RESEARCH ARTICLE

Design of Customized Garments Towards Sustainable Fashion Using 3D Digital Simulation and Machine Learning-Supported Human–Product Interactions

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Abstract

This paper put forward a new interactive design approach for customized garments towards sustainable fashion using machine learning techniques, including radial basis function artificial neural network (RBF ANN), genetic algorithms (GA), probabilistic neural network (PNN), and support vector regression (SVR). First, RBF ANNs were employed to estimate the detailed human body dimensions to fulfill consumers' ergonomics requirements. Next, the GA-based models were developed to generate the formalized design solutions following the consumer profiles (demands). Afterwards, the evaluation model was established to quantitatively characterize the relations between consumer profiles and garment profiles from the generated design solutions. The design solutions would be digitally demonstrated and recommended to the consumer following the evaluation results in descending order. Meanwhile, the PNN-based models were created to predict garment fitness based on virtual try-on. Moreover, the SVR-based self-adjustment mechanism was built to estimate and control garment design parameters according to the consumer's feedback. Based on these mathematical models, the approach enhances the interactions among digital garment demonstration, the designer's professional knowledge and the user's perception to find out the most relevant design solution. The effectiveness of the new approach was verified by a real application case of leisure pants customization. The results show that the proposed method can powerfully support the designers' quality personalized design solutions for consumers more accurately, fast, intelligently, and sustainably, compared with the existing approaches. More importantly, it also establishes an effective and reliable communication channel and mechanism among consumers, fashion designers, pattern designer, and garment producer.

Keywords Interactive garment design · Machine learning · Sustainable fashion · Garment e-mass customization · Radial basis function artificial neural network · Genetic algorithm · Probabilistic neural network · Support vector regression

1 Introduction

Over the past few decades, the fashion industry has been criticized to be one of the most polluting industries in the world [1–4]. To change this situation, an innovation named sustainable fashion (SF) has occurred presently in the fashion industry [5]. The SF concentrates on the efforts to minimize the fashion industry's adverse environmental and social impacts [4]. Hence, classical garment design and manufacturing should be innovated to satisfy the requirements of the SF in a more optimized manner [6]. For this purpose, garment e-mass customization (e-MC), aiming at enhancing the quality of products and their manufacturing to fulfil the consumer's personalized demands, has been adopted by many fashion companies [7–9]. Conventionally, quality customized garments are obtained by repeatedly performing

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the circle of "design–evaluation–adjustment" using physical prototypes. This design process is rather tedious and material wasting, leading to negative impacts on the environment [10–12]. To overcome these shortcomings, cutting-edge digital technologies (i.e. 3D human body scanning and virtual reality) have been utilized for reshaping the entire garment customization process in a more sustainable way [13–16]. One of the most representative technologies is 3D digital simulation, also named virtual fitting, virtual try-on, etc. Since this technology can simulate the garment design process without making real garments [17], the targets of material saving, environmental protection, and sustainability can be achieved. In the past few years, researchers have attempted to apply digital technologies for optimizing the quality of garment design. For example, Liu et al. suggested that a "what you see is what you get" way to design garment patterns efficiently [18]. Tao et al. originally put forward a customized 3D garment collaborative design process by integrating interactions between the designer and the specific consumer [6]. In Ref. [19], an intuitive method that seamlessly integrates the whole process of garment design including 3D modelling, pattern development, garment simulation, and grading was proposed by Zhang et al. Hong et al. present a virtual reality (VR)-based collaborative customized garment design methodology for disabled people with scoliosis [20]. Mulat et al. put forward a bra pattern design process for customizing female seamless soft armour based on innovative 3D reverse engineering approaches [21]. Han et al. proposed a 3D prototyping method and procedure for middle-aged women's swimsuit [22]. Yan et al. established a novel approach of virtual e-bespoke design permitting the ready completion of a well-fitted and balanced men's shirt [23]. A new 3D pattern-making approach based on graphic coding was put forth by Lei et al. in [24], for generating garment patterns in any constructions intuitively, accurately, and quickly. These research results present fine prospects for the 3D digital simulation-based design process of customized garments, but the generality and accuracy of the techniques in the above-mentioned work still need further verification in real production scenarios using more cases.

Meanwhile, for realizing sustainable fashion by providing consumers with more accurate and personalized products, there has been a trend in that fashion companies wish to involve the consumer in the garment customization process and make him/her directly interact with the product [25]. Thus, efficient human–product interactions, aiming at offering decision support for designers by unveiling and applying the sophisticated quantified relationships between consumers' equivocal needs and product design parameters, have become a key to success in garment e-MC. Presently, diverse computational tools have been put forward to provide decision supports in key links of the personalized garment design process, such as design solution generation [26–28], fabric selection [29, 30], colour coordination [31–33], fashion sketch design [34–36], garment pattern design [37–42], and so forth. For instance, in Ref. [28], an e-customized garment co-design system was developed by Li et al. based on the evolutionary algorithm and fuzzy logic theory, to optimize the size and affect the customized skirt with communication and expert evaluation. Takatera et al. created a fabric retrieval system for designers based on Kansei information that allows designers to find the most relevant fabric with the Kansei values and experience without technical knowledge of fabrics [30]. Mok et al. set up a web-based design support system using interactive genetic algorithm that enables users to design realistic and interesting skirts in the form of technical sketches over the Internet [35, 36]. Shukla et al. originally developed an interactive fashion and garment design system for men's shirts by combining garment design recommendation, 3D virtual demonstration, design knowledge base, and design parameters adjustment [41]. These proposed tools have facilitated the optimization of the garment e-MC process. However, there still exist several shortcomings as follows:

- The previous methods mainly focused on resolving the problems existing in a specific garment style, such as skirt, shirt, brassiere, and jeans. A generalized customization solution for a wide range of garment styles is still lacking.
- The techniques mentioned above paid major attention to one or several concrete key links in the garment e-MC process, especially the fabric selection, fashion sketch design, and garment pattern design. However, from the perspectives of the whole design process, they still have weaknesses in systematicness and integrity.
- Due to the expensive and time-consuming physical and sensory experiments, as well as the consumer's concern for personal privacy, sufficient modelling data (i.e. anthropometric data, user perception and experience data) can hardly be acquired, leading to the emergence of poor garment quality. How to conquer this technical bottleneck by reliable computational models has been rarely mentioned in the above-mentioned research.

In this context, we propose a knowledge-driven approach with an adaptive self-adjustment mechanism for generating personalized garment design solutions. Compared with the current techniques, our approach can predict and control the garment style and structural design parameters from a limited quantity of consumers' anthropometric and personalized demand data. It will enable to design and manufacture garments sustainably by promoting accuracy, fitting, and efficiency and mitigate the adverse impacts on the natural environment.

In practice, garment e-MC is regarded as a knowledge-intensive work dealing with implicit and complex relationships among multidisciplinary knowledge, such as the general design rules and specific adaptation rules characterizing the relations among design elements (fabrics, style, and human body shapes). Due to the outstanding merits in learning, generalizing, and handling uncertain and nonlinear relationships and solving optimization problems, machine learning (ML) techniques, such as artificial neural network (ANN), fuzzy logic (FL), and genetic algorithm (GA), have been introduced and broadly utilized in garment e-MC recently [43–45]. Therefore, ML technologies integrated with 3D digital simulation, including radial basis function (RBF) ANN, probabilistic neural network (PNN), support vector regression (SVR) and GA, were employed to enhance the human-product interactions in this study.

The proposed design approach with the process for customized garments (See Fig. 1) is majorly supported by five design knowledge models. First, Model 1 is created to estimate the detailed human body dimensions, which were critical to garment pattern making and inconvenient to be acquired in a real garment e-MC scenario. The predictive data enable the formation of more complete and accurate consumer profiles constituted by personalized body dimensions and demands. Next, Model 2 generates a series of initial personalized garment design solutions following consumer profiles, to satisfy consumers' demands. Afterwards, Model 3 evaluates the generated design solutions following

the quantified relationships between consumer profiles and garment profiles from the generated design solutions firstly. Then, the design solutions will be digitally demonstrated and recommended to the consumer following the evaluation results in descending order. Sequentially, Model 4 predicts the recommended garment fitness by fully taking the consumer's human body dimensions, fabric properties, and garment ease allowances (or digital pressures) into account. After that, the consumer is available to select the most preferred garment from the recommended solutions. If none of the recommended solutions is selected, Model 5 will be activated to adjust the most relevant design solution. The circle of "design solution generation–3D demonstration–evaluation–adjustment" will be performed repeatedly until a satisfactory design solution is achieved, in terms of garment style and fitness. In the end, the production patterns of the determined customization solution will be generated and delivered to the following department for manufacturing.

The major contributions of this study are in presenting:

- Resolving the critical technical bottleneck of providing high-quality garments to satisfy consumer's vague demands under the circumstances of a limited quantity of available data in garment e-MC.
- Proposing an applicable and potential solution for sustainable development in the fashion industry by designing more accurate garments through enhancing human–product interaction using ML technologies.
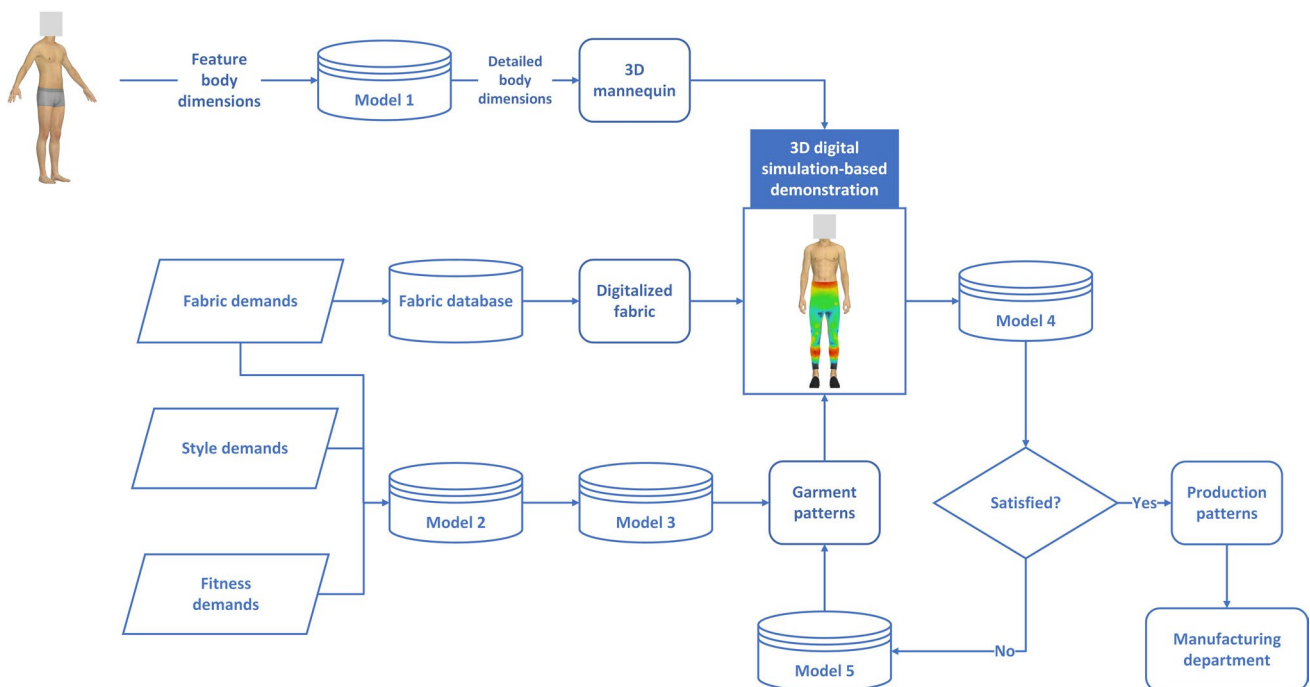

Fig. 1 The proposed ML-enhanced design approach and process for customized garments

- Providing reliable communication channels and interaction mechanisms among products, consumers, designers, and manufacturers based on more robust and intelligent computational tools.
- Facilitating the creation of sustainable manufacturing mode in the fashion industry by combining the proposed garment design process with the advanced clothing assembly line;
- Conveniently extending the general principles of the proposed method to establish a generalized fashion product e-MC framework or platform by systematically considering human aesthetic preferences, ergonomic requirements, and product parameters.
- Supporting the formation of a new O2O (order online and receive services off-line) business model in the fashion industry by upgrading the level of e-MC.

The remainder of this article is structured as follows. Section 2 introduces the general formalization of this study. The construction of the design knowledge models is described in detail in Sect. 3. Section 4 elaborates the implementation of the proposed method using a real application case. The extensibilities of the proposed approach are discussed in Sect. 5. Lastly, Sect. 6 presents the conclusion and future research directions.

2 General Formalization

Let $CP = \begin{bmatrix} SD & FD \end{bmatrix}$ be a vector of profiling the consumer's demands, where SD and FD refer to the demands of garment style and fitness, respectively.

Let $SD = \{SD_1, \dots, SD_i, \dots, SD_m\}$ be a set of normalized vectors representing the demands for m categories of style design elements. For a specific garment style, the SD can be constituted by various categories of style design elements. For example, pants' style can be constituted by the combination of various design elements, such as the silhouette, pant length, waist line position, darts, pleats, pockets, ornaments, and so on.

Let $SD_i = \begin{bmatrix} sd_{i_1} & \cdots & sd_{i_j} & \cdots & sd_{i_u} \end{bmatrix}$ be an i_u-dimensional normalized or one-hot vector expressing the demands for the i-th category style design element. The value of sd_{i_j} is defined as the nearness degree of the style demand to the i_j-th style element.

For example, if the pants' silhouette includes five types, namely H type, A type, T type, X type and S type, then it can be expressed by $SD_{\text{pants silhouette}} = \{$H type, A type, T type,

X type, S type$\}$. If $SD_{\text{pants silhouette}} = \begin{bmatrix} \text{H type} & \text{A type} & \text{T type} & \text{X type} & \text{S type} \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$, it means that the demand for silhouette is H type. If the pants' length includes five types, such as mini length, thigh length, knee length, ankle length, and full length, then it can be represented by $SD_{\text{pants length}} = \{$mini length, thigh length, knee length, ankle length, and full length$\}$. If $SD_{\text{pants length}} = \begin{bmatrix} \text{mini length} & \text{thigh length} & \text{knee length} & \text{ankle length} & \text{full length} \\ 0 & 0 & 0 & 0.7 & 0.3 \end{bmatrix}$, it indicates that the demand for the length is close to ankle length by 70% and full length by 30%.

Let $FS = \{$extremly tight, tight, neutral, loose, extremely loose$\}$ be a semantic set for evaluating garment fitness.

Let $FD = \{FD_1, \dots, FD_j, \dots, FD_q\}$ be a set of q normalized vectors representing the demands for garment fitness at q feature positions.

Let $FD_j = \begin{bmatrix} \text{extremely tight} & \text{tight} & \text{neutral} & \text{loose} & \text{extremely loose} \\ fd_{j_1} & fd_{j_2} & fd_{j_3} & fd_{j_4} & fd_{j_5} \end{bmatrix}$ be a five-dimensional normalized vector representing the demands on garment fitness at the j-th feature position. The value of $fd_{j_p} (p \in \{1, 2, 3, 4, 5\})$ is defined as the nearness degree of the garment fitness demand to a certain fitness evaluation semantics at the j-th feature position. For example, if $FD_{\text{waist girth}} = \begin{bmatrix} \text{extremely tight} & \text{tight} & \text{neutral} & \text{loose} & \text{extremely loose} \\ 0 & 0 & 0.55 & 0.45 & 0 \end{bmatrix}$, it means that the demanded garment fitness for waist girth is close to neutral by 55% and loose by 45%.

Let $S = \{S^1, \dots, S^k, \dots, S^n\}$ be a set of n generated garment design solutions in this study.

Let $GP = \{GP^1, \dots, GP^k, \dots, GP^n\}$ be a set of n garment profiles corresponding to the set of garment design solutions S, where GP^k is denoted as the k-th garment profile corresponding to the k-th garment design solution S^k.

Let $GP^k = \begin{bmatrix} SF^k & FF^k \end{bmatrix}$ be a vector of profiling the features for garment profile GP^k, where SF^k and FF^k represent the features of garment style and fitness, respectively. The elements of GP^k have a one-to-one correspondence with those of CP.

Let $SF^k = \{SF_1^k, \dots, SF_i^k, \cdots, SF_m^k\}$ be a set of formalized vectors expressing the style features of the k-th garment from the aspects of the m categories style design elements, represented by normalized vectors or one-hot vectors.

Let $SF_i = \begin{bmatrix} sf_{i_1} & \cdots & sf_{i_j} & \cdots & sf_{i_u} \end{bmatrix}$ be an i_u-dimensional vector expressing the concrete style feature of a specific garment in the i-th category style design element. The structure of SF_m has a one-to-one correspondence with that of SD_m. Furthermore, the value of sf_{i_j} is defined by using the same method as sd_{i_j} mentioned above.

Let $FF^k = \{FF_1^k, \dots, FF_i^k, \dots, FF_n^k\}$ be a set of normalized vectors expressing the features of garment fitness of the k-th garment. The elements of FF^k have a one-to-one

correspondence with those of FD. The definition of FF_i^k is the same as that of FD_i.

3 Construction of Design Knowledge Models for Customized Garments

The general principles of the present method can be easily spread to other garment styles. For simplicity, we expound it using a real case of males' leisure pants from the companies involved in our projects in this study.

3.1 Estimation Model for Human Body Dimensions (Model 1)

In practice, the acquisition of precise human body dimensions has become a challenging issue in real garment e-MC scenarios, due to either the lack of necessary anthropometric instruments and knowledge or the worry of privacy protection. To address this issue, we proposed an estimation model for human body dimensions. The inputs of the model are the easy-to-measure feature body dimensions, such as stature, waist girth, and hip girth. The outputs are defined as the difficult-to-measure detailed body dimensions corresponding to the garment style.

Contributing to its advantages of simple topological structure, fast convergence, and acceptable predictive accuracy [46], RBF ANN was employed in our study. The concrete modelling procedure is described below:

Step 1: To obtain the data quickly and precisely [47], we collected the anthropometric measurements of 500 Chinese adult males by the Vitus Bodyscan. Considering the garment type, ten relevant anthropometric measurements were chosen (see Fig. 2), including stature, waist height, hip height, crotch height, knee height, waist girth, hip girth, thigh girth, knee girth, and ankle girth.

Step 2: We set up seven RBF ANN models for human body estimation, respectively, corresponding to waist height, hip height, crotch height, knee height, thigh girth, knee girth, and ankle girth.

3.2 Generation Model of Design Solution (Model 2)

The garment design solution generation model (see Fig. 3) is constituted by two parts, namely the GA model and linear model supported by a garment design knowledge base. The garment ease allowances corresponding to the standard design solutions were predefined by professional and experienced garment pattern makers based on the real cases from the fashion brand companies involved in our

study. The inputs of the solution generation model are the style demands (SD) and the garment fitness demands (FD) for the feature positions. The outputs of the model are the garment ease allowances, which are denoted as an indicator expressing the extra space difference between the human body and the garment to present the diverse features of the garment style and fitness [42].

In the application process, we can utilize the GA-based model to generate the normalized design solution corresponding to a new garment style and fitness firstly. Next, the garment design solutions (garment ease allowances) can be calculated by combining the outputs of the GA model with the standard design solutions from the garment design knowledge base in a linear combination way. In the end, the obtained ease data are utilized for garment pattern making.

The creation of the garment design solution generation model is given below:

Let the fitness value $f_{\mathrm{SD}_j}^{\mathrm{fitness}}$ for the garment style demand SD_j be denoted in Eq. (1) and the fitness value $f_{\mathrm{FD}_j}^{\mathrm{fitness}}$ for the garment fitness demand FD_j be denoted in Eq. (2).

$$f_{\mathrm{SD}_j}^{\mathrm{fitness}} = \left| \mathrm{SF}_j^{\mathrm{new}} - \mathrm{SD}_j \right| \left(\mathrm{SD}_j \in \mathrm{SD} \right), \tag{1}$$

where $\mathrm{SF}_j^{\mathrm{new}}$ represents the generated new garment style features corresponding to the garment style demand SD_j.

$$f_{\mathrm{FD}_j}^{\mathrm{fitness}} = \left| \mathrm{FF}_j^{\mathrm{new}} - \mathrm{FD}_j \right| \left(\mathrm{FD}_j \in \mathrm{FD} \right), \tag{2}$$

where $\mathrm{FF}_j^{\mathrm{new}}$ represents the generated new garment fitness features corresponding to the garment fitness demand FD_j.

From Eqs. (1) and (2), a smaller value of the $f_{\mathrm{SD}_j}^{\mathrm{fitness}}$ or $f_{\mathrm{FD}_j}^{\mathrm{fitness}}$ indicates a more optimal degree of fitness.

The execution process of the GA-based model is as follows. The termination criteria of the GA-based model were as follows: (1) the preset maximum iterations achieved; (2) the average variation in the fitness function values with a specific number of generations less than a predefined tolerance; (3) reaching the consumer's demands. For each SD_j or FD_j, the consumer's demand can be denoted by two sets $\mathrm{SD}_j^{\mathrm{constraint}}$ and $\mathrm{FD}_j^{\mathrm{constraint}}$. If the terminal criteria were not reached, the process of "selection–crossover–mutation–calculation–evaluation" would be repeatedly performed till the terminal criteria were satisfied. The objective functions of GA are defined in Eqs. (3) and (4).

$$\underset{\mathrm{SF}_j^{\mathrm{new}}}{\mathrm{argmin}} \left(f_{\mathrm{SD}_j}^{\mathrm{fitness}} \right) \left(\mathrm{SD}_j \in \mathrm{SD}, \ \mathrm{SF}_j^{\mathrm{new}} \in \mathrm{SF}_j^{\mathrm{constraint}} \right), \tag{3}$$

$$\underset{\mathrm{FF}_j^{\mathrm{new}}}{\mathrm{argmin}} \left(f_{\mathrm{FD}_j}^{\mathrm{fitness}} \right) \left(\mathrm{FD}_j \in \mathrm{FD}, \ \mathrm{FF}_j^{\mathrm{new}} \in \mathrm{FF}_j^{\mathrm{constraint}} \right). \tag{4}$$
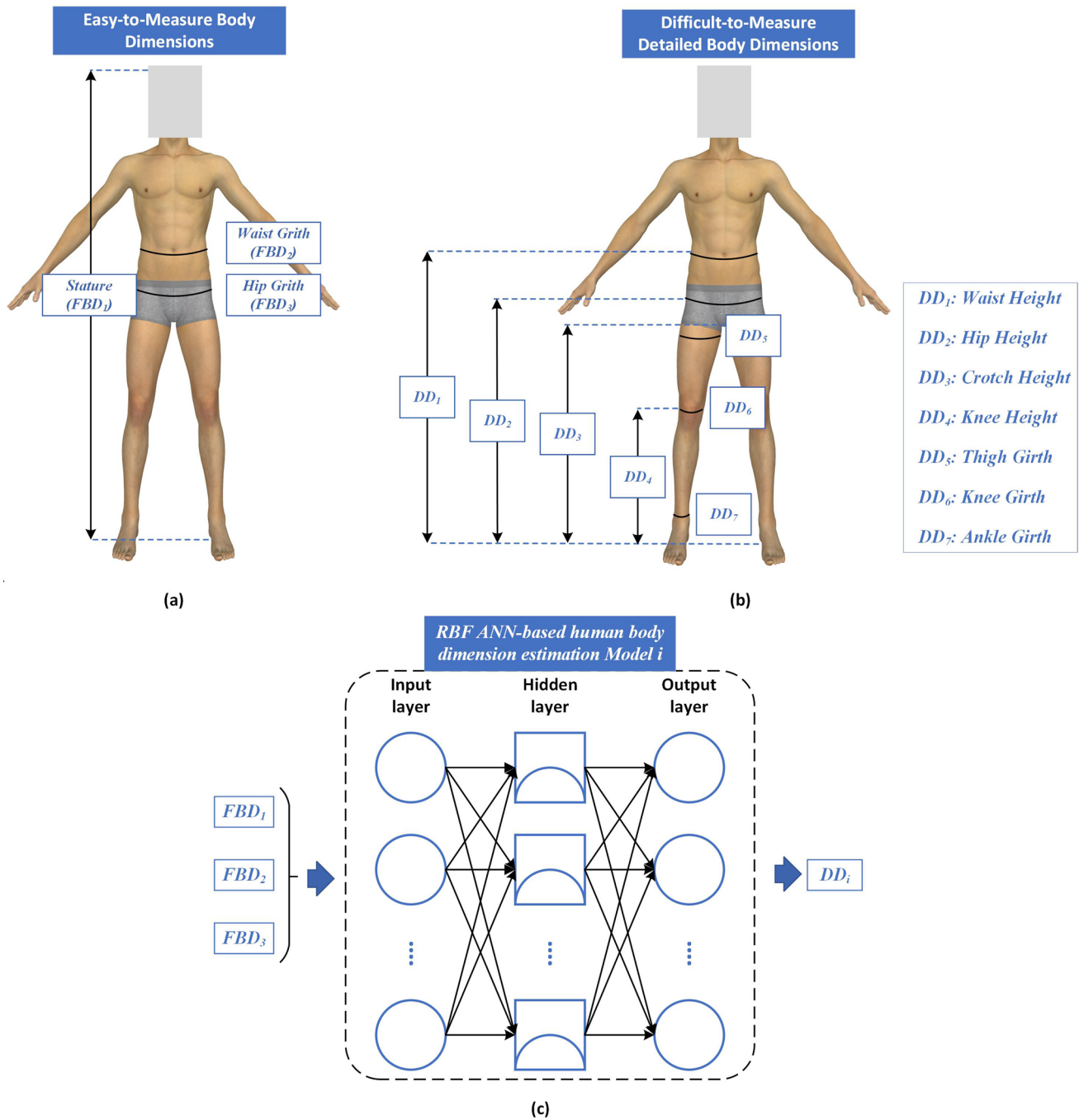
Fig. 2 The general structure of the proposed estimation model for detailed human body dimensions

The new garment ease allowance is computed following Eq. (5):

$$GE_i^{new} = OP_i \cdot GE_i^{std}, \quad OP_i \text{ is } SF_i^{new} \text{ or } FF_i^{new}, \tag{5}$$

where GE_i^{new} is defined as the new garment ease allowance of the new garment design solution at i feature position; OP_i represents the i output of the GA-based model, which could be SF_i^{new} or FF_i^{new}; GE_i^{std} refers to a standard garment ease

allowance vector at i feature position in the garment design knowledge base.

For instance, if $OP_i = SF_{waist\ line}^{new} = \begin{bmatrix} \text{lower waist line} & \text{normal waist line} & \text{high waist line} \\ 0 & 0.65 & 0.35 \end{bmatrix}$, meaning that the new waist line was close to the normal waist line by 65% and the high waist line by 35% $GE_{waist\ line}^{std} = \begin{bmatrix} \text{lower waist line} & \text{normal waist line} & \text{high waist line} \\ ge_1 & ge_2 & ge_3 \end{bmatrix}^T$, then the new garment ease for the waist line position $GE_{waist\ line}^{new}$ can be computed by $GE_{waist\ line}^{new} = 0 \times ge_1 + 0.65 \times ge_2 + 0.35 \times ge_3$.
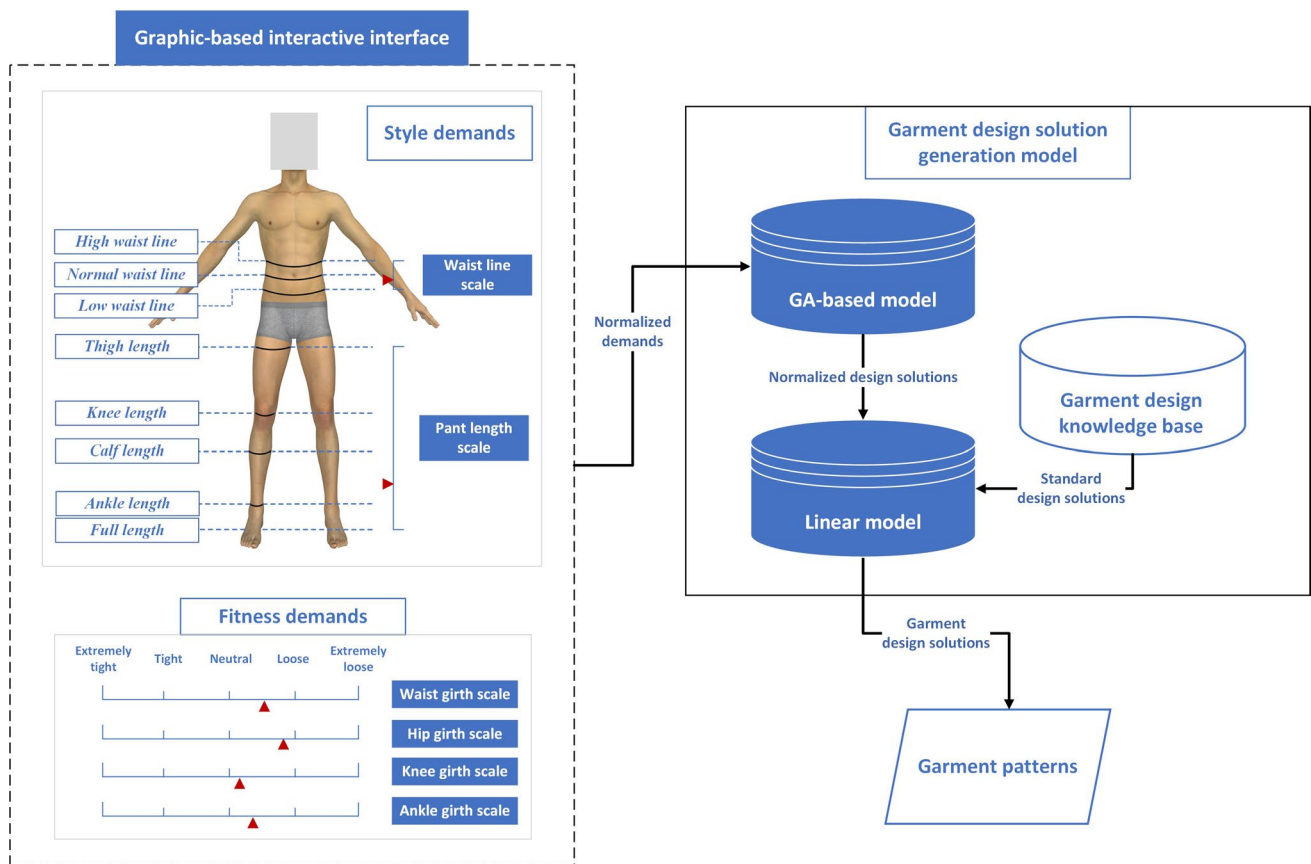
Fig. 3 The general scheme of garment design solution generation model

If $\text{OP}_i = \text{FF}_{\text{hip girth}}^{\text{new}} = \begin{bmatrix} \text{extremely tight} & \text{tight} & \text{neutral} & \text{loose} & \text{extremely loose} \\ 0 & 0 & 0.55 & 0.45 & 0 \end{bmatrix}$, meaning that the new garment fitness of the hip girth was close to the neutral fitness by 55% and the loose fitness by 45%, and $\text{GE}_{\text{hip girth}}^{\text{std}} = \begin{bmatrix} \text{extremely tight} & \text{tight} & \text{neutral} & \text{loose} & \text{extremely loose} \\ gf_1 & gf_2 & gf_3 & gf_4 & gf_5 \end{bmatrix}^{\text{T}}$, then the new garment ease for the fitness of hip girth $\text{GE}_{\text{hip girth}}^{\text{new}}$ can be computed by $\text{GE}_{\text{hip girth}}^{\text{new}} = 0 \times gf_1 + 0 \times gf_2 + 0.55 \times gf_3 + 0.45 \times gf_4 + +0 \times gf_5$.

3.3 Evaluation Model of Design Solution (Model 3)

In the garment design solution evaluation model, we defined a similarity degree indicator $r\left(\text{CP}, \text{GP}^k\right)$ to express the quantitative relationships between the consumer profile (CP) and the garment profile $\left(\text{GP}^k\right)$. In this study, $r\left(\text{CP}, \text{GP}^k\right)$ is defined and calculated by Eq. (6).

$$r\left(\text{CP}, \text{GP}^k\right) = \alpha \times r\left(\text{SD}, \text{SF}^k\right) + \beta \times r\left(\text{FD}, \text{FF}^k\right), \quad (6)$$

where α and β represent the weights of garment style and fitness, respectively. The weights, varying between 0 and 1, can be set by the designer or consumer following the specific scenario. $r\left(\text{SD}, \text{SF}^k\right)$ is denoted as the indicator for characterizing the similarity degrees between the style demands (SD) and the style features $\left(\text{SF}^k\right)$ of a garment profile $\left(\text{GP}^k\right)$. $r\left(\text{SD}, \text{SF}^k\right)$ is defined by Eq. (7).

$$r\left(\text{SD}, \text{SF}^k\right) = \frac{\sum_j \sum_i \min\left(\text{sd}_i, \text{sf}_i\right)}{\sum_j \sum_i \max\left(\text{sd}_i, \text{sf}_i\right)},$$
$$\left(\text{sd}_i \in \text{SD}_j \in \text{SD}, \text{sf}_i \in \text{SF}_j \in \text{SF}^k\right). \quad (7)$$

From Eq. (7), we can find that the values of $r\left(\text{SD}, \text{SF}^k\right)$ vary between 0 and 1. If all style elements of SD and SF^k are close to each other, the value of $r\left(\text{SD}, \text{SF}^k\right)$ is close to 1. Otherwise, it tends to 0.

$r\left(\text{FD}, \text{FF}^k\right)$ refers to the indicator for representing the similarity degrees between the global garment fitness demands (FD) and the global fitness features $\left(\text{FF}^k\right)$ of a garment profile $\left(\text{GP}^k\right)$. $r\left(\text{FD}, \text{FF}^k\right)$ is defined and computed with Eq. (8) and (9).

$$r\left(\mathrm{FD}_i, \mathrm{FF}_i^k\right) = \frac{\min\left(et_i^d, et_i^f\right) + \min\left(ti_i^d, ti_i^f\right) + \min\left(nl_i^d, nl_i^f\right) + \min\left(lo_i^d, lo_i^f\right) + \min\left(el_i^d, tl_i^f\right)}{\max\left(et_i^d, et_i^f\right) + \max\left(ti_i^d, ti_i^f\right) + \max\left(nl_i^d, nl_i^f\right) + \max\left(lo_i^d, lo_i^f\right) + \max\left(el_i^d, tl_i^f\right)}, \tag{8}$$

$$r\left(\mathrm{FD}, \mathrm{FF}^k\right) = \mathrm{avg}\left(r\left(\mathrm{FD}_i, \mathrm{FF}_i^k\right)\right), \left(\mathrm{FF}_i^k \in \mathrm{FF}^k, \mathrm{FD}_i \in \mathrm{FD}\right), \tag{9}$$

where $r\left(\mathrm{FD}_i, \mathrm{FF}_i^k\right)$ is defined as the indicator for evaluating the similarity degrees between the local garment fitness demands $\left(\mathrm{FD}_i\right)$ and the local fitness features $\left(\mathrm{FF}_i^k\right)$ of a garment profile $\left(\mathrm{GP}^k\right)$ at the i-th feature position.

Both the values of $r\left(\mathrm{FD}_i, \mathrm{FF}_i^k\right)$ and $r\left(\mathrm{FD}, \mathrm{FF}^k\right)$ are between 0 and 1. From Eq. (8), if the local fitness features $\left(\mathrm{FF}_i^k\right)$ is close to the fitness demands $\left(\mathrm{FD}_i\right)$, the value of $r\left(\mathrm{FD}_i, \mathrm{FF}_i^k\right)$ is close to 1. Otherwise, it tends to 0. Similarly, following Eq. (9), if the value of $r\left(\mathrm{FD}, \mathrm{FF}^k\right)$ is close to 1,

it means that the global fitness features $\left(\mathrm{FF}^k\right)$ is close to the fitness demands (FD) and vice versa.

3.4 Prediction Model of Garment Fitness (Model 4)

Thanks to its powerful performance in dealing with pattern recognition and classification problems in the textile and apparel industry [48], PNN was applied to build the garment fitness prediction models in this study. A series of PNN-based models were created to predict garment fitness
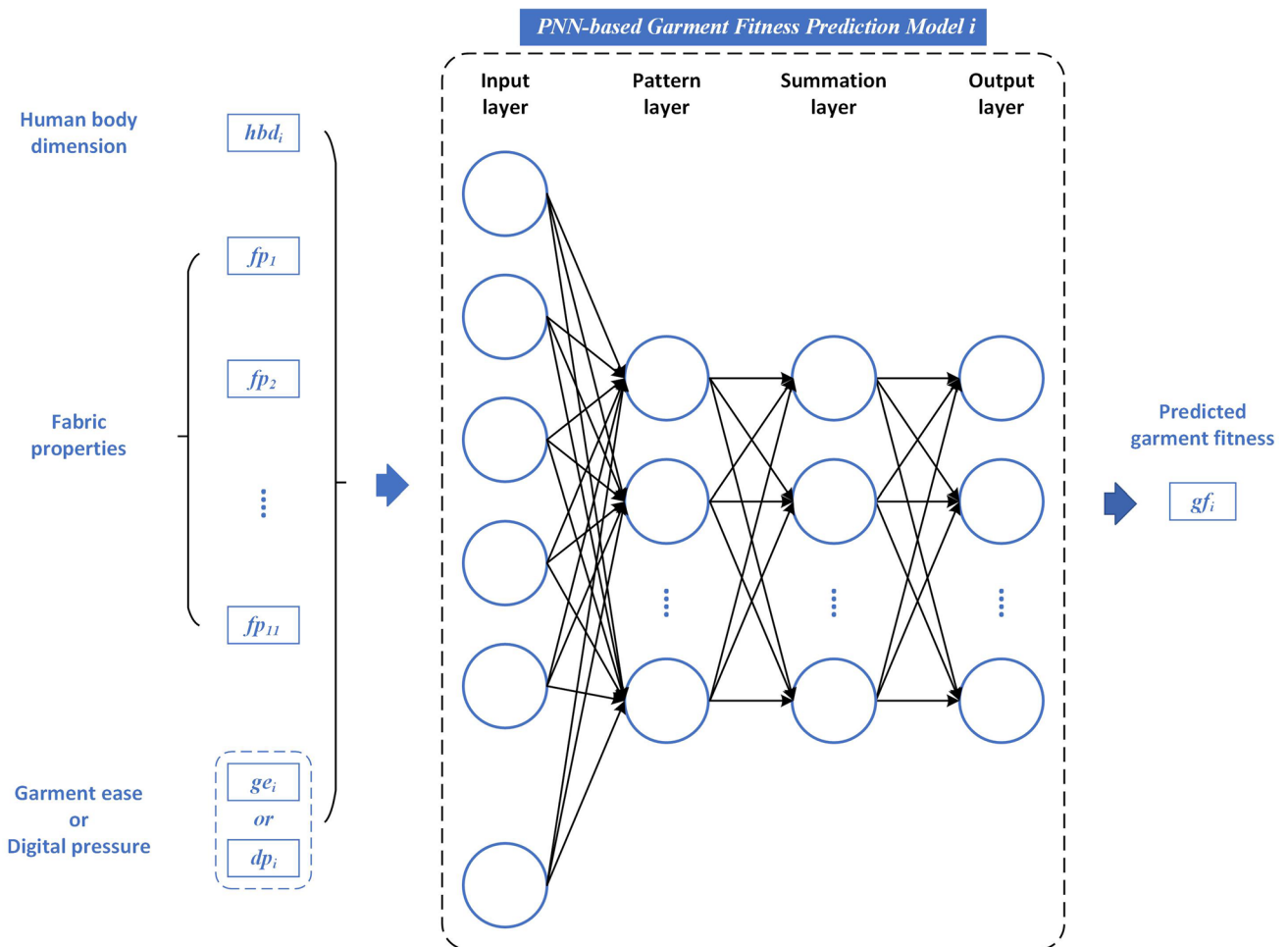

Fig. 4 The general scheme of the garment fitness prediction model for feature position

at various feature positions, such as waist, hip, thigh, knee, ankle, and so on. Each model had an identical four-layer structure, with thirteen inputs and one output (see Fig. 4). The inputs were constituted by the body dimension at feature position, fabric properties, and garment ease allowance (for loose-fit garments) or digital pressure (for tight-fitted garments) measured in a 3D digital design environment. The output was the predicted real garment fitness.

The detailed procedure for creating the garment fitness prediction model is presented as follows:

Step 1: A series of real try-on-based sensory experiments were conducted to collect the real garment fitness data on various feature positions. Considering the target markets of the fashion companies involved in our study, 14 male subjects with various figure types in China were recruited to participate in the experiments. The involved figure types included 160/80A, 160/84A, 160/88A, 165/84A, 165/88A, 165/92A, 170/84A, 170/88A, 170/92A, 175/84A, 175/88A, 175/92A, 180/88A, and 185/92A. They were selected according to the accommodation rate demonstrated in the China National Standard (GB/T 1335.1–2008) [49]. Meanwhile, we invited an expert with over 20 years of experience in sizing systems to join our research. With her in-depth knowledge and rich experience, we can guarantee the recruited subjects were in line with the China National Standard.

Step 2: Every subject performed his try-on with the experimental garments in static and dynamic scenarios.

Meanwhile, they recorded the garment fitness data represented by {1, 2, 3, 4, 5}, corresponding to the semantics {εextremelytight(1)ε, εtight(2)ε, εneutral(3)ε, εloose(4)ε, ε extremelyloose(5)ε}. These data were used to form the output dataset to construct the proposed models.

Step 3: 25 pieces of real experimental garments (leisure pants) of five sizes with five types of fabrics were selected in this research (see Tables 1 and 2). The inputs for creating the proposed models were procured using the software CLO 3D, thanks to its cutting-edge simulation techniques. First, 14 mannequins corresponding to the subjects were modelled. Next, we created 25 pieces of digital garments corresponding to the real experimental garments. Then, these digital garments were tried on the 14 digital mannequins one by one. For each virtual try-on, the garment ease allowances at each feature position were measured. Finally, all the collected ease data were aggregated to form the input dataset. Additionally, 11 indicators for characterizing the mechanical properties of the digital fabric were measured by the Fabric Kit of CLO 3D, including thickness (TH), stretch weft (SWT), stretch warp (SWP), shear (SH), bending weft (BWT), bending warp (BWP), bending ratio–weft (BRT), bending ratio–warp (BRP), buckling stiffness–weft (BST), buckling stiffness–warp (BSP), and density (DE).

Step 4: For each feature position, 350 records of data were collected to form the learning dataset in total. The PNN-based models were determined using the k-fold ($k = 10$) cross-validation approach.

3.5 Adjustment Model of Design Solution (Model 5)

Step 1: The garment patterns for a specific style were divided into the main panel and the associated panels based on the knowledge of experienced and skillful pattern makers. For leisure pants in this study, the front panel was selected as the main panel with other panels as the associated panels.

Step 2: Since its excellent advantages of tackling the problems of function approximation [50, 51], SVR was employed to model the relationships between the length variation of the structural line and the movements of its corresponding controlling points. Initially, we set up five

Table 1 Feature dimensions of the involved experimental garment (unit: cm)

Size	Garment length	Waist girth	Hip girth	Knee girth	Ankle girth
XS	103	70	91	45	43
S	104.5	74	95	46	44
M	106	78	99	47	45
L	107.5	82	103	48	46
XL	109	86	107	49	47

Table 2 Fabric properties of the involved experimental garment

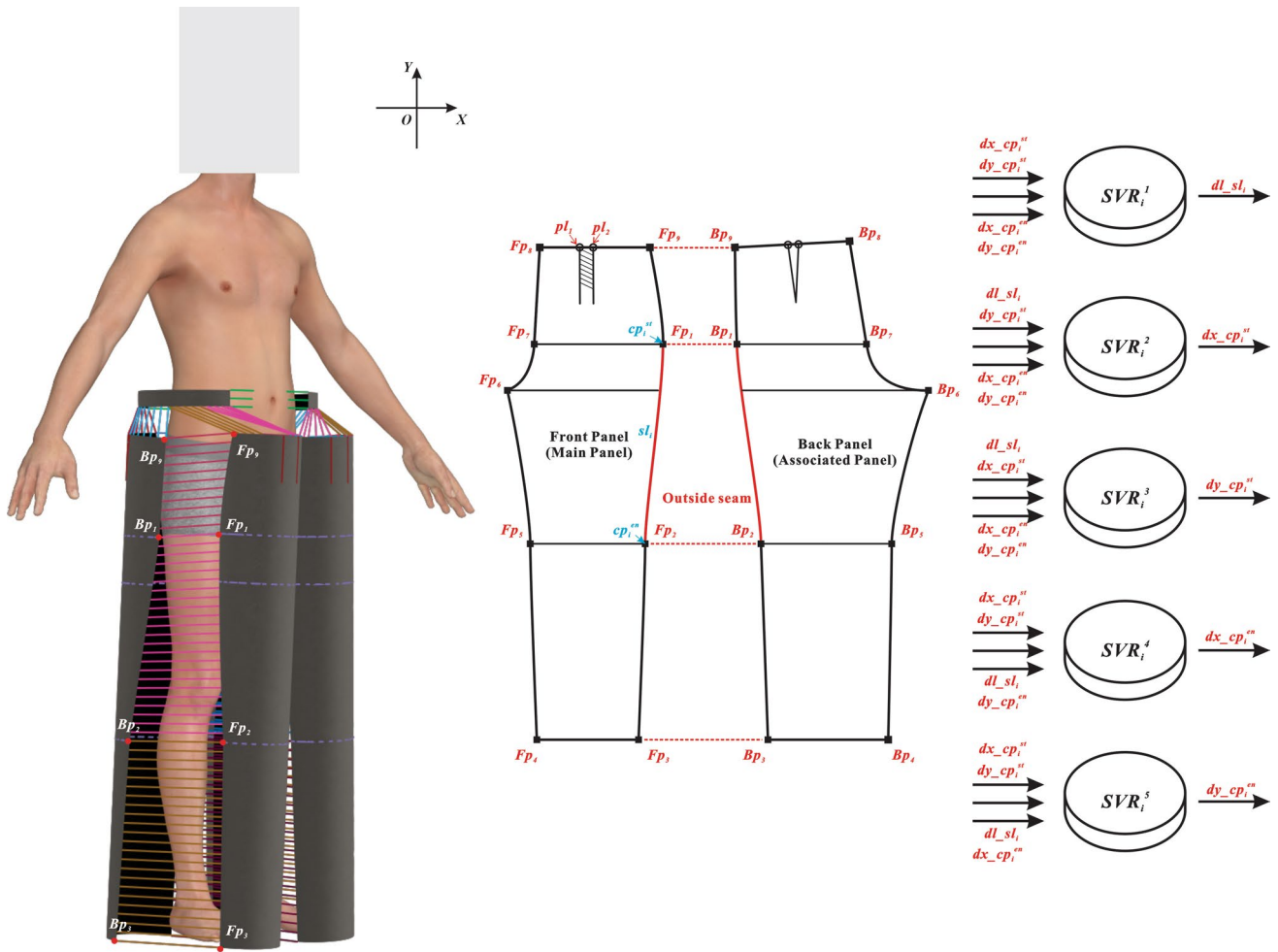| No.	Composition	Structure	Weight (g/m^2)	Thickness (cm)	Bending resistance B (1e-6N.m)	
					Warp	Weft
1	100% cotton	Woven	153	0.03	40.63	13.82
2	75% polyester, 25% cotton	Woven	210	0.03	23.56	15.96
3	100% wool	Woven	268	0.07	17.66	11.77
4	100% polyester	Knit	125	0.06	1.03	0.25
5	90% polyamide 10% elasthane	Knit	200	0.05	0.66	0.63

Fig. 5 The SVR-based adaptation models for the structural line sl_i

SVR-based adaptation models for each structural line (see Fig. 5). Meanwhile, we utilized the Bayesian optimization approach to determine the parameters of the SVR-based models. Afterwards, all the SVR-based models were aggregated to form a complete adaptation model for the main panel.

Table 3 The relationships of movements of controlling points in the front and back panels

Controlling points of the front panel	Movement		Controlling points of the back panel	Movement	
	Horizontal direction	Vertical direction		Horizontal direction	Vertical direction
Fp_1	dx^{Fp_1}	dy^{Fp_1}	Bp_1	$-dx^{Fp_1}$	dy^{Fp_1}
Fp_2	dx^{Fp_2}	dy^{Fp_2}	Bp_2	$-dx^{Fp_2}$	dy^{Fp_2}
Fp_3	dx^{Fp_3}	dy^{Fp_3}	Bp_3	$-dx^{Fp_3}$	dy^{Fp_3}
Fp_4	dx^{Fp_4}	dy^{Fp_4}	Bp_4	$-dx^{Fp_4}$	dy^{Fp_4}
Fp_5	dx^{Fp_5}	dy^{Fp_5}	Bp_5	$-dx^{Fp_5}$	dy^{Fp_5}
Fp_6	dx^{Fp_6}	dy^{Fp_6}	Bp_6	$-dx^{Fp_6}$	dy^{Fp_6}
Fp_7	dx^{Fp_7}	dy^{Fp_7}	Bp_7	$-dx^{Fp_7}$	dy^{Fp_7}
Fp_8	dx^{Fp_8}	dy^{Fp_8}	Bp_8	$-dx^{Fp_8}$	dy^{Fp_8}
Fp_9	dx^{Fp_9}	dy^{Fp_9}	Bp_9	$-dx^{Fp_9}$	dy^{Fp_9}

Step 3: The associate adjustment rules of other panels (see Table 3) were defined following the correspondence between the associated panels and the main panel. For example, Fp_1 and Bp_1 (see Fig. 5) belong to the outside seam of the front panel and back panel respectively. They have one-to-one correspondence. Therefore, once the adjustment parameter of Fp_1 in the front panel (the main panel) is determined, the adjustment parameter of Bp_1 in the back panel (the associated panel) will be obtained simultaneously.

4 Application and Implementation

In this section, the application and implementation of our proposed method will be elaborated on using a real case of men's leisure pants customization for a specific consumer. The key body dimensions of the consumer, namely stature, waist girth, and hip girth, were 170.8 cm, 69.8 cm, and 88.6, respectively. The detailed human body dimensions were estimated by the proposed RBF ANN-based models, as follows:

$$DD = \left\{ \begin{array}{ccccccc} \text{waist height} & \text{hip height} & \text{crotch height} & \text{knee height} & \text{thigh girth} & \text{knee girth} & \text{ankle girth} \\ 105.9 & 83.3 & 77.5 & 45.8 & 48.7 & 35.2 & 22.3 \end{array} \right\}.$$

4.1 Creation of Consumer Profile

In this study, the consumer profile is defined by the combination of the demands on garment style and fitness. The style of leisure pants was constituted by ten categories of style elements, involving silhouette, length, waist line position, waist band, leg opening, dart, pleat, yoke, ornament, and pocket. Each category of style can be further divided into several types (see Table 4). The consumer's demands on the style and fitness are expressed by vectors in Tables 5 and 6. The value of the vector element refers to the nearness degree to the corresponding type of style design element and fitness.

4.2 Generation of Design Solutions

It was assumed that all the other style elements met the consumer's demands except the leisure pants' style and fitness. Hence, we first set up six GA-based models to generate new normalized pants' style and fitness feature vectors based on the method as presented in Sect. 3.2. In this article, the population size of the individuals was set to 50. To eliminate the effects of the raw fit scores returned by the fit function, rank scaling was utilized. Next, the roulette method was employed to choose the individuals. Additionally, we used the single-point crossover method to generate new individuals. The constraint-dependent method was utilized to execute the mutation. According to the consumer profile defined in Sect. 4.1, we randomly generated 100 normalized design solutions for further research.

Afterwards, the ease allowances of the new design solution can be calculated by linearly combining the outputs of the GA-based models with the standard ease allowances, as follows:

$$GE_l^{std} = \left[\begin{array}{ccccc} \text{mini length} & \text{thight length} & \text{knee length} & \text{ankle length} & \text{full length} \\ -0.8WH & -0.7WH & -0.5WH & -0.1WH & 0 \end{array} \right]^T,$$

Table 4 The classification of leisure pants style elements	Category	Type
	Silhouette (SD_1)	H type; A type; X type; T type; S type
	Length (SD_2)	Mini length; thigh length; knee length; ankle length; full length
	Waist line position (SD_3)	High waist line; normal waist line; lower waist line
	Waist band (SD_4)	No waist band; straight waist band; curved waist band
	Leg opening (SD_5)	Tapered opening; straight opening; flared opening
	Dart (SD_6)	No front dart; single front dart; double front darts; multiple front darts; No back dart; single back dart
	Pleat (SD_7)	No front pleat; single front pleat; double front pleats; multiple front pleats
	Yoke (SD_8)	No yoke; straight yoke; curved yoke; special yoke
	Ornament (SD_9)	Embroidery; printing; riveting; quilting; hollow cut; no ornament
	Pocket (SD_{10})	No front pocket; front straight inserted pocket; front diagonal inserted pocket; front curved inserted pocket; front curved inserted pocket with coin pocket; front patched pocket; no back pocket; back inserted pocket; back inserted pocket with flap; back patched pocket; back patched pocket with flap

Table 5 Consumer's demands on leisure pants style elements *SD*

S.N	Category	Normalized style demands	Style demands
1	Silhouette	$SD_1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	H type
2	Length	$SD_2 = \begin{bmatrix} 0 & 0 & 0 & 0.75 & 0.25 \end{bmatrix}$	Close to ankle length by 75% and full length by 25%
3	Waist line position	$SD_3 = \begin{bmatrix} 0.2 & 0.8 & 0 \end{bmatrix}$	Close to normal waist line by 80% and lower waist line by 20%
4	Waist band	$SD_4 = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}$	Straight waist band
5	Leg opening	$SD_5 = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}$	Straight opening
6	Dart	$SD_6 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	No front and single back dart
7	Pleat	$SD_7 = \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix}$	Sing front pleat
8	Yoke	$SD_8 = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$	No yoke
9	Ornament	$SD_9 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	No ornament
10	Pocket	$SD_{10} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$	Front straight inserted pocket and back inserted pocket

$$GE_{wl}^{std} = \begin{bmatrix} \text{lower} & \text{normal} & \text{high} \\ -3 & 0 & 3 \end{bmatrix}^T,$$

$$GE_{wg}^{std} = \begin{bmatrix} \text{extremely tight} & \text{tight} & \text{neutral} & \text{loose} & \text{extremely loose} \\ -2 & 0 & 2 & 4 & 6 \end{bmatrix}^T,$$

$$GE_{hg}^{std} = \begin{bmatrix} \text{extremely tight} & \text{tight} & \text{neutral} & \text{loose} & \text{extremely loose} \\ 0 & 4 & 8 & 12 & 16 \end{bmatrix}^T,$$

$$GE_{kg}^{std} = \begin{bmatrix} \text{extremely tight} & \text{tight} & \text{neutral} & \text{loose} & \text{extremely loose} \\ 0 & 3 & 6 & 9 & 12 \end{bmatrix}^T,$$

$$Input_{wg}^{S^1} = \begin{bmatrix} \text{waistgirth} & \text{TH} & \text{SWT} & \text{SWP} & \text{SH} & \text{BWT} & \text{BWP} & \text{BRT} & \text{BRP} & \text{BST} & \text{BSP} & \text{DE} & \text{easeallowance} \\ 69.8 & 0.23 & 55 & 58 & 14 & 23 & 29 & 90 & 90 & 30 & 30 & 7 & 2.816 \end{bmatrix}.$$

$$GE_{ag}^{std} = \begin{bmatrix} \text{extremely tight} & \text{tight} & \text{neutral} & \text{loose} & \text{extremely loose} \\ 0 & 4 & 8 & 12 & 16 \end{bmatrix}^T.$$

4.3 Evaluation and Recommendation of the Generated Design Solutions

First, the weights α and β in Eq. (6) were set to 0.5 and 0.5 based on the analytic hierarchy process. Next, according to Eq. (7), we obtained the relationships $r(\text{SD}, \text{SF}^k)$ between the pants style demands and the style features from the generated design solutions. After that, according to Eq. (8) and (9), we obtained the relationships $r(\text{FD}, \text{FF}^k)$ between the pants fitness demands and the fitness features of the pants from the generated design solutions. Sequentially, the relationships $r(\text{CP}, \text{GP}^k)$ between the consumer profile and the generated pants profiles were calculated by Eq. (6). Finally, the generated design solutions were sorted by $r(\text{CP}, \text{GP}^k)$ in

descending order, and then recommended to the consumer. The top-5 design solutions are shown in Table 7.

4.4 Prediction of Garment Fitness from the Recommended Design Solutions

For each recommended design solution, we predicted the garment fitness at various feature positions using the created PNN-based models. We take the fitness prediction of waist girth in design solution 1 (S^1) for instance. The inputting vector was denoted as follows:

The predicted garment fitness $output_{wg}^{S^1} = fitness_{wg}^{S^1} = 3.468$, indicating that the predictive garment fitness at waist girth was between neutral and loose in general, but a little close to neutral. For the prediction of garment fitness at other feature positions, we only replaced waist girth and its ease allowance with other feature body dimensions with their corresponding ease allowance. Finally, the complete leisure pants design solution, which consisted of 3D digital garments and predicted garment fitness, was demonstrated to the consumer to support his further decision-making.

4.5 Adaptation of Garment Design Solutions

If the consumer is not satisfied with the recommended design solutions, the adaptation mechanism will be activated, for example, if the consumer is satisfied with most of the parts of the design solution 1 (S^1), but prefers the hip girth of the solution $p (S^p)$ and the length of the solution $q (S^q)$. Meanwhile, $FF_{hg}^p = \begin{bmatrix} 0 & 0 & 0.792 & 0.218 & 0 \end{bmatrix}$ and

Table 6 Consumer's demands on leisure pants fitness *FD*

S.N	Feature position	Normalized fitness demands	Fitness demands
1	Waist girth	$FD_1 = \begin{bmatrix} 0 & 0 & 0.5 & 0.5 & 0 \end{bmatrix}$	Close to neutral by 50% and loose by 50%
2	Hip girth	$FD_2 = \begin{bmatrix} 0 & 0 & 0.2 & 0.8 & 0 \end{bmatrix}$	Close to neutral by 20% and loose by 80%
3	Knee girth	$FD_3 = \begin{bmatrix} 0 & 0 & 0.8 & 0.2 & 0 \end{bmatrix}$	Close to neutral by 80% and loose by 20%
4	Ankle girth	$FD_4 = \begin{bmatrix} 0 & 0 & 0.65 & 0.35 & 0 \end{bmatrix}$	Close to neutral by 65% and loose by 35%

$SF_l^q = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.563 & 0.437 \end{bmatrix}$. The adaptation process is described concretely below:

Step 1: The overall adaptation requirements were computed and distributed to each panel. For the main panel (front panel), the adaptation requirement of waist girth and pants length was determined to be −0.71 cm and 1.80 cm, respectively.

Step 2: We adjusted the front panel from the structural line l_1 (see Fig. 6). First, the movement of the point Fp_2 was calculated; next, the length deviation of the adjacent line l_2 under the condition of the movement of Fp_2. If the length deviation dll_2 is less than a predefined threshold ε, then we will continue to check the adaptation results of the whole panel; otherwise, we will compute the movement of the point Fp_3. Afterwards, if all the adaptation demands

Table 7 Top-5 leisure pants design solutions

Solution	Feature position	Normalized design solutions	$r(SD, SF^k)$	$r(FD, FF^k)$	$r(CP, GP^k)$
S^1	Length	$SF_l^1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.726 & 0.274 \end{bmatrix}$	0.9942	0.9871	0.9907
	Waist line position	$SF_{wl}^1 = \begin{bmatrix} 0.189 & 0.811 & 0 \end{bmatrix}$			
	Waist girth	$FF_{wg}^1 = \begin{bmatrix} 0 & 0 & 0.512 & 0.488 & 0 \end{bmatrix}$			
	Hip girth	$FF_{hg}^1 = \begin{bmatrix} 0 & 0 & 0.207 & 0.793 & 0 \end{bmatrix}$			
	Knee girth	$FF_{kg}^1 = \begin{bmatrix} 0 & 0 & 0.802 & 0.198 & 0 \end{bmatrix}$			
	Ankle girth	$FF_{ag}^1 = \begin{bmatrix} 0 & 0 & 0.645 & 0.355 & 0 \end{bmatrix}$			
S^2	Length	$SF_l^2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.761 & 0.239 \end{bmatrix}$	0.9975	0.9818	0.9897
	Waist line position	$SF_{wl}^2 = \begin{bmatrix} 0.196 & 0.804 & 0 \end{bmatrix}$			
	Waist girth	$FF_{wg}^2 = \begin{bmatrix} 0 & 0 & 0.501 & 0.499 & 0 \end{bmatrix}$			
	Hip girth	$FF_{hg}^2 = \begin{bmatrix} 0 & 0 & 0.211 & 0.789 & 0 \end{bmatrix}$			
	Knee girth	$FF_{kg}^2 = \begin{bmatrix} 0 & 0 & 0.823 & 0.177 & 0 \end{bmatrix}$			
	Ankle girth	$FF_{ag}^2 = \begin{bmatrix} 0 & 0 & 0.652 & 0.348 & 0 \end{bmatrix}$			
S^3	Length	$SF_l^3 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.777 & 0.223 \end{bmatrix}$	0.9950	0.9827	0.9889
	Waist line position	$SF_{wl}^3 = \begin{bmatrix} 0.203 & 0.797 & 0 \end{bmatrix}$			
	Waist girth	$FF_{wg}^3 = \begin{bmatrix} 0 & 0 & 0.488 & 0.512 & 0 \end{bmatrix}$			
	Hip girth	$FF_{hg}^3 = \begin{bmatrix} 0 & 0 & 0.197 & 0.803 & 0 \end{bmatrix}$			
	Knee girth	$FF_{kg}^3 = \begin{bmatrix} 0 & 0 & 0.791 & 0.209 & 0 \end{bmatrix}$			
	Ankle girth	$FF_{ag}^3 = \begin{bmatrix} 0 & 0 & 0.661 & 0.339 & 0 \end{bmatrix}$			
S^4	Length	$SF_l^4 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.758 & 0.242 \end{bmatrix}$	0.9955	0.9701	0.9828
	Waist line position	$SF_{wl}^4 = \begin{bmatrix} 0.219 & 0.781 & 0 \end{bmatrix}$			
	Waist girth	$FF_{wg}^4 = \begin{bmatrix} 0 & 0 & 0.493 & 0.507 & 0 \end{bmatrix}$			
	Hip girth	$FF_{hg}^4 = \begin{bmatrix} 0 & 0 & 0.188 & 0.812 & 0 \end{bmatrix}$			
	Knee girth	$FF_{kg}^4 = \begin{bmatrix} 0 & 0 & 0.831 & 0.169 & 0 \end{bmatrix}$			
	Ankle girth	$FF_{ag}^4 = \begin{bmatrix} 0 & 0 & 0.639 & 0.361 & 0 \end{bmatrix}$			
S^5	Length	$SF_l^5 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.733 & 0.267 \end{bmatrix}$	0.9942	0.9658	0.9800
	Waist line position	$SF_{wl}^5 = \begin{bmatrix} 0.182 & 0.818 & 0 \end{bmatrix}$			
	Waist girth	$FF_{wg}^5 = \begin{bmatrix} 0 & 0 & 0.467 & 0.533 & 0 \end{bmatrix}$			
	Hip girth	$FF_{hg}^5 = \begin{bmatrix} 0 & 0 & 0.191 & 0.809 & 0 \end{bmatrix}$			
	Knee girth	$FF_{kg}^5 = \begin{bmatrix} 0 & 0 & 0.811 & 0.189 & 0 \end{bmatrix}$			
	Ankle girth	$FF_{ag}^5 = \begin{bmatrix} 0 & 0 & 0.633 & 0.367 & 0 \end{bmatrix}$			

Adjustment requirements of the front panel

1. *Front waist girth:* $d \mid dx_{Fp8} - dx_{Fp9} \mid = dl_{vg\_f} = 0$
2. *Front hip girth:* $d \mid dx_{Fp1} - dx_{Fp7} \mid = dl_{hg\_f} = 0.71$
3. *Front knee girth:* $d \mid dx_{Fp3} - dx_{Fp6} \mid = dl_{kg\_f} = 0$
4. *Front ankle girth:* $d \mid dx_{Fp3} - dx_{Fp4} \mid = dl_{ag\_f} = 0$
5. *Front waist line:* $d \mid dy_{Fp9} - dy_{Fp8} \mid = dl_{wl\_f} = 0$
6. *Front pants length:* $d \mid dy_{Fp8} - dy_{Fp4} \mid = dl_{pl\_f} = 1.8$

Start

General adjustment requirements of the pattern panel

Adjustment requirement of the structure line l_i

Inputs for adjustment of the structure line i

l_i — $dll_1 = 0.9$ $dx_{Fp1} = -0.71$ $dy_{fp1} = 0$ $dy_{fp2} = -0.9$

SVR4 l_i

$dx_{fp2} = -1.0457$

Movement of the controlling point cp_{i2}

l_2 — $dx_{fp2} = -1.0457$ $dy_{fp2} = -0.9$ $dx_{fp3} = 0$ $dy_{fp3} = -1.8$

SVR1 l_{i+1}

$dll_2 = 0.3456$

Length deviation of the adjacent structure line $i+1$

Checking all the adaptation requirements of the pattern — No/Not satisfied / Yes/Satisfied — Terminate

$i = i+2$

Yes/Satisfied

Checking the length of the adjacent structure line $dll_{i+1} < \xi$

No/Not satisfied

SVR4 l_{i+1} — Movement of the controlling point $cp_{(i+1)2}$

l_2 — $dll_2 = 0.9$ $dx_{fp2} = -1.0457$ $dy_{fp2} = -0.9$ $dy_{fp3} = -1.8$

$dx_{fp3} = -1.4710$

Front Panel (Main Panel)

Fp_8 l_6 Fp_9
l_7 l_9
Fp_7 Fp_1
l_8
Fp_6 l_1
l_5 l_1
Fp_5 Fp_2
l_2
l_4 l_2
Fp_4 l_3 Fp_3

Fig. 6 General adaptation flowchart for the main panel

Table 8 The movements of controlling points in the front and back panels

Controlling points of the front panel	Movement		Controlling points of the back panel	Movement	
	Horizontal direction	Vertical direction		Horizontal direction	Vertical direction
Fp_1	−0.7100	0	Bp_1	0.7100	0
Fp_2	−1.0457	−0.9000	Bp_2	1.0457	0.9000
Fp_3	−1.4710	−1.8000	Bp_3	1.4710	1.8000
Fp_4	−1.4702	−1.8000	Bp_4	1.4702	1.8000
Fp_5	−1.5663	−0.9000	Bp_5	1.5663	0.9000
Fp_6	−1.8070	0	Bp_6	1.8070	0
Fp_7	0	−0.2564	Bp_7	0	−0.2564
Fp_8	0	−0.2521	Bp_8	0	−0.2521
Fp_9	0	−0.2517	Bp_9	0	−0.2517

of the front panel are satisfied, then the adaptation of the main panel terminates; otherwise, the adaptation of the structure line l_3 will be activated. The process of "checking–adaptation" will be repeatedly performed until all the adjustment targets are approached.

Step 3: According to the relationships defined in Table 3, we determined the movements of the controlling points of the back panel (see Table 8).

Step 4: The movements of other controlling points were furtherly determined by modelling the relationships between them and the key points in the panel (i.e. Fp_1, Fp_2, Fp_3, etc.). We take the movements of the pleat points pl_1 and pl_2 (see Fig. 5) in the main panel for example. The movements of pl_1 can be calculated by the following

relationships: $dx^{pl_1} = \frac{dx^{Fp_8} + dx^{Fp_9}}{2}$, $dy^{pl_1} = dy^{Fp_8} = dy^{Fp_9}$. Then, the movements of pl_2 can be computed by the relationships: $dx^{pl_2} = dx^{pl_1}$, $dy^{pl_2} = dy^{pl_1}$. Finally, the movements of all the controlling points are obtained.

5 Discussion

5.1 Extensibility in the Design of the Production Patterns

Garment production patterns play pivotal roles by linking fashion design with garment manufacturing. They can
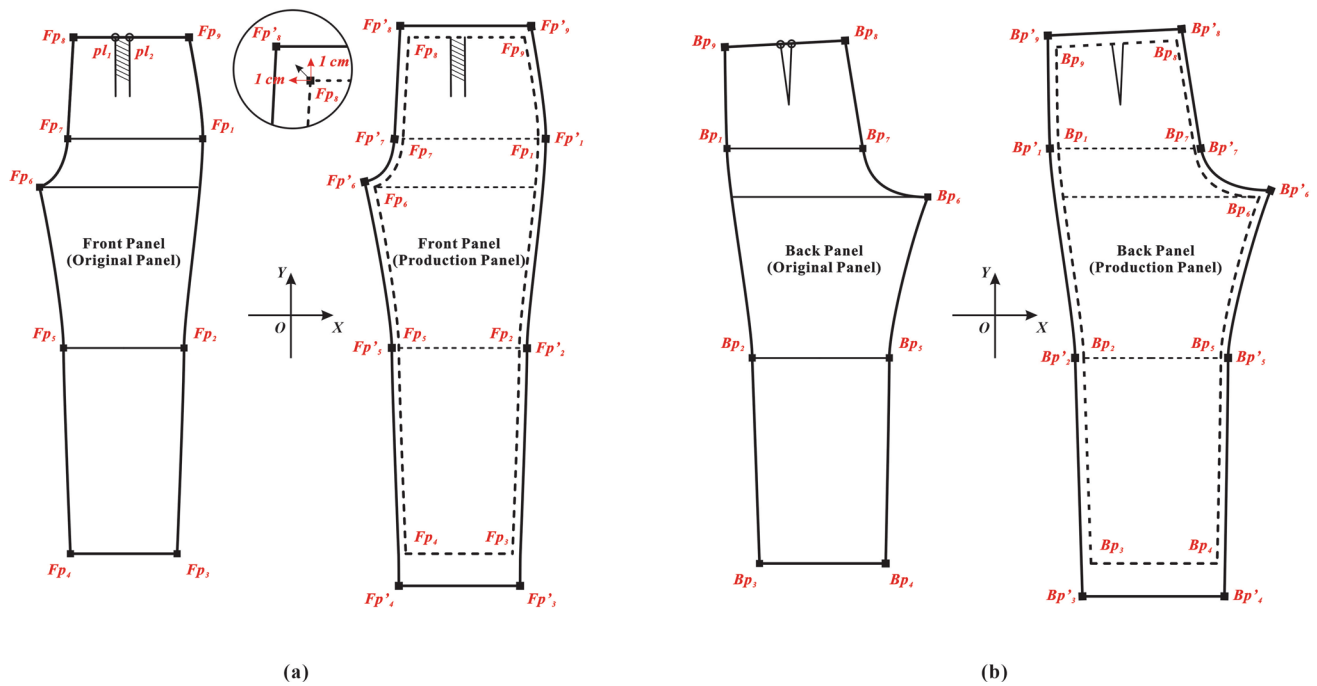
Fig. 7 The original and production panels

Table 9 The design rules of the production patterns (unit: cm)

	Controlling points of the original panel	Coordinates		Controlling points of the production panel	Coordinates	
		Horizontal direction	Vertical direction		Horizontal direction	Vertical direction
Front panel	Fp_1	x^{Fp_1}	y^{Fp_1}	$Fp_1^{'}$	$x^{Fp_1} + 1$	y^{Fp_1}
	Fp_2	x^{Fp_2}	y^{Fp_2}	$Fp_2^{'}$	$x^{Fp_2} + 1$	y^{Fp_2}
	Fp_3	x^{Fp_3}	y^{Fp_3}	$Fp_3^{'}$	$x^{Fp_3} + 1$	$y^{Fp_3} - 3.5$
	Fp_4	x^{Fp_4}	y^{Fp_4}	$Fp_4^{'}$	$x^{Fp_4} - 1$	$y^{Fp_4} - 3.5$
	Fp_5	x^{Fp_5}	y^{Fp_5}	$Fp_5^{'}$	$x^{Fp_5} - 1$	y^{Fp_5}
	Fp_6	x^{Fp_6}	y^{Fp_6}	$Fp_6^{'}$	$x^{Fp_6} - 1$	y^{Fp_6}
	Fp_7	x^{Fp_7}	y^{Fp_7}	$Fp_7^{'}$	$x^{Fp_7} - 1$	y^{Fp_7}
	Fp_8	x^{Fp_8}	y^{Fp_8}	$Fp_1^{'}$	$x^{Fp_8} - 1$	$y^{Fp_8} + 1$
	Fp_9	x^{Fp_9}	y^{Fp_9}	$Fp_1^{'}$	$x^{Fp_9} + 1$	$y^{Fp_9} + 1$
	Controlling points of the original panel	Coordinates		Controlling points of the production panel	Coordinates	
		Horizontal direction	Vertical direction		Horizontal direction	Vertical direction
Back panel	Bp_1	x^{Bp_1}	y^{Bp_1}	$Bp_1^{'}$	$x^{Bp_1} - 1$	y^{Bp_1}
	Bp_2	x^{Bp_2}	y^{Bp_2}	$Bp_2^{'}$	$x^{Bp_2} - 1$	y^{Bp_2}
	Bp_3	x^{Bp_3}	y^{Bp_3}	$Bp_3^{'}$	$x^{Bp_3} - 1$	$y^{Bp_3} - 3.5$
	Bp_4	x^{Bp_4}	y^{Bp_4}	$Bp_4^{'}$	$x^{Bp_4} + 1$	$y^{Bp_4} - 3.5$
	Bp_5	x^{Bp_5}	y^{Bp_5}	$Bp_5^{'}$	$x^{Bp_5} + 1$	y^{Bp_5}
	Bp_6	x^{Bp_6}	y^{Bp_6}	$Bp_6^{'}$	$x^{Bp_6} + 1$	y^{Bp_6}
	Bp_7	x^{Bp_7}	y^{Bp_7}	$Bp_7^{'}$	$x^{Bp_7} + 1$	y^{Bp_7}
	Bp_8	x^{Bp_8}	y^{Bp_8}	$Bp_8^{'}$	$x^{Bp_8} + 1$	$y^{Bp_8} + 1$
	Bp_9	x^{Bp_9}	y^{Bp_9}	$Bp_9^{'}$	$x^{Fp_9} - 1$	$y^{Bp_9} + 1$

be designed by the relationships between the controlling points in the production panels and the original panels. For instance, if the final coordinates of the Fp_8 in the original panel (see Fig. 7) were x^{Fp_8} and y^{Fp_8}, then the coordinates of Fp_8' will be $x^{Fp_8'} = x^{Fp_8} - 1$ and $y^{Fp_8'} = y^{Fp_8} + 1$. Table 9 shows the design rules of the production panels.

5.2 Extensibility in the Associate Adaptation of the Production Patterns

Based on the relationships of the controlling points in the original and production panels, the associate adaptation rules of the production patterns can be further defined (see Table 9). For example, when the movements of the Fp_2 in the original panel (see Fig. 6) are $dx^{Fp_2} = -1.0457$ and $dy^{Fp_2} = -0.9000$, the movements of Fp_2' in the production panel are set to $dx^{Fp_2'} = dx^{Fp_2} = -1.0457$ and

$dy^{Fp_2'} = dy^{Fp_2} = -0.9000$. Finally, the associated adaptation rules of the production patterns are presented in Table 10.

5.3 Extensibility in the Development of Interactive Garment Pattern Recommendation System

We further developed an interactive pants pattern recommendation system 2022 (IPPRS 2022) using MATLAB computer language. In the system, the user (consumer or designer) can intuitively input the feature body dimensions and determine the pants style and fitness demands using the interactive interfaces (see Fig. 8). The output of the system is a set of personalized pants production patterns.

With the help of IPPRS 2022, the consumer can conveniently express his/her personalized demands that usually cannot be presented in words accurately. More than that, the proposed system can support the pattern designer (especially the novice) to put forward accurate design

Table 10 The associate adjustment rules of the production patterns

| Front panel	Controlling points of the original panel	Movements		Controlling points of the production panel	Movements	
		Horizontal direction	Vertical direction		Horizontal direction	Vertical direction
	Fp_1	dx^{Fp_1}	dy^{Fp_1}	Fp_1'	dx^{Fp_1}	dy^{Fp_1}
	Fp_2	dx^{Fp_2}	dy^{Fp_2}	Fp_2'	dx^{Fp_2}	dy^{Fp_2}
	Fp_3	dx^{Fp_3}	dy^{Fp_3}	Fp_3'	dx^{Fp_3}	dy^{Fp_3}
	Fp_4	dx^{Fp_4}	dy^{Fp_4}	Fp_4'	dx^{Fp_4}	dy^{Fp_4}
	Fp_5	dx^{Fp_5}	dy^{Fp_5}	Fp_5'	dx^{Fp_5}	dy^{Fp_5}
	Fp_6	dx^{Fp_6}	dy^{Fp_6}	Fp_6'	dx^{Fp_6}	dy^{Fp_6}
	Fp_7	dx^{Fp_7}	dy^{Fp_7}	Fp_7'	dx^{Fp_7}	dy^{Fp_7}
	Fp_8	dx^{Fp_8}	dy^{Fp_8}	Fp_8'	dx^{Fp_8}	dy^{Fp_8}
	Fp_9	dx^{Fp_9}	dy^{Fp_9}	Fp_9'	dx^{Fp_9}	dy^{Fp_9}
Back panel	Controlling points of the original panel	Movements		Controlling points of the production panel	Movements	
		Horizontal direction	Vertical direction		Horizontal direction	Vertical direction
	Bp_1	dx^{Bp_1}	dy^{Bp_1}	Bp_1'	dx^{Bp_1}	dy^{Bp_1}
	Bp_2	dx^{Bp_2}	dy^{Bp_2}	Bp_2'	dx^{Bp_2}	dy^{Bp_2}
	Bp_3	dx^{Bp_3}	dy^{Bp_3}	Bp_3'	dx^{Bp_3}	dy^{Bp_3}
	Bp_4	dx^{Bp_4}	dy^{Bp_4}	Bp_4'	dx^{Bp_4}	dy^{Bp_4}
	Bp_5	dx^{Bp_5}	dy^{Bp_5}	Bp_5'	dx^{Bp_5}	dy^{Bp_5}
	Bp_6	dx^{Bp_6}	dy^{Bp_6}	Bp_6'	dx^{Bp_6}	dy^{Bp_6}
	Bp_7	dx^{Bp_7}	dy^{Bp_7}	Bp_7'	dx^{Bp_7}	dy^{Bp_7}
	Bp_8	dx^{Bp_8}	dy^{Bp_8}	Bp_8'	dx^{Bp_8}	dy^{Bp_8}
	Bp_9	dx^{Bp_9}	dy^{Bp_9}	Bp_9'	dx^{Bp_9}	dy^{Bp_9}
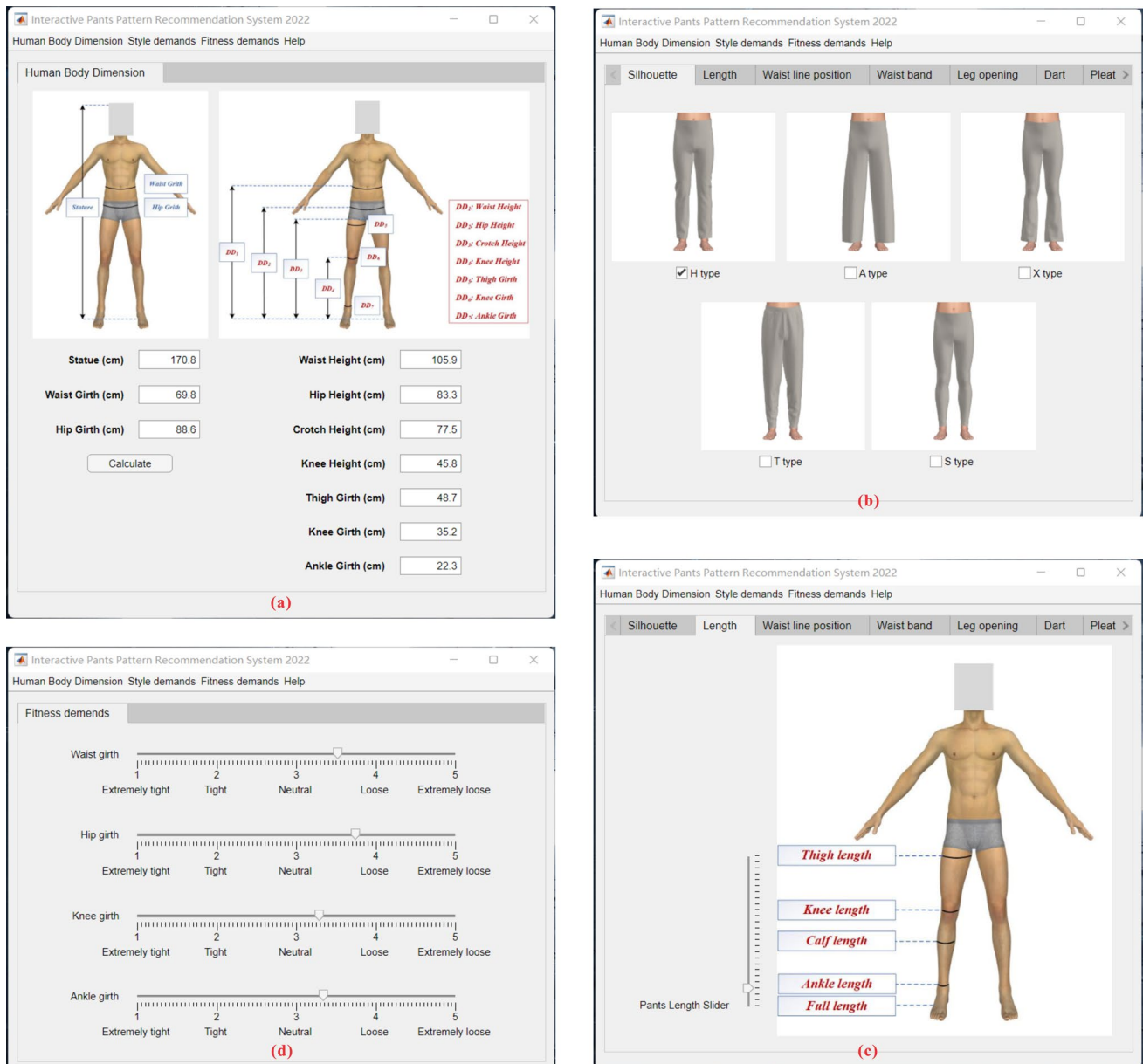
Fig. 8 Parts of the interfaces of interactive pants pattern recommendation system 2022. **a** The interactive interface of anthropometric data acquisition. **b** The interactive interface of collecting style demand on pants silhouette. **c** The interactive interface of collecting style demand on pants length. **d** The interactive interface of collecting fitness demands

solutions quickly and intelligently, to fulfil consumers' personalized demands. Figure 9 shows a case of the pants production patterns generated by IPPRS 2022, corresponding to the design solutions S^1 presented in Table 6. The proposed system is feasible to generate various pants production patterns according to the input parameters.

Compared with the existing garment pattern design methods, the IPPRS 2022 has the advantages below. First, it helps the consumer express their demands more intuitively and exactly, so that the communication gap between consumer and designer can be greatly narrowed. Second, it enables the designers to make patterns easier, more rapid and more accurate by integrating the machine learning models into the conventional design process. Third, it facilitates fashion companies to form a sustainable garment design and development process based on 3D digital simulation and machine learning-supported human–product interactions.
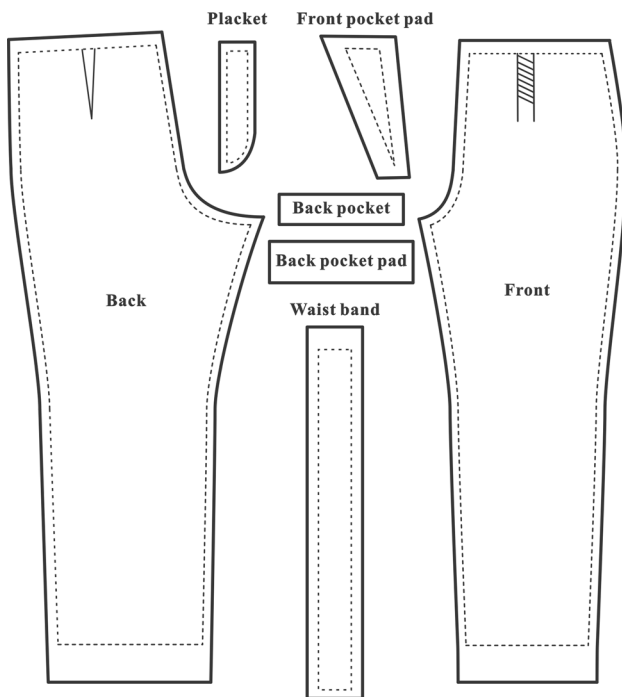
Fig. 9 A case of pants production patterns generated by IPPRS 2022

6 Conclusions

In this paper, we put forward a new design approach for customized garments towards sustainable fashion. It was based on 3D digital simulation and a series of machine learning techniques, involving radial basis function artificial neural network, probabilistic neural network, genetic algorithms, and support vector regression. The proposed approach is available to be applied in various classical 3D garment software, promoting the implementation level of garment e-MC for different fashion brand companies. The proposed design method as well as the process for customized garments are mainly supported by five design knowledge models. It can generate and recommend the most relevant design solution for consumers. Meanwhile, the proposed associate adjustment mechanism for garment patterns can dramatically reduce the difficulties of garment pattern-making without reducing the quality of garment patterns. More importantly, it is also able to generate personalized garment production patterns that can effectively enhance the linkage of fashion design and garment manufacturing which is quite critical in garment e-MC towards sustainable fashion. The contributions of this research can be mainly summarized as follows: (1) providing a feasible solution to resolve the critical technical bottleneck of offering quality products to satisfy consumer's personalized demands under the circumstances of a limited quantity of available data in garment e-MC;

(2) presenting potential prospects for sustainable fashion by designing quality customized products using 3D simulation and machine learning-based interaction technology; (3) offering reliable communication channels and mechanisms among products, consumers, and designers using more robust and intelligent computational tools; (4) facilitating the formation of sustainable manufacturing mode in the fashion industry by integrating the proposed approach into the advanced clothing assembly line; (5) supporting the form of a new generalized fashion product e-MC framework or platform by fully and systematically taking human aesthetic preferences, ergonomic demands, and product parameters into account; (6) boosting the emergence of a new O2O (order online and receive services off-line) business model in the fashion industry under the scenario of sustainable development.

Due to the length limitation of the paper, the proposed approach was verified using a real case of leisure pants customization only. Nonetheless, the general principles can be suitable for various garment styles. The validation of the proposed approach in other garment styles has become one of our future research works. Meanwhile, as the interactions among products, consumers, and designers are rather complicated and influenced by multiple factors (e.g. sociocultural backgrounds and human emotions), more affecting factors as well as their coupling effects should be taken into consideration in the future. Moreover, the performance promotion of the proposed approach through more advanced intelligent technologies constitutes one of our crucial future research directions.

Authors' Contributions Conceptualization, ZW and XZ; methodology, ZW and YX; software, ZW, XT, and PB; validation, ZW, YX, and ZX; resources, XZ and ZX; writing—original draft preparation, ZW, XT, and YX; writing—review and editing, ZW, XT, and XZ; visualization, ZW and YX; supervision, XT and XZ; project administration, ZW and YX; funding acquisition, ZW and YX. All authors have read and agreed to the published version of the manuscript.

Availability of Data and Material Since the data and materials are business secrets for the enterprises involved in this study, the authors are very sorry to declare that the data are not applicable and cannot be presented in public.

Declarations

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