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Article

Intelligent Clothing Design System Based on AIGC and Virtual Simulation Technology

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Abstract: In this paper, an intelligent clothing design system with characteristic features is developed through virtual reality technology, and the system contains three functional modules, namely, 3D mannequin, personalized design and virtual fitting, and intelligent matching recommendation of clothing styles, to realize the creative clothing design experience. Aiming at the insufficiency of traditional collaborative filtering algorithms, a clothing recommendation algorithm incorporating user preference trust (PCUCF) is proposed, and the proposed algorithm is applied to the system to complete the functional integrity of the system. The clothing features are summarized into four modules: color features, style features, pattern features and decorative features, and the feature importance score and feature preference are calculated, and the 16 best feature sets are summarized in the feature preference part, and the recommendation algorithm has an accuracy rate of 86.1% for the classification of clothing styles, which is significantly improved compared with other models. After human try-on test, the results show that the intelligent clothing design system can track the respiratory state of human body through the change curve of human body temperature, and at the same time meet the comfort requirements.

Keywords: virtual reality; collaborative filtering; intelligent clothing design; recommendation system; clothing recommendation

1. Introduction

Artificial Intelligence Generated Content (AIGC) technology represents a significant breakthrough in the field of artificial intelligence in recent years [1]. This technology leverages deep learning and machine learning algorithms to enable computers to develop and fine-tune strategies through pre-training on multi-modal large datasets and knowledge graphs, thereby simulating human creative thinking and autonomously generating content that is both creative and aligned with human cognitive patterns [2-4]. Notably, the integration of AIGC technology into the field of fashion design breaks through the spatial and temporal constraints of physical prototypes, significantly reducing the time required to transform creative ideas into tangible designs while enhancing cultural adaptability and market responsiveness [5-7]. Additionally, designers can use virtual simulation technology to complete pattern and style design as well as material and color selection, while manufacturers can utilize virtual simulation technology to provide customers with personalized garment production and wearing demonstrations [8-9]. The combination of AIGC and virtual simulation technology can effectively improve fashion design efficiency, reduce design and production costs, and provide designers and consumers with intuitive garment display effects, thereby driving innovative development across the entire industry [10].

According to surveys, there have been numerous reports on the use of AIGC and virtual simulation technology for intelligent design in the apparel design field. For example, literature [11] utilized AIGC technology for children's apparel intelligent design, with results showing that intelligent apparel design scored over 8 points in terms of comfort, functionality, and safety, effectively improving users' wearing experience and demonstrating the superiority of intelligent apparel design. Literature [12] applied AIGC technology to establish a smart clothing design model architecture and explored human-machine collaboration modes in different design scenarios through practical cases. The results indicated that human-machine collaboration in clothing design models can achieve higher-quality clothing outcomes. Literature [13] An AIGC-based intelligent clothing design and manufacturing platform was developed.

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By capturing customers' multimodal data and integrating their multidimensional needs, the platform generates personalized clothing tailored to specific users, thereby optimizing the entire cycle of fashion design and clothing production. Literature [14] uses software such as Fashion CAD and CLO 3D to perform virtual sewing simulation design for clothing style, structure, color, and materials, achieving dynamic and static virtual displays of Mazu clothing, highly reproducing the clothing design process. Literature [15] introduces Midjourney and Style 3D virtual clothing modeling technology, enhancing designers' inspiration while effectively adjusting clothing design patterns and sizes, simplifying traditional design processes, and improving design efficiency. Literature [16] proposes a physics-based virtual fabric design and simulation system that predicts clothing shapes by embedding physical principles such as constraint Newtonian dynamics, enabling clothing generation processes like panel sewing in a virtual graphical environment. The above literature demonstrates the significant potential of AIGC and virtual simulation technology in clothing design, providing valuable reference for this study.

The research designed an intelligent clothing design system based on AIGC and AR, realizing the whole process of creative design experience in the intuitive feeling of clothing design effect and three-dimensional clothing virtual display. Based on this, a clothing recommendation algorithm integrating user preference trust is proposed to extract the attribute information in clothing goods and establish a user preference model, calculate the preference trust between users based on the user attribute matrix, and select the nearest neighbor by integrating the rating trust and preference trust to realize clothing recommendation. The feature types of clothing are divided into color features, style features, pattern features and decorative features, and at the same time, each feature module is subdivided to complete the calculation of the importance score of features. The recommendation algorithm is compared and experimented with support vector machine, decision tree and linear regression, and combined with the intelligent clothing design system to monitor the human body temperature to verify the reliability of the clothing.

2. Intelligent Clothing Design System Based on AIGC and VR

2.1. Design and Development of Virtual Clothing

2.1.1. Determination of the Basic Model of the Virtual Garment

According to the market research, 2 sets of formal wear (male formal wear, female formal wear), 2 sets of business casual wear (male business casual wear, female business casual wear), 2 sets of sportswear (male sportswear, female sportswear) and men's outdoor wear are selected as the basic styles of 3D clothing modeling of this design system.

2.1.2. Specification of Virtual Clothing Model Construction

(1) Each clothing set shows good 3D style characteristics, highlighting the advantages of VR over traditional CAD drawing preview.

(2) The jacket, pants, vest, shirt and other components of the suit are produced independently, and the user can set the display state and take-off state of the suit components in the MR/VR system.

(3) Each garment component in the suit is modeled by stitching the parts together, which is defined by the CAD layout data of the garment.

2.1.3. Virtual Clothing Model Construction

VRDS system requires 3D format clothing pattern data to be rendered in VR equipment. At present, the communication medium between domestic fabric producers, clothing manufacturers and clothing brands is mainly 2D clothing pattern files, and 2D clothing pattern files can not be directly applied on top of the 3D model, which need to be converted into 3D model data. In the process of system development, VRDS adopts Marvelous Designer, a professional 3D garment design software, to convert 2D garment pattern to 3D garment model data, and produce virtual garments that can vividly reflect the real effect.

2.1.4. Design of the Virtual Model

In the virtual reality clothing design & show system produced male and female each set of three-dimensional dynamic mannequins. The mannequins are accompanied by a series of action animations for the runway show, including walking, turning, stopping to show the action, etc. The mannequins are designed in a simple style with simple facial outlines. The mannequins adopt simple design style, simple facial contour, white basic mapping to show the skin of the characters, and no additional clothing to wear.

2.2. Virtual Reality Clothing Design & Show System Development

2.2.1. Virtual Clothing Design Logic

In order to realize the fabric design function that different parts can be flexibly carried out in the process of clothing design, first of all, according to the characteristics of different clothing suites, subdivided into different components according to the functional requirements, and then start designing for different parts one by one. Take the design of a suit jacket as an example, the suit jacket can be structurally divided into the front piece, back piece, collar, sleeves and other parts, in the program, the generation of the jacket first need to have the main body of the model, but also need to be each part of the garment fabric, so the program will be numbered for each part, and corresponds to the fabric, only the main body of the model and the details of the settings combined with the design effect will be shown to the user. When the user completes the design of a garment and saves it to the cloud, the program also uploads to the cloud the different codes corresponding to each part of the garment and the sequence of fabric materials.

2.2.2. PC Virtual Show Production Function

PC virtual show production function is the most basic and essential function of the virtual reality clothing design & show system, the main realization process of this function is as follows.

(1) Interconnection between PC terminal and VR terminal: after connecting PC terminal and VR terminal through cable, the virtual show produced by PC terminal can be played in VR terminal, and the modification made by VR terminal will be timely transmitted back to PC terminal for preservation.

(2) Client Login: Manage user account login, connect different database files by obtaining user's permission, which is used to cooperate with the cloud storage module to let users read and update the data in the cloud.

(3) New or use show: first time users need to

Users who use the system for the first time need to create a new show, while users who have already created a show can not only create a new show, but also edit and modify the show by calling the show files that have been created and stored in the cloud. The new show includes model selection, appearance order adjustment, clothing selection, fabric selection, appearance interval setting and show atmosphere setting.

(4) Cloud data access: The newly created or modified show files in the previous step will be automatically saved to the cloud for different clients to call.

2.2.3. VR Virtual Costume Design and Show Function

Users wearing the VR headset will be directly immersed in the virtual showroom created in the previous step on the PC. Users can walk around freely in the show environment and view the fashion design results and model walk demonstration from various angles. If the user experience system site is large enough, it can be in the real environment for free movement, and with the virtual environment of the movement of real-time synchronization; if the user's real environment is more limited, but also through the system set a fixed anchor point for the virtual instantaneous transfer.

In order to ensure that the user can clearly see the clothing display effect and details, the system in the VR of the key parts of the clothing to carry out an accurate reproduction. In order to obtain a smooth and soft display effect, the system utilizes the flexible selection method to construct a specialized algorithm to select the vertex selection in the 3D rendering process.

2.3. Functional Module Design

2.3.1. Digital 3D Simulation of Virtual Fitting

Digital 3D simulation fitting is the beginning module of the intelligent clothing design method. Different from other clothing design systems in which users directly select the style, the first step is to let the user select a 3D model similar to his/her own body shape and size, and then virtually wear the model.

After logging into the app or software, users need to enter their height, weight, shoulder width, bust, waist, hips, arm and leg length, and other major body measurements, which are part of the user's personal information and can be stored for next time's use or can be modified at any time.

2.3.2. High-Degree-of-Freedom Personalized Design

After determining the size data and generating the model, the user enters the module of style design. In order to facilitate the user to quickly select models or rapid customization, this method provides two types of design modes for the user to choose.

(1) Personalized customization mode

Similar to most of the personalized customization platforms in the market, in the personalized customization mode of this method, the user can independently choose the style, fabric and the type of each component of the garment. To enter the personalized customization mode, the user needs to first select male or female clothing. Although the gender has already been selected when matching the 3D model, the user can still select male or female clothing for personalized customization in order to enable the user to experience more comprehensive functions.

(2) Garment style selection

In the style design module, in addition to customizing the shape of the clothing, the system also provides users with a large number of ready-to-wear styles can be directly selected, this part is mainly for the brand to build a platform for selling products. In order to allow users to enjoy a variety of choices, affordable prices and excellent quality on this platform, in addition to introducing as many clothing brands as possible, it is also necessary to make strict restrictions on the quality of the products and reputation and credit of these brands, which mainly include three aspects: first, the price can not be higher than in other platforms, second, the quality of the products are in line with the national standards or industry standards, and the speed of new products should be timely, third, after-sales service should be timely, and third, the after-sales service should be warm.

2.3.3. Intelligent Style Recommendation

Intelligent style recommendation emerged to solve the negative impacts of information overload, such as difficulty in choosing, and has been applied to many online shopping platforms. By collecting historical behavioral data and selection paths that users have browsed, analyzing and building different models, we calculate the styles that users may be interested in and recommend them.

There are many rules and algorithms for intelligent recommendation, such as recommendation based on content rules, recommendation based on association rules, recommendation based on collaborative filtering, etc. Because the selection of clothing is more about pursuing the appearance of collocation, the recommendation based on association rules is used in this method.

The association rule refers to discovering the correlation between items from a large amount of data, which was first proposed to solve the shopping cart problem. Association rules analyze and mine the user's historical purchase records to find out the items that will be purchased at the same time, i.e., to find out the items with high correlation. The commonly used algorithms based on association rules are STEM algorithm, Apriori algorithm [17], FP-Growth algorithm, etc. The biggest advantage of the algorithms based on association rules is that they are simple to apply and easy to implement.

2.3.4. User Center

The user center module is mainly for the management and maintenance of various user information, the user center module features user order management, personal information management, management of the local material library, my messages, as well as problem feedback, contact customer service and other parts.

(1) Order management

The order management function is used for the management of all the user's orders. When the user designed a clothing style, and save to confirm the purchase will enter the order center, the order center requires the user to choose to go to the store to measure the body or the nearby store door-to-door measurements, and will display the details of the order (including the design of the product style, quantity, amount), the user to use the system to provide the payment method for online payment. The order center module also allows you to save the history of order details and the latest orders, as well as evaluation of completed orders or share them with the community.

(2) Personal Information Management

The personal information management function is used to store the user's personal information for next time's use, including the user's body size information, shipping address information, concerned stores and users, etc. The personal information management function is used to store the user's personal information for next time's use. After the user has been measured once, the system will store this detailed body data information, so that when shopping for clothes or customizing again, the user does not need to input the size again, and can directly get a virtual model with accurate size.

(3) Local material library management

The local library management function is the user's creation center. Users can save the styles in the customization to the local library, and then share them to the community or other platforms. The local library also supports users to upload hand-drawn design materials, including mannequins, color sample libraries, patterns, etc. These materials can be uploaded to the library for designers and other users to use. The role of the local library is to allow users to constantly update and improve the resources in the system to create an open and shared design platform.

3. Clothing Recommendation Algorithms Incorporating Preference Trustworthiness

3.1. Collaborative Filtering Algorithm

The basic idea of collaborative filtering is to predict the target user's ratings for unrated items based on the rating data of the target user's nearest neighbors, so that a number of items with the highest predicted ratings are recommended to the target user [18].

Discover a number of neighbors with the most similar ratings to the target user. The traditional method of finding nearest neighbors is to calculate the similarity between the target user and every other user, and use a number of users with the highest similarity as neighbors. Modified cosine similarity is a better measure of similarity between users:

$$sim_{xv} = \frac{\sum_{ieI_i} (R_{xi} - \overline{R_x}) \times (R_{ni} - \overline{R_v})}{\sqrt{\sum_{ieI_i} (R_{xi} - \overline{R_x})^2 \sum_{ieI} (R_{vi} - \overline{R_v})^2}} \tag{1}$$

where sim_{uv} denotes the similarity between user u and user v, I_u, I_v are the set of rated items for user u, v, respectively, I_{uv} is the set of jointly rated items, R_{ui}, R_{vi} are the ratings of users u, v ratings for item i, and $\overline{R}_u, \overline{R}_v$ is the average rating of user u, v.

Based on the nearest-neighbor rating data, the target user's ratings for unrated items are predicted, and a number of items with the highest predicted ratings are recommended to the target user. The prediction method is as follows.

$$P_{mi}^{MB} = \overline{R_m} + \frac{\sum_{v \in NBS} sim_w \times (R_{vi} - \overline{R_v})}{\sum_{v \in NBS} (|sim_w|)} \tag{2}$$

where P_{ui}^{NBS} denotes the predicted score of user u on item i, and NBS is the set of nearest neighbors of user u.

3.2. User preference model based on text content extraction

3.2.1. Clothing Attribute Library

Clothing, as a necessity of human life, has appeared as early as the beginning of the development of human society, and with the continuous change of history, the types and attributes of clothing have also changed. Clothing development to modern times, has accumulated a considerable number of clothing class related attributes, this paper is mainly applied to e-commerce system, for the current popular clothing class on the market for recommendation, through the literature research and the summary of the experts of the School of Clothing, and finally identified 500 modern clothing attributes, including style, style, print, etc. and these attributes are included in the text database of clothing attributes.

3.2.2. Clothing Attribute Extraction

In the system, commodities usually contain rich information, and a large number of clothing attributes can be mined from clothing commodities related to users' historical behavior data. By processing the textual content of apparel merchandise, useful attribute information is extracted to provide support for the establishment of user preference models.

3.2.3. User Preference Modeling

The positive and negative preferences of user a for each attribute p are first calculated:

$$sim_{ap}^{p} = \frac{1}{I_a^p(p)} * \sum_{i \in I_a^p(t)} \frac{R_{ai} - \overline{R}}{\sqrt{\sum_{j=1}^{I} R_{aj}^2}} \tag{3}$$

$$sim_{ap}^{n} = \frac{1}{I_a^n(p)} * \sum_{i \in I_a^n(t)} \frac{\overline{R} - R_{ai}}{\sqrt{\sum_{j=1}^{I} R_{aj}^2}} \tag{4}$$

where sim_{ap}^{p} denotes positive preferences, sim_{ap}^{n} denotes negative preferences, I_a^p denotes the set of positive preference attributes of user a, I_a^n denotes the set of negative preferences of user a, I_a^n is the user a's item i's ratings, and $\overline{R}$ is the average rating of the users.

The preference values calculated according to the formula are all positive, so combining the positive and negative preferences, the degree of preference of the end user a for the attribute p is:

$$sim_a(p) = sim_{ap}^{p} - sim_{ap}^{n} \tag{5}$$

It can be seen from the above formula that if the degree of user preference for an attribute is greater than 0, it means that the attribute has a positive impact, indicating that the user is more interested, and vice versa, it means that the user is less interested. The degree of user's interest in an attribute reflects the user's preference information, and also reflects the preference trust relationship between users to some extent, and the preference trust between users is shown in Equation (6):

$$sim_p(a,b) = \frac{\sum_{p \in T_a \cap T_b} sim_a(p) * sim_b(p)}{\sqrt{\sum_{p \in T_a} sim_a^2(p)} * \sqrt{\sum_{p \in T_b} sim_b^2(p)}} \tag{6}$$

where T_a and T_b denote the set of attributes contained in the items rated by user a and user b respectively.

3.3. Personalized Recommendation Generation Algorithm for Clothing Incorporating Preference Trustworthiness

In this paper, the preference trust for clothing attributes combines the rating trust based on common rating items and the clothing preference trust for non-common rating items to propose the clothing recommendation algorithm incorporating user preferences (PCUCF), which is a parameter that is weighted to obtain the final trust relationship among users:

$$t(a,b) = \partial sim_t(a,b) + (1-\partial) sim_p(a,b) \tag{7}$$

where ∂ is used as a regulating parameter with a value range of [0, 1]. When $\partial > 0.5$ indicates that the user's rating trust occupies a higher proportion, i.e., the user's common rating items have a greater impact on the recommendation results, and when $\partial < 0.5$ indicates that the user's preference trust occupies a higher proportion, i.e., the attribute preference for the non-common rating items has a more positive impact on the recommendation results. The value of ∂ is determined by taking the best value through multiple comparative experiments on the research and implementation of collaborative filtering-based clothing personalization system.

The trust relationship matrix about the user is obtained through the above steps, and finally the rating prediction is performed by Equation (8)

$$p_{ap} = \overline{r_a} + \frac{\sum_{b \in U_N} t(a,b)(r_{bp} - \overline{r_b})}{\sum_{b \in U_N} t(a,b)} \tag{8}$$

where $t(a,b)$ represents the final trust between user a and user b, and U_N is the set of N users who are most trusted with user a.

4. Application and validation of smart clothing design models

4.1. Recommendation Modeling Applications

4.1.1. Feature Optimization Establishment

(1) Feature importance score

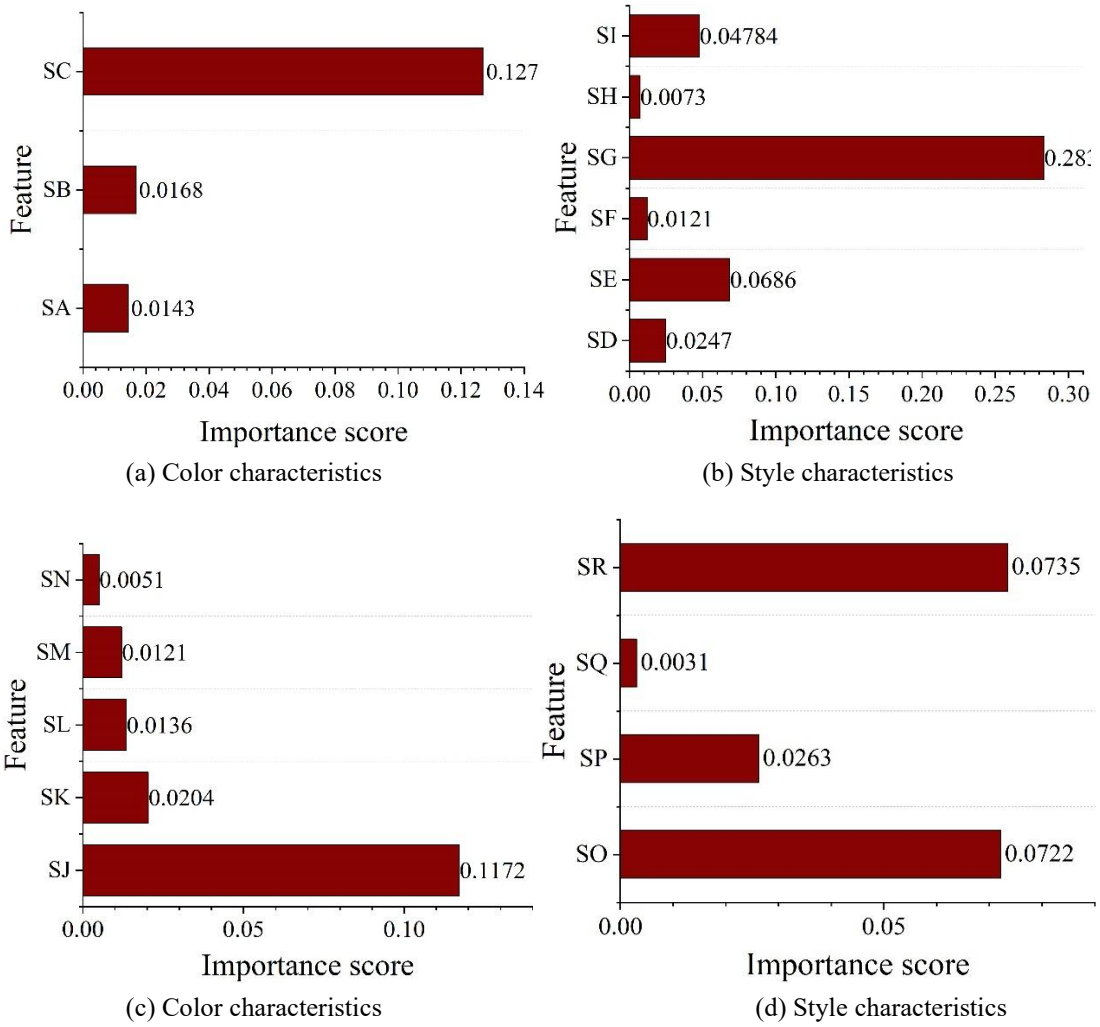
Clothing features are shown in Table 1.

Table 1. Clothing features and code.

Clothing characteristics	
Color characteristics	
Tone	SA
Saturation degree	SB
Brightness	SC
Style characteristics	
Gown	SD
Profile	SE
Sleeve length	SF
Sleeve type	SG
Opening	SH
Material	SI
Pattern characteristics	
Pure color	SJ
Text	SK
Geometry	SL
Nature	SM
Lattice	SN
Decorative characteristics	
Splicing	SO
Fold	SP
Inclaim	SQ
Open wire	SR

The importance weights of 18 features are calculated by the algorithm according to the 4 feature modules of color, style, pattern, and decoration respectively, and the specific importance weight scores are shown in Figure 1. (a)~(d) are the importance of the 4 clothing feature modules.

Figure 1 (a) in which the degree of influence of brightness features for clothing style is the largest, the degree of influence of hue for clothing classification is the smallest, the importance of brightness features is much higher than the hue features and saturation features, the degree of influence of hue features and saturation features for clothing style is more similar; Figure 1 (b) in which the degree of influence of sleeve features for clothing style is the largest, the degree of influence of lapel features for clothing style is the smallest Figure 1(c) shows that the importance of other features increases in the order of garment length, material, silhouette, and sleeve length; Figure 1(c) in which the solid color feature has the greatest influence on clothing style, the plaid feature has the least influence on clothing style, the importance of the solid color feature is much higher than the other features, and the importance of the other features increases from natural, geometric, and textual order; Figure 1(d) in which the bright line feature has the greatest influence on clothing style, the asymmetric feature has the least influence on clothing style, the spliced features and the pleated features are in the middle of the importance score, and the importance score of the spliced features is twice as much as the pleated features.



(a) Color characteristics (b) Style characteristics

(c) Color characteristics (d) Style characteristics

Figure 1. Feature importance score.

The heat map of correlation between features and features of clothing samples is shown in Figure 2, the study calculated the Pearson correlation coefficient between features and features, the more the color of the features is inclined to pink, the lower the correlation, the more the color is inclined to red, the higher the correlation, it can be seen from the figure, the correlation between features of the clothing features and the features are low, the features have independence and representativeness.

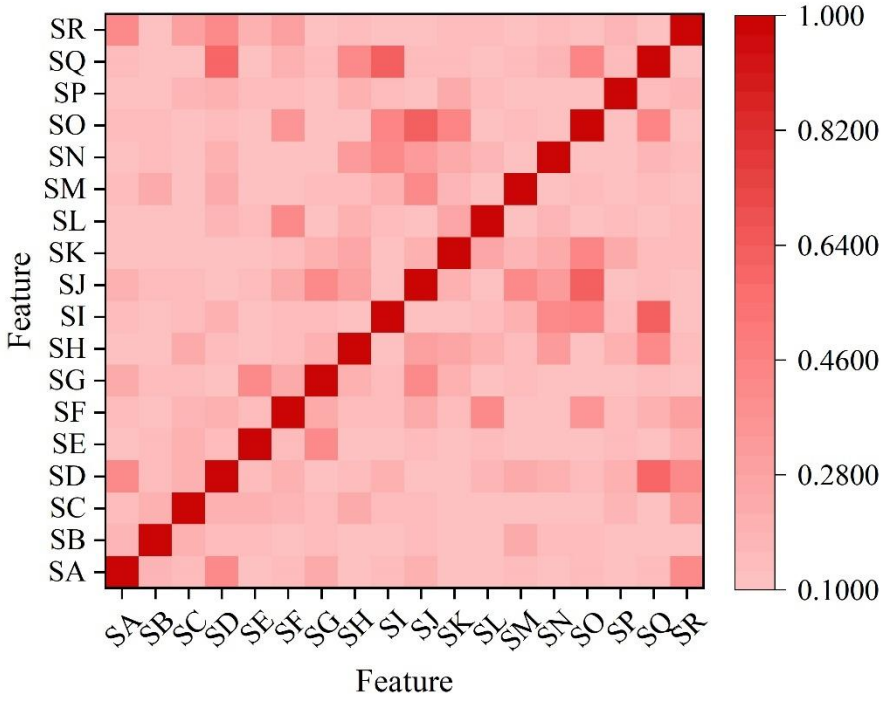


Figure 2. Characteristic and characteristic intercorrelation heat diagram.

(2) Feature optimization

Through the PCUCF algorithm to screen 18 features, the feature variables in accordance with the feature importance score from high to low in order, to change the number of feature variables in steps of 1, the number of features from 1 to 18 in order to transform, calculate the classification accuracy of the model for clothing samples, as shown in Figure 3. The first 7 feature variables with the increase of the number of features, the classification accuracy of the model for apparel samples shows an increasing trend from 19.2% to 76%, which can be seen that the correlation between the first 7 feature variables is low, and the features are more conducive to the classification of the model to a greater extent, and the number of features from 8 to 20, due to the existence of redundancy of some features, which makes the classification accuracy decline, when the number of feature variables is 16, the model's classification accuracy reaches its peak. When the number of feature variables is 16, the classification accuracy of the model reaches the peak, and the subsequent increase in the number of feature variables will increase the burden of the model operation, so the study preferred 16 feature variables, which are hue, saturation, luminance, length, silhouette, sleeve length, sleeve type, placket, material, solid color, text, geometric, natural, splicing, pleating, and bright lines, respectively.

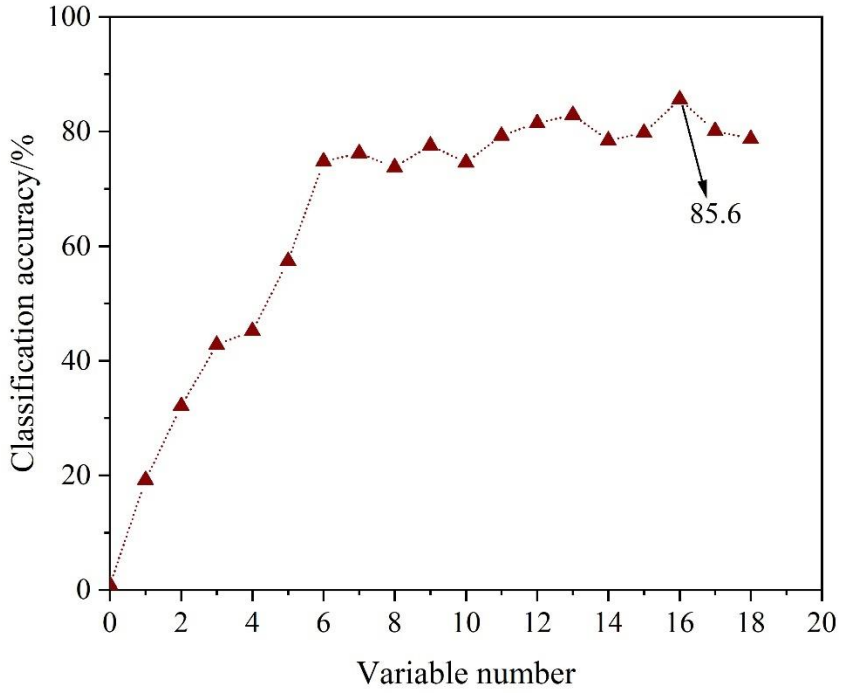


Figure 3. The relationship between model classification accuracy and feature variables.

4.1.2. Classification model parameters

The number of decision trees k is an important parameter in the algorithm model, the research results show that when the number of decision trees k value is small, the classification accuracy of the model for clothing samples is low, with the increase of the number of decision trees, the classification accuracy of the model will rise in the fluctuation, when the k value reaches a certain number of the model's classification accuracy will reach the highest, and after that, with the increase in the value of k, the classification accuracy of the model when it tends to be stable, when the value of k is too When k value is too large, the marginal benefit of the model will be reduced, and at the same time the running time and running volume of the model will increase. Therefore, in order to find the optimal number of decision trees k for the model, the study continuously changes the number of decision trees k by changing the n_estimators parameter while keeping other variables unchanged, as shown in Fig. 4, the classification accuracy of the model reaches a maximum of 85.8% when k=20, and then tends to be stable or even reduced, so in the case of taking into account the classification accuracy and the amount of the modeling task, the study uses the number of decision trees k as the number of decision trees k for the model. The number of decision trees k used in the study is 20.

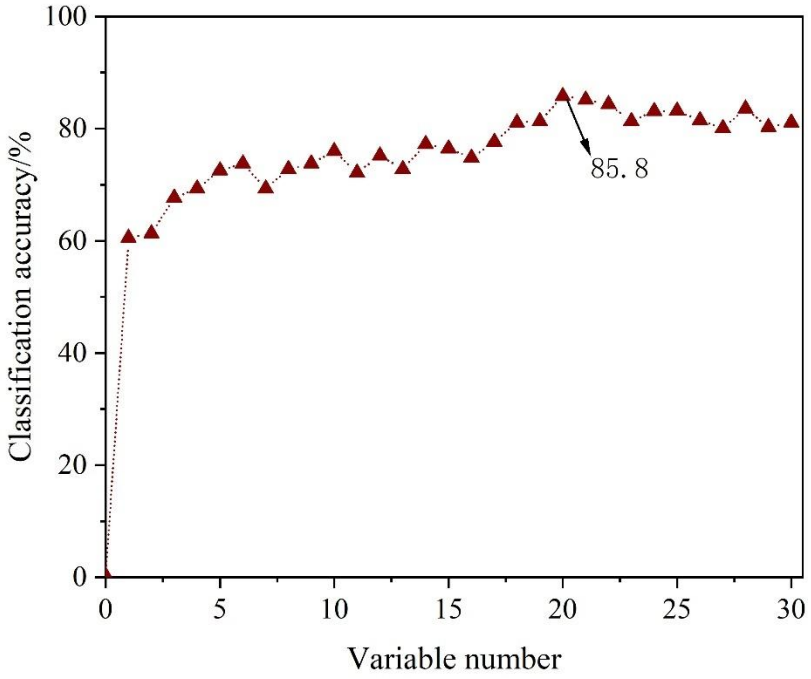


Figure 4. Model classification accuracy and decision tree number k relationship.

In order to verify the accuracy of style classification, the model is examined using the accuracy rate A_f, precision rate P, recall rate R and comprehensive evaluation index F_1 of style recognition. The precision rate P indicates the probability of user satisfaction with the results recommended by the model, and the comprehensive evaluation index F_1 indicates the comprehensive evaluation of the recommended results. The formulae for each indicator are shown in equations (9) to (12):

$$A_f = (TP + TN)(TP + FP + FN + TN)^{-1} \tag{9}$$

$$P = TP(TP + FP)^{-1} \tag{10}$$

$$R = TP(TP + FN)^{-1} \tag{11}$$

$$F_1 = 2TP(2TP + FP + FN)^{-1} \tag{12}$$

where TP(true positives) is the positive class judged as positive, i.e., the correct style; FP(false positives) is the negative class judged as positive, i.e., the sample style Z_1 is judged as the style Z_2; FN(false negatives) is the positive class judged as negative, i.e., the sample style Z_2 is judged as style Z_1; TN(true negatives) is the negative class judged as negative class, i.e., the sample style Z_1 is judged as style Z_1 while the actual judgment style Z_2.

The results of the comparison experiments between different feature modules, unpreferred feature combinations and preferred feature combinations with different classifiers are shown in Table 2. The classifiers for comparison with PCUCF algorithm include support vector machine, decision tree and linear regression.

From the table, it can be seen that the accuracy of PCUCF algorithm for the classification of clothing style is 86.1%, and the precision rate P, the recall rate R and the comprehensive evaluation index F1, including the accuracy rate, are all significantly higher than the classification of other classifiers (support vector machine, decision tree and linear regression) for the experimental samples. Among the other classifiers, the classification accuracy A_f of linear regression is only 36.7%, which shows that the clothing samples do not conform to the form of continuous values. The classification accuracy of the model after feature optimization A_f is higher than the 83.4% before optimization, which shows the necessity of feature optimization.

Table 2. Comparison experiment results.

Scheme	Feature module	Classifier	P (%)	R (%)	F_1 (%)	A_f (%)
1	A1: colour	PCUCF	41.5	43.9	40.9	42.2
2	A2: style	PCUCF	75.9	74.5	72.7	74.3
3	A3: pattern	PCUCF	16.1	36.3	21.1	31.4
4	A4: garnish	PCUCF	35.7	50.7	39.9	51.2
5	A1: colour+style + pattern+garnish	PCUCF	83.1	84.5	82.7	83.4
6	Preference combination	PCUCF	86.9	87.5	85.5	86.1
7	Preference combination	SVM	82.5	83.1	80.7	82.2
8	Preference combination	DT	75.9	76.3	75.5	76.7
9	Preference combination	Linear regression	34.3	31.5	31.1	36.7

4.1.3. Recommendation list creation

With the help of leaf nodes of a sample the style prediction path of that sample is analyzed, the higher the path overlap the higher the similarity between the samples. The similarity between the test samples and the training samples is shown in Table 3, from the table it can be seen that the similarity S between the test set sample V and the training set sample T, the larger S represents the higher the similarity of the samples.

Table 3. The similarity of some samples.

V/S/T	1	2	3	…	174	175	176
1	5	1	1	…	3	5	8
2	3	1	1	…	5	3	14
3	1	1	13	…	1	1	2
…	…	…	…	…	…	…	…
77	1	7	1	…	1	1	1
78	2	1	2	…	2	11	2
79	1	1	1	…	5	19	5

For the similarity between the obtained training samples and the test samples, the similarity ranking for the training samples is performed, and the results are shown in Table 4, which shows the results of the first three training set samples from high to low similarity S with the test set samples V. The samples corresponding to the target samples required by the user are identified in the test set samples V to form the final recommendation list $d = \{d_1, d_2, d_3\}$.

Table 4. Recommended list.

Test set V sample serial number	The top 3 training sets r sample numbers are ranked by similarity s		
	d_1	d_2	d_3
1	58	45	91
2	133	87	22
3	47	4	117
…	…	…	…
77	81	31	43
78	10	165	151
79	35	61	176

4.1.4. Recommended results fitting software

In order to facilitate the display of the recommendation results to the user, the study designed a clothing fitting display interface, the fitting interface mainly consists of four parts, the first part is the image presentation area of character images, clothing images and fitting results, the second part is the image input button area, the third part is the image processing button area, the fourth part is the image synthesis button area. Users can click the “Import Clothing Images” button to import photos of recommended products output by the recommendation module, and click “Import Model Photos” to import photos of the user himself or the target model, and the user can provide photos by taking selfies,

but the photos must be Users can provide photos by self-timer, but the photos should be a half-body photo with a solid color background and the character standing in front, the clearer the photo is and the brighter the ambient light is, the better the trying on effect will be. The pixel value of the input photo should be kept at 256 × 192 pixels according to the model requirements.

4.2. Recommended Model Validation

In this section, firefighter clothing is used as a case study to validate the effectiveness of a clothing recommendation algorithm that incorporates user preferences.

4.2.1. Combined Design of Clothing and Hardware

Considering the actual wearing comfort and convenience of firefighters and the washability of the garment, the related hardware in this design are all of detachable design. In order to monitor the concentration of toxic and hazardous gases in the flowing air, the gas sensor and processor are placed in the front chest area. The KY-038 module, which is responsible for the intercom function, and the buzzer are placed at the collar and the left/right ear of the mask respectively. The LCD screen is placed on the left glove for easy viewing of the location of the firefighter and his/her teammates on the map. Since firefighters often need to face the fire directly, the rest of the hardware modules are placed at the back of the jacket to ensure the stability and safety of the hardware system.

4.2.2. Clothing Testing and Improvement

In order to verify whether the comfort of this smart firefighting suit is improved and to test the garment safety monitoring function, it is necessary to design experiments to test the above. The test for this new firefighting suit is divided into clothing safety test and clothing comfort test.

(1) Safety test

According to the main points of functional design, the safety test of the new fire suit can be divided into two aspects: the protective performance test of clothing and the harmful gas monitoring function test.

Test method: The fabric performance test standard is based on the requirements of GA10-2014 "Firefighter Fire Fighting Protective Clothing", and the flame retardant performance of the outer fabric is determined in accordance with GB/T 5455-2014 "Determination of the vertical damage length, smoldering and continuous combustion time of textile combustion performance"; The breaking strength is determined in accordance with GB/T 3923.1-2013 "Tensile properties of textile fabrics Part 1: Determination of breaking strength and elongation at break (strip method)"; The thermal protection performance (TPP value) of the fabric combination is determined in accordance with the NFPA1976-2000 "Field Fire Protection Clothing Standard" standard.

According to the requirements of GA10-2014 "Firefighter Fire Extinguishing Protective Clothing", 5 fabric samples were selected, the size of the samples was set to (180±2) mm× (180±2) mm (excluding seams), the total experimental heat flow was set to (80±2) Kw/m, and the heat exposure time was set to 30s. Before the test, the sample should be humidified in a constant temperature and humidity chamber with a temperature of (20±2) °C and a relative humidity of (65±4)% for 24 hours. Test within 3 minutes after removal. The experimental test instrument uses TPP-II. Thermal protection performance tester (Tianjin Nikos Testing Technology Co., Ltd., China).

The results of fabric performance tests are shown in Table 5. Among them, the numbered A, B and C specimens are the outer fabric, waterproof and moisture permeable layer fabric, and heat insulation and comfort layer fabric respectively. Their test results are in line with the standard requirements.

Table 5. Performance test results.

Numbering	Warp		Latitude		Breaking strength /N		Fabric combination
	Afterburning time /s	Damage length /mm	Afterburning time /s	Damage length /mm	Warp	Latitude	TPP value /kW·s/m^2
A	0	5.8	0	5.5	1753.2	1563.2	32.3
B	/	/	/	/	/	/	
C	/	/	/	/	/	/	
Standard requirement	≤2	≤100	≤2	≤100	≥650	≥650	≥28

(2) Harmful gas monitoring function test

The monitoring of harmful gases was carried out in a closed chamber, with the humidity in the environmental chamber adjusted to 50% and the wind speed adjusted to 0.5 m/s. The new fire suit was put on a dummy, and the new fire suit was injected into the environmental chamber by injecting methane, liquefied petroleum gas, and carbon monoxide respectively, and observing the value of the serial plotter, the state of the buzzer, and the change of the data displayed by the terminal equipment in the Arduino IDE to determine the overall hardware performance of the new fire suit. The overall hardware performance of the new fire suit was determined by observing the changes in the value of the serial plotter, buzzer status and data displayed by the terminal equipment in Arduino IDE.

After the tuning time, the corresponding gas is injected, the digital signal rises sharply, and the buzzer starts to alarm; after stopping the gas injection, the digital signal slowly becomes smaller, and then after a period of time the digital signal is lower than the threshold, and the buzzer stops alarming. The changes are shown in Figure 5.

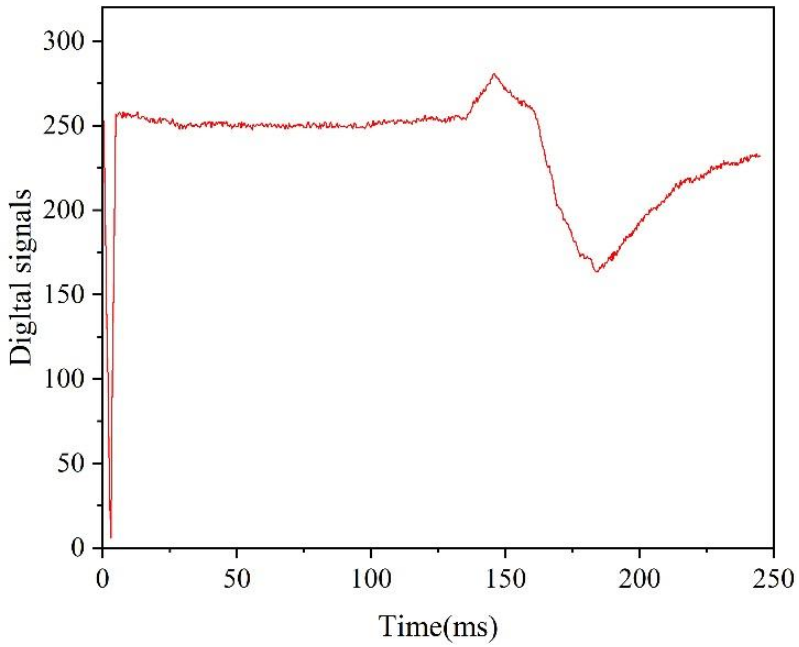


Figure 5. The sequence of serial port plotters.

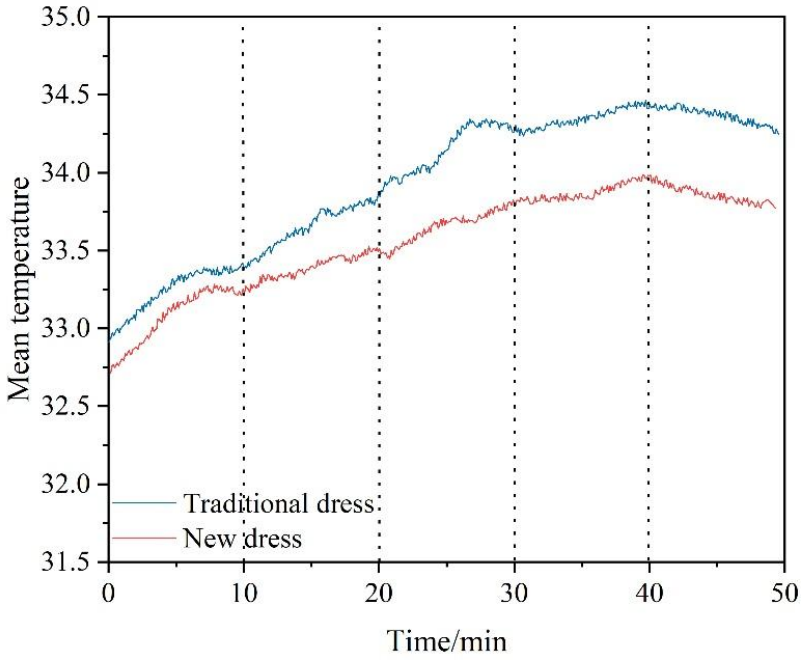
(3) Clothing comfort test

The participants in the objective evaluation experiment were 10 firefighters from a city rescue detachment. The test objects were the new type of firefighting clothes and ordinary firefighting clothes proposed in this study. The brand of the artificial climate chamber for the test was Japan Espex, the temperature control range was -35~65℃, and the humidity adjustment range was 0~100%. Data were recorded once per second during the experiment; the environmental conditions were exactly the same in the comparison experiment, and the tested personnel wore the new firefighting suits to conduct the test. The data were summarized after all the experiments were completed. The experimental instrument used MSRl45 temperature and humidity sensor (MSR Switzerland) to record the temperature and humidity data of the environment inside the subject's clothing.

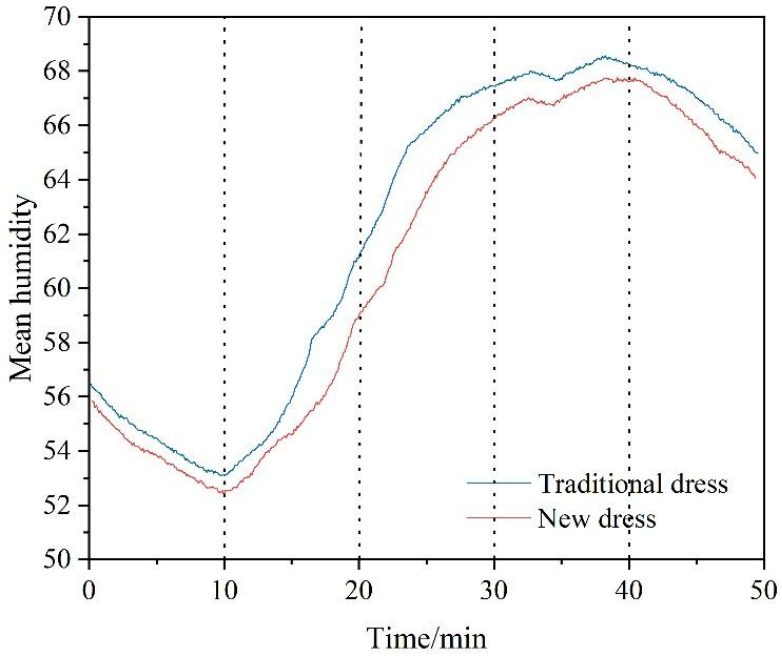
The objective data of the comfort test are shown in Fig. 6, (a) and (b) for temperature and humidity tests, respectively. (a) shows the values of the average skin temperature of the 10 test subjects over time during the test. During the sedentary phase, the difference between the average temperatures inside the clothing of the two garments was not significant, but during the jogging phase, the rate of temperature increase of the regular fire suit was significantly higher than that of the modified fire suit, and there was an increasing gap between the temperatures of the two garments with the increase of time and intensity of the exercise. In the fourth stage, the tested person started to rest, the temperature inside the garment decreased, and the temperature of the modified fire suit decreased faster, and it had more excellent thermal comfort compared with the ordinary fire suit.

(b) shows the changes of the average values of skin humidity at the armpit, forehead, back, thigh and knee of the 10 test subjects with time during the test. It can be seen that in the sedentary and slow walking stage, the difference between the average humidity in the clothing of the two garments is not large, and the change tends to be peaceful; however, as the exercise time becomes longer and the intensity of the

exercise is enhanced, the average humidity in the clothing of the ordinary fire suit rises faster than that of the new type of fire suit; in the fourth stage, the new type of fire suit's humidity in the clothing decreases significantly faster than that of the ordinary fire suit. This shows that the new fire suit has better moisture absorption and moisture dissipation.



(a) Temperature test(℃)



(a) Humidity test(%)

Figure 6. Objective evaluation data for comfort.

4.3. Wear Temperature Sensitivity

4.3.1. Testing of Human Body Temperature Distribution

Before using the temperature-sensitive clothing with intelligent clothing design system for human body temperature monitoring, the average temperature distribution of each monitoring area of the subject needs to be tested. In this paper, the temperature of different parts of the human body during calm breathing is tested. 1 subject sits in a constant temperature and humidity environment for 30 min to ensure that his/her state is in dynamic equilibrium with the current environment, and the results of the test are shown in Fig. 7.

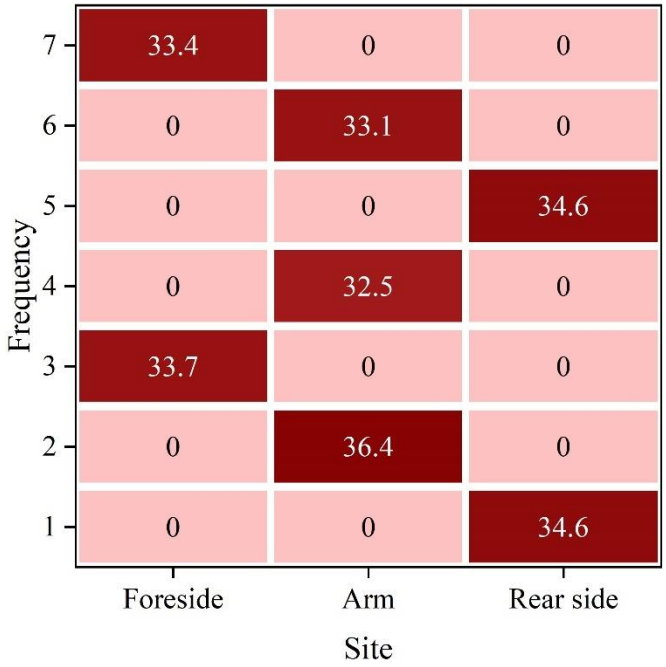


Figure 7. Distribution of skin temperature in different parts.

4.3.2. Real-time temperature of different parts of the human body

In a constant temperature and humidity environment, the temperature-sensitive clothing is laid flat on the surface of the experimental bench for 30min; at the same time, the subject maintains a calm state of mind and sits quietly for 30min in a constant temperature and humidity environment, and ensures that there is no strenuous exercise within 1h before the test. Subjects slowly put on the test suit and then stood still for 10min in a constant temperature and humidity environment to improve the reliability of the experimental data, and to ensure that the sensor's front temperature-sensing area closely fits the human skin without causing physical damage to the skin or hindering normal human activities. Body temperature was monitored according to a predetermined protocol. Experimental program: calm breathing 60 s for 1 group; calm breathing frequency: inhale 1s → exhale 1s → pause 2s, 4s for 1 cycle.

The all-fabric sensing network showed excellent reliability during the test, and all fabric-based temperature sensor components operated well without failures. The temperature test results at different test points are shown in Figure 8. The change of the subject's skin temperature has a certain regularity: the change of temperature takes 4s as 1 cycle, and there are wave peaks in each cycle, and there are a total of 15 cycles in 60s (i.e., 15 obvious wave peaks, and there are outliers in the individual cycles, which have been eliminated), which is consistent with the frequency and cycle of the calm breathing, and the surface temperature of the skin always rises gradually with inhalation, and decreases gradually with exhalation.

From the figure, it can be seen that different regions have different amplitude of temperature change during human respiration, with more obvious fluctuation amplitude in the abdomen and posterior waist, followed by the chest, and the least in the scapula. Basically, we can track the human respiratory state through the human body temperature change curve, the signal curve is relatively smooth, there are small fluctuations, which is due to the sensor resistance has a small fluctuation state when breathing, but does not affect the basic judgment on the respiratory state.

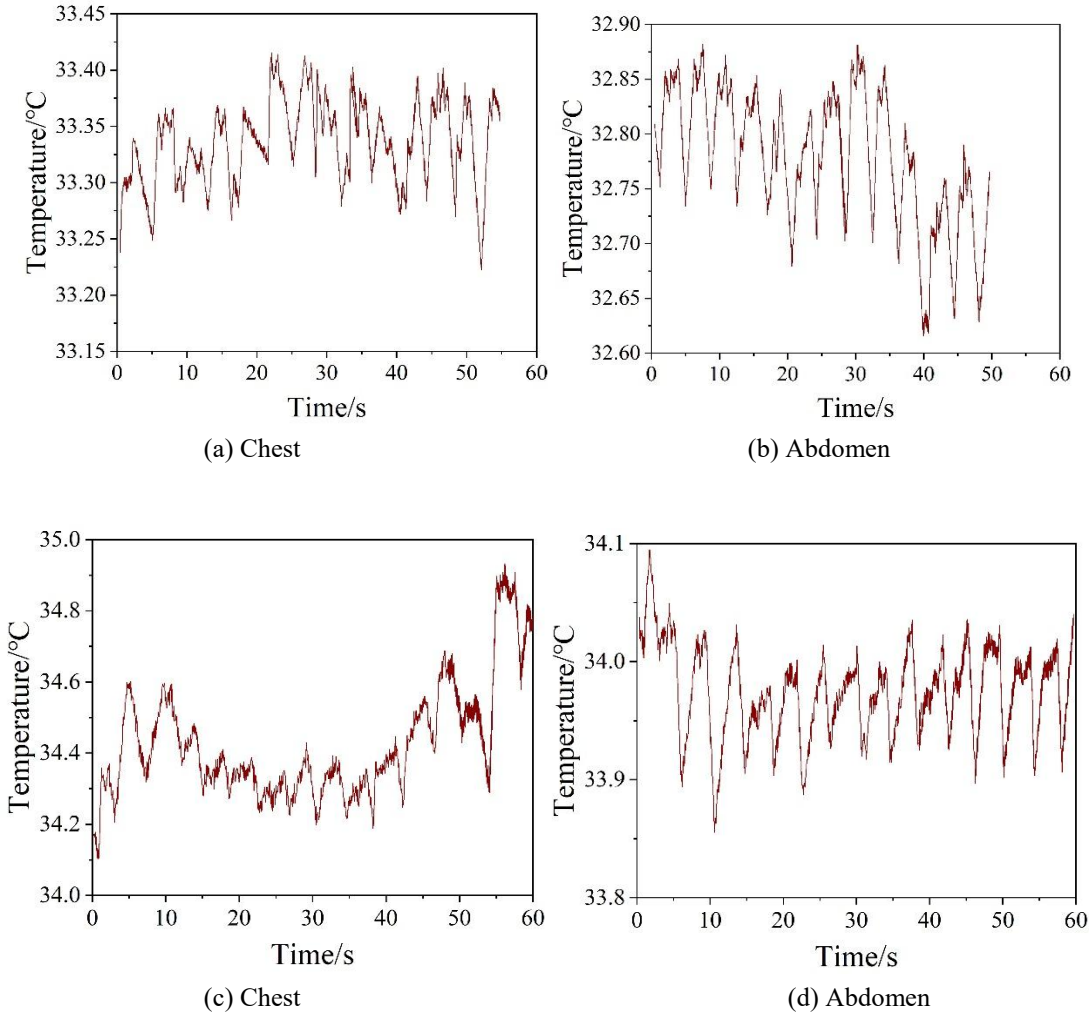


Figure 8. Test results of different test points.

5. Conclusion

The research designed the intelligent clothing design system, through the extraction of attribute information in the clothing to establish a trust preference model, based on the preference trust between users, and ultimately fusion of scoring trust and preference trust to calculate the selection of the nearest neighbor, to achieve the recommendation of clothing. Through experiments to verify the effectiveness of the recommendation model and intelligent system, the experimental results show that the model can more accurately identify the user's preference of clothing style and recommend similar style reference goods for the user, while the user can choose according to their own needs, to meet the user's needs. Secondly, from the perspective of clothing testing, it is found that the clothing strategy recommended by the recommendation model meets the standard requirements, while the intelligent clothing design system is able to monitor the human skin temperature in real time, and the tester can adjust the breathing according to the temperature.

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