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Research on Enhancing the Efficiency of Creativity and Process Integration in Customized Garment Design through Meta-Learning Empowered by Artificial Intelligence

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ABSTRACT

The intelligent transformation of the apparel design industry needs to simultaneously meet the requirements of both efficiency improvement and personalization promotion. This paper proposes an intelligent design framework that integrates curve theory, garment prototyping and meta-learning technology. It optimizes the design of apparel by using the smoothness constraints of interpolation curves, the flexibility expression of parametric curves, and the local optimization characteristics of B-spline curves. Combine the prototype-based thinking model with meta-learning method to solve the generalization problem under small sample data and improve the model adaptation speed. The practical efficiency enhancement level and application value of the methods in this paper are verified through practice and testing, etc. The results show that the parametric design can realize the fast garment styling change of single parameter and multi-parameter. The optimization algorithm combining prototyping and meta-learning always takes less than 20 seconds in the 10-parameter range adjustment experiments, which is faster than the comparison algorithm. In the comprehensive fuzzy evaluation of experts and consumers, "very satisfied" and "good" account for 63.99% and 58.42%, respectively. The method based on technology fusion in this paper can significantly improve the design efficiency and user satisfaction of clothing personalization.

Keywords: interpolation curve; B-spline curve; parametric design; prototyping thinking model; meta-learning; apparel design

1. Introduction

The apparel industry is a highly competitive industry facing a series of challenges such as diversified consumer demands, long design cycles, and low production efficiency [1-2]. In the past, personalized

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customization mainly served high-end people, and customized clothing design in this field mainly relied on the designer's intuition and experience, and creativity was limited by the designer's personal ability and sensitivity to market trends [3-5]. However, with the improvement of living standards, more and more people want to show their own style through clothing and apparel, and consumers' demand for personalization and customization is increasing [6-7]. Traditional mass production has been unable to meet consumer demand, in response to which many apparel companies have applied artificial intelligence technology to layout the upstream and downstream tracks of apparel design [8-9].

The introduction of artificial intelligence, especially the application of machine learning, computer vision and other technologies provides favorable conditions for designers [10]. With the help of AI-assisted design system, designers can complete the steps in the traditional apparel design process in a short period of time, and only need to choose and adjust among multiple ideas provided by the system, which greatly improves the design efficiency [11-13]. At the same time, the system is also able to analyze the market feedback and consumer demand changes in real time and accordingly make dynamic adjustments to the design scheme to ensure that the design can keep up with the trend, enhance the flexibility and innovation of the design, but also for the brand to provide a more scientific product positioning and market strategy [14-17]. In apparel design idea generation, AI can generate innovative apparel styles or design elements on the basis of analyzing a large amount of historical design data, pattern elements, color matching, etc., to create design solutions with originality [18-20]. In addition, AI also has a unique advantage in the application of virtual fitting, using artificial intelligence and computer vision technology, it can realize rapid fitting, more intuitive and accurate display of the characteristics of the clothing, significantly improving the consumer experience and the matching of customized clothing [21-24]. In the future, AI will continue to play a more important role in apparel design and production, and apparel brands and designers should make full use of this technology to provide consumers with a more personalized and customized apparel experience, thus further enhancing brand competitiveness [25-27].

With the rapid growth of consumer demand for personalized clothing customization, it is more and more urgent to improve the efficiency and adaptability of traditional design methods. This paper focuses on this core issue, analyzing the mathematical basis of curve theory in the enhancement of the efficiency of apparel design integration. It establishes the thinking model of apparel design based on prototype, and researches how to improve the design efficiency through the steps of prototype implementation-improvement-modification. Aiming at the problem of insufficient small samples of the prototype, the meta-learning algorithm is selected to improve it, so as to prompt the model to achieve rapid adaptation even in small sample scenarios, and to improve the speed of personalized clothing customization. We study the feasibility of parameter-driven clothing shape adjustment and compare the running speed of the optimized algorithm, and finally verify the feasibility of this paper's method through the fuzzy comprehensive evaluation by experts and consumers.

2. Technical support for efficiency gains in fashion design integration

The efficiency improvement of apparel design relies on the co-optimization of mathematical modeling and intelligent algorithms. This chapter systematically elaborates the application of curve theory in apparel modeling generation. At the same time, it proposes a design thinking model based on prototypes and introduces a meta-learning method to solve the problem of rapid adaptation under small sample data of prototypes.

2.1. Curve Theory

2.1.1. Interpolation curves. An interpolation curve is a curve generated by interpolating a set of ordered data points $Pi, i = 0,1,\cdots,n$, and constructing a curve that passes sequentially through these data points, known as interpolation of these data points.

1) Linear interpolation. Suppose that given the values of the function $f(x)$ at two different points $x1$ and $x2$, a linear function: $y = a * x + b$, approximating instead of $f(x)$, is known as $f(x)$ the linear interpolation function. Where the coefficients a, b of the linear function function are determined by the conditions $\Phi(x1) = y1$ and $\Phi(x21) = y2$.

2) Parabolic Interpolation. Parabolic interpolation is also known as quadratic interpolation. Given a known function of $f(x)$ at three mutually exclusive points $x1, x2, x3$ with values $y1, y2, y3$, it is required that a function be constructed as follows: $\Phi(x) = a * x^2 + bx + c$ such that the value at the node $xi(i = 1,2,3)$ is equal to the value of $f(x)$ at xi. From this, a system of linear equations can be constructed to find a, b, c, i.e., the constructed interpolating function.

Constructing a curve that is closest in some sense to the given data points is called approximating these data points, and the constructed curve is the approximation curve. Interpolation and approximation are collectively referred to as fitting.

The style parts in the system are generated by fitting the curve function, in order to better reflect the effect of fitting, the curve must first ensure smooth. Graphics, smooth common meaning is that the curve can not be too many points of inflection, the curve turns around, it will not be smooth, for plane curves, relatively smooth conditions are: with second-order geometric continuity $(G2)$; there is no redundant points of inflection and singularity; curvature change is small.

2.1.2. Parametric curves. Computer-generated curves can be distinguished between parametric and nonparametric representations. Parametric equations are commonly used to represent curves because nonparametric equations are not easy to compute and program, among other reasons. Curves, in turn, can be divided into two categories: regular and irregular curves. Regular curves such as conic curves, involute lines, etc., they can be represented by simple function or parametric equations to represent the complete curve form. While irregular curves cannot be defined by simple math. If we are given a number of sample points on a plane, we can roughly sketch by hand the curve passing through the set of sample points. In a computer, however, it must be depicted in a strictly mathematical way.

Parametric equations of the form $x = fx(u), y = fy(u)$ are chosen as the equations for approximating the curve, and polynomials, trigonometric or exponential functions, etc., may also be chosen. The rationale for choosing a parametric equation is that a three-dimensional function requires only one additional fz component to the two-dimensional function, and the parametric equation treats the components in all three directions equally. In addition it can express multi-valued functions, i.e., for a given value of x there can be multiple values of y, so the curve can intersect itself back and forth.

A cubic parametric curve has the algebraic form:

$$\begin{aligned} x(t) &= a_{3x}x^3 + a_{2x}t^2 + a_{1x}t + a_{0x} \\ y(t) &= a_{3y}y^3 + a_{2y}t^2 + a_{1y}t + a_{0y} \quad t \in [0.1,1.1] \\ z(t) &= a_{3z}t^3 + a_{2z}t^2 + a_{1z}t + a_{0z} \end{aligned} \tag{1}$$

$a3x \sim a_{0z}$ These algebraic coefficients determine the shape and location of a parametric curve. If two identical parametric curves have different coefficients it means that the two parametric curves do not have the same spatial location.

There are many ways to represent parametric curves, such as spline curves, Bezier curves, B spline curves and so on. In order to simulate a real sense of clothing styles, the selection of the curve function is particularly important. To control the specific shape of the curve with the function parameters, so that the shape of the clothing parts and parameter values form a correspondence, we first thought of a parametric curve with localization, continuity, geometric invariance, modeling flexibility and other very good properties - B spline, the following is a further explanation of the B spline curve.

2.1.3. B-Spline Curve. This intelligent style structure design software requires that the composition curves of the style parts can be changed independently without affecting other parts when the parts are selected for splicing and when the user makes minor adjustments to the local styles. Bitmap method is the easiest to enter, but it can't realize the accurate change of style parts with the change of style as required by the system, and it's also not conducive to the splitting and splicing of the parts; therefore, we adopt the graphic way to store the number of digs.

The B-spline curve is mainly divided into four types: uniform B-spline curve, quasi-uniform B-spline curve, segmented B-spline curve, and non-uniform B-spline curve. It is a curve constructed with B-spline function characterized by:

1) The algorithm can be realized faster and is suitable for real-time computing.

2) The local modification property of B-spline curve is good, changing a certain sample point only affects a section of curve near it. A point function value $P(t)$ with parameter t belonging to $[t_i, t_{i+1}]$ on a k-ordered B-spline curve has at most one function value $P(t)$ associated with k control vertices $P_j(j = I + k + 1,\ldots,i)$, independently of the other control vertices; shifting the ith control vertex of the curve P_i affects, at most affects the shape of that part of the curve defined on the interval (t_i, t_{i+k}), and has no effect on the rest of the curve.

3) Good continuity.

4) BSpline curve is more intuitive, can be easily programmed to control the input parameters or sample points to change the shape of the curve.

5) Geometric invariance, B the shape and position of the spline curve, independent of the choice of coordinate system, and control polygon degraded to a straight line, the curve also degraded to a straight line.

6) Flexibility of modeling, as long as the choice of the location of the control point and the number of node repetitions, with B spline curve can also be constructed straight line segments, cusps, tangents and other special cases.

7) Mathematical tools are relatively simple, easy for those who do not have much mathematical training designers or drafters to accept.

8) Easy to record and store, because the points on the curve in addition to the sample points are obtained by the program operations, therefore, B spline record and store only need to save the location and order of those sample points can be.

It can be seen that the B spline curve, as a broadened Bezier curve, can be modified locally and the curve is closer to the characteristic polygon, in addition to the advantages of the Bezier curve such as intuition and convex envelopment. Meanwhile, the order of the curve is also independent of the vertices, thus it is more convenient and flexible and has been more and more widely used.

2.2. Prototype-based thinking model for apparel design

Creative thinking can be explicitly divided into two stages: turning unfamiliar into familiar and turning familiar into unfamiliar. That is to say, when a person faces a new pair, he always tries to incorporate it into his existing knowledge system, and find out a matching prototype from his mind for comparison, so as to make the unfamiliar things gradually become familiar with it, in order to complete the understanding and analyzing of the new things; and then he consciously jumps out of the original thinking point of view and mode, and looks at it with a brand-new and unfamiliar vision to produce new ideas and thoughts. And this viewpoint has been well verified in clothing design. Clothing style over the long history of evolution, has formed a lot of fixed style form and style. From the style point of view, there are clothes, mountain clothes, shirts, jackets and other clothing with a fixed form; from the style point of view, the formation of casual wear professional clothing, sportswear, banquet clothing and other clothing with a clear style definition. Designers will intentionally or unintentionally refer to this socially recognized standard of clothing classification and style definition to carry out their own design. At the same time, a garment usually consists of several parts, each of which has a corresponding style prototype. Therefore, we propose a model of prototype-based apparel design thinking method, which is divided into three steps:

1) Implementation of the prototype: the implementation of the prototype means that all the elements of a design prototype have been determined, and then according to the domain knowledge of the knowledge base, the description of the basic types of different parts and the generation method, gradually synthesized, so as to get the model corresponding to the design concept, the implementation of the prototype does not change the current knowledge of the prototype of the knowledge base, which is formally described as follows:

Let C be a design object concept and S be a prototype that conforms to the concept C.

$$S=\{P,m,F\} \tag{2}$$

where P is the set of style components, $P=\{P_1,P_2,\dots P_n\}$, and $(n\le 5)$; m is the topology that describes how the n components make up a piece of clothing; and F denotes the effect field of each component's field of influence on the overall garment style. The definition of f_1 is as follows:

$$f_1:\{C\}\to S \tag{3}$$

Then f_l is called the implementation of the prototype.

2) Refinement of a prototype: refinement of a prototype is the process of refining a prototype in order to obtain a complete description of the design space. The prototype refinement operation is a recursive activity that occurs in a multilevel prototype space.

Let I be the set of instances of S and f_2 is defined as follows:

$$f_2:\{C\}\to I \tag{4}$$

Then f_2 is called the refinement of the prototype.

3) Modification of the prototype: if, through evaluation, it is found that some of the prototypes in the system are not applicable, appropriate modifications can be made to the prototype to adapt to the new design state. The modification operation of the prototype must be within the scope allowed by the transformation rules of the prototype. The prototype modification operation results in an improved prototype, but this prototype modification is only temporary or non-substantial and does not affect the reuse of the old prototype in the knowledge base. However, for the convenience of the user, it can be used as a design instance and deposited in the instance repository for ease of invocation. Let f_c,g_c and h_c be transformation relations bounded by the design concepts C, respectively, such that:

$$f_c(P)=P';g_c(F)=F';h_c(m)=m' \tag{5}$$

This gives $I'=\{P',m',F'\}$. Define f_3 as follows:

$$f_3:\{I\}\to I' \tag{6}$$

Then f_3 is said to be a modification operation on the prototype S. At the same time, $\forall a\in I'$ and $a\notin I$, is stored a in the instance repository.

2.3. Meta-learning based learning method for prototyping small samples

The prototype small-sample problem with insufficient data is often formalized as the $C-wayK-shot$ problem, where $C-wayK-shot$ denotes that the dataset used for training contains C categories of K images each. While in traditional deep learning methods the label sets of the training, validation and test sets are shared, in prototypical small-sample learning the labels of the images used for training, validation and testing are disjoint. Specifically, given a dataset f_M, divide it into f_A, X_1, and X_2. Where X_3 denotes the original feature vector and labeling information of the X_4 th image. Where the label sets X_j and L_{test} are disjoint and their concatenated set is the total label set.

Meta-learning based approaches provide optimized learning parameters for the current task through cross-task learning to accelerate the adaptation process of the model on new tasks. The model completes learning under the meta-learning framework, i.e., multiple meta-tasks are generated cyclically, and the meta-tasks are utilized to complete training, validation and testing. Taking the training task as an example, the experiment randomly selects C samples of different categories from h_{γ}^{em}, and randomly selects M images from each category sample from D_{train}. Where M images of each category sample are divided into two sets of images, K and $M-K$ images, i.e., the LOSS images are used as the support set S_i, and the $C\times(M-K)$ images are used as the query set Q_i, which constitutes a meta-training task. Similarly, a meta-validation task as well as a meta-testing task are generated on the validation set and the test set following the same methodology. The goal is to train the neural network in the meta-tasks of the training set to learn the transferable meta-knowledge, adjust the hyper-parameters by the meta-tasks on the validation set, and finally report the recognition accuracy by the average of the model accuracy in the meta-tasks of the test set.

The main advantages of the meta-learning based approach are reflected in the following aspects:
1) Meta-learning significantly improves the learning efficiency under limited sample conditions by enhancing the model's rapid adaptability to new tasks, so that the model can absorb new knowledge and make effective predictions in a very short time;
2) The meta-learning strategy enables the model to achieve accurate prediction of unknown tasks even after learning only a small number of prototype samples by optimizing the model's generalization performance;
3) The meta-learning approach enhances the model's ability to understand the structure and requirements of a new task and improves its recognition ability in a variable learning environment through the experience accumulated in the multi-task learning process.

Despite the above advantages of meta-learning methods, there are still some limitations in practical applications. First, the design and implementation of meta-learning algorithms are relatively complex and require careful design of task distribution and learning strategies to ensure that the model can effectively learn from a variety of tasks with generalized learning capabilities. Second, the complexity of meta-learning models and the adaptability requirements of diverse tasks lead to a significant amount of computational resources and time required for their training process. In addition, the effectiveness of the meta-learning approach relies heavily on the selection and design of the task distribution, which can lead to a limited generalization ability of the model if the task distribution differs too much from the actual application scenario.

3. Meta-learning-based practices for improving the efficiency of apparel design integration

This chapter applies the technical approach of collaborative optimization to practical scenarios to verify its effectiveness. Analyze the consumer demand for personalized clothing customization, and formulate the corresponding practice scheme. Analyze the influence of single parameter and multi-parameter on the personalized clothing styling through parametric design, and optimize the response speed by combining with meta-learning algorithm. The practical value of the technology integration is further judged by collecting the dual evaluation from experts and consumers.

3.1. Practice program structure

In order to better improve the efficiency of the integration of clothing design based on meta-learning and to plan for the intelligent design method of clothing, this paper investigates the market demand of different consumer groups for intelligent design and personalized customization of clothing by distributing questionnaires online and offline. According to the statistical results of 60 online questionnaires and 60 offline questionnaires, there are 50 male consumers and 70 female consumers in this research, which is slightly skewed toward females in the proportion due to the fact that there are more females among the consumers of apparel goods in real life. Figure 1 shows the basic information of the survey respondents generated. In terms of age, consumers aged 20 to 35 years old accounted for 38% of the total, 36 to 45 years old accounted for 30% of the total, 46 to 55 years old accounted for 25% of the total, 55 years old and above accounted for 7% of the total, 45 years old and below accounted for 68% of the total, is the mainstay of the consumption of apparel goods. In terms of education level, consumers with high school and below accounted for 18%, specialized consumers accounted for 33%, undergraduate consumers accounted for 40%, postgraduates and above accounted for 9%, and consumers with specialized and undergraduate education level accounted for 77% of the total, which is the main force of apparel commodity consumption. In the distribution ratio of average monthly income, consumers with average monthly income of 5,000-10,000 yuan accounted for 80%, which is the main force in the consumption of clothing goods.

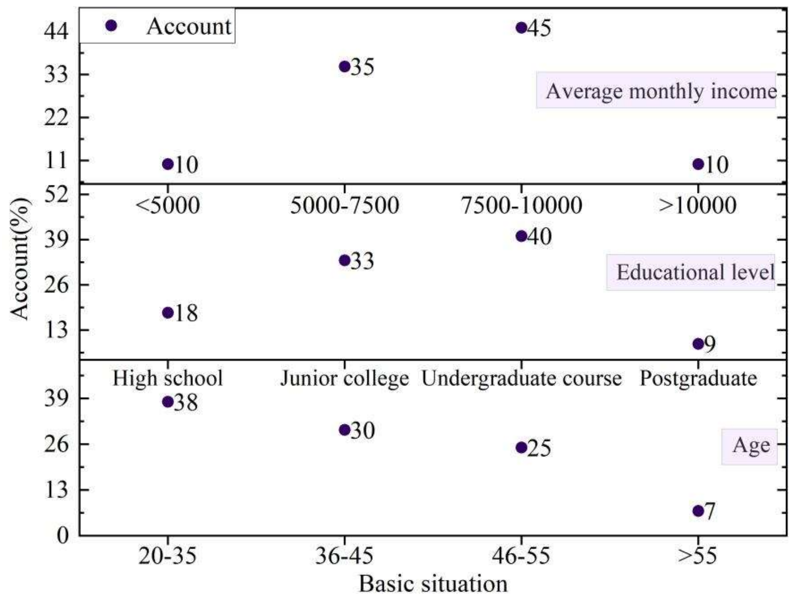

Fig. 1. Basic information of survey respondents

In the survey results, 70% of the consumers mainly purchased apparel from online channels, while 30% chose to purchase apparel in physical stores. In terms of apparel shopping, among the 120 consumers, 40% of the total purchased apparel once in less than 1 month, 35% of the total purchased apparel once in less than 3 months, and 25% of the total purchased apparel once in greater than 3 months. Further investigation of consumer clothing preferences and factors affecting the purchase of clothing, each survey respondent can choose a variety of preferred clothing and influencing factors. Figure 2 shows the survey respondents clothing style preferences and factors affecting consumers to buy clothing. Clothing style preference of survey respondents is dominated by professional style and casual style, with more than 110 choices. The top 2 factors influencing consumers to buy clothing are style and quality, followed by price and comfort.

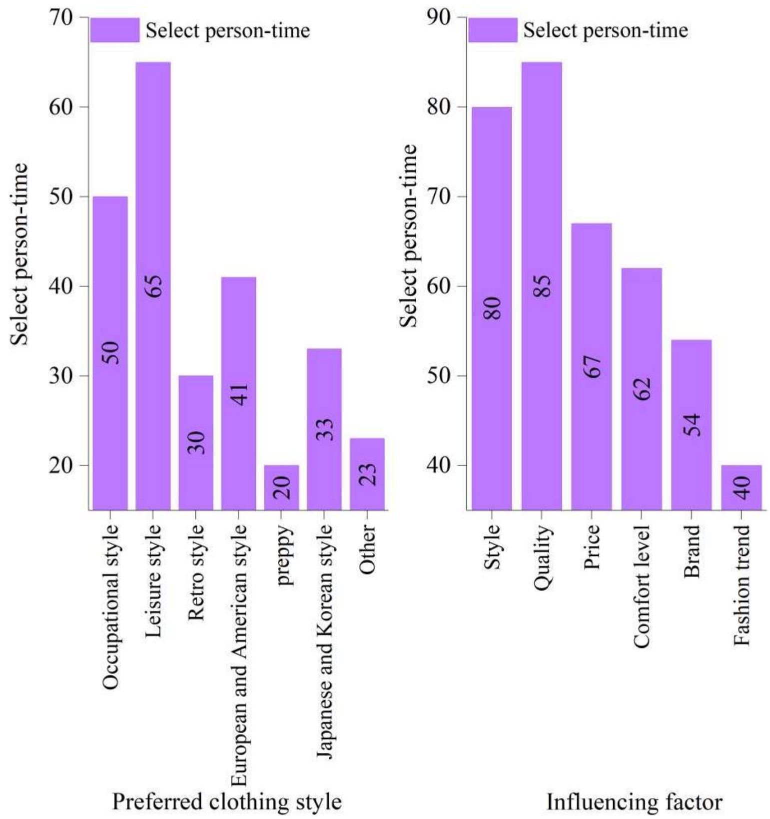

Fig. 2. Clothing style preference and influencing factors

After the above survey, the consumers were then surveyed on their knowledge and acceptance of intelligent design of clothing. In the statistical results, although only 40% of the consumers have some knowledge about clothing intelligent design and personalized customization, more than 90% of the survey respondents said that they are willing to design or customize clothing by themselves, and 85% of the consumers chose the ideal price of a piece of customized clothing which is less than 1500 RMB, and for the functions that should be possessed by the apps in the apparel and customization category, the top 3 are personalized design, clothing virtual fitting and clothing style recommendation. Figure 3 shows consumers' bias towards important parts of personalization. In terms of personalization, consumers are most concerned about the “personalized highlights” of apparel, accounting for 52% of the total. Figure 4 shows consumers' concerns about apparel customization applications. Among the concerns of customization applications, consumers are most concerned about the “richness of resources” of customization platforms, accounting for 33%.

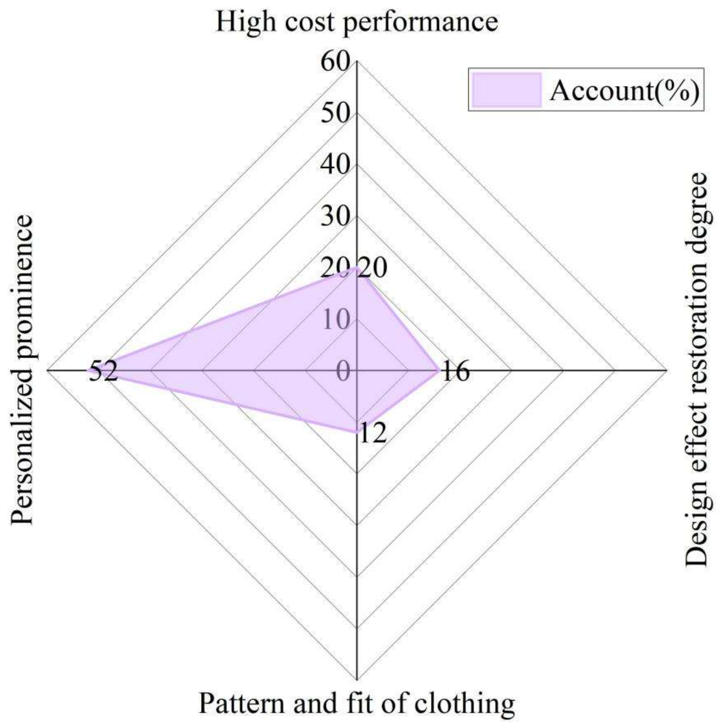

Fig. 3. Consumers are biased towards an important part of personalization

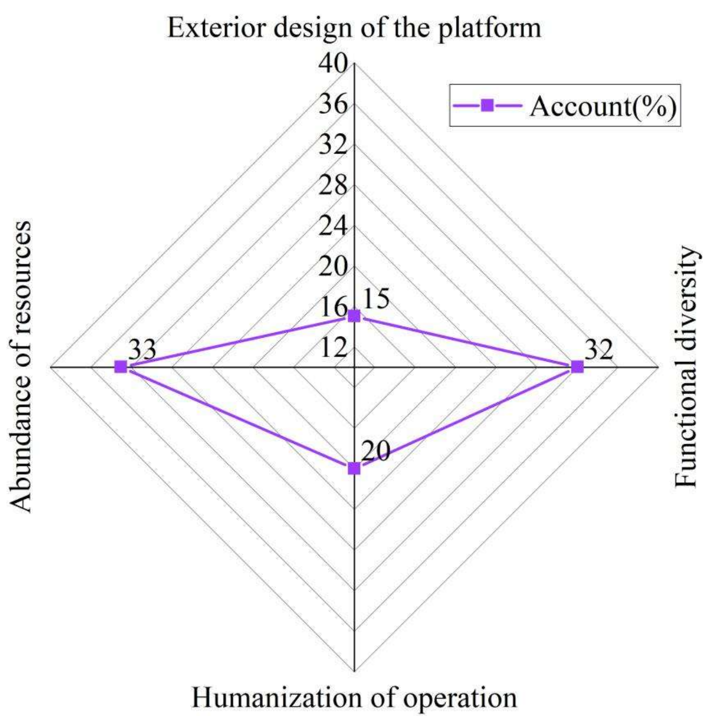

Fig. 4. Consumers focus on clothing customization applications

In view of the feedback and opinion statistics of different consumers, combined with the technical support mentioned above, the following contents are implemented to achieve the above planning objectives:

Digital 3D simulation fitting: through small programs or apps to implement intelligent clothing design methods, through 3D modeling technology to store a number of different body models, the user input their own general body data will be able to get a virtual model similar to their own body type.

Then the user can choose to customize by style structure or pick a style online to try on, different modules have different functions, but the principle is the same, 3D modeling and rendering technology and data storage of prototype clothing style resources.

High degree of freedom of personalized design: Intelligent design system provides users with a large number of options to independently design a garment, including gender, clothing category, color, process structure, fabrics and accessories, etc., so that users can realize the freedom of design. The principle of personalized design is to adjust the curve parameters and meta-learning methods, the structural components of the garment and then re-combined, the more types of structural components, the stronger the appearance design, the more obvious the differences in clothing styles.

Intelligent style recommendation: After the user determines the style, the system will automatically recommend the appropriate style to the user, which facilitates the user's secondary purchase and opens up sales for the supplier. The principle of intelligent recommendation is not only the user's path selection and favorite preference, but also integrates the knowledge of clothing style matching, aesthetics, psychology and other comprehensive categories of theory.

Whether it is digital 3D simulation fitting or high degree of freedom personalized design, or intelligent style recommendation, all highly dependent on the algorithmic model behind. In order to improve the efficiency of the integration of creativity and craftsmanship in customized apparel design, and to bring consumers a better apparel customization experience, it is necessary to solve for the optimal value of algorithmic parameters and so on.

3.2. Application of Parametric Design in Clothing Styling Changes

3.2.1. Effect of individual parameters on modeling. In order to analyze the influence of curve parameter calculation as well as parametric design on the styling of personalized customized garments, the influence of a single parameter on the styling of garments and the influence of multiple parameters on the styling of garments are discussed in 2 aspects.

When only one parameter is modified, local changes can be made to the sample composition curve of personalized customized clothing. For example, the bust will have an effect on the sleeve depth, back width line and chest width line; the garment length will have an effect on the length of the garment (long, short); and the back length will have an effect on the waist styling (normal waist, high waist and low waist). Figure 5 shows the parameter values for different busts, different dress lengths and different back lengths. The parameter values include bust (B), bodice length L), back length (BL), shoulder width (S), waist circumference (W), hip circumference (H), rib circumference (RG), hem circumference (HG), and rib length (RL). As can be seen from Fig. 5, the use of parametric design can quickly change the composition curve of the prototype garment and make changes to the shape of the garment, and when a parameter is modified, local shape changes can be quickly realized while the constraint relationship of other parts remains unchanged. For example, when the basic garment length parameter L is increased or decreased by 10cm from 120cm, and the rest of the parameters remain unchanged, it is possible to change the garment from the basic model to a long or short model, to quickly realize the local modeling changes, and to provide consumers with a variety of personalized experiences.

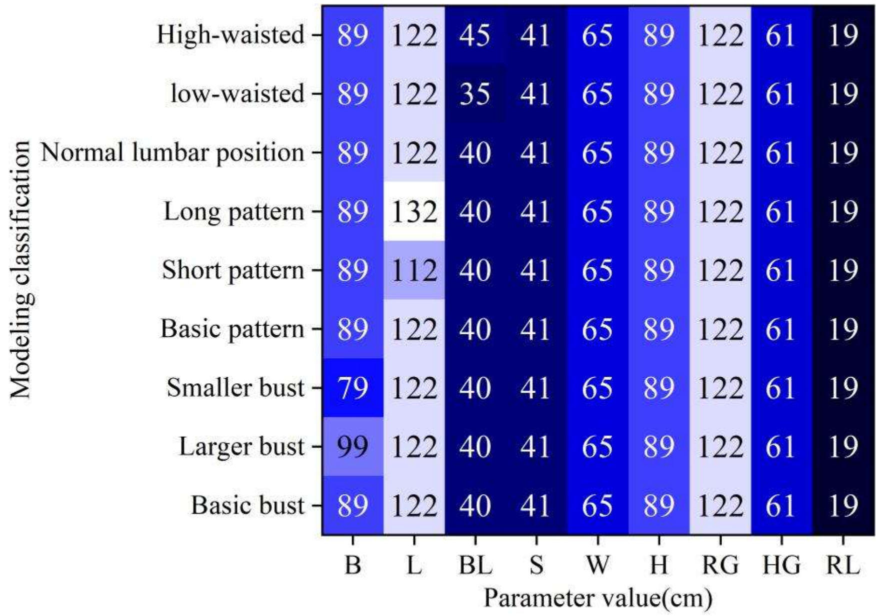

Fig. 5. Parameter values of different parts of the garment

3.2.2. Effect of multiple parameters on modeling. The above analysis shows the effect of a single parameter on the styling of personalized garments, and the following analysis shows the effect of multiple parameters on the styling, taking waist circumference, hip circumference, ribbed circumference, and hem circumference as examples. Figure 6 shows the effect of different parameters on the styling of five different lower body garments. Changing multiple parameters at the same time can quickly achieve changes in the overall styling of a personalized customized garment based on the garment prototype, without redrawing the paper pattern for each style. For example, when the waist circumference W, hip circumference H, ribbed circumference RG, and hem circumference HG are changed from 92, 99, 111, and 124 cm to 101, 123, 110, and 62 cm at the same time, the prototype garment is changed from an A-shaped skirt to a lantern skirt. Changing multiple parameters at the same time can quickly change the curve of the prototype garment and achieve a wide range of modeling changes, bringing consumers a refreshing experience of personalized clothing customization.

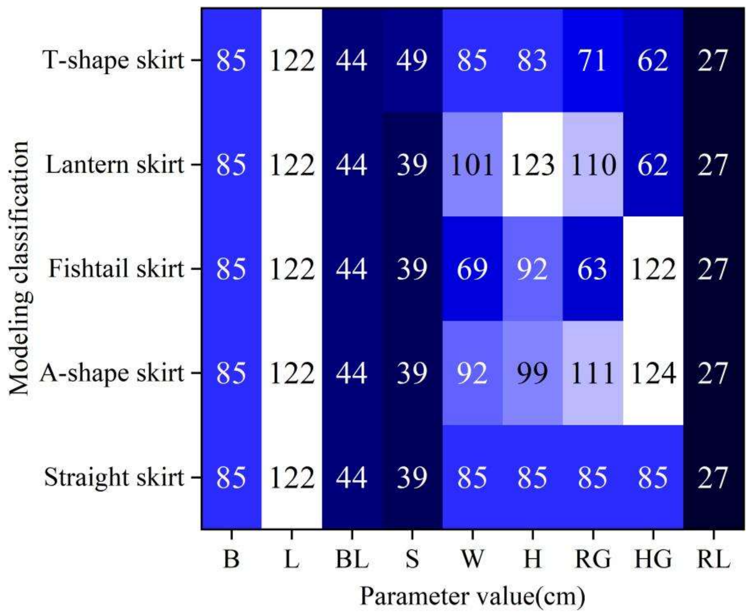

Fig. 6. Influence of different parameters on lower body

3.2.3. Comparison of algorithm execution time under parametric design. Personalized clothing customization through the calculation and change of curve parameters of prototype clothing composition involves a large number of operations such as meta-learning algorithms to learn prototype clothing samples and curve parameter calculation and modification. Therefore, the running time of the algorithm determines whether the user can obtain a fast customization response. This section sets up comparative experiments to study the running efficiency of this paper's algorithm and several parametric design algorithms of the same type, and to determine whether this paper's meta-learning-based prototype small-sample algorithm has an advantage in running speed.

Figure 7 shows the comparison of the algorithm execution time under varying the number of parameters. Observing the running time of the four algorithms of transfer learning (TL), meta-learning (ML), small-sample learning (FSL), and meta-learning-small-sample (ML-FSL) in Fig. 7, it is found that this paper's meta-learning-small-sample (ML-FSL) algorithm maintains its running time in the range of 10s-20s when 1-10 parameters are changed and there is no substantial increase in time. It shows that the algorithm in this paper meets the fast response requirements of personalized clothing customization, with high running efficiency and low loss. Applied to the intelligent style structure design software in this paper, it can effectively support the application of the software.

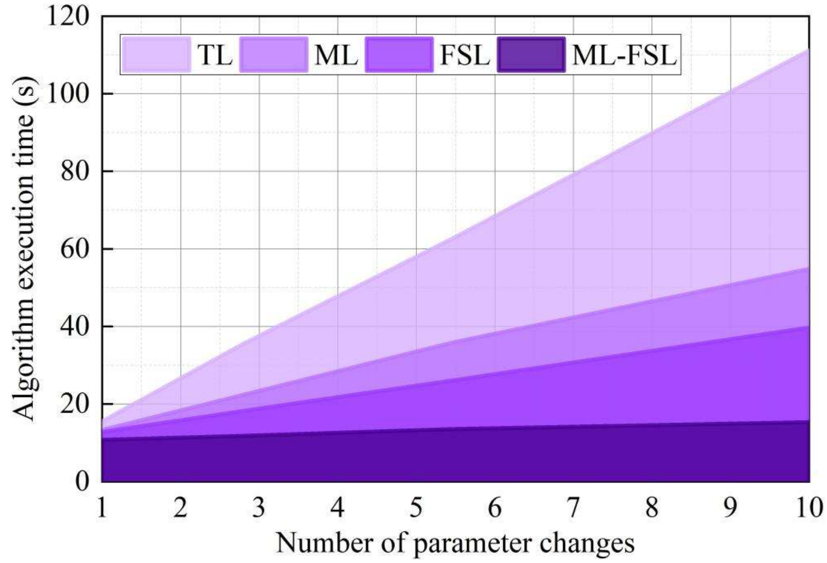

Fig. 7. Algorithm execution time for varying the number of parameters

3.3. Intelligent style structure design software testing and evaluation

3.3.1. Expert integrated fuzzy evaluation. In order to better evaluate the personalized clothing customization effect of the intelligent style structure design software, this paper invites expert volunteers and consumer volunteers to test the intelligent style structure design software that introduces the algorithm of this paper. The test lasts for one month. After the test, a fuzzy comprehensive evaluation method is set up for evaluation. Since experts and consumers focus on different software priorities, minor adjustments are made in terms of evaluation item indicators.

Specifically, in the expert's perspective, this paper determines the evaluation item indicator U for design effectiveness, which is a set of six indicators U consisting of six aspects: aesthetics (u1), design innovativeness (u2), technology integration concept (u3), cost-benefit prediction (u4), user interaction design (u5), and sustainability planning (u6). In the evaluation process, a 5-level scale criterion was used, i.e., good, very good, poor, poor, and fair, and 5 experts who participated in the test were invited as judges to score the indicators of design effectiveness. Table 1 shows the evaluation results obtained by the 5 experts. Through this evaluation process, we were able to comprehensively and objectively assess the design effect of personalized clothing customization, providing a strong basis for subsequent improvement and optimization.

Table 1. Expert design evaluation score statistics

Expert sequence number	Aesthetic	Design innovation	Technology integration concept	Cost-benefit forecasting	User interaction design	Sustainability planning
Expert 1	3	4	5	4	5	4
Expert 2	5	5	4	5	3	4
Expert 3	4	5	4	4	5	5
Expert 4	4	3	3	4	4	3
Expert 5	4	4	4	5	3	5
Total	20	21	20	22	20	21
Weight	0.16	0.17	0.16	0.18	0.16	0.17

First, the weights of the indicators were calculated. Subsequently, ratings were made based on the fuzzy comprehensive evaluation method to obtain more objective results. In order to capture the experts' feelings and ratings more realistically and accurately, 16 experts who participated in the test were randomly invited as research subjects to evaluate the design scheme. These 16 experts were required to fill out a feedback form for each indicator according to the five-level scale criteria. After completing the survey, the author conducted a detailed analysis of the percentages of different evaluation levels and integrated these assessment results with the previously assigned weights into the table for subsequent data processing and analysis. Its 16 experts are a group of smart clothing personalization professionals, and their feedback provides a better understanding of the actual effectiveness of the personalization process, which leads to improvement and optimization of personalization. Therefore, evaluating the personalization effect based on the experts' feedback can effectively verify the feasibility and applicability of the personalization method. Table 2 shows the statistical results of expert evaluation.

Table 2. Personalized customized evaluation scoring statistics

Evaluation index	Index weight	Very satisfied	Satisfaction	Normal	Dissatisfy	Very dissatisfied
Aesthetic	0.16	0.77	0.07	0.16	0.00	0.00
Design innovation	0.17	0.84	0.16	0.00	0.00	0.00
Technology integration concept	0.16	0.69	0.16	0.15	0.00	0.00
Cost-benefit forecasting	0.18	0.01	0.60	0.39	0.00	0.00
User interaction design	0.16	0.68	0.32	0.00	0.00	0.00
Sustainability planning	0.17	0.91	0.00	0.09	0.00	0.00

A fuzzy comprehensive judgment matrix R is obtained from the intelligent style structure design software evaluation based on the personalization evaluation scoring statistics.

$$R = \begin{bmatrix} 0.7700 & 0.0700 & 0.1600 & 0.0000 & 0.0000 \\ 0.8400 & 0.1600 & 0.0000 & 0.0000 & 0.0000 \\ 0.6900 & 0.1600 & 0.1500 & 0.0000 & 0.0000 \\ 0.0001 & 0.6000 & 0.3900 & 0.0000 & 0.0000 \\ 0.6800 & 0.3200 & 0.0000 & 0.0000 & 0.0000 \\ 0.9100 & 0.0000 & 0.0900 & 0.0000 & 0.0000 \end{bmatrix} \tag{7}$$

Using the multiplicative-bounded algorithm formula $B = A \cdot R$ the evaluation result B can be calculated using the weight vector matrix A with the constructed weight judgment matrix R.

$$B = \begin{bmatrix} 0.16 & 0.17 & 0.16 & 0.18 & 0.16 & 0.17 \end{bmatrix} \cdot R \tag{8}$$

Normalized from the calculation results $B = [0.6399\ 0.2232\ 0.1351\ 0.0000\ 0.0000]$. It can be concluded that the fuzzy comprehensive evaluation results are: 63.99% of the participants are very satisfied with the program, 22.32% of the participants are satisfied with the program; 13.51% of the participants are average for the program. The final rating is very satisfactory according to the principle of maximum affiliation. This also proves that the intelligent style structure design software by introducing the algorithm of this paper has been recognized by most experts and has good practical value.

3.3.2. Comprehensive Fuzzy Evaluation of Consumers. At the consumer level, the same evaluation is carried out through the fuzzy comprehensive evaluation method. Specifically, an evaluation item indicator U for design effectiveness was identified, and the indicator set U consisted of five aspects: aesthetics (U1), comfort (U2), functionality (U3), interactivity (U4), and safety (U5). During the evaluation process, a set of five-level measurement guidelines (very good, good, fair, poor, very poor) was followed to ensure the objectivity and comprehensiveness of the evaluation. To this end, five consumers who participated in the test were invited to act as judges responsible for scoring the effectiveness of personalization on various indicators. Table 3 shows the final evaluation results after comprehensive consideration and scoring by consumers. Through this evaluation process, we can comprehensively and objectively assess the garment personalization effect of the intelligent style structure design software, which provides a strong basis for subsequent improvement and optimization.

Table 3. Consumer evaluation index weight scoring statistics

Expert sequence number	Aesthetic	Comfort	Functionality	Interactivity	Security
Consumer 1	4	4	4	4	4
Consumer 2	5	4	5	4	5
Consumer 3	4	5	5	5	4
Consumer 4	4	4	4	3	4
Consumer 5	3	5	3	4	5
Total	20	22	21	20	22
Weight	0.19	0.21	0.20	0.19	0.21

First, the weights of the indicators were calculated and scored based on the fuzzy comprehensive evaluation method to obtain more objective results. In order to more accurately assess the real feelings and ratings, 16 consumers who have had actual personalized clothing customization experience were randomly selected from the participating consumers as the research targets and invited to evaluate the design scheme in detail. These 16 consumers were required to assess each index according to the five-level scale standards set, and fill out the corresponding feedback form to ensure the objectivity and accuracy of the evaluation results. After completing the survey, the author conducted a detailed analysis of the percentages of different evaluation levels and integrated these assessment results with the previously assigned weights into the table for subsequent data processing and analysis. Table 4 shows the statistics of consumer evaluation results. Its 16 experiencers are people who have had actual personalized clothing customization experience, and through their feedback, they can better understand the personalized customization effect of the intelligent style structure design software, so as to adjust and optimize the design of the intelligent style structure design software. Therefore, the feasibility and applicability of the design method can be effectively verified by evaluating the actual effect based on the feedback of consumers who have had actual personalized clothing customization experience.

Table 4. Consumer personalized customization evaluation score statistics

Evaluation Index	Weight	Very good	Good	Normal	Bad	Very bad
Aesthetic	0.19	0.64	0.25	0.11	0.00	0.00
Comfort	0.21	0.55	0.27	0.18	0.00	0.00
Functionality	0.20	0.66	0.27	0.07	0.00	0.00
Interactivity	0.19	0.48	0.40	0.12	0.00	0.00
Security	0.21	0.59	0.30	0.11	0.00	0.00

According to the consumer evaluation scoring statistics obtained from the evaluation of software clothing personalization program to get a fuzzy comprehensive judgment matrix R.

$$R=\begin{bmatrix}0.6400 & 0.2500 & 0.1100 & 0.0000 & 0.0000\\0.5500 & 0.2700 & 0.1800 & 0.0000 & 0.0000\\0.6600 & 0.2700 & 0.0700 & 0.0000 & 0.0000\\0.4800 & 0.4000 & 0.1200 & 0.0000 & 0.0000\\0.5900 & 0.3000 & 0.1100 & 0.0000 & 0.0000\end{bmatrix} \tag{9}$$

Using the multiplicative-bounded algorithm formula $B=A\cdot R$ the evaluation result B can be calculated using the weight vector matrix A with the constructed weight judgment matrix R.

$$B=\begin{bmatrix}0.19 & 0.21 & 0.20 & 0.19 & 0.21\end{bmatrix}\cdot R \tag{10}$$

Normalized by the result of the calculation after $B=\begin{bmatrix}0.5842 & 0.2972 & 0.1186 & 0.0000 & 0.0000\end{bmatrix}$. The results of the fuzzy comprehensive evaluation are as follows: 58.42% of the participants are "very good" to the program; 29.72% of the participants were "good" about the program; 11.86% of the participants rated the program as "average". The final rating is "Very Good" based on the principle of maximum affiliation. This also proves that the intelligent style structure design software that introduces the algorithm in this paper has been recognized by most consumers.

4. Conclusion

This paper investigates the design efficiency enhancement effect of apparel personalization through the integration of curve theory, prototyping design thinking model and meta-learning method. User research data shows that 68% of consumers are under 45 years old, and the demand for personalization focuses on style and quality. Consumers are most concerned about the “personalization highlight” and “resourcefulness” of the customization platform. Experiments show that the method in this paper always maintains high response speed (10-20 seconds) in single-parameter or multi-parameter parameter adjustment, and can respond to the user's personalized design needs in a fast and energy-saving way. The “very satisfied” and “good” rates of experts and consumers on the design solutions reach 63.99% and 58.42%, respectively. Future research can explore the lightweight meta-learning model and introduce multi-source data to enhance the generalization ability, which can promote the intelligent design of apparel to the direction of low-cost, high creativity and multi-process development.

References

[1] Shang, X., Wang, F. Y., Xiong, G., Nyberg, T. R., Yuan, Y., Liu, S., ... & Bao, S. (2018). Social manufacturing for high-end apparel customization. IEEE/CAA Journal of Automatica Sinica, 5(2), 489-500.

[2] Indrie, L., Bellemare, J., Zlatev, Z., Tripa, S., Diaz-Garcia, P., Montava-Seguí, I., & Ilieva, J. (2021). Contemporary customized clothes using folk motifs. Industria Textila, 72(6), 632-638.

[3] Lahoda, O., Gurdina, V., & Pasichnyk, V. (2021). Mass customization of clothing as a concept of individualization in modern design practices. Art and Design, 2(4), 129-140.

[4] Sun, H. (2025). Exploration and Construction of Personalized Customization Mode in Modern Fashion Design. In SHS Web of Conferences (Vol. 213, p. 02036). EDP Sciences.

[5] Spahiu, T., Almeida, H., Manavis, A. K. P., & Kazlacheva, Z. (2021). PRODUCT CUSTOMIZATION–A GROWING TREND IN FASHION INDUSTRy. Contemporary trends and innovations in textile industry.

[6] Yan, W. J., & Chiou, S. C. (2020). Dimensions of customer value for the development of digital customization in the clothing industry. Sustainability, 12(11), 4639.

[7] Whig, P., Kumar, V., Raj, V., Chaudhary, S. K., Sharma, S., Jain, A., & Yathiraju, N. (2024). Exploring the

Intersection of Computer Vision and Fashion Industry. In Illustrating Digital Innovations Towards Intelligent Fashion: Leveraging Information System Engineering and Digital Twins for Efficient Design of Next-Generation Fashion (pp. 105-123). Cham: Springer Nature Switzerland.

[8] Guo, Z., Zhu, Z., Li, Y., Cao, S., Chen, H., & Wang, G. (2023). AI assisted fashion design: A review. IEEE Access, 11, 88403-88415.

[9] Herath, H. B., Navodya, K. T., Samoon, T. F., Thushan, P. V., De Silva, D. I., & MVN, G. (2023). Customize your clothing through 3D models: a new trend in the fashion industry. Tuijin Jishu/J Propul Technol, 44(4), 2975-2983.

[10] Deng, H., & Liu, M. (2022). Personalized smart clothing design based on multimodal visual data detection. Computational intelligence and neuroscience, 2022(1), 4440652.

[11] Li, P., & Chen, J. H. (2018). A model of an e-customized co-design system on garment design. International Journal of Clothing Science and Technology, 30(5), 628-640.

[12] Sharma, S., Koehl, L., Bruniaux, P., Zeng, X., & Wang, Z. (2021). Development of an intelligent data-driven system to recommend personalized fashion design solutions. Sensors, 21(12), 4239.

[13] Wu, X. (2025). Local image style transfer algorithm for personalized clothing customization design. Systems and Soft Computing, 7, 200183.

[14] Hu, Y. (2021, November). Personalized clothing design support system for special crowds based on artificial intelligence technology. In Journal of Physics: Conference Series (Vol. 2066, No. 1, p. 012015). IOP Publishing.

[15] Wang, Y., & Liu, Z. (2021). Personalized custom clothing for intelligent interaction design. In Emerging Trends in Intelligent and Interactive Systems and Applications: Proceedings of the 5th International Conference on Intelligent, Interactive Systems and Applications (IISA2020) (pp. 698-709). Springer International Publishing.

[16] Liu, Z., & Luo, M. (2022). Modern clothing design based on human 3D somatosensory technology. Journal of Sensors, 2022(1), 2455103.

[17] Meng, X. (2022). Application of digital technology to the construction of the fashion design system under mass customization mode. Mathematical Problems in Engineering, 2022(1), 8734113.

[18] Wang, Z., Tao, X., Zeng, X., Xing, Y., Xu, Y., Xu, Z., ... & Wang, J. (2022). An interactive personalized garment design recommendation system using intelligent techniques. Applied Sciences, 12(9), 4654.

[19] Butteddi, R. K., & Butteddi, S. (2024). Revolutionizing fashion: a generative ai approach to personalized apparel design and custom fitting. INTERNATIONAL JOURNAL OF COMPUTER ENGINEERING AND TECHNOLOGY (IJCET), 15(4), 871-881.

[20] Tangchaiburana, S., & Techametheekul, K. W. (2017). Development model of web design element for clothing e-commerce based on the concept of mass customization. Kasetsart journal of social sciences, 38(3), 242-250.

[21] Porterfield, A., & Lamar, T. A. (2021). A framework for incorporating virtual fitting into the costume design and production process. International Journal of Fashion Design, Technology and Education, 14(1), 91-100.

[22] Zhu, X. J., Lu, H., & Rätsch, M. (2018). An interactive clothing design and personalized virtual display system. Multimedia tools and applications, 77(20), 27163-27179.

[23] Zhu, X. J., Wu, X., Shi, X., & Xu, B. G. (2017). Framework of personalized clothing visualization. International Journal of Clothing Science and Technology, 29(3), 417-426.

[24] Zhou, Q. I. N. G. Y. A. N., He, L. I. L. I., & Li, R. E. N. W. A. N. G. (2017). Research on the Application of Personalized Customized Virtual Design Method in Clothing. DEStech Transactions on Computer Science and Engineering, 39-49.

[25] Kędzia, K., & Dziuba, R. (2020). A system for personalized clothing production as a model for supporting the competitiveness of SMEs on the example of Lodz province. Autex Research Journal, 20(1), 93-99.

[26] Zhang, S., Fang, N., Qiu, L., Liu, Y., & Wang, Z. (2022). Toward Clothing Personalized Customization Multi-Perspective Silhouettes 3D Human Body Rapid Reconstruction. Journal of Computer-Aided Design & Computer Graphics, 34(11), 1753-1762.

[27] Ji, Y., & Jiang, G. (2020). Garment customization big data–processing and analysis in optimization design. Journal of Engineered Fibers and Fabrics, 15, 1558925020925405.