively fast, so much so that clothing designers need to collect a lot of materials for creation. Although style migration can transfer the style of patterns into garments, it is difficult to ensure that the textures and colors of garments reach the ideal natural state. In addition, it is difficult to express the needs of the audience with too abstract clothing patterns. In order to improve the realism of clothing pattern style migration and enhance the details of style migration, for regular texture patterns, this paper proposes a pattern fusion method, which joins the high-resolution network to improve the resolution of the image, and uses the VGG-19 model to complete the style migration of the texture pattern, which mainly realizes the style conversion of the pattern color. Then after the conversion of the clothing pattern is completed, the style migration of the clothing pattern is completed by the method of pattern integration.

2.2.1. Pattern Style Migration and Improvement of Fusion Network Structure

Much of the semantic information of the garment pattern is lost as the resolution of the image decreases with the convolution, pooling, and other operations during the convolution process. If only resolution enhancement is used, the representational information of the original image is not recovered. Therefore, in order to retain more feature information of the clothing pattern, inspired by the high resolution network, a high resolution network is used for retaining high resolution features before feature extraction. The structure of the high resolution network used in this paper is shown in Fig. 2, which contains three structural forms to realize multi-scale fusion: flat layer convolution, upsampling and downsampling. Flat layer convolution only changes the number of channels of the feature map and does not change the resolution of the image, downsampling is used to reduce the image resolution to half of the original image, and upsampling is used to restore the original resolution, expanding the resolution by a factor of two through convolution. Unlike previous high-resolution networks, in order to better achieve style migration, the network uses all the normalization methods after convolution as instance normalization with a padding number of 1. In the first and last convolution, a convolution kernel of size 1 × 1 is used and the rest of the convolution kernel sizes are all 3 × 3, and the bilinear difference method is used to enhance the resolution of the image. Unlike other serial convolutional feature extraction, this network enhances the high resolution representation by concatenating high resolution and low resolution sub-networks in parallel with repeated multi-scale fusion.

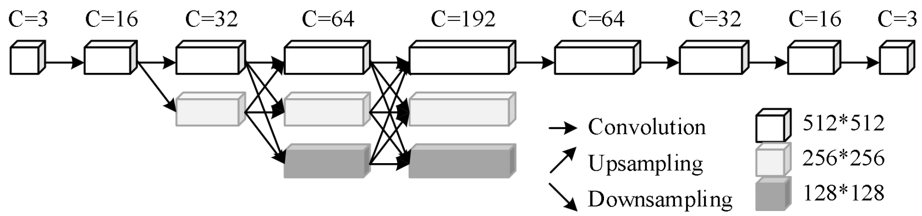

Figure 2. HRNet Network Structure.

2.2.2. Pattern Style Migration and Fusion Function Optimization

In this paper pattern style migration, the style loss is defined as the sum of squares of the difference between the input content image and the output image, i.e., equation (6):

$$L_{cont} = \frac{1}{C^l H^l W^l} \| I^l_{cont} - I^l_{out} \|_2^2 \tag{6}$$

where C, H, W represent the size of the feature map [C, H, W], I^l_{cont} denotes the input image of the l th network layer, and I^l_{out} denotes the output image of the l th layer, and the equation follows the L_2 paradigm.

A Gram matrix G with matrix size C × C is created as the style feature representation. If we set F as the l th layer content feature, c and c' are different channels, in order to obtain the relationship between the feature matrices, the inner product of the feature matrices is performed to obtain equation (7):

$$G_{(c,c')} = \frac{1}{C^l H^l W^l} \sum_h \sum_w F^l_{(c,h,w)} F^l_{(c',h,w)} \tag{7}$$

The feature matrix is reconstructed shape as a C × HW matrix, and the pattern style migration loss is the square of the difference between the Gram matrix of the output image and the content image and follows the L_2 paradigm as in Eq. (8):

$$L_{style} = \| G_{cont}^{l} - G_{out}^{l} \|_2^2 \tag{8}$$

Therefore, the pattern style migration loss is, as in equation (9):

$$L_{pat} = \alpha L_{cont} + \beta L_{style} \tag{9}$$

where α and β are content weights and style weights, respectively.

In order to make the newly generated pattern can be displayed in the target area of the garment, this paper proposes a pattern fusion method, such as Eq. (10), which fuses the garment with the processed pattern in a certain proportion through mask, so that the pattern texture can be better displayed in the garment, and a more novel garment image is obtained:

$$I_{mer} = (I_{ori} - t_1 * I_{seg}) + t_2 * I_{pat} * I_{mask} \tag{10}$$

where: I_{ori} is the original clothing image, I_{seg} is the part of the costume to be fused after segmentation, I_{pat} is the pattern to be fused, I_{mask} is the mask of the part of the costume to be fused, t_1 is the proportion of the original costume texture, and t_2 is the proportion of the texture of the fused pattern. It is used to adjust the degree to which the pattern is displayed in the garment and the degree of wrinkles in the garment, and $t_1 + t_2 \approx 1$.

2.3. Clothing Design Image Generation Based on Diffusion Modeling

2.3.1. LoRA-Based Stabilizing Diffusion Models

In this paper, LoRA is integrated into the stable diffusion model, and an improved stable diffusion-based generative framework, LoRA-DAE, is proposed to optimize the performance of the generative task while enhancing the training efficiency.The LoRA technique optimizes the weight adjustment mechanism across the attentional and convolutional layers through low-rank decomposition, which effectively reduces the number of parameters of the model, and thus reduces the computational overhead, while enhancing the model's Adaptability.

By reducing redundant parameters, LoRA not only improves the training efficiency, but also ensures that the model can maintain high generation quality when dealing with complex tasks. In the cross-attention layer, the ability to capture conditional information is enhanced, enabling the model to more accurately handle the fusion problem of text description and image generation. In the convolutional layer, the texture and material details in image generation are further optimized to make the generation results more realistic and detailed. The overall model architecture is shown in Figure 3.

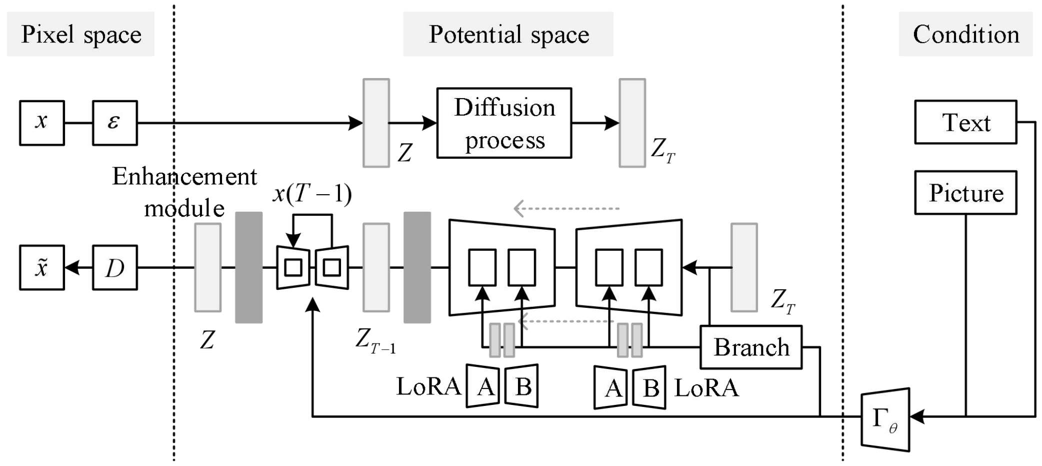

Figure 3. Overall structure diagram of the model.

2.3.2. Fashion Clothing Models Dataset

In the data preprocessing stage, this study ensures the consistency of the samples and the accuracy of the annotation by cleaning and screening the images. In this paper, OpenPose is used for key point detection to eliminate samples with incomplete poses, and YOLOv8 is utilized for human body detection to screen single model images to avoid multiple people scene interference. And accurately segment fashion elements by Grounding-SAM combined with cues to extract the dress region and remove background noise. In addition, the dataset annotation adopts the WD Tagger tool, which combines automated annotation and manual calibration to fine-tune the labels such as dress type, style, sleeve length, and so on. The dataset covers multiple dimensions with excellent quality, providing sufficient data support for model training.

2.3.3. Customized Stable Diffusion Model Based on LoRA

Since LoRA is a lightweight fine-tuning method, the introduction of the LoRA module in the generative task enables the dynamic adjustment of the model's weights to make them more adaptable to the needs of a specific task while maintaining the generality of the pre-trained model.

In the concrete implementation, the LoRA module accomplishes weight optimization in the following way. Assuming that the original weight matrix of a layer is w, the weight update during the fine-tuning process is represented as the product of two low-rank matrices and superimposed to the original weights. The final weight representation is shown in equation (11):

$$\Delta W = A \cdot B \tag{11}$$

$$W' = W + \Delta W = W + A \cdot B \tag{12}$$

where is the original weight matrix, ΔW is the weight update, W' is the updated weight matrix, and the ranks of A and B are significantly smaller than the dimensions of W, satisfying $rank(A) \ll d$ and $rank(B) \ll d$. Compared to full fine-tuning, this approach only requires optimizing the low-rank matrices A and B, while the original weights W remain frozen, and only a small number of parameters need to be trained (the dimensions of A and B are much smaller than those of the original weight matrices), which can dramatically reduce the training cost of the model while guaranteeing the performance, and thus significantly reduce the computational and storage costs.

In this study, the LoRA module is integrated into the UNet network of the stable diffusion model for the optimization of clothing model image generation.U-Net, as the core structure of the diffusion model, is not only responsible for the feature extraction of the image, but also carries out the key function of the ox-formation task.The LoRA technique is mainly applied to the trans-attention module in U-Net, which enhances the ability of conditional information (e.g., text description) to guide the image generation by performing a low-rank matrix decomposition of the Query, Key, and Value linear transformations for low-rank matrix decomposition, which enhances the ability of conditional information (e.g., textual descriptions) to guide image generation. This approach improves the fitness of conditional information in the generation process, making the generated image more consistent with the input textual description. Meanwhile, the LoRA module is also applied in the convolutional layer to achieve optimization of garment texture, material, and lighting details through low-rank weight updating, which further improves the accuracy and quality of the generated images. With this optimization, the model shows significant advantages in generating complex garment details and natural visual effects. In addition, the LoRA module is added to the convolutional layer to achieve fine optimization of garment texture, material, and light and shadow details through low-rank weight updating, thus improving the quality of the generated images:

$$W'_Q = W_Q + A_Q \cdot B_Q \tag{13}$$

$$W'_K = W_K + A_K \cdot B_K \tag{14}$$

$$W'_V = W_V + A_V \cdot B_V \tag{15}$$

where W_Q is the query weight matrix, W_K is the key weight matrix, and W_V is the value weight matrix.

The design of LoRA not only ensures the training efficiency, but also makes the model more adaptable to diverse tasks. In the clothing model image generation task, the LoRA module is able to dynamically adjust the weights according to the features of the target image, focusing on enhancing the texture and structural details of the clothing region, while reducing the computational overhead on the background or irrelevant regions.

2.4. Adaptive Enhancement Module

In the task of generating high-quality images of clothing models, the detail performance of the image, the material texture of the clothing, and the lighting effect are the key factors that determine the merits of the generated results. In order to improve the accuracy of the generated images in these aspects, an adaptive enhancement module is proposed in this study.

2.4.1. ControlNet Network

ControlNet is a technique for augmenting and controlling pre-trained generative models by introducing additional control signals and network structures to achieve fine-grained control of the generative process. The core idea is to combine control signals as additional inputs with the original generative process to influence the final output.

ControlNet is widely used in generative tasks, especially for scenarios that require fine control of the generation results. For example, the introduction of control signals such as edge detection maps or gesture maps enables the generation or precise editing of images in a particular style, and the use of control signals such as gesture sequences enables the generation of video content that conforms to a particular motion trajectory or action. In text generation, the introduction of additional context or topic information enables finer text control, and the combination of control signals from different modalities, such as text descriptions in image generation, enables multimodal generation and conversion.

2.4.2. Two-Stage Generation Algorithm

To ensure that the model can accurately capture different key information at each stage, this paper designs a regular expression-based information filter and embeds it before the CLIP text encoder of the stable diffusion model. The filter is used to filter the text information and assign different information with different weights, so that the model is more focused on capturing the key information. Specifically, the information filter contains 2 keyword sets for identifying clothing style information and color pattern information, respectively. By matching specific lexical patterns with regular expressions, the filter extracts style information in stage 1 and assigns a larger weight, while other information is labeled as general information. After CLIP coding, the weight of the style information will be retained and processed in the hidden space of the diffusion model so that the model focuses more on the style features of the garment at this stage. In stage 2, the filter turns to extract the color and pattern information, assigns it a higher weight and inputs it into the CLIP encoder, which is subsequently fed into ControlNet along with the line sketch to control the diffusion process to generate the image. The formula is as follows:

$$E_1 = w_{style} \sum_{t_i \in T_{style}} E(t_i) + w_{normal} \sum_{t_i \in T_{normal}} E(t_i) \tag{16}$$

$$E_2 = w_{color} \sum_{t_i \in T_{color}} E(t_i) + w_{normal} \sum_{t_i \in T_{normal}} E(t_i) \tag{17}$$

where E_1 and E_2 are the text embedding vectors after weighting in stage 1 and stage 2, respectively, w_{style} is the weight of the style word (set to 2 in this paper), w_{color} is the weight of the color word (set to 2 in this paper), and w_{normal} is the normal word's weight (set to 1 in this paper), and $E(t_i)$ is the embedding vector of each word.

In stage 1 of the text-generated graph diffusion process, the LoRA-fine-tuned stabilized diffusion model receives the weighted text embedding vectors E_1 and generates the corresponding line sketches. The focus at this stage is to ensure that the generated line sketches can clearly express the key style features of the garment, e.g., the structural contours of skirts and shirts. The formula is expressed as:

$$I_i = G_{style}^{LoRA}(E_1) \tag{18}$$

where G_{style}^{LoRA} denotes the stable diffusion model fine-tuned by LoRA, which generates the clothing line sketch I_i based on the weighted text embedding vector E_1.

In the 2nd stage of the graph-generated graph diffusion process, the ControlNet model combines the line sketch I_i generated in the 1st stage and the weighted text embedding vectors E_2 to constrain the generating process by taking the line sketch as a control signal to ensure the accurate presentation of the garment style, color and pattern information. Its formula is expressed as:

$$I_f = G_{color}^{ControlNet}(I_i, E_2) \tag{19}$$

where $G_{color}^{ControlNet}$ denotes the image generation process under ControlNet control, E_2 is the weighted text embedding vector containing color and pattern information, and I_f is the final effect image.

The two-stage generation algorithm has the following advantages: by separating the generation tasks of style and color, the model is able to process the respective information more precisely at each stage, avoiding the ambiguity caused by the simultaneous processing of multi-dimensional features in the traditional method. ControlNet is used to enhance the control of color and pattern, so that the generated image is not only accurate in style, but also highly reproducible to the user input in both color and detail, making the model accurate in capturing and combining the clothing style and color pattern information in the textual information.

3. Combining AIGC and Virtual Simulation Technology to Enhance Apparel Design

3.1. Application of AIGC in the Field of Clothing Design

In this paper, Generative Adversarial Networks (GANs) under AIGC are utilized to extract features from the huge amount of existing data and then generate content that matches the input requirements.

3.1.1. Design Inspiration and Idea Generation

With the development of AIGC technology, the generation of design inspiration and creativity will no longer rely on the designer's intuition, and AI can provide designers with more diversified sources of inspiration at the early stage of creativity through the advantages of deep learning and big data analysis. Specifically, AIGC technology can generate innovative and forward-looking design inspiration through the analysis of a large amount of design data, fashion trends, historical patterns and user behavior. For example, based on image recognition and Generative Adversarial Networks (GANs), AIGC can extract valuable elements and reorganize them from a huge amount of images and styles in a short period of time to create new visual effects. This approach can provide designers with a unique creative perspective that breaks the limitations of the traditional creative process, allowing design inspiration to emerge more quickly and accurately. At the same time, AIGC technology can also help designers cross the traditional style boundaries and explore new design languages by learning and imitating the characteristics of different design styles. For example, AI can automatically generate a series of creative design solutions that meet the market demand based on current color trends, fabric materials and consumer preferences. Through the interaction with AI, designers will be able to filter and make secondary creations among the multiple creative solutions provided by AI, which will further inspire and enhance the innovation of design [32].

3.1.2. Automated Garment Sketching and Pattern Generation

The generation of sketches and patterns is a crucial part of the apparel design process. Traditionally, designers usually need to complete the initial design concepts by hand-drawing or digital drawing. Although this process is creative, it takes a lot of time and energy, and it is difficult to ensure that each design element can be perfectly rendered. AIGC technology, on the other hand, can utilize algorithms such as deep learning and Generative Adversarial Networks (GANs) to generate new garment sketches and patterns after training on a large number of existing designs and patterns. For example, through the analysis of fashion trends, historical patterns and color combinations, AI can automatically generate sketches that meet these characteristics based on specific input conditions (such as “modern, minimalist, retro”). This effectively saves designers' time and provides a wider range of creative options in the early stages of design, allowing for greater diversity and innovation. In addition, pattern generation is not limited to two-dimensional graphic design, but also involves the texture of the fabrics, the color palette, and the integration of design elements.

3.1.3. Personalization and Customized Design Implementation

The application of AIGC technology provides a new solution for realizing personalized and customized design. Through intelligent content generation, it enables apparel design to be tailored to the specific needs of consumers and breaks the inherent framework in the traditional design mode. In terms of personalized design, AIGC technology can tailor design solutions for each consumer by analyzing a large amount of consumer data, including personal preferences, body type characteristics, lifestyle, cultural background, and so on. For example, AI can automatically generate design sketches suitable for a user's body shape based on photos uploaded or body type information inputted by the user, and automatically adjust the design details according to the user's color preference, style orientation, and so on. This personalized design process can effectively shorten the design cycle and greatly improve design accuracy and customer satisfaction. In terms of customized design, AIGC technology enables consumers to get a more intuitive preview of the garment effect at the design stage by combining virtual try-on and real-time feedback systems. Consumers can view the combination of different styles, fabrics and colors in the virtual environment and make adjustments according to their own preferences.

3.2. Virtual Fitting Technology

3.2.1. Application of Virtual Fitting Technology

Virtual display technology is another important application of virtual reality technology in the field of apparel design, which through three-dimensional modeling, material rendering, animation and other technical means, the design concept of apparel products, style details, material texture and other information vividly and three-dimensionally presented in the virtual environment, so that the audience immersed in the visual impact of the clothing and the charm of art.

3.2.2. Application of Virtual Design Techniques

Virtual design technology is one of the most core and transformative applications of virtual reality technology in the field of apparel design. By combining advanced technologies such as three-dimensional design software, digitization platform, physical simulation engine and traditional garment design process, virtual design technology builds a highly simulated digital design environment, where designers can freely create and experiment in virtual space, realizing the full-process digital design and validation of garment styles, fabrics, processes, etc., which greatly improves the efficiency and accuracy of garment design.

At present, virtual design technology has been widely used in domestic garment design enterprises and institutions. For example, Shenzhen apparel designers use CLO3D and other virtual design software to carry out three-dimensional design and virtual matching of apparel styles on the digital platform, and accurately control the apparel pattern and proportion through realistic fabric texture and draping effect, which significantly shortens the cycle from design to sampling. Beijing Institute of Fashion Technology, as a leading institution of domestic apparel education, is the Marvelous Design-er, CLO Virtual Fashion and other professional virtual design software into the teaching curriculum, so that students in the virtual environment to master the three-dimensional design of garments and digital layout and other advanced skills, to cultivate the industry's need for digital design talent. In Shengze, Humen and other domestic textile and garment industry clusters, virtual design technology has also been innovatively applied. Local apparel enterprises utilize domestic virtual design software, such as Huayi Assistant and Fashion Magic, to rapidly design and iterate in the virtual sample room, and seamlessly connect with the back-end of the supply chain for manufacturing, which greatly improves the speed of new product launch and style richness. This agile and flexible virtual design mode has greatly enhanced the market responsiveness and profitability of domestic apparel enterprises.

4. Clothing Design Personalization Results

4.1. GAN-Based Quality Evaluation of Clothing Images

4.1.1. Analysis of Qualitative Results

The experimental environment for this paper was configured with Ubuntu 16.04 64-bit operating system, Intel(R) Xeon(R) Gold 6226R CPU @29.GHz, A100-PCIE-40GB graphics card, Python 3.8 and PyTorch 1.9.1 training framework. The batch size was set to 16 for a total of 500,000 epochs. a constant learning rate of 0.001 was trained using a combination of the Ranger optimizer, a calibrated Adam, and the look-ahead technique.

In this paper, the experimental results of GAN are compared with pixel2style2pixel, EdgeGAN, SSS2IS with the method of this paper. The images generated by each method are compared separately under the condition of using the dataset proposed in this paper as a benchmark.

In order to better compare the quality of the generated garment images, this paper adopts a perceptual research approach, where ten images are extracted for each method separately from the human visual perspective, and 25 people who are not related to the experiment are randomly selected to score each image in five aspects, including overall, shape, color, shadow, and detail, where overall, shape, color, shadow, and detail texture perception account for 30, 15, 15, and 15 points, respectively, 20, 20, and 15 points, for a total of 100 points.

Raters need to give due consideration to the overall appearance and quality of the image, as well as the degree of internal similarity between the image and the original. In addition, the rater needs to pay attention to the shape and size of the image, as well as whether the color distribution of the image is uniform and natural. Finally, raters also need to focus on the realism of the image and assess the detailed texture of the photograph.

Each image is worth one hundred points, and each person scores the ten images and aggregates their average scores as a way to represent the average score for the sample images. Figure 4 shows the results of the combined average scores.

The method proposed in this paper has high ratings from the human visual perspective, and compared to the other three baseline methods, this paper received the highest ratings from the participants in terms of overall, shape, shadow, and detail texture viewing scores, with ratings of 27.1585, 14.4955, 17.6485, and 13.8486, respectively. It is further shown that the method presented herein is more effective in comparison with other methods.

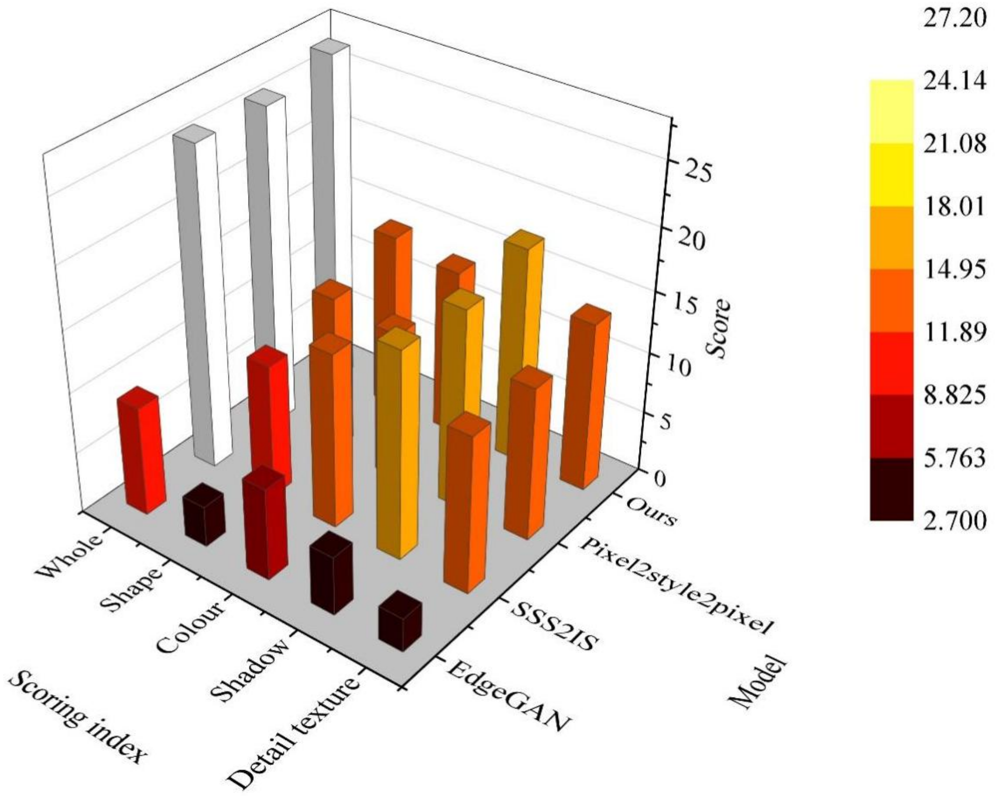

Figure 4. The comprehensive mean score results

4.1.2. Subjective User Evaluation

Based on the show clothes line drawing image design coloring is a user subjective task, the objective index is only a quantitative representation of the quality of the generated image according to a certain calculation, the calculation is not necessarily suitable for all images, that is, the larger the PSNR value, the smaller the FID value, does not necessarily mean that the method of coloring the image effect is better. Therefore, this section focuses on the user subjective evaluation approach to compare the method proposed in this paper with Pixel2style2pixel, EdgeGAN, and SSS2IS. In this section, 20 clothing line drawings were selected from the homemade show clothing line drawings dataset, in which 10 female clothing line drawings images containing 5 top and bottom and 5 dress images were selected, and 10 male clothing line drawings images containing 5 top and bottom and 5 knee-length trench coat images were selected. A total of 25 users aged 22-30 were invited to select their personal favorite colorized image and the colorized image containing less edge color spillage from the above three methods of colorizing the show clothing line drawings.

In order to obtain more objective and fair results, for subjective user evaluation, 25 users were shown the real showwear image, the relative showwear line art image, and the final colorized line art image, and asked to complete the voting independently. Finally, through the collection and analysis, Figure 5 shows the subjective user evaluation.

The box-and-whisker plot visualizes the maximum, minimum, median, and upper and lower quartiles of a set of data. The difference between the upper and lower quartiles is the height of the box called the interquartile range (IQR), the box reflects the distribution of the data, so the height of the box reflects the fluctuating state of these data, and the flatter the box is indicates that the data distribution is more centralized.The turnout rate of the Pixel2style2pixel, EdgeGAN, and SSS2IS methods is much lower than that of the methods proposed in this paper. According to the data the method proposed in this paper is better than other algorithms and the average score of subjective evaluation from users is 27.9588.

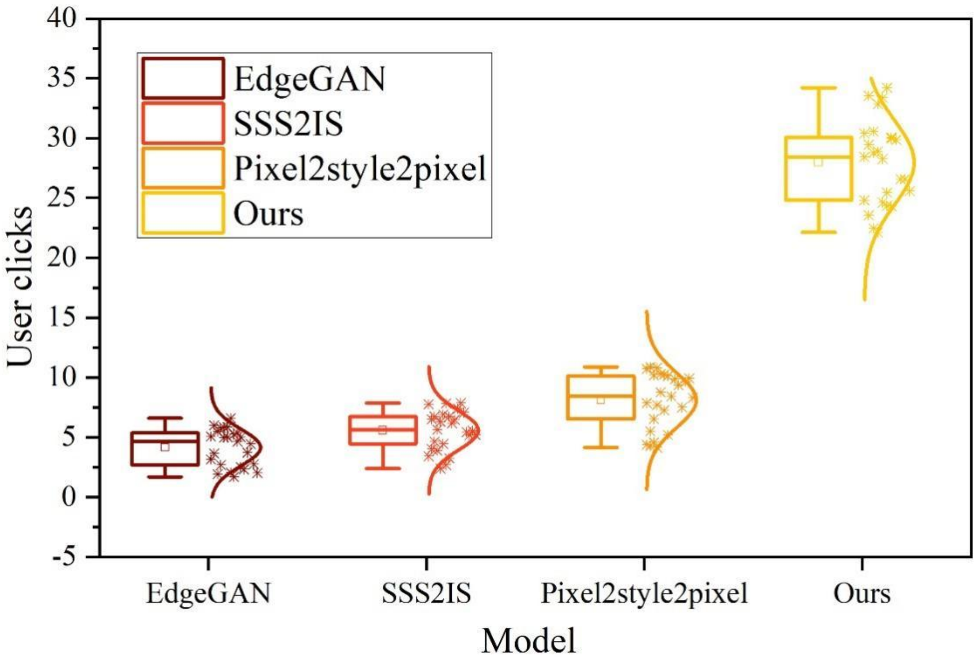

Figure 5. Subjective user evaluation.

In addition to the PSNR and FID evaluation metrics, another evaluation of style relevance (SR) and LPIPS is added to their base in this chapter.

Style relevance (SR) can be used to evaluate the consistency between the model-generated garment design images and the internal consistency of the input pictures, which measures the consistency of color and texture by measuring the distance of the low-level perceptual features from each other, so as to better reflect the separation performance of the model's content and style from each other.

Fig. 6 shows the quantitative comparison of clothing design images, and it can be found that the proposed method in this paper maintains good experimental performance on the evaluation methods of FID, LPIPS, SR and PSNR, with the index values of 65.7485, 21.68, 97.59 and 27.6489, respectively.

To some extent, the method in this paper has good extraction performance in terms of content feature extraction for garment design sketches and fabric information feature extraction for fabric patterns.

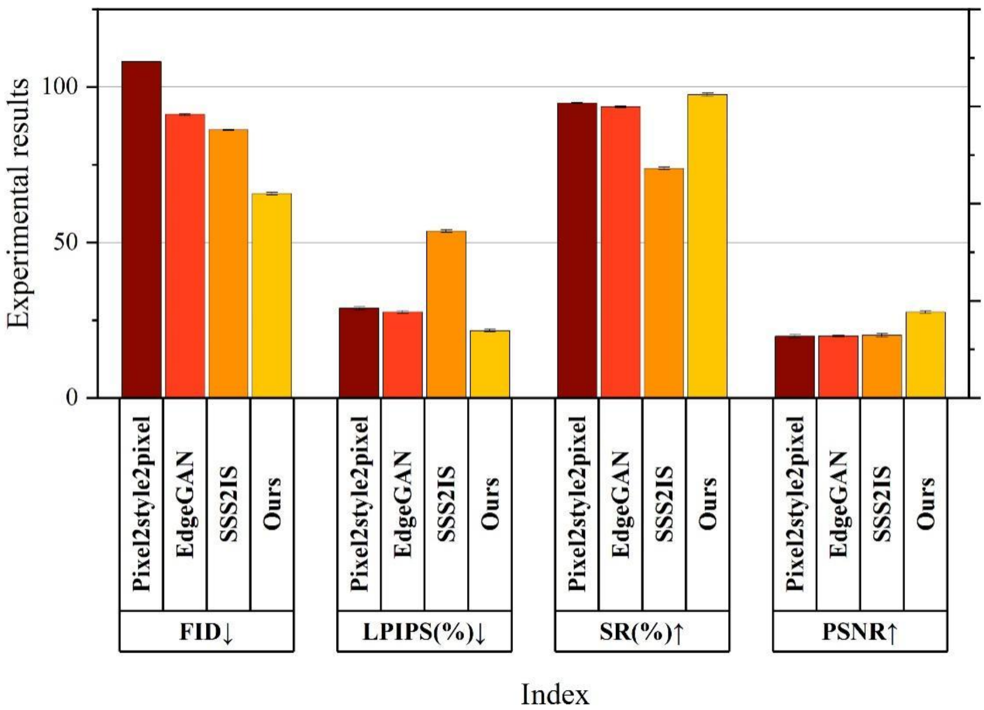

Figure 6. Quantitative comparison of garment design images.

4.2. Analysis of the Effect of Personalization

4.2.1. Comparative Experiments

The model designed in this paper is built in a clothing customization applet, and in order to verify the intention guidance effect of the clothing design model elemental priority constructed in this paper, this paper conducts a comparison test between the clothing customization applet and a known YBR suit customization applet with the help of eye-tracking experimental equipment, respectively. The sampling frequency of the SMIETG desktop eye-tracking device is 60 Hz. 6 consumers with experience in online customization of suits, shirts, or culture shirts, with an average age of 25 years old, including 3 male students, participated in the experiment. The participants independently controlled the picture playback time, viewed the UI interface of the apps in order, the pictures consisted of the same specifications of swimsuit customization and suit customization apps placed symmetrically on the left and right, with the interface introduction in the middle, and then filled out the "Subjective Evaluation of User Experience" at the end of the experiment. IBM SPSS Statistics 21 software was used to conduct a comprehensive evaluation of the eye movement test data, and the results of the comparison test are analyzed in Table 1. Before the eye movement test test participants on the two small program expectations are relatively close, with the comparison test, the test participants of this article clothing customization small program "attention time" for 1834.6985 ms, suit customization small program for 1294.6344ms, the former is higher than the latter 41.7156%. The "first time watching time" of each applet shows a strong user purchase guidance, indicating that the testers participated in the experiment with the same mindset. The average value of subjective experience rating of the apparel customization applet in this paper is 4.2663, which is 13.3027% higher than the average value of the suit customization applet, indicating that the apparel customization applet based on the model designed in this paper provides a higher psychological experience.

Table 1. Descriptive analysis of control trials.

Clothing customization	Trial value		Time of observation /ms	
	Mean	Standard deviation	Mean	Standard deviation
This article	4.4485	0.4985	1834.6985	945.6975
YBR	4.2648	0.7969	1294.6344	1298.9584
Clothing customization	Duration of the first gaze /ms		· Subjective experience	
	Mean	Standard deviation	Mean	Standard deviation
This article	265.4698	128.4698	4.2663	0.6425

YBR	268.9854	140.9634	3.7654	0.7968

4.2.2. User Experience

Figure 7 shows the analysis of the user experience value of the apparel customization applet, showing the visual heat map corresponding to the high and low peak points and end points of consumers' apparel purchases. The results show: The average user experience value of this paper's clothing customization experience and YBR suit customization applet, i.e., the result of the peak value - low peak value + end point value, is 32.3105% and 17.9157%, respectively. The apparel design customization applet in this paper is 14.3948% higher than the YBR suit customization applet. Since the effective consumption experience only comes from the peak value and the feeling at the end, and the customization and ordering process is the key to the conversion of user demand, in this key section, the clothing customization applet in this paper maintains two peak values in the customization process and continues to maintain the peak value until the end of the customization and ordering process, whereas the YBR suit customization applet has four peaks in the process of customization and ordering, but it ends with two low peak values.

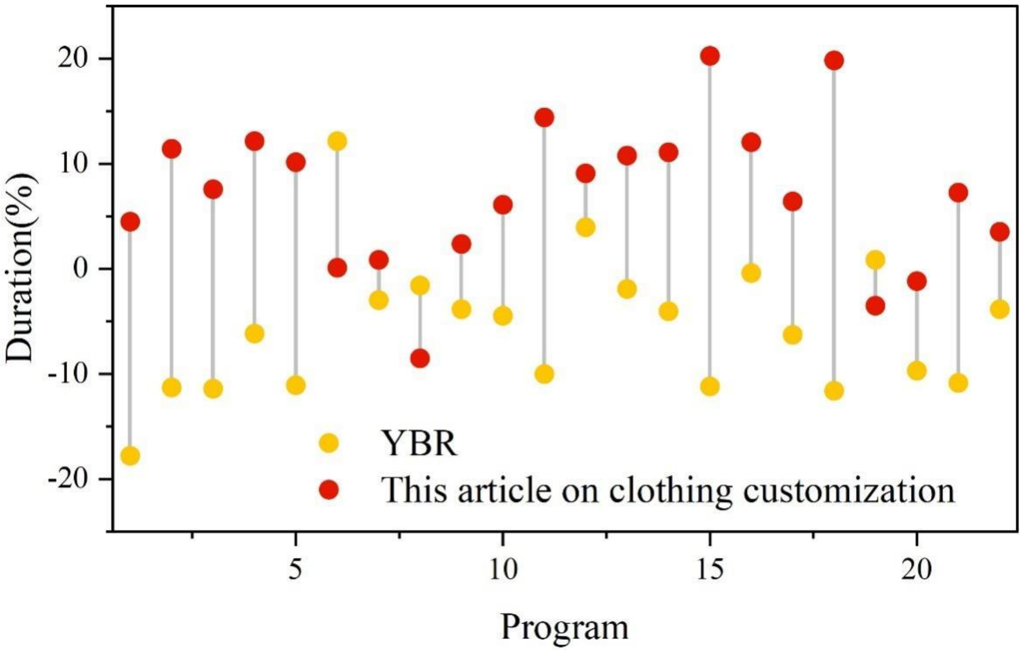

Figure 7. Custom small sequence user experience value analysis.

4.3. Evaluation of Garment Design Effect

For the garment dressing effect generated by the automatic generation system, this paper evaluates it by 20 garment professionals, scholars, and experts to verify the reasonableness and feasibility of the system.20 garment professionals, scholars, and experts rate the dressing effect of the blouse prototype as shown in Table 2, the dressing effect of the skirt as shown in Table 3, and the dressing effect of the jeans as shown in Table 4. The mean values of the overall ratings of the top, skirt, and jeans were 3.0082, 3.8233, and 4.0384 points, respectively.

After 20 clothing professional staff, scholars, and experts scored, the scores of the blouse prototype, skirt, and jeans dressing effect scores were imported into SPSS software, and the frequency distribution characteristics of the overall scores of the clothing paper samples were statistically analyzed by SPSS software, and the histogram of its frequency distribution is shown in Figure 8. The overall scoring score of the clothing top prototype real-life try-on is mainly distributed in 3~4 points, the overall scoring score of the skirt real-life try-on is mainly distributed in 3~4.5 points, and the scoring score of the jeans real-life try-on is mainly distributed in 3~5 points. The data are all in line with normal distribution, indicating that the data are reliable.

Table 2. Tops prototype dressing effect scores.

Expert number	Whole	Front	Side	Backside
1	2.4978	2.0495	2.4919	2.4896

2	2.8286	3.0134	2.4999	2.995
3	3.5691	4.0045	2.1057	4.4249
4	3.0208	2.9973	3.0822	3.0712
5	3.307	2.9631	3.4129	3.4351
6	3.0536	3.5202	2.4721	3.1296
7	3.1776	2.992	3.509	2.9768
8	3.4611	2.9639	2.998	3.9973
9	2.7839	3.0203	2.4779	3.1734
10	3.4362	3.0275	2.9161	4.0111
11	2.9247	1.9613	2.0236	4.0729
12	1.5381	1.4617	1.4611	1.5446
13	3.7418	3.9106	2.995	3.9775
14	2.3694	1.9035	2.5079	2.509
15	3.983	4.5012	3.0109	4.4966
16	1.9747	2.0324	2.5453	1.5589
17	3.1975	2.5025	3.6255	3.4502
18	1.9974	0.9225	3.5144	1.518
19	3.4744	3.0454	3.521	3.9536
20	3.827	3.9807	3.5145	3.4774

Table 3. Skirt dressing effect scores.

Expert number	Whole	Front	Side	Backside
1	3.5674	4.0541	3.9732	3.0766
2	3.0143	2.94	2.9484	2.9902
3	4.1607	3.9971	4.0219	4.4937
4	3.5461	3.4623	3.5311	3.4941
5	3.7603	4.0729	4.0066	3.5023
6	3.5859	3.498	3.4963	3.4922
7	4.3167	3.96	4.4874	4.5278
8	4.1195	3.9466	3.9525	4.4323
9	3.0208	2.9399	2.9645	3.0389
10	4.7918	4.9707	4.9997	3.97
11	3.7687	3.5101	3.9802	4.0424
12	4.5666	4.4858	4.5076	4.5441
13	2.3485	4.0322	4.5777	3.9945
14	4.2557	4.4891	4.0236	4.4878
15	4.382	4.474	4.6007	4.5172
16	4.0393	4.0267	4.019	3.9846
17	3.1982	2.9943	2.9714	3.5219
18	3.9296	4.0196	4.033	4.0297
19	3.8448	3.5226	3.9933	4.009
20	4.2497	4.4842	4.0064	3.9217

Table 4. Jeans dressing effect score.

Expert number	Whole	Front	Side	Backside
1	3.4915	3.427	3.9508	2.4567
2	2.7304	2.9995	2.9628	2.4728
3	4.9609	4.9809	5.0757	5.0644
4	3.7983	3.9874	3.4261	4.0286
5	4.0699	3.5165	4.375	3.4863
6	3.4563	3.4687	3.4332	3.5119
7	4.4943	4.4794	4.5117	4.5274
8	4.2488	4.1317	4.4704	4.0229
9	3.0585	3.0304	3.0696	3.1025
10	4.5913	4.468	5.0223	4.0543
11	5.0639	5.0535	4.9873	4.9633
12	4.0009	4.4525	4.0558	3.4426

13	4.3597	4.0019	5.0188	4.009
14	4.7915	4.4383	4.9595	4.5248
15	4.4854	4.0041	5.0297	4.5162
16	4.0464	4.0214	4.011	4.0183
17	2.8018	3.4881	2.4709	2.4885
18	3.507	3.5074	3.4679	3.5656
19	4.2207	3.9971	4.5787	3.9801
20	4.5911	4.4852	4.4713	4.5018

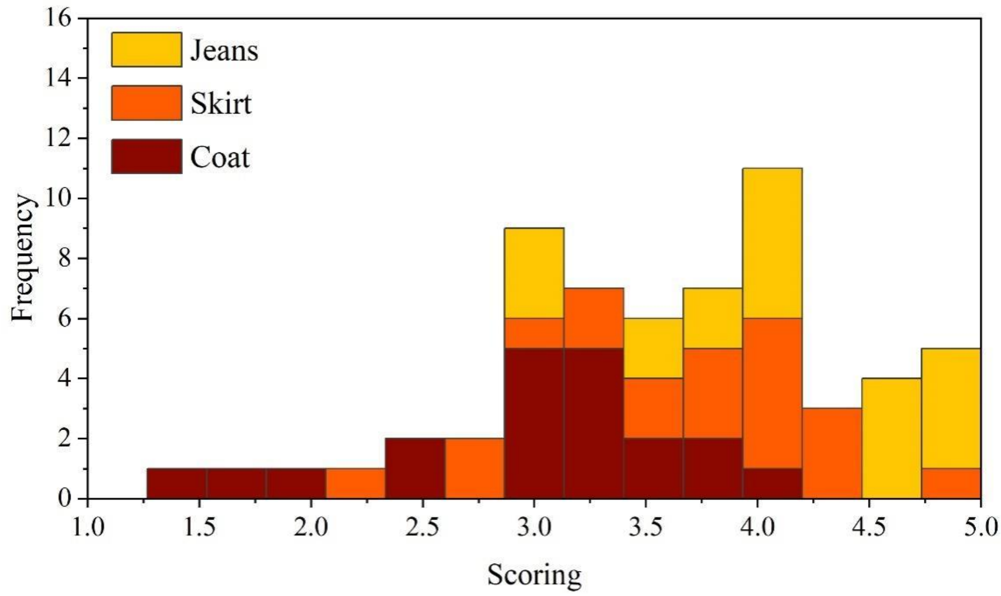

Figure 8. The overall grading of children's garments is distributed.

5. Conclusion

In this paper, we first realized the clothing image style migration through GAN model, and integrated the information obtained from the migration into the LoRA stable diffusion model to generate the fashion clothing model dataset. Subsequently, an adaptive enhancement module is added and a two-stage generation algorithm is introduced to accurately capture different key information for personalization of clothing design. Finally, a clothing design concept combining AIGC and virtual reality is proposed to analyze the personalization results.

(1) In this paper, from the human visual perspective, the generated clothing design image scores, the model in this paper obtains scores in the overall, shape, shadow, detail texture and other viewing scores are 27.1585, 14.4955, 17.6485, 13.8486, respectively, and the method is effective.

(2) At the user experience level, the average user experience value score of the garment customization experience in this paper is 32.3105, which is 14.3948% higher than that of YBR suit customization. For the automatically generated ready-to-wear dressing effect of the system, the overall rating mean values of tops, skirts, and jeans are 3.0082, 3.8233, and 4.0384 points, respectively.

(3) In the real-life try-on experience, the try-on rating scores for tops, skirts, and jeans were distributed at 3 to 4, 3 to 4.5, and 3 to 5, respectively. The data all conformed to normal distribution, indicating that the data were reliable.

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