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Article

Analysis of AIGC-Based Virtual Apparel Design System as An Alternative to Traditional Manual Design Process

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Abstract: Traditional manual design is often overly complex and time-consuming to measure, leading to its gradual elimination from the market. To achieve digital design in clothing, this paper aims to realize the personalization and virtuality of modern clothing design while reducing design costs. This paper designs a virtual clothing design system based on AIGC, combining web interface design processes to simulate customized design content, and introduces a particle-spring model for mechanical analysis. It explores collision detection and response methods between the human body and clothing using AABB bounding boxes. Through experiments with 30 samples, the reliability and accuracy of the proposed method are validated, and cotton and silk garments are selected for design rationality prediction. The experiment on the design rationality prediction of silk clothing showed that the correlation coefficient between the predicted values of the BP prediction model and the measured values was 75.22%, while the correlation coefficient of the method proposed in this paper was 90.33%. Thus, the method proposed in this paper has a better prediction effect on the design rationality of silk clothing. The AIGC-based virtual clothing design system has a better alternative to the traditional manual design process.

Keywords: AIGC; virtual clothing design; particle-spring model; traditional manual design

1. Introduction

Artificial Intelligence-Generated Content (AIGC) technology, with its powerful data processing and generation capabilities, is rapidly penetrating the field of fashion design. By interacting with designers through efficient image generation, creative inspiration, and decision-making assistance, AIGC significantly enhances design efficiency, shortens design cycles, and produces a wealth of diverse, innovative, and unique design works, sparking a revolution in fashion design productivity [1]. AIGC technology is founded on AI algorithms such as machine learning and deep learning [2]. Machine learning trains models using large datasets, enabling machines to learn patterns and rules from data [3]. Deep learning is a branch of machine learning that uses deep neural networks for feature extraction and pattern recognition [4].

Virtual clothing refers to the use of computer algorithms to precisely simulate the physical characteristics of clothing in the real world, including fabric texture, clothing patterns, and human-machine interaction [5]. In the design and presentation of virtual clothing, all work processes are presented in a digital format, which not only simplifies the cumbersome steps in traditional design processes but also improves design efficiency [6-7]. Designers can freely create and modify designs in a virtual environment, further expanding their creative space. The greatest advantage of the deep integration of virtual clothing and AIGC technology is the significant cost-saving and efficiency-enhancing benefits it brings to the field of clothing design [8]. Designers can accurately and efficiently create designs that meet requirements within a relatively limited creative cycle.

In the context of digital intelligence, AIGC demonstrates immense potential and broad application value, offering unprecedented opportunities for clothing design. Zhang et al. proposed an AIGC-based clothing design approach, using case studies to demonstrate the specific application of Dongguan's Seven-Color Weaving Unicorn elements in clothing design, including the integration of color, patterns, and silhouettes [9]. In AIGC systems, generative adversarial networks (GANs) not only generate images and videos aligned with specific themes but also continuously optimize output quality through discriminator feedback, ultimately producing intelligent content tailored to user needs [10-11]. Zhou proposed a GAN-based 3D clothing design generation approach, applying deep learning neural network models to identify 3D human body morphology features, and constructing 3D clothing prototypes based on this. The feasibility and effectiveness of the designed clothing design modeling algorithm were validated through experiments [12]. Junlian et al. integrated advanced technologies from variational autoencoders and generative adversarial networks to propose a virtual fabric design optimization strategy. Experiments demonstrated that this method can effectively generate high-quality, realistic clothing fabric designs, reducing design cycles and costs [13]. Dik et al. proposed constructing a generative adversarial network model to generate new human body size data and clothing parameter data. This method improved the virtual clothing fitting prediction model, enabling a more comprehensive evaluation of clothing fit and enhancing design efficiency [14]. Yuan et al. developed a design attribute generative adversarial network model for automatically generating virtual fashion images with visual attributes, experiments on the dataset demonstrated the model's potential in design generation, with generated images showing high accuracy compared to the original images [15]. Wu et al. proposed a model for designing new clothing patterns and styles based on an innovative framework combining generative adversarial networks and style transfer algorithms. Experiments were conducted on a custom-made clothing dataset, and the results showed that the model generated new clothing patterns and styles with Dunhuang elements, with initial scores, human preference scores, and generation scores all outperforming the comparison model [16]. Wang et al. utilized an optimized GAN model to edit the image attributes of women's shirts. Experimental results showed that the optimized model significantly reduced issues of attribute missing or visual redundancy, with the model's generated images achieving a 27.4% increase in SSIM and a 2.8% increase in PSNR [17].

Research indicates that the application of virtual clothing design can complete the virtual design of multiple styles in a short period of time. Liu, H proposed a virtual reality-based 3D clothing design modeling method, designing and implementing functions such as character virtual modeling, clothing virtual modeling, and accessory virtual modeling. The results showed that this method promotes the digital transformation of corporate clothing design and improves corporate clothing production efficiency [18]. Liu, Z et al. proposed a modern clothing design solution based on human body 3D motion sensing technology, utilizing the combination of clothing components to offer more options for clothing styles, colors, and sizes. This solution shortens the time required for clothing design and enhances user satisfaction with the design [19]. Shin employed 3D virtual simulation design for casual wear, and the research results indicated that the application of 3D virtual clothing simulation technology in clothing design reduces human and material resources, as well as the time and costs associated with reviews, and the Untouch fashion production system effectively improves work efficiency [20]. Kuzmichev explored the application of artificial intelligence and computer-aided design systems in generative design, personalized clothing models, virtual try-on technology, and sustainable production optimization. Experimental results showed that this method achieves high accuracy for AI-generated images, reaching 95% under stable diffusion [21]. Hong et al. used Unity3D to design clothing runway scenes and garments, combined with virtual reality technology for an immersive experience to achieve a realistic feel. Results showed that users' sensory evaluations improved by 22.02%, and their ratings of viewing smoothness in the fashion runway increased by 10.99% [22].

The application of virtual clothing and AIGC technology marks a new phase of development in the fashion industry, significantly expanding the boundaries of fashion design, lowering technical barriers, and enabling a new era of innovation from content production to intelligent generation [23].

The article first establishes a computer-aided clothing design system, integrating 3D scanning and 3D virtual fitting, and applying remote video communication and intelligent style design. Through various computer technology applications, it analyzes the fundamental characteristics of clothing customization. Based on the system research, a particle-spring model is introduced to perform virtual digital clothing simulation on a 3D human body model. The use of AABB bounding boxes is proposed for collision detection and collision response algorithms between the human body and clothing, enabling clothing visualization. Finally, waist and bust measurements were validated on 30 test subjects of different genders and body types. Predictive experiments and parametric pattern-making technology validation were conducted to assess the rationality of different clothing designs. Based on the experimental results, the application of the integration of art and technology in clothing design was explored.

2. Design of a virtual clothing design system based on AIGC

2.1. Basic System Content

2.1.1. System Requirements

The construction of today's clothing design system requires an increase in customizable style options to fully meet personalized needs. During the virtual try-on process, consumer experience should be enhanced. The virtual try-on process should integrate 3D virtual try-on technology with a virtual display of a human body model to improve product quality and thereby reflect the quality of high-end customization [24]. Regarding the customization process for high-end fabrics, it is necessary to combine the application of high-quality shirts to fully meet the primary needs of high-end consumers. It is essential to incorporate manual measurement data as much as possible and apply 3D human body scanning technology to accurately obtain consumer body data, thereby effectively avoiding errors from manual measurements.

2.1.2. System Content

Regarding the process of high-end custom clothing, remote custom clothing categories are shown in Figure 1. Regarding the 3D virtual clothing design process, 3D virtual clothing is generated by expanding upon the initial clothing prototype. User-interactive clothing design involves mapping 3D human body data onto a 2D space to form human body contour lines, and then using interpolation methods to remove noise from the contour lines, identifying the most suitable combinations to achieve the best results. This significantly reduces the time from design to production, enhancing production efficiency and product quality. In the clothing database, various clothing data tables are established, including clothing fabric parameters, clothing fabric images, clothing style names, 3D virtual clothing files, 2D clothing contour line files, and other related files.

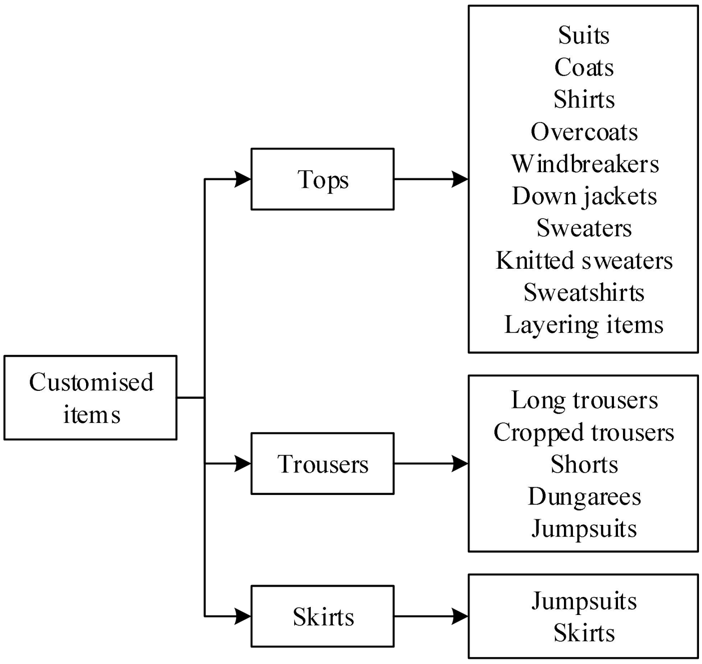


Figure 1. The remote clothing customization category.

2.1.3. System Process

The custom clothing process often requires customers to collect body measurements, combine them with manual measurements, select styles on a mobile device customization interface, perform virtual try-ons, and place orders.

(1) Collecting measurements and customization options

The measurement collection process primarily combines 3D body scanning with manual measurement. During the 3D body scanning phase, an effective 3D virtual interface is displayed to minimize the number of virtual try-ons required. The customization selection process involves choosing categories and silhouettes based on customization requirements, optimizing material and decorative elements [25]. For category customization and services, customers can participate in the design process to achieve localized customization and decorative customization, thereby gradually fulfilling their needs.

(2) Virtual Display and Order Confirmation

The virtual display process involves selecting appropriate 3D fitting images based on the basic customization options, and using human models to achieve effective customization of clothing. The virtual display process also involves analyzing customers' perceptions of the wearing effect through the design of the interface and the actual application of mobile terminals. Through the virtual display process, customers can finalize their selections, which leads to the order placement and payment stage. Customers fill in the delivery address, select the invoice format, confirm the order information, and enhance communication and interaction with the designer to propose relevant modification suggestions.

(3) Service Experience

The service experience process primarily combines remote planning services with customers' actual interests and hobbies to design the customization process and plan for post-production modifications and maintenance.

2.2. Research on 3D clothing simulation and visualization

2.2.1. Clothing Fabric Performance

Fabric is not only a flexible object but also a highly complex physical system in terms of its physical structure and mechanical behavior, requiring description of its dynamic behavior from multiple parameters and perspectives. This paper provides a brief overview of the physical complexity of textiles and identifies common characteristics among them. The fabric being studied is assumed to be an ideal textile with uniform thickness and density, constant mass, and high deformability. The KES (Kawabata Evaluation System) algorithm involves conducting various types of tension tests on the same fabric and categorizing the internal interactions of the fabric into three types: tensile, shear, and bending. The tensile properties of fabrics are one of the key indicators for evaluating their physical performance, and uniaxial tensile testing is currently the primary consideration in the textile industry when assessing fabric tensile properties. When subjected to uniaxial tensile forces, fabrics first contract due to inertia before being stretched. When the tensile force reaches a certain limit, the fabric will rupture. The bending performance of fabrics is another important indicator for evaluating fabric properties, directly affecting the effectiveness of garment shaping, garment quality, and garment lifespan. The shear performance of fabrics is a core factor determining fabric tactile feel and garment shaping efficiency. When fabrics undergo bending deformation due to external forces, it causes the viscoelasticity of fibers and the redistribution of fibers within yarns, generating internal friction and viscoelastic forces.

2.2.2. Point-spring model

The particle-spring model is constructed based on the intrinsic composition of the fabric and the external forces acting upon it. The primary concept utilized in this paper is to treat the three sides and vertices of a triangle as springs and particles, respectively, with their geometric positions directly influencing the external form of the garment. The reason for selecting the particle-spring model is twofold: first, it is widely used for simulating flexible objects; second, it is both simple and easy to implement. The particle-spring model treats the fabric as a network composed of individual particles, where the position of each particle represents the spatial location of a point on the fabric [26].

After constructing a particle-spring model on the garment, the motion equations of each particle on the garment are determined by the resultant force acting on it. The resultant force $F_{sum}(i, j)$ acting on the particle is calculated using Newton's second law, as shown in Equation (1).

$$F_{sum}(i, j) = F_{out}(i, j) + F_{in}(i, j) = ma(i, j) \tag{1}$$

Among these, $F_{out}(i, j)$ is the external force acting on particle $P(i, j)$, $F_{in}(i, j)$ is the internal force acting on the point, m is the mass of the point, and $a(i, j)$ is the acceleration of the point.

The forces acting on the fabric can be divided into external forces and internal forces. External forces refer to the interaction between the fabric and the external environment, consisting of forces such as gravity, air resistance, and collision forces. Internal forces include spring forces and damping forces. To reduce the computational load, this paper only considers two types of external forces—gravity G and air resistance $F_a(i, j)$—as well as spring forces, as shown in Equation (2).

$$F_{out}(i,j) = G + F_a(i,j) \tag{2}$$

Among them, the gravitational force acting on the particle is given by equation (3), and the air resistance acting on the particle is given by equation (4).

$$G = m(i,j) * g \tag{3}$$

$$F_a = -m(i,j) * k_a * v(i,j) \tag{4}$$

Among them, $m(i,j)$ is the mass of particle $P(i,j)$, g is the gravitational acceleration, which is a fixed value, k_a is the air resistance coefficient, and $v(i,j)$ is the velocity vector of the particle.

Since this paper uses an ideal particle-spring system, the spring force can be calculated using Hooke's law, as shown in equation (5).

$$F_{in}(i,j) = -\sum_{(k,l)\in R} k \left(\overline{P_{i,j}P_{k,l}} - \left\| \overline{P_{i,j}P_{k,l}} \right\|_0 - \frac{\overline{P_{i,j}P_{k,l}}}{\left\| \overline{P_{i,j}P_{k,l}} \right\|} \right) \tag{5}$$

Among them, R is the set of adjacent points of $P_{i,j}$, k is the elastic deformation coefficient of the spring, and $\left\| \overline{P_{i,j}P_{k,l}} \right\|_0$ is the original distance between particles $P_{i,j}$ and $P_{k,l}$.

This paper uses the Euler method to solve the deformation model of the garment, as shown in equation (6).

$$\begin{cases} a_{i,j}(t+\nabla t) = \dfrac{1}{m_{i,j}} F_{i,j}(t) \\ V_{i,j}(t+\nabla t) = V_{i,j}(t) + \nabla t a_{i,j}(t+\nabla t) \\ P_{i,j}(t+\nabla t) = P_{i,j}(t) + \nabla t V_{i,j}(t+\nabla t) \end{cases} \tag{6}$$

Among these, $m_{i,j}$ is the mass of particle $P_{i,j}$, $F_{i,j}$ is the resultant force acting on particle $P_{i,j}$, ∇t is the time step, and the acceleration, velocity, and displacement of particle $P_{i,j}$ at time t are $a_{i,j}(t)$, $V_{i,j}(t)$, and $P_{i,j}(t)$, respectively.

2.2.3. Collision Detection

(1) Constructing an AABB tree

The bounding box AABB of a collision object is the smallest hexahedron that contains the collision object, and each edge of the AABB is parallel to the coordinate axis. The partitioning plane selected in this paper is a plane that is perpendicular to and bisects the longest axis of the AABB. The method described here is extremely simple: the direction in which the original geometric element should belong to the partitioning plane is determined by the projection coordinates of the center of gravity of the original geometric element on the longest axis. If the partitioning plane coordinates are smaller than the projection coordinates, the element is on the positive side; otherwise, it is on the negative side.

After moving or rotating the garment piece, the AABB is updated. First, the six maximum values of the AABB are defined, then these maximum and minimum values are combined, to obtain the eight points of the AABB. After moving or rotating these eight points, new points are obtained, and the new AABB is calculated. If the garment piece undergoes deformation, the AABB of the changed leaf nodes in the AABB tree must be recalculated, new leaf node AABBs are generated, and their parent node AABBs are calculated. The specific calculation method for the parent node AABB is as follows:

Step 1: Set the AABB of the two deformed leaf nodes as $\left(X_{\max 1}, X_{\min 1}, Y_{\max 1}, Y_{\min 1}, Z_{\max 1}, Z_{\min 1}\right)$ and $\left(X_{\max 2}, X_{\min 2}, Y_{\max 2}, Y_{\min 2}, Z_{\max 2}, Z_{\min 2}\right)$.

Step 2: From Step 1, the AABBs of the parent nodes are $\max\left(X_{\max 1}, X_{\max 2}\right)$, $\min\left(X_{\min 1}, X_{\min 2}\right)$, $\max\left(Y_{\max 1}, Y_{\max 2}\right)$, $\min\left(Y_{\min 1}, Y_{\min 2}\right)$, $\max\left(Z_{\max 1}, Z_{\max 2}\right)$, and

$\min\left(Z_{\min 1}, Z_{\min 2}\right)$.

(2) AABB Tree-Based Collision Detection Algorithm

Efficiently traverse the two AABB trees to determine whether the two colliding objects have collided. This is the core of the AABB tree-based collision detection algorithm. The algorithm undergoes two recursive traversals throughout the process. The detailed algorithm steps are as follows:

Step 1: Construct corresponding AABB trees for all 3D human models and clothing pieces in this simulation experiment.

Step 2: Traverse the root nodes of the garment piece AABB tree and the 3D human model AABB tree. If the bounding box of a node in the garment piece AABB tree does not intersect with the bounding box of the root node in the human model AABB tree, there is no need to continue traversing downward. If the traversal of the leaf nodes in the garment piece AABB tree is completed, then use this leaf node to traverse the human model AABB tree. If the leaf node of the human model AABB tree is reached, perform intersection testing on the geometric elements.

Step 3: Test whether the geometric elements intersect. If they intersect, perform intersection calculation; otherwise, do not perform intersection calculation.

(3) Collision response

There are two collision response algorithms. The first algorithm involves adding factors that suppress the generation of collision particles. The second algorithm involves adding a vector field or applying an outward force of instantaneous high magnitude to the collision particles. In practical applications, the first method is typically chosen, which involves applying geometric constraints to the collision particles and promptly updating the position and velocity of the collision particles to prevent penetration and clipping phenomena.

3. Simulation experiment

3.1. Human Body Measurement

3.1.1. Experimental setup

A total of 30 participants were included in this experiment, comprising 15 females and 15 males, aged between 20 and 30 years old, of Han ethnicity, with heights ranging from 150 cm to 185 cm. These parameters were used to narrow the range of variability in the study results. Prior to the measurement process, participants were required to wear a custom-made tight-fitting garment designed for this experiment. The garment featured a pattern of yellow, orange, purple, and blue colors arranged in a repeating pattern on its adjustable surface. Additionally, the subject's posture during measurement is critical for obtaining reliable data. When measuring waist or chest circumference in our experiment, the arms might obstruct the measurement. Therefore, during the entire experiment, subjects adopted a T-shaped posture while standing to collect image sequences using a multi-viewpoint system. Subjects must hold their breath and maintain a stable body posture throughout the measurement process. To enhance the reliability of the measurement results, each subject was measured five times using both manual measurement and the method described in this paper, and the average of the five measurements was taken as the final measurement result for that item. A set of materials showing the measurement of male waist circumference during the experiment is displayed. The subject was positioned approximately 70 cm away from the stereo camera. The experiment measured male waist circumference using a 0° stereo camera and a 90° stereo camera.

3.1.2. Male size measurement results

The total sample size of our experiment was 30 participants, including 15 females and 15 males. We selected data from 10 participants out of the 30 male participants, and the results of their chest and waist measurements are shown in Table 1, with participant numbers ranging from 1 to 10. As shown in the analysis table, the circumference measurement data obtained using the method described in this paper is consistent with the results of manual measurements. The largest measurement error for the chest circumference was observed in subject number 7. The average value of five manual measurements using a soft tape measure was 90.53 cm, while the average value of five measurements using the method described in this paper was 92.17 cm. The absolute error between the two is 1.64 cm, which meets the requirements of the allowable deviation table for the main parts of men's upper garments specified in the National Standard of the People's Republic of China GB/T2664-2017 “Men's Suits and Coats,” where the allowable deviation for the chest circumference is ±2 cm. The minimum absolute error for chest circumference data is 0.72 cm, with a relative error range of 0.88% to 1.81%. The largest measurement error for the waist circumference was observed in subject number 5. The average value of five manual tape measure readings was 79.05 cm, while the average value of five measurements using the method described in this paper was 80.99 cm, The absolute error between the two is 1.94 cm, which meets the requirement of ±2 cm for waist circumference specifications in the “Allowed Deviation Table for Main Parts of Finished Products” of the Chinese National Textile Industry Standard FZ/T 81006-2017 “Denim Apparel.” The minimum absolute error for waist circumference data is 0.23 cm, with a relative error range of 0.25% to 2.45%. In summary, the human body dimension data obtained by the multi-viewpoint human body parameter measurement system in this study is relatively accurate and fast, and it meets both national standards and textile industry standards.

Table 1. Results of the chest circumference and waist circumference of the subjects.

Volunteer number	Measuring position	Ours(measured value)/cm	Flexible rule’s measuring value (real value)/cm	Absolute error/cm	Relative error (error rate) %
1	Chest Circumference	81.1	79.86	1.24	1.55
	Waistline	76.78	75.83	0.95	1.25
2	Chest Circumference	82.71	81.99	0.72	0.88
	Waistline	76.72	75.55	1.17	1.55
3	Chest Circumference	83.36	82.14	1.22	1.49
	Waistline	79.17	77.68	1.49	1.92
4	Chest Circumference	86.96	86.21	0.75	0.87
	Waistline	79.99	79.33	0.66	0.83
5	Chest Circumference	87.23	85.88	1.35	1.57
	Waistline	80.99	79.05	1.94	2.45
6	Chest Circumference	89.64	88.08	1.56	1.77
	Waistline	82.51	82.13	0.38	0.46
7	Chest Circumference	92.17	90.53	1.64	1.81
	Waistline	88.89	87.26	1.63	1.87
8	Chest Circumference	92.78	91.72	1.06	1.16
	Waistline	89.27	88.46	0.81	0.92
9	Chest Circumference	96.03	95	1.03	1.08
	Waistline	93.09	92.86	0.23	0.25
10	Chest Circumference	94.23	93.16	1.07	1.15
	Waistline	83.8	82.62	1.18	1.43

The accuracy of circumference measurements is shown in Table 2. The table presents the statistical analysis of waist and chest circumference data from 47 male participants in the overall sample. The average and standard deviation of waist circumference for 15 male participants were calculated using both manual measurements with a soft tape measure (5 measurements) and measurements from this system (5 measurements), as well as the average and standard deviation of chest circumference. As shown in the table, the measurement values obtained using the method described in this paper are closely aligned with those obtained using a soft tape measure, with an average error of only 0.8 cm for chest circumference. This indicates that the method described in this paper possesses a high degree of accuracy.

Table 2. Accuracy of circumference measurement.

Boys		N	Mean/cm	SD/cm
Chest Circumference	Ours	15	89.25	4.31
	Flexible rule's measuring size	15	88.45	4.87
Waistline	Ours	15	83.36	4.51
	Flexible rule's measuring size	15	81.98	4.3

3.1.3. Female size measurement results

Another set of experiments involved measuring the sample sizes of female participants. Ten female participants were selected and assigned numbers from 11 to 20. The results of the chest and waist measurements for participants numbered 11 to 20 are shown in Table 3. As can be seen from the table, the circumference data measured using the method described in this paper is consistent with the results of manual measurements. The largest error in the chest circumference measurement was observed in subject number 18. The average value of five manual measurements using a soft tape measure was 92.24 cm, while the average value of five measurements using the method described in this paper was 93.78 cm. The absolute error between the two is 1.54 cm, which meets the requirements of the allowable deviation table for the main parts of women's upper garments specified in the National Standard of the People's Republic of China GB/T2665-2017 "Women's Suits and Coats," where the allowable deviation for the chest circumference is ±2 cm. The minimum absolute error for the chest circumference data is 0.58 cm, and the relative error ranges from 0.64% to 1.67%. The largest error in waist circumference measurements was observed in subject number 18. The average value of five manual tape measure measurements of the waist circumference was 82.49 cm, while the average value of five measurements using the method described in this paper was 84 cm, with an absolute error of 1.51 cm between the two. This meets the requirement of ±1.5 cm for waist circumference specifications and dimensions as described in the "Allowed Deviation Table for Main Parts of Women's Ready-to-Wear Garments" in the Chinese National Textile Industry Standard FZ/T 81004-2012 "Dresses and Skirts." The human body dimension data obtained using the method described in this paper is relatively accurate and fast, while also meeting national standards and textile industry standards.

Table 3. Measurements of measured dimensions of 11 to 20.

Volunteer number	Measuring position	Ours (measured value)/cm	Flexible rule's measuring value (real value)/cm	Absolute error/cm	Relative error (error rate) %
11	Chest Circumference	80.51	79.22	1.29	1.63
	Waistline	73.44	72.75	0.69	0.95
12	Chest Circumference	80.68	79.69	0.99	1.24
	Waistline	73.91	72.85	1.06	1.46
13	Chest Circumference	82.16	80.94	1.22	1.51
	Waistline	64.36	63.21	1.15	1.82
14	Chest Circumference	82.14	81.52	0.62	0.76
	Waistline	72.42	71.13	1.29	1.81
15	Chest Circumference	82.52	81.38	1.14	1.40
	Waistline	69.26	68.06	1.2	1.76
16	Chest Circumference	83.75	82.91	0.84	1.01
	Waistline	72.97	72.34	0.63	0.87
17	Chest Circumference	91.21	90.63	0.58	0.64

	Waistline	81.02	80.33	0.69	0.86
18	Chest Circumference	93.78	92.24	1.54	1.67
	Waistline	84	82.49	1.51	1.83
19	Chest Circumference	96.34	94.92	1.42	1.50
	Waistline	85.69	84.37	1.32	1.56
20	Chest Circumference	85	84.25	0.75	0.89
	Waistline	73.14	72.34	0.8	1.11

The accuracy of chest and waist circumference measurements is shown in Table 4. The table presents the statistical analysis of waist and chest circumference data from 15 female participants in the overall sample. The average and standard deviation of waist circumference were calculated using both manual measurements with a soft tape measure (5 measurements) and the system measurements (5 measurements) for the 15 female participants. The average and standard deviation of chest circumference were also calculated using the same methods. As shown in the table, the average measurement values obtained using the method described in this paper are close to those obtained using the soft tape measure. In terms of waist circumference measurement, the difference between the method used in this study and the tape measure measurements is only 0.37 cm.

Table 4. The accuracy of waist circumference measurement.

Girls		N	Mean/cm	SD/cm
Chest Circumference	Ours	15	86.15	5.14
	Flexible rule’s measuring size	15	85.31	4.85
Waistline	Ours	15	75.15	5.62
	Flexible rule’s measuring size	15	74.78	5.92

The dimensional measurement system we have proposed has been validated for measuring waist and chest circumferences on subjects of different genders and on human body models. In our experiments, the maximum error rate was 2.45%, and the measurement errors at the respective measurement sites comply with the corresponding Chinese national standards (for different genders and measurement sites). The absolute error for male chest circumference meets the requirement of the national standard GB/T2664-2017 “Men's Suits and Coats,” which specifies that the allowable deviation for the finished chest circumference of men's upper garments is ±2 cm. The absolute error for male waist circumference complies with the textile industry standard FZ/T81006-2017 “Denim Clothing,” which specifies an allowable deviation of ±2 cm for the finished waist circumference specifications and dimensions. The absolute error for female waist circumference complies with the national standard GB/T2665-2017 “Women's Suits and Coats,” which specifies an allowable deviation of ±2 cm for the finished chest circumference specifications and dimensions of women's upper garments. The absolute error of the female bust circumference meets the requirements of the textile industry standard FZ/T81004-2012 “Dresses and Skirts,” which specifies an allowable deviation of ±1.5 cm for the finished bust circumference of women's garments. Additionally, the method described in this paper offers high measurement accuracy at a relatively low cost. The device can also simultaneously measure circumference dimensions of different body parts.

3.2. Experiment on predicting the rationality of clothing design

This section of the experiment uses the least squares univariate leading regression method to validate the predictive performance of the virtual clothing design rationality method based on AIGC and the clothing design rationality analysis method based on the BP prediction model designed in this paper. The predicted value of the clothing skin comfort index, that is, the prediction results of different methods, is set as e . The expected value, that is, the measured value, is set as U . The least squares univariate regression method is then used to perform linear regression analysis on e and U to obtain the straight line $y = kx + b$. If the two obtained straight lines have a high degree of similarity, it indicates that the model has high predictive accuracy. The correlation between the predicted values and the measured values is also analyzed; if the correlation coefficient exceeds 0.7, it indicates that the corresponding method has high predictive precision for clothing design rationality.

3.2.1. Predicting the rationality of cotton clothing design

The experimental sample set consists of data obtained from comfort tests conducted on 10 participants wearing three different types of cotton clothing, specifically to assess the rationality of the clothing design. Fifteen samples were selected from this dataset to evaluate the predictive performance of different methods. The prediction results of the BP prediction model and the method proposed in this paper for the rationality of cotton garment design are shown in Figures 2 and 3, respectively. As shown in Figures 2 and 3, the correlation coefficient between the predicted values of the BP prediction model and the measured values is 63.29%, while the correlation coefficient of the method proposed in this paper is 83.95%, indicating that the method proposed in this paper has better predictive performance.

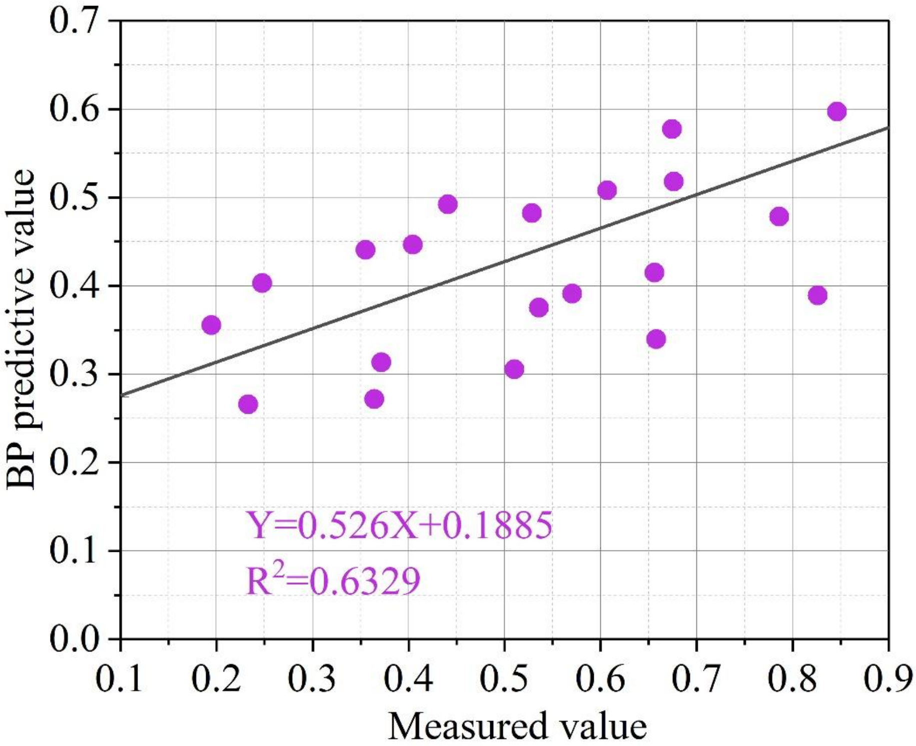


Figure 2. The design rationality of cotton garment design is predicted by BP prediction model.

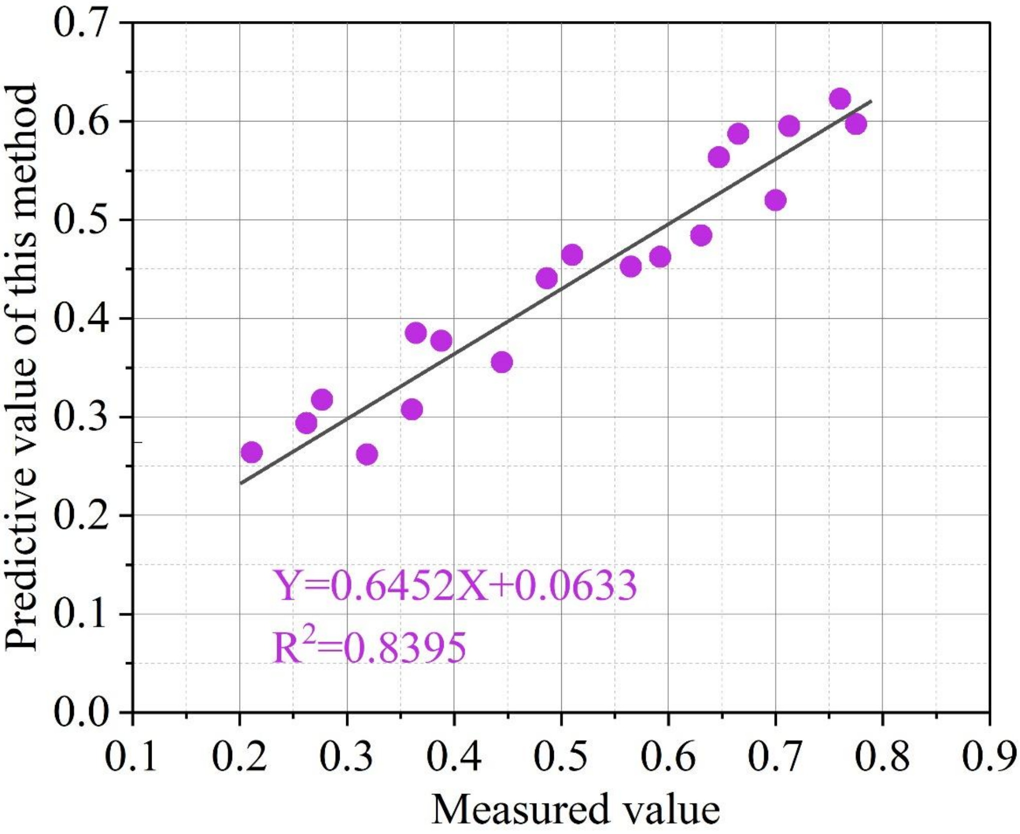


Figure 3. The design rationality of cotton clothing design is predicted.

The significance of the correlation coefficients was tested using the F-test. The significance test of the correlation coefficients for the cotton clothing design rationality prediction method is shown in Table 5. The correlation coefficients of both methods are significantly correlated, but the correlation coefficient of the method in this paper is the most significant. This indicates that the prediction ability of the method in this paper for the rationality of cotton clothing design is superior to that of the BP prediction method.

Table 5. Significance test.

Method	F statistics	F threshold	P value	Significance
BP prediction method	12.596	5.7698	0.0017	**
Ours	39.446		0.0085	**

3.2.2. Predicting the rationality of silk clothing design

The experimental sample set consists of data collected from 10 participants wearing three different types of silk garments during a comfort test, which is essentially an assessment of the garments' design rationality. From this set, 15 samples were selected as the validation sample set to evaluate the predictive performance of different methods. The prediction results of the BP prediction model and the method proposed in this paper for assessing the design rationality of silk garments are shown in Figures 4 and 5, respectively. Analyzing Figures 4 and 5, the correlation coefficient between the BP prediction model's predicted values and the actual measured values is 75.22%, while the correlation coefficient for the method proposed in this paper is 90.33%, indicating that the method proposed in this paper achieves superior predictive performance for the rationality of silk garment design.

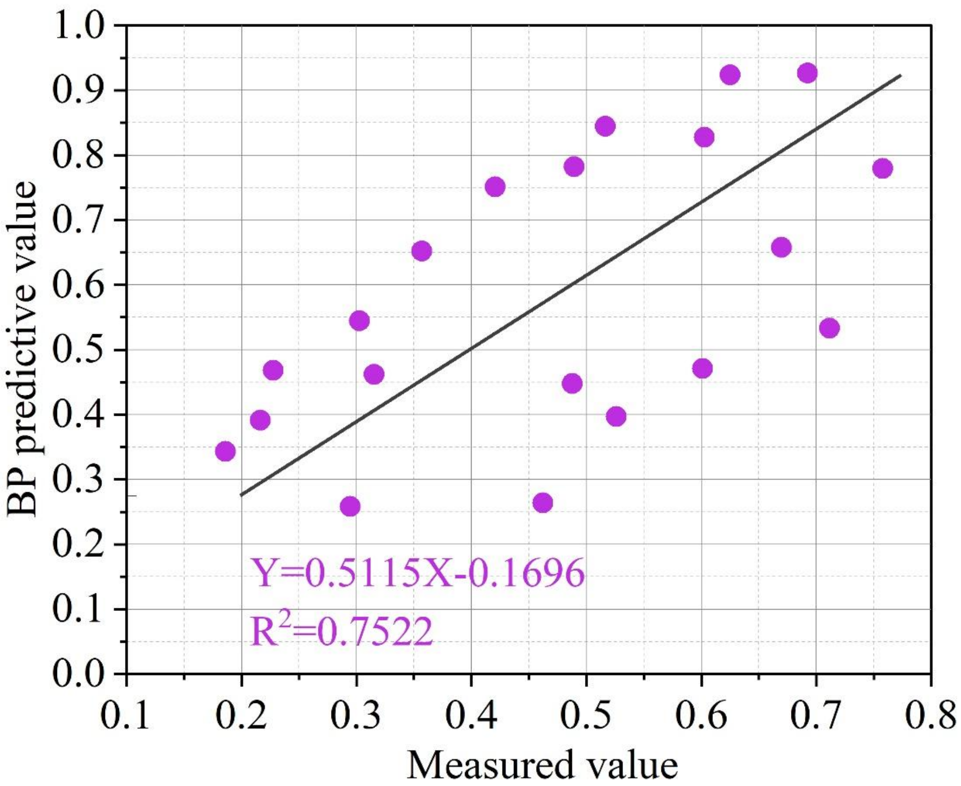


Figure 4. Design rationality BP prediction model prediction.

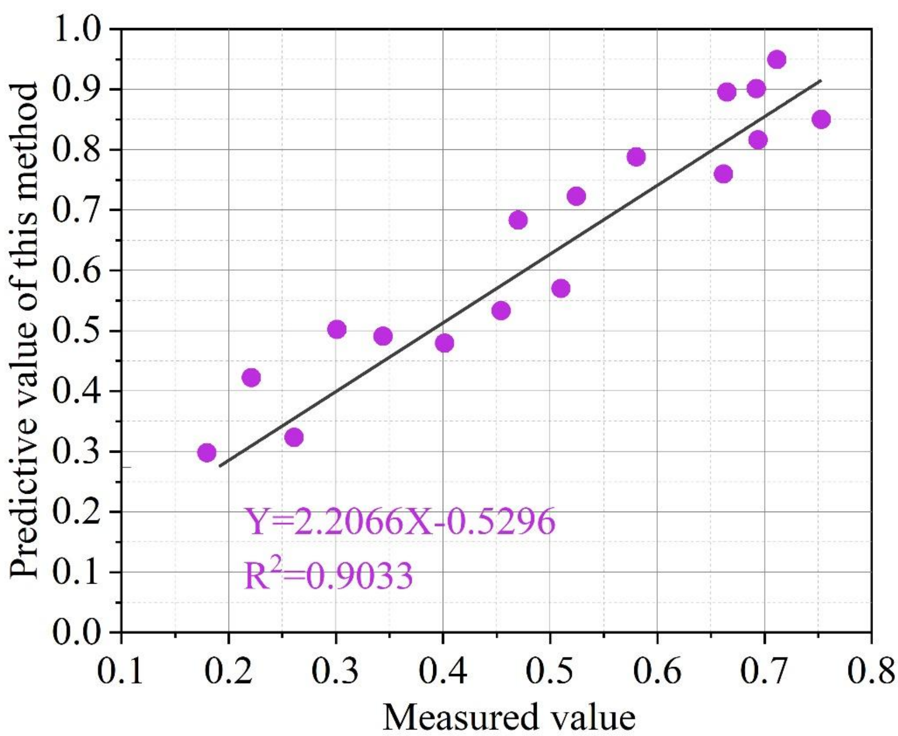


Figure 5. The design rationality of silk garment design is predicted.

Further significance tests were conducted on the correlation coefficients using the F-test method. The significance tests for the correlation coefficients of the two methods for predicting the rationality of silk garment design are shown in Table 6. Analysis of Table 6 reveals that the correlation coefficients of both methods are significantly correlated, with the correlation coefficient of the method proposed in this paper being more significant. This indicates that, compared to the BP prediction method, the method proposed in this paper demonstrates superior predictive performance for the rationality of silk garment design.

Table 6. The significance of the correlation coefficient of the design rationality.

Method	F statistics	F threshold	P value	Significance
BP prediction method	32.559	4.306	0.00015	**
Ours	78.631		1.44385E-05	**

3.3 Verification of parametric plate-making technology

The author collected data on key body parts from four female subjects of different heights and body types. The body type analysis of the four subjects is shown in Table 7.

Table 7. Four subjects were analyzed.

Subject number	height/cm	Neck circumference/cm	Chest circumference/cm	Shoulder width/cm	waistline/cm	Back length/cm	Arm length/cm
1	155	35	75	39	64	35	51
2	162	35	86	31	72	34	53
3	169	37	101	37	73	41	46
4	175	35	82	46	66	43	61

3.3.1. Sample Data Results

The following will adjust the parameters of four key areas (neck circumference, bust circumference, garment length, and sleeve length) in women's shirts based on the body measurements of four test subjects to validate the model. The comparison between automatically generated data and the test subjects' garment dimensions is shown in Table 8 (A represents the garment data of the four test subjects, and B represents the parameterized automatically generated sample data). All key data are garment measurements after adding ease allowances: collar circumference increased by 2 cm, bust circumference increased by 10 cm, garment length increased by 15 cm based on back length, and sleeve length unchanged. As shown in the table, the error between the subjects' garment measurements and the Python-parametrized automatically generated sample data is controlled within ±0.5 cm, which is within a reasonable range and does not affect the overall silhouette of the shirt.

Table 8. Automatic generation of data and the size of the participants' ready-to-wear size.

Subject number	source	Collar circumference /cm	Chest circumference /cm	Gown length /cm	Sleeve length /cm	Generation time /s
1	A	31	86	58	54	0.15241
	B	31.28	86.23	58.94	54.15	
2	A	33	97	54	47	0.12978
	B	33.11	97.56	54.38	47.67	
3	A	35	111	55	47	0.10646
	B	35.08	111.36	55.53	47.22	
4	A	38	92	56	52	0.11228
	B	38.87	92.14	56.81	52.38	

3.3.2. Comparison experiment of true value error of sample

① Experimental subjects and process

The MatLab Curve Fitting Toolbox was used to compare the true values of the curves and test the fitting errors between the automated pattern making and manual pattern making methods mentioned above. This experiment used the garment data of four subjects as the fitting experiment subjects. The original patterns created by patternmakers using FuYi CAD and the patterns automatically generated using the method described in this paper were selected for comparison. The overlap comparison was conducted on the front neckline curve, sleeve cap curve, and sleeve opening curve. The first step was to export the coordinate data of the control points from the manually drawn pattern draft and the automatically generated pattern. The second step was to load the x and y axis data. The third step was to select the SmoothingSpline spline fitting method as the fitting method, and the fourth step was to perform the fitting.

② Experimental Parameters

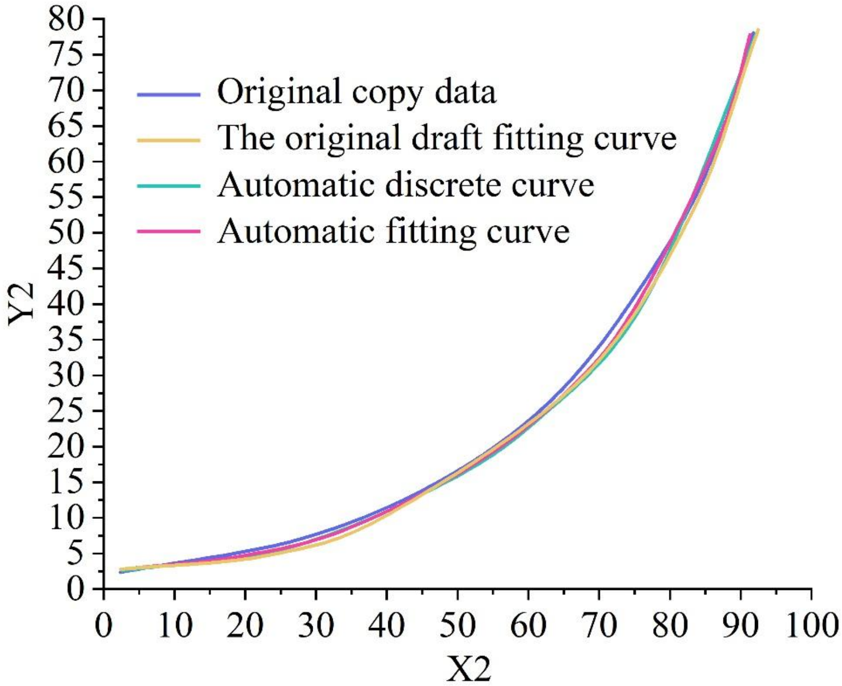
The quality of the fitted curve can be evaluated using relevant parameters. The Curve Fitting Toolbox provides four parameters for reference. 1) SSE: Sum of squared errors. The closer this value is to 0, the better the curve fits the original experimental data. 2) R-square: Coefficient of determination. The closer this value is to 1, the better the fitting effect. This influence is an important criterion for determining whether the fitted curve equation is appropriate. 3) Adjusted R-square: Adjusted coefficient of determination. The closer this value is to 1, the better the fitting effect. 4) RMSE: Root Mean Square Error. The closer this value is to 0, the better the fit. This parameter indicates to some extent whether the fitted curve describes the experimental data with better precision.

③ Experimental results

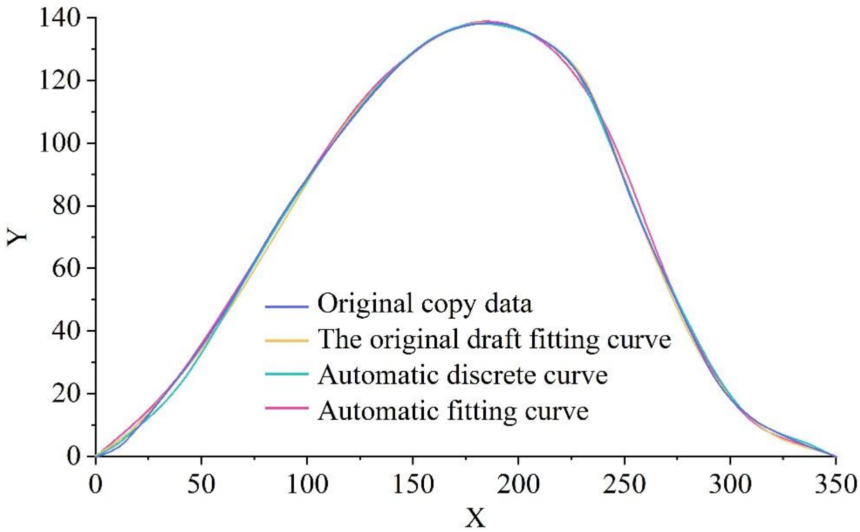
The standard deviation of the four experimental parameter results was calculated to obtain the original draft of the sample and the parameter values of the automatically generated sample. The standard deviation of the true value error between the four groups of manually drawn samples and the method described in this paper is shown in Table 9. Three sets of curve fitting results from the third tester, who was overweight among the four test subjects, were selected as examples. The true value errors of the front neckline curve and sleeve cap curve are compared in Figure 6 (Figures a–c represent the front neckline curve, sleeve cap curve, and sleeve opening curve, respectively). As can be seen from the figure, the three original draft curves and the curves automatically generated based on the method described in this paper show a high degree of overlap after fitting. From the perspective of the four experimental parameters, the parameters of the automatically generated fitting curves are superior to those of the manually drafted curves, and the errors in the parameter results are close to the optimal results for each parameter.

Table 9. Standard deviation.

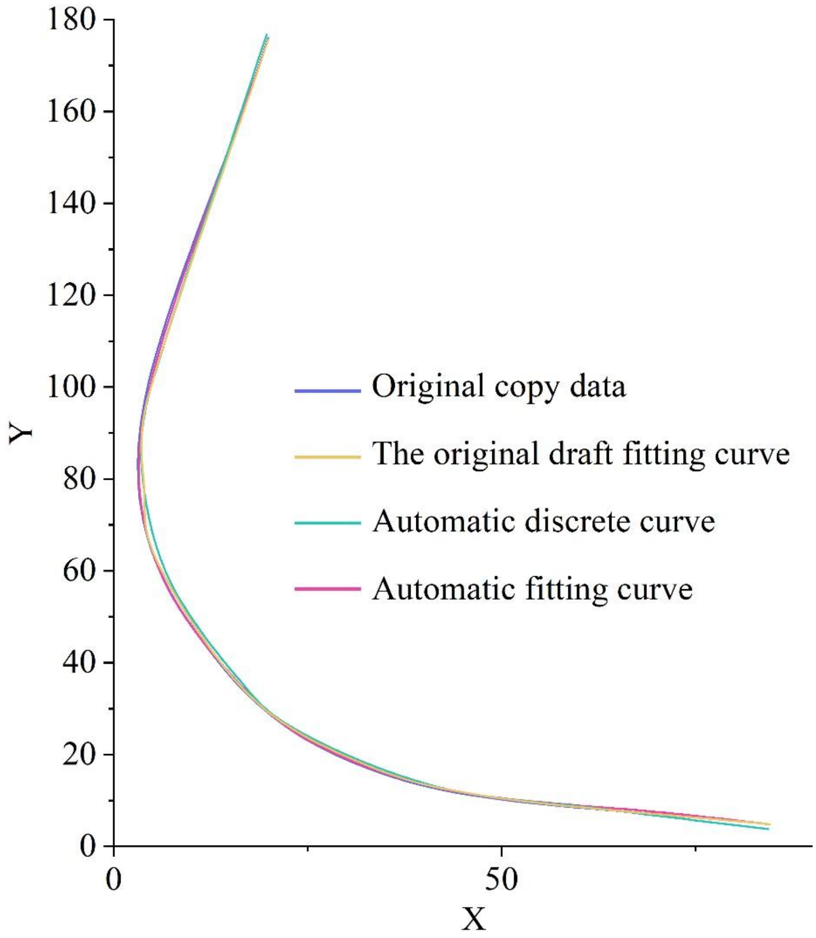
Curve name	Experimental parameter	SSE	R-square	Adjusted R-square	RMSE
Front collar curve	Manuscript	10.26395	0.9937	0.98474	3.04709
	Automaticity	0.08396	1	1	0.0649
	Standard deviation	5.07009	0.00206	0.00765	1.4934
Sleeve mountain curve	Manuscript	14.72435	0.98668	0.95964	6.02615
	Automaticity	0.04262	1	1	0.0089
	Standard deviation	7.34093	0.00967	0.0175	3.00512
Sleeve curve	Manuscript	12.24319	0.98828	0.951	4.36288
	Automaticity	0.74963	0.99399	0.95692	0.42192
	Standard deviation	5.74797	0.00255	0.00191	1.97238



(a) Front collar



(b) Sleeve mountain curve



(c) Sleeve curve

Figure 6. Error contrast.

4. The alternative integration of art and technology in fashion design

4.1. Enriching the content of clothing design expression

The fusion of art and technology in enriching the expression of fashion design is also reflected in the fabrics used in clothing. With the assistance of technology, new types of fabric have emerged. For example, Japanese fashion designer Issey Miyake utilized cutting-edge technology to develop a new type of pleated fabric. This fabric is highly durable, does not require frequent dry cleaning or ironing, and retains its shape even with frequent wear. Color in clothing is another manifestation of the fusion of art and technology in fashion design. In clothing color, dyeing techniques are used to create different artistic effects. Clothing design has a broader scope for development in color coordination and harmony, highlighting the artistic value of clothing design. Compared to traditional dyeing techniques, modern dyeing techniques make greater use of the latest technology, promoting the organic integration of traditional dyeing techniques with modern machine dyeing techniques. This enables clothing to achieve more possibilities in color expression, meeting the requirements of designers and people for clothing.

4.2. Expanding the scope of clothing design expression

As fashion design concepts and forms continue to evolve, the integration of art and technology has become a major trend in the field of fashion design. In this process, designers leverage technology to realize their artistic vision, while technology itself is elevated to an artistic form through the influence of artistic concepts and aesthetics. This deep integration enhances the artistic expressiveness of fashion design and enables abstract and complex scientific technologies to be presented in the form of fashion art, thereby increasing public acceptance of scientific and technological advancements. Following the promotion of the integration of technology and art, traditional ways of thinking have been challenged, leading to greater diversity in the application of artistic forms in fashion design expression. With the assistance of scientific and technological advancements, a single garment design can now incorporate multiple artistic forms, such as theater, literature, film, and animation. Through technical means, these artistic forms can be harmoniously integrated into fashion design, expanding the scope of expression in fashion design and enhancing its artistic expressiveness and aesthetic impact.

4.3. Innovative forms of expression in clothing design

Building on computer-aided design software, virtual reality technology has also been widely applied in the field of fashion design. During the design process, designers can utilize virtual reality technology for modeling and directly modify design outcomes on three-dimensional models, enabling a panoramic display of garment details. Additionally, virtual reality technology can create multiple model figures of different proportions, allowing designers to tailor garments for diverse demographics, ensuring the designed garments meet the wearing requirements of multiple groups.

5. Conclusion

This study builds a clothing design system based on AIGC technology and introduces a point-spring model to perform virtual digital clothing simulation on 3D human models, conducting a series of simulation experiments. The conclusions of the article are as follows:

(1) In the measurement results of chest and waist circumferences for subjects numbered 1 to 10, the average value of five measurements using the method proposed in this paper was 92.17 cm, with an absolute error of 1.64 cm. The human body measurement error of the method proposed in this paper is within the acceptable range.

(2) In the cotton garment design rationality prediction experiment, the correlation coefficient between the BP prediction model's predicted values and the measured values was 63.29%, while the correlation coefficient for the method proposed in this paper was 83.95%. The experimental results demonstrate that the method proposed in this paper can more accurately predict the rationality of different types of garment designs.

(3) Through feasibility and fit verification of the parametric patterns automatically generated by this paper, it was found that the parametric pattern data and the finished garment dimensions of the test subjects are within a reasonable range.

In summary, the integration of art and technology not only enriches the content and scope of clothing design expression but also enables innovation in the form of clothing design expression.

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