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A Machine Learning-Enhanced 3D Reverse Design Approach to Personalized Garments in Pursuit of Sustainability

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Abstract: The fashion industry is facing increasing pressure to move toward sustainable development, especially with concern to cost and environmental sustainability. Innovative digital technologies are regarded as a promising solution for fashion companies to resolve this issue. In this context, this paper put forth a new 3D reverse garment design approach embedded with a garment fit prediction and structure self-adaptive adjustment mechanism, using machine learning (ML) techniques. Initially, the 3D basic garment was drawn directly on the scanned mannequin of a specific consumer. Next, a probabilistic neural network (PNN) was employed to predict the garment's fit. Afterwards, genetic algorithms (GA) and support vector regression (SVR) were utilized to estimate and control the garment structural parameters following the feedback of fit evaluation and the consumer's personalized needs. Meanwhile, a comprehensive evaluation was constructed to characterize the quantitative relationships between the consumer profile and the designed garment profile (garment fit and styles). Ultimately, the desired garment which met the consumer's needs was obtained by performing the routine of "design–fit evaluation–pattern adjustment–comprehensive evaluation", iteratively. The experimental results show that the proposed approach provides a new solution to develop quality personalized fashion products (garments) more accurately, economically, and in an environmentally friendly way. It is feasible to facilitate the sustainable development of fashion companies by simultaneously reducing costs and negative impacts on the environment.

Keywords: interactive 3D garment design; reverse engineering; machine learning; probabilistic neural network; genetic algorithms; support vector regression

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Citation: Wang, Z.; Tao, X.; Zeng, X.; Xing, Y.; Xu, Z.; Bruniaux, P. A Machine Learning-Enhanced 3D Reverse Design Approach to Personalized Garments in Pursuit of Sustainability. *Sustainability* **2023**, *15*, 6235. https://doi.org/10.3390/su15076235

Academic Editor: Wen-Hsien Tsai

Received: 6 March 2023
Revised: 29 March 2023
Accepted: 3 April 2023
Published: 4 April 2023

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1. Introduction

In recent years, there has been increasing pressure on companies in the fashion industry due to adverse impacts on the natural environment [1–6]. The fashion industry accounts for approximately 20 percent of industrial wastewater pollution worldwide, and 8–10 percent of humanity's carbon emissions, is was more than all international flights and maritime shipping combined [7]. This trend reinforces fashion companies' need for new business models for sustainability, in order to gain competitive advantages worldwide [8–10]. More specifically, sustainability in the fashion industry mainly endeavors to design, develop and manufacture quality products in an eco-friendly manner that has few negative impacts on the environment and society [11,12]. Nevertheless, quality fashion products are designed and developed traditionally by running the routine of "design–demonstration–evaluation–adjustment", using real garment prototypes [13]. It is obvious that the conventional garment design and development process, which is tedious, low-efficient, and material-wasting, is unfavorable for the sustainable development of fashion companies [14,15]. In this context, innovative digital technologies (i.e., 3D human body scanning, reverse engineering, virtual reality) have been regarded as key for updating the garment design process in pursuit of sustainability [16–18].

In the past decades, commercial 3D garment computer-aided design (CAD) software systems such as Style 3D, Lectra Modaris 3D, Clo 3D, OpiTex 3D Runway, Browzwear VStitcher, Marvelous Designer, and Assyst-Bullmer Vidya have been developed and made available commercially in the industry [19]. As the simulation of the garment design process can be conducted without manufacturing real garments [20], these systems allow the companies to accomplish objectives of sustainability, including material-saving and environmental protection. In the system, 3D reverse technology (also named 3D-to-2D flattening, 3D flattening, or 3D reverse engineering) has attracted increasing attention. Why is this technology attractive? The main merits of the technology are presented as follows. (1) The 2D garment patterns originate from the scanned 3D human body, which can reflect the surface morphology features of a specific human body, apart from the human body dimensions. The quality of the designed garment can be ensured and significantly improved. This technology facilitates higher levels of garment customization, especially through accomplishing one pattern for one person. (2) Compared with the traditional 2D design approach, the personalized garment is drawn and developed directly from a 3D digital mannequin, which is more intuitive and efficient because it dramatically reduces complicated calculations and manipulations. Therefore, 3D reverse technology embedded in the 3D garment CAD opens up new opportunities for practitioners (i.e., fashion designers, and pattern makers) to design garments more simply, precisely and quickly. Thus, it facilitates the achievement of the vision of sustainability by lessening the heavy environmental burden by reducing unnecessary waste of labor and materials.

In practice, the factors affecting garment quality (i.e., appearance, fitness, comfort, functionality, etc.) are sophisticated and connected [21]. Meanwhile, fashion design is experience and knowledge-dependent work. A novice fashion designer will find it more difficult to deal with the implicit relationships among these factors efficiently and accurately, because they are full of uncertainty and nonlinearity. Machine learning (ML) techniques, such as artificial neural networks (ANN), support vector regression (SVR), and genetic algorithm (GA), have the advantages of learning, generalizing, and dealing with complex nonlinear relationships and solving optimization problems [22,23]. As a result, several ML-based computational intelligence approaches (i.e., naive Bayes classifier, back propagation artificial neural networks, decision tree C4.5, etc.) have been developed to support fashion designers in making decisions during the process of garment design, especially for fit evaluation [20,24,25] and clothing production [26,27]. These pieces of research present good cases and bright prospects for the application of ML techniques in the fashion industry. Therefore, we extended the application of ML techniques, in terms of a probabilistic neural network (PNN), SVR and GA, to optimize traditional 3D reverse engineering technology for the fashion industry in this study.

Figure 1 illustrates our proposed interactive 3D garment design approach embedded with ML models. First, Model 1 was created to predict and evaluate the garment fit of the basic garment, which was designed directly on the 3D mannequin. This model permitted the prediction and control of the garment fit in a 3D digital design space by fully taking the garment's design parameters and the fabric's mechanical properties into consideration. In this way, it was able to ensure that the garment fit of the desired garment is satisfactory. Next, if the evaluation results from Model 1 were dissatisfactory, an adaptive adjustment mechanism for 2D garment patterns supported by the knowledge-based Model 2 would be activated. Then, Model 3 was established to comprehensively evaluate the garment quality, including the characteristics of garment fit and style. If the evaluation results from Model 3 were dissatisfactory, the aforementioned adjustment mechanism would be activated again. Ultimately, the desired garment will be obtained by performing the routine of "2D modification–3D demonstration–evaluation", repeatedly. Moreover, the 2D production patterns of the satisfactory 3D garment will be generated and delivered to the following manufacturing department.

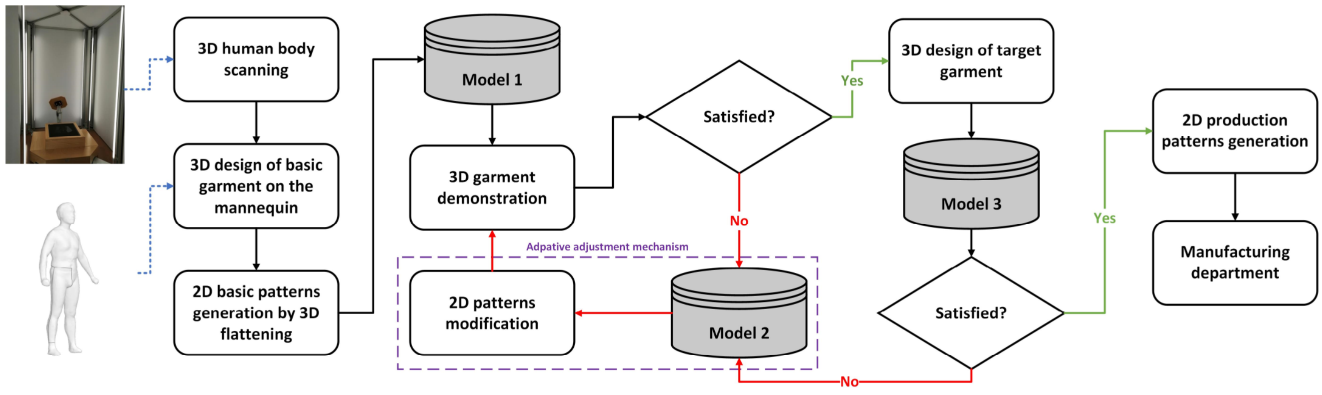


Figure 1. The proposed 3D reverse garment design process integrating machine learning and 3D reverse technology.

Compared with existing 3D reverse engineering-based garment design methods, the main merits of the proposed approach in this study are as follows:

- Reducing the difficulties of personalized garment design for fashion designers (especially the novice) and lessening the heavy dependency on the designer's experiences and skills by modelling profound design knowledge using ML techniques;
- Providing a new solution to overcome the technical drawbacks of current 3D reverse design methods for garment design by using ML techniques to enhance the reliability of flattened 2D garment patterns;
- Boosting the emergence of an innovative personalized design approach for fashion products (i.e., garments, footwear, headwear, etc.) by integrating fit evaluation and an adaptive mechanism into the conventional 3D design process;
- Facilitating the industrialized application of 3D reverse design technology in the fashion industry by resolving the current technical bottlenecks using intelligent computational tools;
- Offering a promising solution for fashion companies aiming for sustainability by designing quality fashion products in a more reliable, intuitive, accurate, efficient, and economical manner.

The remaining sections of this article are structured as below. The research methodology is introduced in Section 2. The production of the models concerned is explained concretely in Section 3. In Section 4, we discuss and validate the implementation of the proposed approach. Finally, the conclusion and future research directions are summarized in Section 5.

2. Research Methodology

2.1. Literature Review

Scholars in academia have attempted to develop new 3D garment design technology, aiming to promote product design quality and efficiency and the satisfaction of consumers while avoiding unnecessary waste of time, labor, and materials. For example, Li and Lu expounded a novel approach to creating 3D new garment models using garment examples rather than 2D patterns [21]. Ref. [28] introduced an evolving framework for designing the styling curves of garments. Bartle et al. presented a system permitting direct editing of garments in 3D space, which was very suitable for users with no experience in 2D garment patterns [29]. Liu et al. put forward a development and dynamic wear comfort evaluation method for cycling clothes patterns based on 3D virtual reality and flattening technology [30]. To develop female seamless soft body armor with ensured fitness and good comfort, Abtew et al. presented a 2D pattern development method based on a 3D adaptive virtual mannequin, using a reverse engineering technique [31]. In Ref. [32], Mesuda et al. put forward a design method for planar patterns using a cloth model by mapping. Liu et al.

proposed a sketch-based 3D garment patten-making technology which was able to deduce the form of a 3D garment based on the structural lines drawn on the virtual mannequin [33]. A 3D prototyping method supporting the automatic generation of swimsuit patterns was presented by Han in [34]. Lei et al. put forth a new 3D garment pattern-making method based on graphic coding to facilitate the transformation of 3D garments to 2D patterns more accurately and intuitively [35]. Liu et al. applied 3D reverse engineering technology to the digital restoration of ancient Chinese clothing [36,37]. Ji et.al proposed a method for flattening the 3D design of the corset to a 2D pattern using 3D point cloud data [38]. The above studies have revealed the bright prospects of the application of 3D reverse technology in the fashion industry.

However, 3D reverse design technology has still seldom been implemented in real garment manufacturing scenarios [35]. The major reason for this situation is that inaccurate 2D patterns are easily generated when the non-developable surfaces are flattened, due to the restrictions of current technology [35]. More importantly, an evaluation and adjustment mechanism to deal with the flattened 2D patterns, by which the generated 2D patterns can meet the requirements of real production, is lacking. To address this issue, we proposed a new interactive 3D garment design method, with the goal of sustainability, by combining machine learning with traditional 3D reverse engineering technology.

2.2. General Research Scheme

The research procedure of this study briefly includes three phases. In the first phase, several sensory experiments were conducted to collect the learning data for building Model 1, involving the sensory data on the garment fit of the actual garments, the fabric properties data, and the garment ease allowance or clothing pressure data measured in a digital 3D design space. The probabilistic neural network (PNN), proposed by Specht originally, is regarded a particular type of ANN model based on Bayesian decision rules [39,40]. Thanks to its excellent characteristics such as fast process speed, simple topology, less sensitivity to noisy data, being easy to model, etc., a PNN was employed to construct Model 1.

In the experiments of the second phase, we acquired the relevant learning data from the garment patterns, in terms of the length variation data of the structural lines (SL) and the movement data of the corresponding controlling points (CP). Compared with other regression techniques, support vector regression (SVR), working on the principles of a support vector machine (SVM), has several outstanding advantages, such as availability in both linear and non-linear regression and high generalizability, which can avoid the local minimum [41]. Furthermore, the genetic algorithm (GA) has been considered a powerful tool for dealing with complicated optimization problems due to its fast convergence and simple encoding. Therefore, an SVR combined with a GA (GASVR) was employed in our research to create Model 2.

In the last phase, we built Model 3 to characterize the quantitative relationships between the designed garment based on the proposed approach and the target garment. The experimental details will be concretely explained in the following Section 3.

Due to its outstanding advantages in intelligent computation, the ML models proposed in this study were developed using MATLAB programming language.

2.3. Formalization

Let $F = \{f_1, f_2, \ldots, f_m\}$ be a set of fabrics involved in this article.

Let $FP = \{fp_1, fp_2, \cdots, fp_{15}\}$ be a set of the fabric mechanical property descriptors, where $fp_1, fp_2, fp_3, fp_4, fp_5, fp_6, fp_7, fp_8, fp_9, fp_{10}, fp_{11}, fp_{12}, fp_{13}, fp_{14}, fp_{15}$ refer to Stretch weft, Stretch warp, Stretch bias, Bending weft, Bending warp, Bending bias, Buckling ratio weft, Buckling ratio warp, Buckling ratio bias, Buckling stiffness weft, Buckling stiffness warp, Buckling stiffness bias, Dynamic friction, Static friction, and Thickness, respectively.

Let $FV = \{fv_1, fv_2, \ldots, fv_{15}\}$ be a set of standardized values of mechanical properties of the fabric $f_i (i \in m)$ measured in the 3D virtual environment (Style 3D). The elements of FV have a one-to-one correspondence with those of FP.

Let $FIT = \{fit_1, fit_2, fit_3, fit_4, fit_5\} = \{1,2,3,4,5\}$ be a set of values representing the garment fit characteristics, corresponding to the linguistic values of sensory descriptors $\{''Too\ tight/short(1)'', ''Tight/Short(2)'', ''Perfect(3)'', ''Loose/Long(4)'', ''Too\ loose/long(5)''\}$.

Let $CP = \begin{bmatrix} FN & SN \end{bmatrix}$ be a vector for profiling the consumer's needs, where FN and SN refer to the needs of garment fit and style, respectively.

Let $FN = \begin{bmatrix} fn_1 & \cdots & fn_i & \cdots & fn_p \end{bmatrix} (fn_i \in nFIT)$ be a p-dimensional normalized vector representing the requirements of garment fit at p feature positions.

Let $SN = \{SN_1, \cdots, SN_j, \cdots, SN_q\}$ be a set of normalized vectors representing the needs for q categories of style design elements. For a specific garment style, the SN can be composed of various categories of style design elements. For example, as a classical style of men's wear, shirt style can be constituted by combining diverse design elements, such as the silhouette, garment length, collar, darts, pleats, pockets, etc.

Let $SN_j = \begin{bmatrix} sn_{j_1} & \cdots & sn_{j_v} & \cdots & sn_{j_u} \end{bmatrix}$ be a j_u-dimensional one-hot vector expressing the need for a j-th category style design element. The value of sn_{j_v} is denoted as the nearness degree of the style needed to the j_v-th style element.

For instance, if the chest pocket (CT) of shirt style includes four basic types, namely no CT, patch CT, patch CT without flap, and insert CT, then it can be defined by:

$$SN_{chest\ pocket} = \{no\ CT,\ patch\ CT,\ patch\ CT\ without\ flap,\ insert\ CT\}.$$

If a $SN_{chest\ pocket} = \begin{bmatrix} \overset{no\ CT}{0} & \overset{patch\ CT}{0} & \overset{patch\ CT\ without\ flap}{1} & \overset{insert\ CT}{0} \end{bmatrix}$, it means that the need for the chest pocket style is patch CT without flap.

Let $GP = \begin{bmatrix} FC & SC \end{bmatrix}$ be a vector for profiling the characteristics of the garment designed by machine learning-enhanced 3D reverse technology, where FC and SC represent the characteristics of garment fit and style, respectively.

Let $FC = \begin{bmatrix} fc_1 & \cdots & fc_i & \cdots & fc_p \end{bmatrix} (fc_i \in nFIT)$ be a p-dimensional normalized vector representing the characteristics for garment fit at p feature positions. The elements of FC have a one-to-one correspondence with those of FN.

Let $SC = \{SC_1, \ldots, SC_j, \cdots, SC_q\}$ be a set of one-hot vectors expressing the style characteristics of the designed garment from the aspects of the q categories of style design elements.

Let $SC_j = \begin{bmatrix} sc_{j_1} & \cdots & sc_{j_v} & \cdots & sc_{j_u} \end{bmatrix}$ be a j_u-dimensional vector expressing the concrete style characteristics of a designed garment in the j-th category style design element. The structure of SC_q has a one-to-one correspondence with that of SN_q. Moreover, the value of sc_{j_v} is defined by using the same method as sn_{j_v}, as mentioned above.

2.4. Acquisition of the Modelling Data

2.4.1. Acquisition of the Learning Data for Model 1 (Experiment I)

Model 1 was denoted as a knowledge base for garment fit prediction. Its main objective concentrated on predicting the garment fit characteristics in a 3D virtual environment without any physical try-on. The output learning data of Model 1 was the sensory data on garment fit collected from the real try-on experiments. The input learning data, including garment ease allowance, clothing pressure, and fabric mechanical properties, were acquired using the 3D garment CAD software Style 3D, thanks to its outstanding simulation effects. The concrete data acquisition procedures are described below:

Step 1: Both loose and tight-fitting garments were considered in our research. Since the experiment objectives focused on the garment fit, simple-style garments without any redundant ornaments (see Figure 2) were prepared and involved in our experiments. For each style of the involved experimental garment, we chose five sizes with five kinds of fabrics.

Figure 2. The involved experiment garment styles. Note: (**a**) loose-fitting top garment; (**b**) loose-fitting lower garment; (**c**) tight-fitting top garment; (**d**) tight-fitting lower garment.

Step 2: Since the fashion companies involved in our research project aimed to expand the Chinese men's wear market, we recruited male experimental subjects in China to participate in this research. The basic idea and principles can be generalized for other companies and institutions to develop target markets by enrolling the subjects from the target population.

To guarantee the procedure and results of the sensory experiments, a professional with over 20 years of experience in studying and developing garment sizing systems was invited to take part in our experiments. With her profound knowledge and rich experience, 16 male subjects with representative human body shapes were screened out. Their body sizes corresponded to the sizes defined in the China National Standard (GB/T 1335.1-2008) [42], which were 155/80A, 155/84A, 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, respectively. There were two major principles of subject selection: (1) the body sizes were selected according to the accommodate rate (AR) of the China National Standard (GB/T 1335.1-2008) in descending order; (2) the aggregated AR value of the selected body sizes should cover most of the Chinese population.

Step 3: In a laboratory with constant temperature (20 ± 2 °C) and relative humidity ($65 \pm 5\%$), we declared the objective of this experiment to the subjects first. Next, when all the subjects agreed to the experiment, each of the 16 subjects performed his try-on with the experimental garments and perceived the fit levels in various scenarios, such as standing, sitting, walking, squatting, etc. After that, they recorded the evaluation value of the garment fit at each feature position of the garment based on the semantic differential method. The evaluation value of garment fit was represented by $\{1, 2, 3, 4, 5\}$, corresponding to the linguistic values $\{\text{too tight/short, tight/short, perfect, loose/long, too loose/long}\}$. Finally, all the evaluation data were aggregated to the output learning data of Model 1.

For each experimental garment style, 400 records of data were collected to form the learning dataset.

2.4.2. Acquisition of the Learning Data for Model 2 (Experiment II)

Model 2 was defined as an adjustment rules knowledge base for garment patterns, enabling the adaptive adjustment of garment patterns. The acquisition of the learning data of Model 2 is presented concretely below:

Step 1: The key pattern panel and the associate panels were identified based on the knowledge of the designer. In our research, for both the top and the lower garment, the front pattern panel was chosen as the key panel, with the other panels as the associate panels.

Step 2: As shown in Figure 3, first of all, we decomposed the key pattern panel, and then extracted a series of SLs, keeping the status of the SLs in original patterns, including length, direction, angle, radian, etc. Next, for all the extracted SLs, we defined the movement directions of the corresponding CPs in the same coordinate system, including horizontal and vertical directions. Lastly, for a certain structural line (sl_i) and its corresponding controlling points (cp_v, cp_{v+1}), we collected the movement data of the two CPs, including dx_cp_v, dy_cp_v, dx_cp_{v+1} and dy_cp_{v+1}, under various moving scenarios, and then record the corresponding length variation data dl_sl_i of the structural line sl_i. These data were stored and utilized as the learning dataset to establish Model 2.

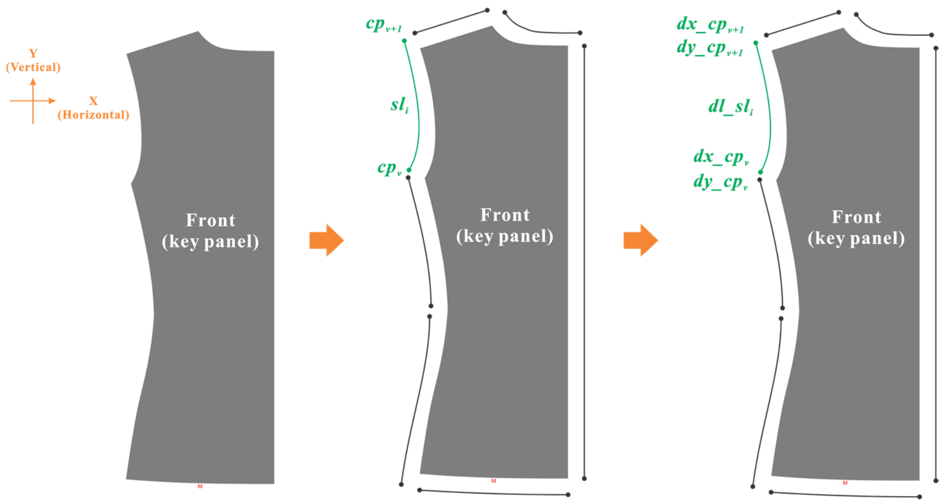


Figure 3. A case of the learning data acquisition of the key pattern panel of a specific garment style.

3. Construction of the Computational Tools for Optimizing the 3D Reverse Design Method

3.1. Creation of Knowledge Base for Garment Fit Prediction (Model 1)

The proposed knowledge base for garment fit prediction (see Figure 4) consisted of three layers, involving the data layer, the computational layer, and the decision layer. In the data layer, the learning data collected from Experiment I were stored in a series of databases, such as the human body dimension database, the garment ease allowance database, the clothing pressure database, and the fabric mechanical property database. The data in the data layer were analyzed quantitatively and modelled in the computational layer, aiming to realize the prediction of garment fit at each feature position. The computational layer constituted the core of Model 1. The decision layer presented the global and local garment fit characteristics aggregated from the computational layer. Due to its excellent performance mentioned in Section 2, a PNN was employed to construct the garment fit prediction models in the computational layer (see Figure 4).

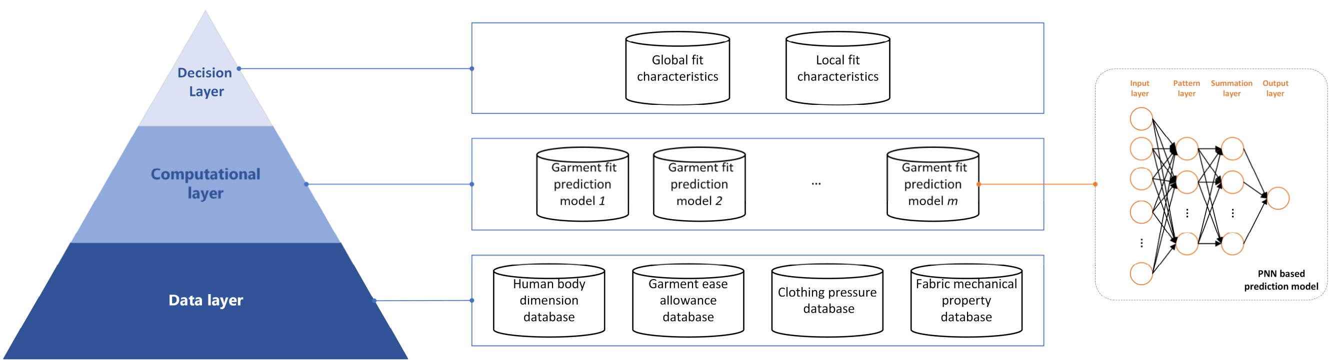


Figure 4. The pyramid structure of Model 1.

For a specific feature position i, the construction of a PNN-based garment fit prediction model is generally described as follows:

Step 1: The inputs were distributed to the input layer of the PNN model, represented by a vector $input_i$:

$$input_i = \{garment\ fit\ indicator, fv_1, fv_2, \cdots, fv_{15},\}$$

where the garment fit indicator was determined by the fit characteristics of the garment style. For the loose-fitting garment style, garment ease allowance was utilized, while the clothing pressure was used for the tight-fitting garment. The parameters ($fv_1 \sim fv_{15}$) were measured and obtained using a fabric property measurement tool associated with the software Style 3D.

Step 2: First, in the pattern layer, the relationship between the input vector $input_i$ and each pattern of the fit characteristics fit_j was calculated by the Euclidean distance, following Equation (1). Afterwards, the neuron output of the pattern layer was activated by a radial Gauss function similar to Equation (2).

$$Ed_{ij} = ||input_i - fit_j|| \quad (1)$$

$$Op_{ij}^{pattern} = exp\left[-\frac{Ed_{ij}}{2\sigma^2}\right] \quad (2)$$

where σ referred to the spread parameter, also named the smoothing parameter.

Step 3: In the summation layer, one summation neuron corresponds to the fit characteristics fit_j. For each summation neuron, the inputs from the pattern layer belonging to the fit characteristics fit_j were aggregated following Equation (3) accordingly.

$$S_{ij} = \sum_{i=1}^{l} Op_{ij}^{pattern} = \sum_{i=1}^{l} exp\left[-\frac{Ed_{ij}}{2\sigma^2}\right] \quad (3)$$

where l was the number of samples belonging to the fit characteristics fit_j.

The class-conditional probability of the i-th sample belonging to the fit characteristics fit_j was computed following Equation (4):

$$Op_j^{summation} = P\left(input_i \middle| fit_j\right) = \frac{S_{ij}}{l} \quad (4)$$

Step 4: Based on the Bayes theory, the fit characteristics of the i-th sample were decided by Equation (5) in the output layer. This meant that the largest $P\left(input_i \middle| fit_j\right)$ would be identified and the corresponding j would be declared as the category of the input vector $input_i$.

$$Categroy(x_i) = argmax\left(Op_j^{summation}\right) = argmax\left(P\left(input_i \middle| fit_j\right)\right) \quad (5)$$

The $K - fold$ $(K = 10)$ cross-validation approach was utilized to create the PNN-based prediction model. Concretely, the learning dataset was randomly split into $K(= 10)$ smaller sets first. Additionally, then, for each of the K "folds", $K - 1(= 9)$ small sets with 360 instances, were employed as the training dataset, in turn, to train the model, with the remaining part of the original dataset as the validation dataset. Finally, the garment fit prediction model at the feature position i was determined after $10 - fold$ cross-validation.

3.2. Creation of Knowledge Base for Garment Pattern Adjustment (Model 2)

The proposed adjustment rules knowledge base for garment patterns (see Figure 5) was composed of a series of basic databases and relational models. The relational models in the key pattern panel aimed to quantitatively characterize the relations between the length change data of the structural lines (SLs) and the movement data of the controlling points (CPs). Based on these models, we further defined the adjustment rules of the key pattern panel. By constructing the model expressing the relations between the associate panels and the key panel, the adjustment rules of the associate panels were achieved. They were key to the success of the implementation of the adaptive self-adjustment mechanism proposed in this study.

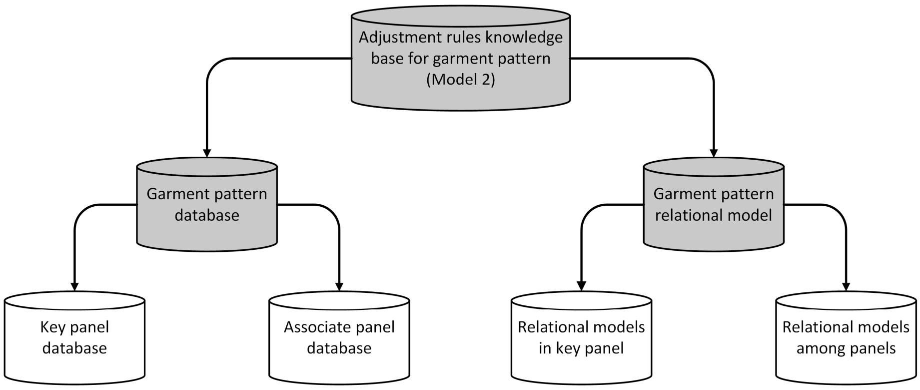


Figure 5. The hierarchical structure of Model 2.

Thanks to the advantages mentioned in Section 2, an SVR combined with GA (GASVR) was employed in our research to create Model 2. Considering the possible movements of the CPs, we created five GASVR-based relational models, respectively for each SL (sl_i) in the key pattern panel. The input and output of the concerned models for the sl_i were defined following the principles presented in Table 1.

Table 1. The inputs and output of the GASVR-based relational models of the structure line sl_i in the key pattern panel.

Model Name	Input	Output
$GASVR_1$	dx_cp_v, dy_cp_v, dx_cp_{v+1}, dy_cp_{v+1}	dl_sl_i
$GASVR_2$	dl_sl_i, dy_cp_v, dx_cp_{v+1}, dy_cp_{v+1}	dx_cp_v
$GASVR_3$	dx_cp_v, dl_sl_i, dx_cp_{v+1}, dy_cp_{v+1}	dy_cp_v
$GASVR_4$	dx_cp_v, dy_cp_v, dl_sl_i, dy_cp_{v+1}	dx_cp_{v+1}
$GASVR_5$	dx_cp_v, dy_cp_v, dx_cp_{v+1}, dl_sl_i	dy_cp_{v+1}

Note: cp_v and cp_{v+1} represent the controlling points corresponding to the structure line sl_i.

The relational models between the associate and key pattern panels were defined following the correspondence between the associate panels and the key panel based on classical garment-making knowledge. These models aimed to realize the associate and adaptive adjustment of the associate panels.

3.3. Creation of the Comprehensive Evaluation Model (Model 3)

A similarity degree indicator $sim(CP,\ GP)$ was defined to represent the quantitative relationships between the consumer profile (CP) and the designed garment profile (GP). In this study, the $sim(CP,\ GP)$ was denoted and calculated by Equation (6).

$$sim(CP, GP) = 0.5 \times sim(FN, FC) + 0.5 \times sim(SN, SC) \tag{6}$$

The $sim(FN, FC)$, as shown in Equation (7), represents the indicator of the similarity degrees between the garment fit needs (FN) and the fitness characteristics (FC) of the designed garment profile (GP).

$$sim(FN, FC) = similarity^{garment\ fit} = \frac{\sum_1^m min(fn_i, fc_i)}{\sum_1^m max(fn_i, fc_i)} \tag{7}$$

where fn_i and fc_i refer to the fit need and fit characteristics at i-th feature position.

The values of $sim(FN, FC)$ are between 0 and 1. From Equation (7), if the fit characteristics are close to the fit needs at each feature position, the value of $sim(FN, FC)$ is close to 1. Otherwise, it tends to be 0.

The $sim(SN, SC)$, as shown in Equation (8), refers to the indicator for expressing the similarity degree between the style needs (SN) and the style characteristics (SC) of a specifically designed garment profile (GP).

$$\begin{aligned} sim(SN, SC) &= similarity^{garment\ style} \\ &= \frac{\sum_j \sum_i min(sn_i, sc_i)}{\sum_j \sum_i max(sn_i, sc_i)},\ (sn_i \in SN_j \in SN, sc_i \in SC_j \in SC) \end{aligned} \tag{8}$$

The values of $sim(SN, SC)$ vary between 0 and 1. If all style elements of SN and SC are close to each other, the value of $sim(SN, SC)$ is close to 1. Otherwise, it tends to be 0.

4. Application, Validation, and Discussion

4.1. Application in the Customization of Personalized Tight-Fitting Garments

4.1.1. Definition of the Consumer Profile for Tight-Fitting Garments

Since the sport legging is a classical and popular tight-fitting garment style, we elaborate our proposed technology using a real customization case of sport leggings for a specific male consumer in this section. After multiple interactions with the consumer, the vector-style consumer profile for the sport leggings was obtained (see Table 2).

Table 2. Consumer profile for the tight-fitting garment.

	S.N.	Category	Normalized Vectors	Notes
Style needs	1	Silhouette	$SN_1 = \begin{bmatrix} H & A & X & T & S \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	S shape ("S" represents Skinny.)
	2	Length	$SN_2 = \begin{bmatrix} Mini & Thigh & Knee & Ankle & Full \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$	Ankle length
	3	Waist line position	$SN_3 = \begin{bmatrix} High & Normal & Lower \\ 0 & 0 & 1 \end{bmatrix}$	Lower waist line
	4	Waist band	$SN_4 = \begin{bmatrix} No & Straight & Curve \\ 0 & 1 & 0 \end{bmatrix}$	Straight waist band
	5	Leg opening	$SN_5 = \begin{bmatrix} Tapered & Straight & Flared \\ 1 & 0 & 0 \end{bmatrix}$	Tapered opening
	6	Dart	$SN_6 = \begin{bmatrix} No\ front & Single\ front & Double\ front & Multiple\ front & No\ back & Single\ back \\ 1 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$	No front and back dart
	7	Pleat	$SN_7 = \begin{bmatrix} No\ front & Single\ front & Double\ front & Multiple\ front \\ 1 & 0 & 0 & 0 \end{bmatrix}$	No front pleat
	8	Yoke	$SN_8 = \begin{bmatrix} No & Straight & Curve & Special \\ 0 & 1 & 0 & 0 \end{bmatrix}$	Straight yoke
	9	Ornament	$SN_9 = \begin{bmatrix} Embroidery & Printing & Riveiting & Quilting & Hollow\ cut & No \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	No ornament
	10	Pocket	$SN_{10} = \begin{bmatrix} NF & FI & FIC & FP & NB & BI & BIF & BP & BPF \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$ [1]	Front inserted pocket
Fit needs			$FN = \begin{bmatrix} Waist\ girth & Hip\ girth & Thigh\ girth & Knee\ girth & Ankle\ girth \\ 3 & 3 & 3 & 3 & 3 \end{bmatrix}$	Perfect

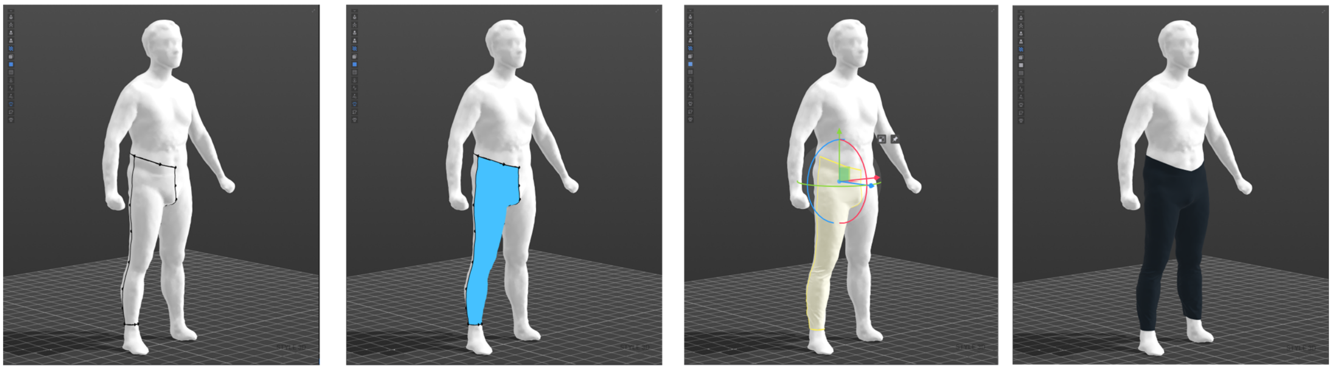
[1] Note: *NF*, *FI*, *FIC*, *Fp*, *NB*, *BI*, *BIF*, *BP*, and *BPF* refer to No front pocket, Front inserted pocket, Front inserted pocket with coin pocket, Front patched pocket, No back pocket, Back inserted pocket, Back inserted pocket with flap, Back patched pocket, and Back patch pocket with flap, respectively.

4.1.2. Design of the 3D Basic Garment

The design process of the 3D garment associated with 2D patterns was generally split into three sequential parts. In the first part, a 3D basic garment with the main structural lines (especially the outlines) was created directly from the scanned mannequin of the consumer. In the second part, a procedure of garment fit evaluation and adjustment was conducted on the created basic garment to ensure the garment fit fulfilled the consumer's needs. In the third part, the desired garment was achieved by supplementing the remaining style design details to the fit-ensured 3D basic garment.

The creation of the 3D basic garment associated with 2D patterns is described below:

Step 1: The reference structural lines (the outlines) were drawn directly on the scanned human body model, see Figure 6a.



(a) **(b)** **(c)** **(d)**

Figure 6. The general design process of the 3D basic garment. Note: (**a**) Drawing the structure lines on the scanned human body mode; (**b**) Peeling the "skin" from the scanned mannequin; (**c**) Generating the 3D garment pieces; (**d**) Forming the 3D garment.

Step 2: The 3D garment pieces associated with 2D patterns were generated by peeling the "skin" from the scanned mannequin, see Figure 6b,c.

Step 3: The 3D tight-fitting garment was obtained by a series of operations of virtual stitching, such as mirroring, sewing, digital fabric assignment, etc., see Figure 6d. The involved digital fabric corresponding to the real fabric selected was measured and modelled by the fabric property measurement tool associated with the Style 3D software. The properties of the involved fabric used to model the 3D tight-fitting garment can be expressed by: $\left\{\overset{fp_1}{61}, \overset{fp_2}{58}, \overset{fp_3}{27}, \overset{fp_4}{32}, \overset{fp_5}{32}, \overset{fp_6}{31}, \overset{fp_7}{0}, \overset{fp_8}{0}, \overset{fp_9}{0}, \overset{fp_{10}}{0}, \overset{fp_{11}}{0}, \overset{fp_{12}}{0}, \overset{fp_{13}}{0.03}, \overset{fp_{14}}{0.03}, \overset{fp_{15}}{0.42}\right\}$.

4.1.3. Fit Evaluation of the Basic Garment

First, the clothing pressures at the feature positions of the initial 3D garment were collected as shown in Figure 7. Additionally, then, they were aggregated following the feature positions. The aggregated pressure data were given as follows:

$$Pr^{initial} = \left\{\overset{W}{8.28}, \overset{H}{55.96}, \overset{T}{81.79}, \overset{K}{55.15}, \overset{C}{35}\right\}$$

where, W, H, T, K, and C refer to waist, hip, thigh, knee, and calf, respectively.

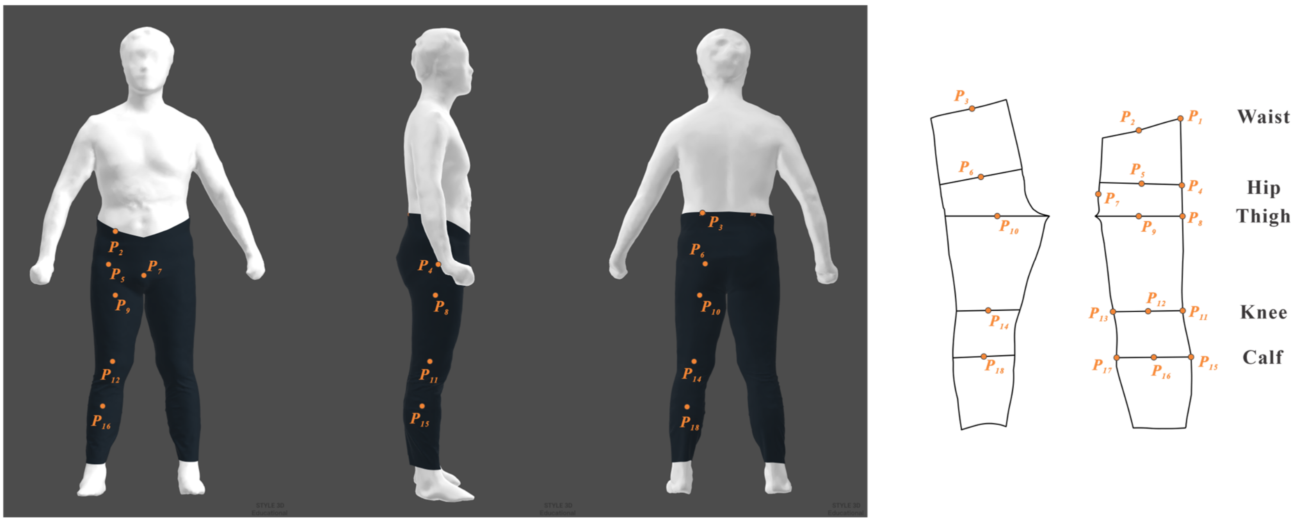


Figure 7. Scheme of acquisition of the clothing pressures.

Second, the input vector, which consisted of integrating the clothing pressure and the fabric properties' parameters, was imported into the proposed PNN-based models. Additionally, then, we obtained the predictive fit characteristics for the basic garment, represented by: $FC^{initial} = \left\{ \begin{matrix} W & H & T & K & C \\ 5, & 3, & 1, & 3, & 4 \end{matrix} \right\}$. This meant that the fit characteristics of the waist, hip, thigh, knee, and calf were too loose, perfect, too tight, perfect, and loose, respectively. Both the hip and knee parts met the consumer's fit needs.

Furthermore, according to Equations (6)–(8), we obtained the similarity between the initial garment profile and consumer profile: $sim\left(FN, FC^{initial}\right) = 0.7222$, $sim\left(SN, SC^{initial}\right) = 0.8000$, and $sim\left(CP, GP^{initial}\right) = 0.7611$. It can be found that the value of $sim\left(CP, GP^{initial}\right)$ was smaller than 0.8, which is relatively low. Therefore, the adjustment mechanism was activated.

4.1.4. Adjustment of the Basic Garment

Initially, an iterative adjustment process of garment fit was conducted. The general principle of the process was described as follows. In the first round of adjustment, we adjusted the garment fit at the target feature positions, using a series of preset adjustment rules. Then, we conducted a process of garment fit evaluation on the adjusted garment. If all the fit characteristics of the feature positions met the consumer's needs, the process of garment fit adjustment was terminated. Otherwise, a second round of adjustment and evaluation continued. The circle of "2D pattern adjustment–3D garment fit evaluation" ran iteratively until all the consumer's needs were fulfilled.

Let $AP^k = \left\{ \begin{matrix} WG & HG & TG & KG & CG \\ ap_{k1}, & ap_{k2}, & ap_{k3}, & ap_{k4}, & ap_{k5} \end{matrix} \right\}$ be a set of garment pattern adjustment parameters of the k-th round, where WG, HG, TG, KG, and CG represent the abbreviation of the garment dimensions at feature positions, in terms of waist girth, hip girth, thigh girth, knee girth, and calf girth, respectively.

At first, the total adjustment rules of the initial garment were set in this study, namely $AP^1 = \left\{ \begin{matrix} WG & HG & TG & KG & CG \\ -4, & 0, & 2, & 0, & -2 \end{matrix} \right\}$. Next, the total adjustment rules were decomposed to each garment pattern panel. The adjustment rules of the key pattern panel (front panel) were defined as $FAP^1 = \left\{ \begin{matrix} WG & HG & TG & KG & CG \\ -1, & 0, & 1, & 0, & -1 \end{matrix} \right\}$. Additionally, then, the first round of the adjustment procedure for the key panel (see Figure 8) was executed. The main steps are described as follows.

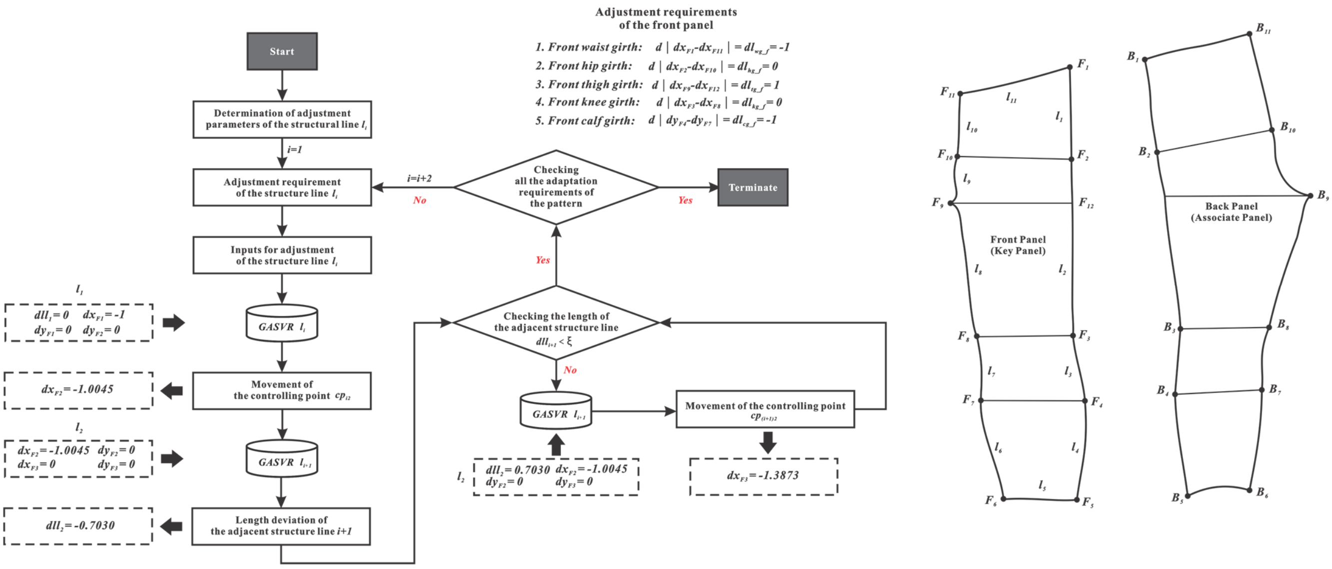


Figure 8. General flowchart of adjustment of the key pattern panel in the first round.

(1) Calculation of the moving data of the controlling point F_2 in the structural line l_1;

(2) Analysis of the influence of the movement of F_2 on the length deviation of the adjacent structural line l_2.

If the deviation was larger than a predefined threshold value ε, we returned to the last step to recompute the moving data of F_2. Otherwise, we continued to compute the moving data of the point F_3.

(3) The cycle of "adjustment–analysis" was performed repeatedly and terminated until all the adjustment requirements of the key panel were achieved.

Afterwards, the associate panels were adjusted using the rules defined by modelling the quantitative relationships of the controlling points between the associate and key panels. The adjustment parameters can be found in Table 3.

Additionally, then, we evaluated the garment fit. The aggregated pressures at six feature positions were defined as $Pr^{1st\ adjustement} = \left\{ \overset{W}{56.76}, \overset{H}{76.33}, \overset{T}{83.40}, \overset{K}{57.93}, \overset{C}{56.58} \right\}$. The garment fit characteristics at feature positions after the first round of adjustment were predicted: $FC^{1st\ adjustment} = \left\{ \overset{W}{3}, \overset{H}{2}, \overset{T}{2}, \overset{K}{3}, \overset{C}{3} \right\}$. This meant that there were still two feature positions not meeting the consumer's fit needs. Meanwhile, as illustrated in Figure 9II, the red region in the side part of the legging had expanded after the first round of adjustment, showing that the fit characteristics of the side parts tend to be tight. Hence, the adjustment proceeded to the second round, the adjustment parameters of which are presented in Table 3.

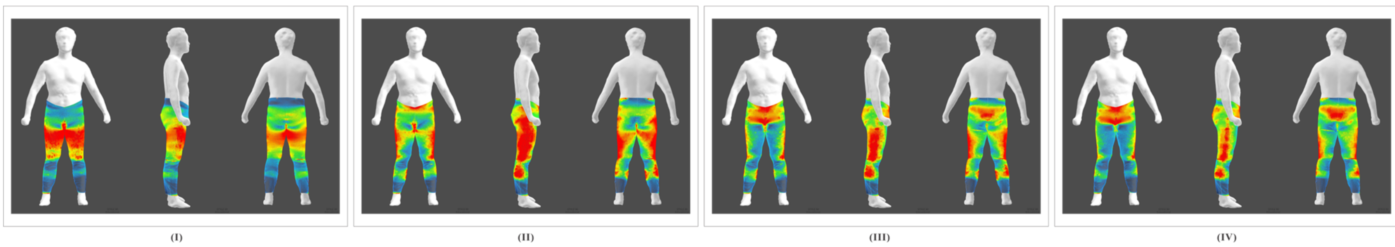


Figure 9. Comparison of the garments before and after adjustment. Note: (**I**) The garment before the adjustment; (**II**) The garment after the first round of adjustment; (**III**) The garment after the second round of adjustment; (**IV**) The garment after the third round of adjustment.

From Figure 9III, it was found that the fit characteristics of the side parts had been improved as the red region had shrunk. The aggregated pressures were expressed by $Pr^{2nd\ adjustement} = \left\{ \overset{W}{62.14}, \overset{H}{65.84}, \overset{T}{57.80}, \overset{K}{57.90}, \overset{C}{68.70} \right\}$, corresponding to the predicted garment fit characteristics $FC^{2nd\ adjustment} = \left\{ \overset{W}{3}, \overset{H}{2}, \overset{T}{3}, \overset{K}{3}, \overset{C}{2} \right\}$. This indicated that the hip and calf parts still needed to be adjusted. Therefore, the third round of adjustment continued. The pressures and garment fit characteristics after this round of adjustment were, respectively, expressed by: $Pr^{3rd\ adjustement} = \left\{ \overset{W}{53.97}, \overset{H}{57.63}, \overset{T}{49.55}, \overset{K}{58.92}, \overset{C}{50.95} \right\}$ and $FC^{3rd\ adjustment} = \left\{ \overset{W}{3}, \overset{H}{3}, \overset{T}{3}, \overset{K}{3}, \overset{C}{3} \right\}$. After three rounds of adjustment, it was concluded that all the garment fit characteristics at feature positions met the consumer's needs. The garment fit adjustment process therefore came to an end. Meanwhile, the similarity $sim\left(FN, FC^{adjusted}\right)$ was computed by following Equation (7), equaling 1.0000. Additionally, the $sim\left(CP, GP^{adjusted}\right)$ increased to 0.9000 from 0.7611.

Table 3. The adjustment rules for the tight-fitting garment.

Controlling Points		1st Round of Adjustment		2nd Round of Adjustment		3rd Round of Adjustment	
		Horizontal Direction	Vertical Direction	Horizontal Direction	Vertical Direction	Horizontal Direction	Vertical Direction
F_1	Front side waist	−1.0000	0	0	0	0	0
F_2	Front side hip	−1.0045	0	0.5000	0.0025	0	0
F_3	Front side knee	−0.9281	0	0	0	0	0
F_4	Front side calf	−0.5000	0.0058	0	0	0	0
F_5	Front side hem	0	0.0163	0	0	0	0
F_6	Front inseam hem	0.0011	0.0163	0	0	−0.5000	0
F_7	Front inseam calf	0.5000	0.0073	0	0	0	0
F_8	Front inseam knee	−0.9281	0.3580	0	0	0	0
F_9	Front crotch	−1.0000	0.6848	−1.0000	0	−1.0000	0
F_{10}	Front center hip	−1.0045	0.1341	0.5000	−0.7651	0	−0.6939
F_{11}	Front center waist	0	0	0	0	0	0
B_1	Back side waist	1.0000	0	0	0	0	0
B_2	Back side hip	1.0045	0	−0.5000	0.0025	0	0
B_3	Back side knee	0.9281	0	0	0	0	0
B_4	Back side calf	0.5000	0.0058	0	0	0	0
B_5	Back side hem	0	0.0163	0	0	0	0
B_6	Back inseam hem	−0.0011	0.0163	0	0	0	0
B_7	Back inseam calf	−0.5000	0.0073	0	0	0.5000	0
B_8	Back inseam knee	0.9281	0.3580	0	0	0	0
B_9	Back crotch	1.0000	0.6848	1.0000	0	1.0000	0
B_{10}	Back center hip	1.0045	0.1341	−0.5000	−0.7651	0	−0.6939
B_{11}	Back center waist	0	0	0	0	0	0

We further designed the garment by adding style design details following the consumer's needs (see Figure 10I). Thus, both the similarity $sim\left(SN, SC^{adjusted}\right)$ and $sim\left(CP, GP^{adjusted}\right)$ reached 1.000. This meant the adjustment process came to an end.

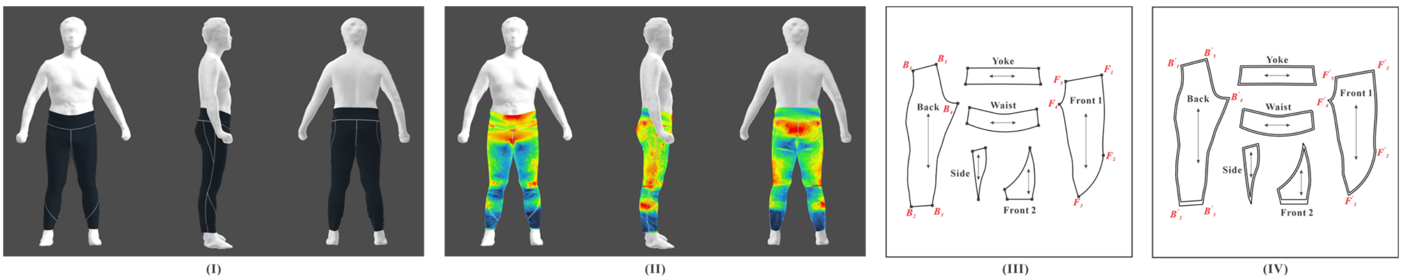


Figure 10. The designed tight-fitting garment. Note: (**I**) The 3D stereogram; (**II**) The garment fitting effects; (**III**) The 2D garment patterns; (**IV**) The garment production patterns.

4.1.5. Design of the Production Pattern Panel

Garment production patterns are regarded as a critical link between fashion design and garment manufacturing. In this study, the 2D patterns determined by the above steps were post-processed first to meet the requirements of garment production. Additionally, then, we designed the production patterns (see Figure 10IV) by defining the quantified relationships between the controlling points in the production panels and the original panels (see Table 4).

Table 4. The design rules of the production panels of the front 1 and back panels.

	Controlling Points of the Original Panel	Coordinates		Controlling Points of the Production Panel	Coordinates	
		Horizontal Direction	Vertical Direction		Horizontal Direction	Vertical Direction
Front 1	F_1	x^{F_1}	y^{F_1}	$F\prime_1$	$x^{F_1}+1$	$y^{F_1}+1$
	F_2	x^{F_2}	y^{F_2}	$F\prime_2$	$x^{F_2}+1$	$y^{F_2}-1$
	F_3	x^{F_3}	y^{F_3}	$F\prime_3$	$x^{F_3}-1$	$y^{F_3}-1$
	F_4	x^{F_4}	y^{F_4}	$F\prime_4$	$x^{F_4}-1$	y^{F_4}
	F_5	x^{F_5}	y^{F_5}	$F\prime_5$	$x^{F_5}-1$	$y^{F_5}+1$
Back	B_1	x^{B_1}	y^{B_1}	$B\prime_1$	$x^{B_1}-1$	$y^{B_1}+1$
	B_2	x^{B_2}	y^{B_2}	$B\prime_2$	$x^{B_2}-1$	$y^{B_2}-1$
	B_3	x^{B_3}	y^{B_3}	$B\prime_3$	$x^{B_3}+1$	$y^{B_3}-1$
	B_4	x^{B_4}	y^{B_4}	$B\prime_4$	$x^{B_4}+1$	y^{B_4}
	B_5	x^{B_5}	y^{B_5}	$B\prime_5$	$x^{F_5}+1$	$y^{B_5}+1$

4.2. Application in the Customization of Personalized Loose-Fitting Garments

4.2.1. Definition of the Consumer Profile for Loose-Fitting Garments

The proposed method can not only be suitable for tight-fitting garments, but also for loose-fitting garments. In this section, we elaborate on its implementation with the customization of straight-legged trousers. The consumer profile for straight-legged trousers was defined by vectors (see Table 5).

Table 5. Consumer profile for loose-fitting garment.

	S.N.	Category	Normalized Vectors	Notes
Style needs	1	Silhouette	$SN_1 = \begin{bmatrix} H & A & X & T & S \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	H shape
	2	Length	$SN_2 = \begin{bmatrix} Mini & Thigh & Knee & Ankle & Full \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	Full length
	3	Waist line position	$SN_3 = \begin{bmatrix} High & Normal & Lower \\ 0 & 1 & 0 \end{bmatrix}$	Normal waist line
	4	Waist band	$SN_4 = \begin{bmatrix} No & Straight & Curve \\ 0 & 1 & 0 \end{bmatrix}$	Straight waist band
	5	Leg opening	$SN_5 = \begin{bmatrix} Tapered & Straight & Flared \\ 0 & 1 & 0 \end{bmatrix}$	Straight opening
	6	Dart	$SN_6 = \begin{bmatrix} No\ front & Single\ front & Double\ front & Multiple\ front & No\ back & Single\ back \\ 1 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	Single back dart
	7	Pleat	$SN_7 = \begin{bmatrix} No\ front & Single\ front & Double\ front & Multiple\ front \\ 1 & 0 & 0 & 0 \end{bmatrix}$	No front pleat
	8	Yoke	$SN_8 = \begin{bmatrix} No & Straight & Curve & Special \\ 1 & 0 & 0 & 0 \end{bmatrix}$	No yoke
	9	Ornament	$SN_9 = \begin{bmatrix} Embroidery & Printing & Riveiting & Quilting & Hollow\ cut & No \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	No ornament
	10	Pocket	$SN_{10} = \begin{bmatrix} NF & FI & FIC & FP & NB & BI & BIF & BP & BPF \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}^1$	Back inserted pocket
Fit needs			$FN = \begin{bmatrix} Waist\ girth & Hip\ girth & Thigh\ girth & Knee\ girth & Ankle\ girth \\ 3 & 5 & 5 & 5 & 5 \end{bmatrix}$	Perfect at waist girth, and loose at other feature positions

4.2.2. Design, Evaluation, and Adjustment of the Desired Loose-Fitting Garment

The design of the desired straight-legged trousers started from the flattened patterns of the 3D basic garment described in Section 4.1.2. First, the circle of "pattern adjustment–garment fit evaluation" was executed until the fit needs of the consumer were met. In our case, we performed two rounds of adjustments to attain the fit goals. The concrete adjustment rules are shown in Table 6. Afterwards, we added the required style details to the adjusted garment. Ultimately, the desired straight-legged trousers were achieved, and the patterns were post-processed following the requirements of industrial garment production.

Table 6. The adjustment parameters for loose-fitting garments.

Controlling Points		1st Round of Adjustment		2nd Round of Adjustment	
		Horizontal Direction	Vertical Direction	Horizontal Direction	Vertical Direction
F_1	Front side waist	1.0000	1.0000	0	0.0049
F_2	Front side hip	1.0000	0.3618	1.0000	0.0061
F_3	Front side knee	1.0000	0.3659	0	0.2564
F_4	Front side calf	0	0	0	0
F_5	Front side hem	0	−0.0702	0	0.2573
F_6	Front inseam hem	−1.9947	−0.0702	−1.9947	0.2573
F_7	Front inseam calf	0	0	0	0
F_8	Front inseam knee	−2.0070	0.3659	−1.9935	0.2564
F_9	Front crotch	−1.9302	0	−1.9935	0
F_{10}	Front center hip	−1.0000	−1.1975	−1	−1.2033
F_{11}	Front center waist	0.3841	1.0000	0	3.0000
B_1	Back side waist	−1.0000	1.0000	0	0.0049
B_2	Back side hip	−1.0000	0.3618	−1.0000	0.0061
B_3	Back side knee	−1.0000	0.3659	0	0.2564
B_4	Back side calf	0	0	0	0
B_5	Back side hem	0	−0.0702	0	0.2573
B_6	Back inseam hem	1.9947	−0.0702	1.9947	0.2573
B_7	Back inseam calf	0	0	0	0
B_8	Back inseam knee	2.0070	0.3659	1.9935	0.2564
B_9	Back crotch	1.9302	0	1.9935	0
B_{10}	Back center hip	1.0000	−1.1975	1	−1.2033
B_{11}	Back center waist	−0.3841	1.0000	0	0

Figure 11 demonstrates the design of the desired straight-legged trousers. The red color represents that the region cannot be worn, while the yellow color indicates that the region is rather tight. From Figure 11I–III, it can be observed that both the areas of red and yellow tend to zero after two rounds of adjustment. These areas may prove that proper garment fitting has been gradually achieved.

4.3. Comparison between the ML-Enhanced 3D Reverse Design Method and the Traditional 2D Method

To evaluate the proposed approach in this study, we compared the garments designed by the ML-enhanced 3D reverse technology (Solution A) and the traditional 2D method (Solution B). As illustrated in Figure 12I,II, the red areas of the B garments (Solution B) are larger than those of the A garments (Solution A). Meanwhile, from the perspective of clothing pressures, all the pressures of the B garments are higher than those of the A garments. This indicates that the B garments are tighter than the A garments. The performance of the A garments is superior to that of the B garments, since the dimensions of the A garments are extracted from the flattened human body, while the dimensions of the B garments are estimated based on the key human body dimensions (i.e., body height, bust girth, waist girth, etc.). Hence, we can conclude that the proposed ML-enhanced 3D reverse design approach is applicable and facilitates the design of personalized garments more accurately and promptly.

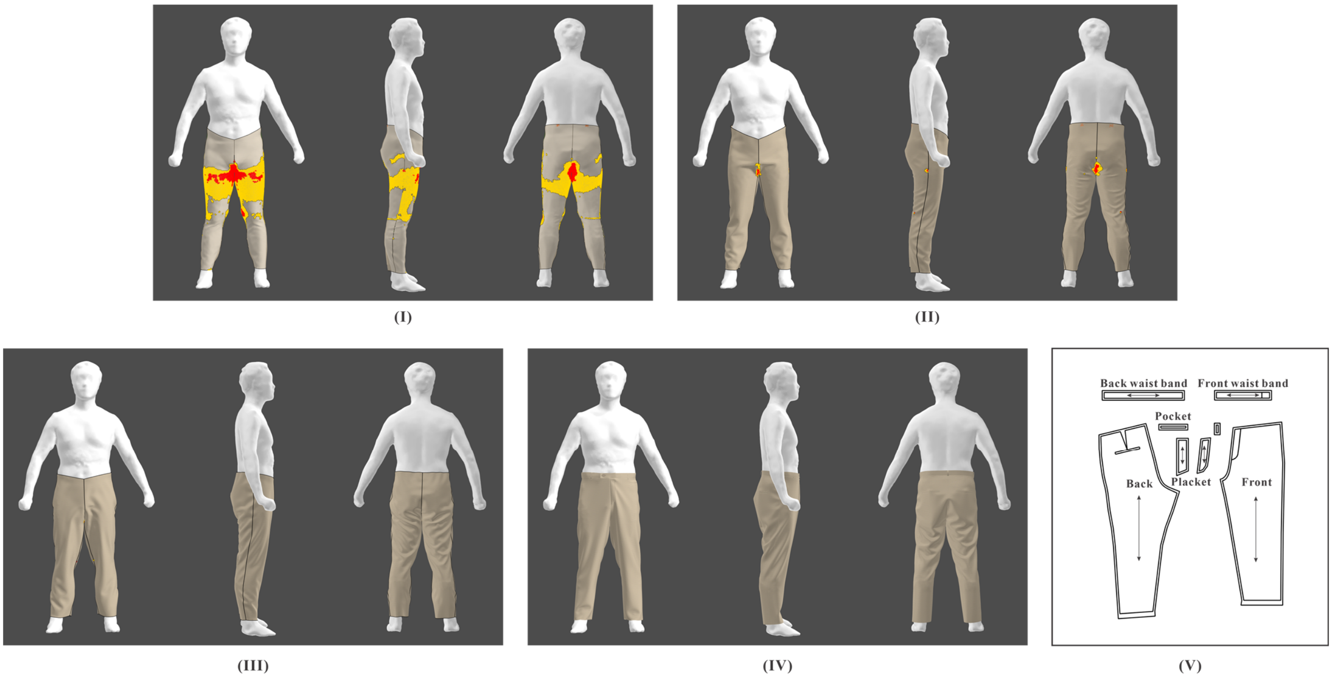


Figure 11. The designed loose-fitting garment. Note: (**I**) The garment before the adjustment; (**II**) The garment after the first round of adjustment; (**III**) The garment after the second round of adjustment; (**IV**) The finally designed garment; (**V**) The garment production patterns.

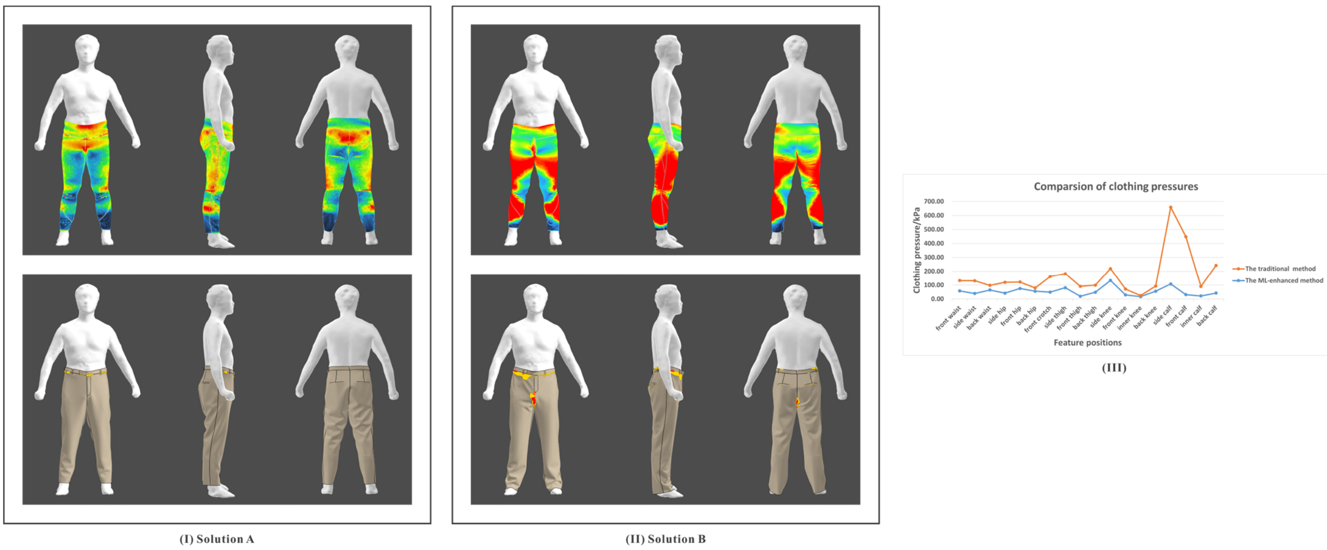


Figure 12. Comparison between the garments designed by the proposed ML-enhanced 3D reverse method and the traditional 2D method. Note: (**I**) Garments designed using the proposed ML-enhanced 3D reverse method; (**II**) Garments designed using the traditional 2D method; (**III**) Comparison of clothing pressures.

4.4. Extention to Development of a Sustainable New O2O Business Model in the Fashion Industry

A new O2O (order online and receive services offline) business model in the fashion industry can be formed based on the proposed 3D reverse design approach. The general implementation process (see Figure 13) mainly consists of three sequential phases. In Phase 1, a consumer profile for a specific consumer is made from the perspectives of garment fit, style, and fabric. Afterwards, the 3D basic garment is then designed based on the

3D reverse design method in Phase 2. In the final Phase 3, we employ machine learning techniques to evaluate and adjust the basic garment created from Phase 2. After a series of garment design evaluations and adjustments, the target garment associated with the garment patterns is determined and delivered to the following department for garment manufacturing.

Compared with the current models, the proposed new business model has the following outstanding merits. First, it is supported by advanced ML models, which can act as an "AI advisor" to provide powerful support for fashion designers without adequate knowledge and experience to make decisions in personalized garment design. Second, an ML-enhanced interactive garment design decision support system can be further developed based on the proposed computational models. Thus, the interaction between humans (i.e., consumers, fashion designers, pattern makers, etc.) and products will be greatly optimized based on the proposed system. Third, the model will enable fashion companies to promote their level of sustainable development by facilitating high-quality and efficient interactions between the stages of online customization and offline production.

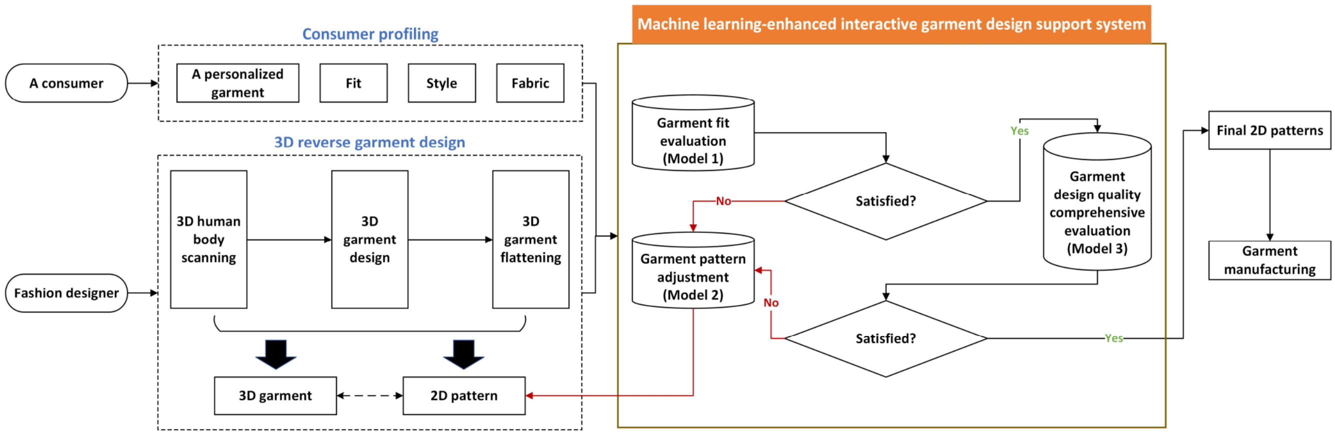


Figure 13. The general implementation process of the proposed O2O business model.

5. Conclusions

In this study, a new reverse design approach for personalized garments, in pursuit of sustainability, was proposed by combining 3D reverse engineering technology with machine learning. The involved ML techniques included probabilistic neural networks, genetic algorithms, and support vector regression. The experimental results have demonstrated that the proposed approach will allow fashion companies to promote sustainable development by providing quality personalized products and services for consumers, and simultaneously reducing costs and environmental burdens. Compared with the current 3D reverse design technologies in fashion industry, the prominent merits of the proposed approach in this study can be summarized as follows: (1) optimizing 3D garment reverse design technology for sustainable fashion by integrating an evaluation and self-adjustment mechanism using ML techniques; (2) constructing an effective and efficient interaction mechanism between humans (i.e., consumers, fashion design, pattern makers, etc.) and products by integrating ML techniques into 3D garment modeling; (3) offering a new idea and solution to overcome the key technical bottlenecks in the industrial implementation of 3D-to-2D garment pattern-making technology; (4) supporting the creation of a new interactive design decision support system for personalized fashion products with the presented ML models; (5) advancing the formation of a new sustainable business mode or ecosystem in the fashion industry by powerfully enhancing the linkage between online customization and offline manufacturing using ML techniques.

As we were limited by the article's length, the proposed technology was validated using garments for the lower body only. However, the basic principles can be generalized to different garment styles, such as shirts, skirts, coats, and so forth. Our research works in the future will mainly comprise the following aspects: (1) promoting the performance of the proposed ML models by progressively expanding their learning datasets, such as human body datasets, fabric datasets, garment style datasets, garment fit datasets, consumer preference and emotion datasets, and so on; (2) further enhancing the performances and generality of the proposed approach by employing more advanced computational technologies (such as deep learning); (3) developing a new decision support system/platform for personalized garment design by integrating the proposed ML models.

Furthermore, the new technologies and mechanisms mentioned in this manuscript can indeed help the sustainable development of clothing design and manufacturing. However, the role of humans (designers) cannot be ignored. The greatest value of humans (designers) lies in their creativity and creative thinking, which cannot easily be replaced by current technologies. With the help of technology, designers can be freed from tedious and repetitive work and focus on creative work in order to produce more value or profit. In this regard, the role and value of designers will become more and more prominent. Therefore, the balance between technology and human nature should be carefully considered; this constitutes one of our most important research directions in the future.

Author Contributions: Conceptualization, Z.W. and X.Z.; methodology, Z.W. and Y.X.; software, Z.W., X.T. and P.B.; validation, Z.W., Y.X. and Z.X.; resources, X.Z. and Z.X.; writing—original draft preparation, Z.W., X.T. and Y.X.; writing—review and editing, Z.W., X.T. and X.Z.; visualization, Z.W. and Y.X.; supervision, X.T. and X.Z.; project administration, Z.W. and Y.X.; funding acquisition, Z.W. and Y.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Scientific Research Start-up Project for Recruited talents of Anhui Polytechnic University (grant No. 2022YQQ062), 2022 Anhui Provincial Quality Engineering Project for Higher Education Institutions (named Garment Industrial Pattern-making, Offline course), the Teaching Quality Promotion Project for Undergraduate of Anhui Polytechnic University (grant No. 2022jyxm95, 2022szyzk37), the Scientific Research Project of Anhui Polytechnic University (Grant No. Xjky2022064), the Social Science Planning Project in Anhui (grant No. AHSKQ2019D085), the Scientific Research Project of the Department of Education of Zhejiang Province (Grant No. Y202148250), the Open Project Program of Anhui Province College Key Laboratory of Textile Fabrics, the Anhui Engineering and Technology Research Center of Textile (Grant No. 2021AETKL04), the Key Teaching and Research project of Colleges and Universities in Anhui (Grant No. 2020jyxm0153), and the China National Arts Fund (named Traditional Chinese Garment Art Training Program on Digitalization).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

Acknowledgments: The authors thank Francois Dassonville for his technical guidance and experimental support.

Conflicts of Interest: The authors declare no conflict of interest.

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