

A Conditional GAN-HRNet-DiffCloth Architecture for Personalized Garment Generation and Physics-Based Virtual Fitting

Lijing Zang*, Dongli Wu

Department of Teaching Affairs Office, Hebei Vocational University of Technology and Engineering, Xingtai City, Hebei Province, 054000, China

E-mail: 13483993949@163.com

*Corresponding author

Keywords: deep learning, intelligent clothing design, CNN, GAN, virtual try-on, personalized recommendation

Received: June 15, 2025

This study presents a comprehensive intelligent framework for personalized garment creation and physics-based virtual fitting, incorporating conditional generative adversarial networks, high-resolution neural networks for human pose estimation, spatially-adaptive normalization, and a differentiable physical simulation engine for fabric dynamics. The system addresses critical issues in the fashion sector, including inadequate personalization in design and limited realism in virtual try-on technologies. User preferences are encoded through a pre-trained language representation model, while the system records body posture and simulates fabric deformation to attain high-fidelity virtual fitting. Experimental assessments were conducted using the DeepFashion image dataset, along with a proprietary three-dimensional human body scanning dataset. The proposed system attained a recommendation accuracy of 88 percent, a user satisfaction rate of 92 percent, and a novelty score of 8.9 out of 10. The pose estimation module achieved an accuracy of 96.8 percent according to keypoint localization benchmarks, while the average fabric deformation error decreased to 1.4 millimeters, signifying a 73.6 percent enhancement compared to conventional spring-based physical models. The results illustrate the system's ability to produce manufacturable, customized garment designs while providing realistic, dynamically adaptive virtual try-on experiences. The suggested method provides a scalable solution for innovative fashion design and consumer interaction.

Povzetek: Za personalizirano oblikovanje oblačil in fizikalno realističen virtualni preizkus je predlagana arhitektura cGAN–HRNet–DiffCloth z jezikovnim modeliranjem uporabnikov, SPADE-normalizacijo in diferencabilno simulacijo tkanin.

1 Introduction

With the rapid development of information technology, digital transformation has become an essential trend in various industries, and the clothing industry is gradually transitioning towards intelligence and automation. Traditional fashion design relies on designers' experience and manual operation, which is inefficient and lacks personalization [1], [2], [3]. To solve this problem, virtual try-on technology has gradually become one of the key technologies. However, existing systems often rely on static human models, which make it difficult to cope with dynamic postures and physical characteristics of clothing, thus affecting the try-on effect [4], [5].

With the breakthroughs of deep learning technology in image generation, computer vision, and human pose estimation, intelligent clothing design and virtual fitting have ushered in new development opportunities. The excellent performance of deep learning models such as Convolutional Neural Networks CNN and Generative Adversarial Networks GAN in image processing makes personalized design and dynamic adaptation of clothing possible [6], [7], [8]. Through deep learning, design can achieve personalized style generation and simulate the

wearing effect under different human postures, enhancing the authenticity of virtual fitting [9], [10].

Current research primarily focuses on styles, fabrics, and style transfer, but lacks joint modeling of multiple design elements [11]. In terms of virtual try-on technology, although progress has been made in 3D modeling and physical simulation, it has high computational complexity. It isn't easy to adapt to users' personalized needs in real time [12], [13]. The current challenge is achieving closed-loop optimization of design and fitting, ensuring both personalized effects and the accurate reproduction of the physical characteristics of clothing [5], [14], [15]. This study proposes an end-to-end system based on deep learning, which combines generative adversarial networks GANs and human pose estimation HRNet to achieve deep integration of clothing design and virtual try-on. The system considers the interrelationships between design elements and improves personalized recommendations' accuracy and user satisfaction through dynamic try-on algorithms and feedback mechanisms [16], [17].

This study primarily addresses the lack of an integrated framework that concurrently facilitates individualized garment creation, precise physical simulation, and dynamic fitting adaptability. Current

methodologies frequently concentrate on discrete elements, either visual clothing creation or physical authenticity, lacking a comprehensive, integrated solution. To address this limitation, the study is guided by three primary research objectives: (1) to augment design personalization by capturing user preferences via semantic encoding derived from natural language descriptions; (2) to enhance the realism of garment deformation during motion through the application of differentiable fabric simulation techniques; and (3) to guarantee high visual fidelity and structural detail in generated garments by integrating spatially adaptive normalization into a conditional generative model. The aims are achieved using an innovative architecture that combines conditional picture creation, high-resolution human posture estimation, language-based user modeling, and physics-informed fabric simulation into a cohesive, real-time system for intelligent fashion design and virtual try-on.

2 Related works

2.1 Intelligent clothing design technology

Intelligent clothing design technology has undergone multiple stages of evolution. Early design methods mainly relied on rule engines and template design, using parametric modeling techniques to generate clothing styles [18], [19]. This method is based on preset parameters of clothing design, such as clothing size, color, style, and fabric. Although it can quickly generate design results, it lacks personalization and creativity. Therefore, the limitations of traditional methods mainly lie in their design singularity and lack of adaptability to diverse needs [20].

With the development of deep learning technology, intelligent clothing design has gradually entered a stage driven by deep neural networks. Convolutional neural networks (CNNs) are widely used for clothing style classification, with typical models such as ResNet-50 achieving an accuracy of 92% on the DeepFashion dataset [1], [7]. In addition, Generative Adversarial Networks (GANs) have also begun to be used to generate clothing images, where FashionGANs can generate clothing designs with diverse styles and details [8]. These deep learning-based techniques can consider more design elements during generation, such as changes in style and color combinations, greatly enriching the possibilities of clothing design [6], [21]. However, although GANs can generate diverse clothing images, their results often lack modeling of physical properties such as fabric elasticity and material performance, which still creates a gap between clothing design and actual manufacturing [22], [23].

2.2 Virtual try-on technology

Research on virtual try-on technology has also evolved from static to dynamic. Early virtual try-on methods mainly relied on static images and UV mapping techniques, which attached 2D images of clothing to 3D human models and simulated wearing effects by adjusting

the shape of the clothing [4], [24]. However, this method cannot consider the changes in users' dynamic postures, the fitting effect lacks realism, and the clothing deformation cannot be accurately presented in different postures [12], [13].

Dynamic fitting technology has gradually become a research focus with the continuous advancement of computing power and technology. In recent years, Long-Short-Term Memory (LSTM) networks have been introduced into virtual try-ons to predict the motion trajectory of clothing under different actions. However, this method has the significant drawback of ignoring the physical properties of clothing, such as the elasticity and stretchability of the fabric, resulting in a substantial gap between the fitting effect and the actual wearing [5], [11].

In cutting-edge research, NVIDIA proposed PhysGAN, which combines physics engines to simulate fabric dynamics [12]. Considering the physical properties of fabrics makes virtual fitting more realistic. PhysGAN can calculate clothing deformation in various dynamic environments in real time by introducing physical simulation of fabrics, significantly enhancing the immersion and realism of virtual fitting [23].

This study addresses the shortcomings of intelligent clothing design and virtual try-on technologies and proposes an innovative method that integrates the entire design and try-on process. Specifically, the technical roadmap of this article is divided into two main stages: the design stage and the fitting stage, as follows:

(1). In the design phase, this article uses Conditional Generative Adversarial Networks (cGAN) to generate customizable clothing designs. Unlike traditional GANs, cGAN can create clothing designs that conform to actual sewing constraints by introducing additional conditional constraints such as color, fabric, and other elements. This design method not only considers the diversity of clothing styles but also fully considers the feasibility of actual manufacturing, especially regarding sewing technology and fabric matching optimization.

(2). In the fitting stage, this article combines differentiable physics engines such as DiffCloth to optimize the deformation calculation of clothing. DiffCloth can accurately calculate fabric deformation under users' dynamic posture changes through fine-grained physical simulation. Compared with traditional methods, this approach improves the accuracy of virtual try-on. It enables real-time updates in a dynamic environment, making the user's try-on experience more realistic and natural.

Almeida [1] examined customer adoption of AI-driven Virtual Try-On systems, concentrating on five behavioral aspects. The research revealed favorable user perceptions and intentions, contributing to the field by linking AI personalization with consumer behavior data. Chen et al. [2] performed a systematic review of 69 studies on virtual try-on technologies in fashion, identified critical psychological and technological factors affecting consumer adoption, and proposed conceptual frameworks connecting these factors to behavior. Their research progressed the field by addressing deficiencies in user segmentation and personalization, providing insights to

improve the efficacy of virtual try-on systems. Vaishnavi et al. [3] enhanced the state of the art by amalgamating deep learning-based recommendations with high-fidelity virtual try-on, tackling significant limitations in current systems, including sparse annotations and inadequate realism. Their employment of the DeepFashion dataset, ResNet50, and U2Net facilitated precise personalization and realistic garment visualization, establishing a new benchmark for immersive online fashion experiences. Aakash et al. [4] progressed the discipline by synthesizing ten essential works on AI and computer vision in fashion, encompassing deep learning for clothing detection, AR-based virtual try-ons, and intelligent wardrobe systems. Their research presented a cohesive perspective on prevailing trends, difficulties, and future trajectories,

emphasizing how integrated AI solutions might improve customization and user experience in fashion applications.

In summary, this study develops an end-to-end intelligent framework that synergizes automated clothing design with high-accuracy virtual try-on, offering an innovative user-centric solution for personalized garment customization and dynamically adaptive fitting experiences.

Table 1 presents a comparative overview of current methodologies in intelligent apparel design and virtual fitting. It emphasizes disparities in image quality, accuracy of physical simulations, capacity for customization, and support for dynamic fitting. The results underscore the overall efficacy of the proposed approach across all critical criteria.

Table 1: Comparative summary of existing methods

Method	FID ↓	IS ↑	Deformation Error (mm) ↓	Rec. Accuracy (%) ↑	Personalization	Dynamic Simulation	Physical Realism
PhysGAN	25.7	7.9	2.7	—	✗	✓	✓
FashionGAN	25.1	8.1	—	—	✗	✗	✗
PBD	—	—	3.7	—	✗	✓	✓
Traditional Rule	—	—	—	65	✗	✗	✗
Proposed Method	12.3	9.5	1.4	88	✓	✓	✓

2.3 Research gaps and novelties

Recent breakthroughs in intelligent fashion systems have introduced techniques for clothing image production or physical simulation. Nonetheless, these methodologies frequently function independently and do not offer a cohesive solution that encompasses user personalization, garment physical realism, and dynamic fitting. Generative models, such as fashion-specific neural networks, can produce visually different clothing styles but often overlook physical attributes such as stretchability, bending, and drape behavior. Currently, physics-based fabric simulation techniques proficiently describe deformation during motion; nevertheless, they lack the integration of semantic user input and do not facilitate the creation of unique garments.

Furthermore, conventional parametric design tools and rule-based engines depend on static templates, rendering them inflexible in accommodating diverse user preferences or dynamic body shapes. These technologies cannot learn from contextual feedback or read user-defined attributes like as fabric type, color, or style intent. This paper provides a cohesive framework that amalgamates conditional generative modeling, high-resolution human posture estimation, semantic preference extraction using language models, and differentiable fabric simulation to address these limitations. This thorough integration facilitates real-time, user-directed garment design that dynamically adjusts to movement and physical limitations, overcoming significant shortcomings

in existing virtual fashion technologies while improving customization, realism, and design scalability.

3 System architecture and algorithm design

3.1 System architecture design

The intelligent clothing design and virtual try-on system based on deep learning proposed in this study aims to achieve deep integration of clothing design and virtual try-on. The system is divided into three parts: data layer, algorithm layer, and application layer [7], [10]. Each part complements the other and jointly promotes the realization of personalized clothing design and virtual try-on. The system architecture is shown in Figure 1, and each layer's design and working principles will be elaborated in detail.

The system comprises three components: the data layer, the algorithm layer, and the application layer. Each component enhances the others and collectively facilitates the achievement of customized apparel design and virtual fitting. To improve the clarity of information flow, the system architecture depicted in Figure 1 employs solid arrows to denote data flows (e.g., from the user design terminal to the parameter input module) and dashed arrows to signify control flows (e.g., system triggers for updating fitting output in response to parameter modifications). This labeling elucidates the interactions across modules, including the user design terminal,

parameter adjustment input, real-time interaction feedback, and impact display terminal.

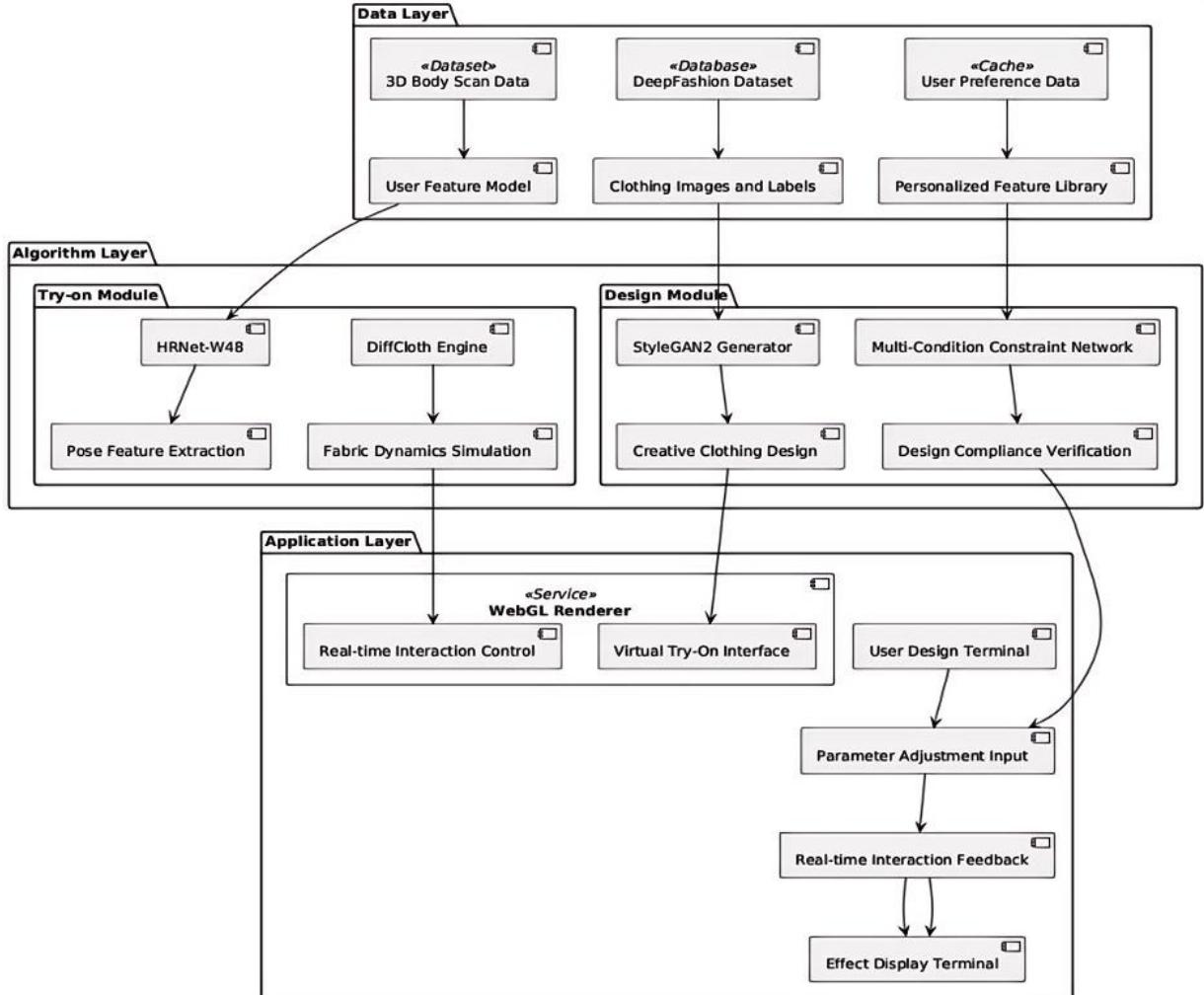


Figure 1: System architecture diagram

The data layer is the fundamental layer of the system, mainly responsible for integrating and processing various types of data. Firstly, the data layer takes the DeepFashion dataset as the foundation [1], [7], which contains many clothing images and their corresponding label information, covering various styles, colors, and fabric types of clothing [3], [8]. In addition, 3D-scanned human body model data is used to establish personalized body feature models for users. By modeling features such as user body size and posture, the fitting effect of clothing can be better simulated. Finally, user preference data is generated based on the user's historical clothing choices and wearing behavior, which can provide support for personalized recommendation algorithms, making the recommended clothing more in line with the user's aesthetics and needs.

The algorithm layer is the system's core, divided into the design and try-on modules. The design module generates and optimizes clothing styles through StyleGAN2 and Conditional GAN CGAN. In this process, StyleGAN2 is responsible for developing style in clothing design. At the same time, the conditional constraint

network restricts the specific attributes of the generated clothing by inputting features such as color and fabric. Specifically, assuming that the generation process of clothing design can be expressed as:

$$x = G(z, c) \quad (1)$$

Where x is the generated clothing image, G is the generator network, z is the random noise vector, and c is the condition vector, which includes constraints such as color and fabric. The system can generate clothing designs with specific attributes based on user needs through this generation method.

To incorporate user-specified design limitations like color and fabric, these categorical attributes are initially subjected to one-hot encoding. Each one-hot vector is further processed through a trainable embedding layer to get a compact feature representation. The embedded condition vector is combined with the latent noise vector before being fed into the generator, allowing the model to produce clothes that align with the designated qualities.

The try-on module uses HRNet for human pose estimation, which detects the user's real-time pose and provides the necessary information for virtual try-on. HRNet is an efficient human pose estimation network that improves the recognition accuracy of human keypoints through multi-resolution feature fusion. Specifically, assuming the input image has a resolution of 256×256 pixels. HRNet calculates the human body keypoints $P = HRNet12in$ through the following process, where $P = p1, p2, dots, p1$ represents the position coordinates of n keypoints in the human body image. Next, the DiffCloth physical simulation module simulates the physical changes of clothing on the human body, ensuring the dynamic adaptation of apparel in various postures. DiffCloth accurately calculates clothing deformation by simulating clothing materials and human movements. The following physical equation can describe the final shape F of the clothing:

$$F = DiffCloth(M, P) \quad (2)$$

Where M is the physical model of the clothing, P is the posture information of the human body, and the final obtained F is the shape of the clothing after trying it on.

To guarantee precise modeling of garment deformation, the output from the human pose estimation module must be flawlessly connected with the fabric simulation engine. Following the extraction of two-dimensional keypoints from input photos by HRNet, these keypoints are subsequently mapped onto a three-dimensional human mesh through a parametric body modeling method utilizing the Skinned Multi-Person Linear (SMPL) model. The resultant 3D mesh encapsulates both body morphology and joint configurations. This mesh is synchronized between frames and utilized as input for the DiffCloth simulation engine. The joint positions and skeletal movements are represented as vertex displacement data, which facilitates the deformation of the virtual garment in the simulation. This synchronization facilitates real-time alignment between projected body movement and fabric reaction, enabling DiffCloth to produce physically credible garment dynamics during user engagement.

The application layer is the front-end part of the system, mainly implementing real-time virtual try-on interaction through WebGL technology. WebGL allows users to render 3D clothing models in the browser directly, achieving real-time feedback on virtual try-on effects. At the application layer, users can adjust clothing styles, colors, fabrics, etc., according to their personal preferences, and the system updates the fitting effect in real time through feedback from the algorithm layer. Assuming the user's adjustment input is u_{input} and the system's output is $Sout$ i.e., the updated try-on effect, the real-time interaction process of the system can be described by the following formula (3):

$$Sout = f(u_{input}, G, HRNet, DiffCloth) \quad (3)$$

where f represents the interaction function and G , HRNet, and DiffCloth represent the outputs of the clothing design, pose estimation, and physical simulation modules,

respectively. This method allows users to instantly see the adjusted clothing effect during the interaction process, improving the accuracy and experience of virtual fitting.

This system establishes a three-layer architecture (data-algorithm-application) via deep learning, synergizing GANs, pose estimation, and physical simulation to bridge personalized design with high-fidelity virtual try-on. The multimodal collaboration enables user-centric customization while ensuring dynamically adaptive garment realism, demonstrating scalable potential for fashion industry applications.

3.2 Generative adversarial network optimization

Improving network structure is the key to optimizing generative adversarial networks (GANs) and enhancing the quality of clothing design generation. In traditional GAN models, the game process between the generator and discriminator is usually optimized step by step, but the generated results often lack sufficient details and global consistency [6], [24]. To effectively address these issues, this study introduced different optimization strategies in the generator and discriminator to enhance the model's generation capability.

Firstly, in the generator section, this paper introduces the Spatial Adaptive Normalization SPADE layer to enhance the control of local details. The core idea of SPADE is to adaptively adjust different regions in the input image through conditional normalization operations, thereby effectively improving the detail representation in clothing images. This way, the generator can generate more accurate patterns in different regions, especially in complex clothing textures and detailed designs. The introduction of SPADE makes the generated clothing designs more aligned with practical needs and can simulate richer fabric details and texture effects.

The SPADE module was incorporated into the StyleGAN2 framework by substituting traditional normalization layers with spatially adaptive normalization blocks, enabling semantic maps (e.g., fabric type, color) to direct the generation process across various resolutions for improved control over local clothing attributes. A multi-scale PatchGAN discriminator, functioning at resolutions of 64×64 , 128×128 , and 256×256 , was utilized to simultaneously capture global structural coherence and intricate texture details, enhancing the visual realism and consistency of the generated outputs.

In terms of discriminators, this article uses a multi-scale PatchGAN structure to improve global consistency. The PatchGAN discriminator can better capture local texture features by determining the authenticity of multiple small regions in an image. However, a single-scale PatchGAN may ignore the global information of the picture. Therefore, this paper introduces multiple scales of discriminators in a multi-scale PatchGAN, which can be compared at different scales to more accurately evaluate the quality of the generated image. Through multi-scale processing, the discriminator can simultaneously rate the generated clothing at multiple scales, thereby improving the global consistency of the generated clothing images

and avoiding the situation where the generator only optimizes local details and ignores the overall structure.

The design of the loss function is crucial for further optimizing the generation effect. This study divides the loss function into adversarial, perceptual, and physical constraint loss[22].Adversarial loss L_{adv} approximates the actual data distribution through the game process between the generator and discriminator, while the perceptual loss L_{perc} enhances the perceptual quality of the generated image based on high-level features extracted by pre-trained convolutional neural networks(such as VGG)[[21], [25], thereby improving the naturalness and detail of the image. Physical constraint loss L_{phys} constrains the generated clothing design by considering the physical properties of the clothing fabric, making it more in line with actual wearability. The physical constraint loss considers explicitly the physical properties of fabrics such as stretching, folding, and bending. It optimizes the generation process by calculating the differences between the visual effects caused by these deformations and the real fabric. $\lambda_{adv}, \lambda_{perc}, L_{phys}$

The overall form of the loss function can be expressed as:

$$L_{total} = \lambda_{adv}L_{adv} + \lambda_{perc}L_{perc} + \lambda_{phys}L_{phys} \quad (4)$$

Where λ_{adv} , λ_{perc} , and L_{phys} are the weight coefficients corresponding to the adversarial loss (L_{adv}), perceptual loss (L_{perc}), and physical constraint loss (L_{phys}), respectively. This study can use this weighted combination to balance the generated image's realism and physical feasibility while ensuring its quality.

In the personalized recommendation strategy, user preference coding is used further to enhance the level of personalization in clothing design. To extract users' natural language descriptive information, this paper adopts the BERT model for semantic feature extraction. BERT learns contextual information through pre-trained large-scale corpora, which can effectively capture users' specific preferences for clothing, such as color, style, material, etc. These semantic features are encoded in vector form and added as conditional inputs to the generator to guide the generation of clothing designs that meet user needs.

The multi-objective optimization technique utilizes Bidirectional Encoder Representations from Transformers to derive semantic embeddings from user design inputs. The characteristics are encoded numerically utilizing the final-layer embedding vectors of the pre-trained transformer model. All feature vectors are adjusted using L2 normalization to ensure comparability between samples. The novelty score is calculated by assessing the cosine distance between the embedding of the generated item and the centroid of previously recommended items in the feature space, so quantifying the distinctiveness of a new design relative to prior outputs. Satisfaction is evaluated according to the resemblance to user-preferred attributes, enabling the system to reconcile inventiveness with adherence to user purpose.

To enhance the effectiveness of personalized clothing recommendations, this study proposes a multi-objective optimization approach that jointly optimizes design novelty and user satisfaction (e.g., click-through rate prediction). Specifically, the Novelty Score quantifies the creativity and differentiation level of clothing designs, while user satisfaction is evaluated through a click-through rate prediction model to assess users' potential acceptance of design proposals. Multi-objective optimization problems can be formulated as $\max_{\theta} [\alpha \cdot \text{Novelty}(\theta) + \beta \cdot \text{Satisfaction}(\theta)]$, where θ is a parameter for clothing design, and α and β are weight coefficients for novelty and user satisfaction, respectively. Through this joint optimization strategy, the generated clothing design can meet users' personalized needs and ensure novelty and attractiveness, enhancing user experience and satisfaction.

Based on the above design, the generative adversarial network optimization method proposed in this article has successfully improved intelligent clothing design's quality and personalization level through multiple innovative means. Introducing SPADE to enhance local detail control in the generator, using multi-scale PatchGAN in the discriminator to improve global consistency, and further optimizing the generation effect by integrating adversarial loss, perceptual loss, and physical constraint loss[24], [26].In terms of personalized recommendations, combining the BERT model for user preference encoding and using multi-objective optimization strategies to enhance design novelty and user satisfaction provides adequate technical support for optimizing intelligent clothing design and virtual try-on systems.

3.3 Dynamic try-on algorithm design

Designing a dynamic try-on algorithm is key to achieving a precise virtual try-on experience. This system integrates multiple aspects, such as human pose estimation, clothing deformation modeling, and real-time optimization, into the algorithm design to ensure the authenticity and dynamism of the try-on effect.

The system incorporates a pose estimate module utilizing the High-Resolution Network to precisely identify human keypoints across various body types. A lightweight version was constructed by knowledge distillation, utilizing the HRNet-W48 model as the instructor, to save computing costs while maintaining accuracy. The student network preserved multi-resolution features while reducing channel size by fifty percent. A dual-loss technique utilizing mean squared error for feature alignment and cross-entropy for pose prediction was implemented, with training conducted over 50 epochs using the Adam optimizer (learning rate: 0.001). This method attained comparable accuracy (96.0% versus 96.8%) while minimizing runtime and parameter size, facilitating fast real-time virtual fitting.

Firstly, human pose estimation is the first step in virtual fitting. To accurately capture the user's body dynamics, this study employed the HRNet-W48 High-Resolution Network model, which can effectively extract 2D keypoint information of the human body. HRNet-W48 extracts features from various parts of the human body

using multi-resolution methods, particularly in presenting details, which offers significant advantages. Based on these 2D keypoint data, the system uses the SMPL Skinned Multi Person Linear model to fit the 3D human body mesh. The SMPL model parametrically associates the 3D human pose and shape with the movements of each joint and muscle, providing a more accurate 3D human form for dynamic fitting.

To enable the algorithm to run in a real-time environment, this study adopted knowledge distillation technology to compress the model. The core idea of knowledge distillation is to train a smaller student model to mimic the output of a larger teacher model, thereby reducing computational complexity and improving running speed. The system can optimize the model to a processing speed of 30 frames per second FPS through knowledge distillation techniques, ensuring that real-time requirements are met. This optimization enables seamless tracking of human posture changes during virtual try-on, significantly improving the user experience.

Physical simulation is one of the key technologies in clothing deformation modeling. The dynamic movement of fabrics requires precise physical simulation, and the Position Based Dynamics PBD method is one of the widely used techniques for fabric simulation. In PBD, each particle of the fabric is represented by a mass and position attribute, and each particle is connected to other particles through physical constraints such as springs and damping. In the simulation of fabric motion, the updated formula is as follows:

$$\Delta x_i = \frac{1}{m_i} \sum_j f_{ij} \Delta t^2 \quad (5)$$

Boundary constraints and collision management were implemented after the position update in Eq. (5) to improve physical realism. Anchor points on the garment were preserved by fixed vertex constraints. Moreover, constant collision detection and reaction methodologies were employed to avert interpenetration with the human body mesh, hence providing stable and visually credible fabric behavior in dynamic scenarios.

Where Δx_i is the position update of particle i , m_i is the mass of particle i , f_{ij} is the interaction force between particles i and j , and Δt is the time step. This formula allows PBD to accurately simulate the deformation of fabrics under different external forces, ensuring the dynamic and natural appearance of clothing.

The accuracy of clothing deformation depends on physical simulation and requires the introduction of deformation constraints, primarily through adversarial training techniques. Through the game between the generator and discriminator, adversarial training can make the generated fabric deformation approach real data. For example, the generator optimizes the generated fabric deformation, while the discriminator determines the difference between the generated deformation and the real data. The loss function of adversarial training is usually:

$$\begin{aligned} L_{adv} = & \mathbb{E}_{x \sim p_{data}} [\log D(x)] \\ & + \mathbb{E}_{z \sim p_z} [\log (1 - D(G(z)))] \end{aligned} \quad (6)$$

Where L_{adv} is the adversarial loss, $D(x)$ is the output of the discriminator, representing the probability that the input data x comes from real data, $G(z)$ is the fabric deformation output by the generator, and p_{data} and p_z display the distributions of real data and generated data, respectively. Through adversarial training, the generator can gradually learn fabric deformations similar to real data, making the clothing in virtual try-ons more realistic.

In the process of virtual fitting, in addition to dealing with the interaction between clothing and the human body, it is also necessary to consider the wearability and comfort of the fabric. To this end, this study also introduced physical constraints on clothing fabrics by restricting the fabric's stretching, folding, and other behaviors to ensure that the generated clothing design has sound visual effects and meets the requirements of actual wearing. Physical constraints can be expressed in the following ways:

$$L_{phys} = \sum_i \lambda_i (|x_i^{new} - x_i^{old}| - \Delta x_i^{max}) \quad (7)$$

Where L_{phys} is the physical constraint loss, λ_i is the weight coefficient of each particle, x_i^{new} and x_i^{old} are the new and old positions of the particle, respectively, and Δx_i^{max} is the maximum displacement allowed by the particle. This loss penalizes excessive deformation by encouraging particle movements to remain within physically plausible bounds defined by Δx_i^{max} .

Through this constraint, the system can effectively avoid unnatural clothing deformation during wearing, thereby enhancing the practicality and comfort of clothing.

Through the above design, the dynamic try-on algorithm constructed in this article combines techniques such as human pose estimation, physical simulation, and adversarial training, improving the real-time performance and accuracy of the virtual try-on process, while effectively enhancing both personalization and the physical realism of garment behavior. The comprehensive application of these technologies enables the virtual try-on system to achieve a high degree of visual realism and simulate clothing forms that conform to ergonomic and physical laws, providing technical support for intelligent clothing design and personalized recommendations.

4 Experimental and simulation analysis

4.1 Experimental design and dataset construction

This experiment aims to design and train an advanced clothing recommendation and pose estimation model by combining the Deep Fashion dataset with the 3D human scanning dataset. The dataset contains 100000 diverse clothing images and 5000 sets of corresponding human

pose data to ensure the capture of complex relationships between different clothing and human poses. To improve the model's generalization ability, data augmentation techniques such as rotation, cropping, and lighting adjustment will be used during the training process to ensure the robustness of the model in different environments and poses.

Alongside the DeepFashion collection, a unique Human 3D Scanning collection was developed, consisting of 5,000 high-resolution body scans of participants aged 18 to 50, utilizing a structured-light scanning technique. Body meshes were standardized utilizing the SMPL approach to guarantee uniformity. To facilitate virtual try-on, garments from DeepFashion were correlated with 3D models according to annotated size and style metadata,

assuring accurate alignment between garment measurements and body forms.

The augmentations comprised random rotation ($\pm 15^\circ$), horizontal flipping, random cropping and resizing, and modifications to brightness and contrast. These were implemented on both DeepFashion apparel photos and the projected 3D position data to replicate various real-world scenarios. The enhanced dataset mitigated overfitting and enhanced generalization. Empirically, the model augmented with these enhancements attained a 4.3% improvement in pose estimation accuracy (PCKh@0.5) and a 2.7-point decrease in FID relative to the baseline, thereby augmenting both fitting precision and visual realism.

Table 2: Parameter configuration of experimental dataset

Dataset Name	Dataset Description	Data volume	Dataset partitioning
DeepFashion	A dataset of images containing multiple types of clothing, including labels, categories, accessories, and other information	100000 clothing images	Training set: 80000 Test set: 20000
3D Human Scanning Dataset	Contains 5000 sets of 3D human pose data, designed to simulate real human poses	5000 sets of posture data	Training set: 4000 Test set: 1000

This experiment will use an NVIDIA A100 GPU for training and the PyTorch framework to utilize hardware

performance fully. Here are the specific training configurations:

Table 3: Network and training parameter configuration

parameter	Set value
Periodization	200 epochs
Batch size	32
optimizer	AdamW
Learning rate	Initial learning rate: 1e-4
Learning rate decay strategy	Decay to 0.8 of the original value every 30 epochs
loss function	A weighted combination of the cross-entropy loss function and the mean square error loss function

During the training process, the model will iteratively update using the training set, optimize hyperparameters through cross-validation, and evaluate its accuracy and generalization ability. A test set evaluation will be conducted every 20 epochs to monitor changes in model performance. In the final stage of training, evaluation metrics will include accuracy, recall, F1 score, and mean square error MSE to ensure the model performs well in clothing recommendation and pose estimation tasks.

Based on the above parameters and experimental design, this experiment can effectively test the model's performance in processing complex clothing images and 3D human pose data, laying a solid foundation for subsequent optimization and practical applications.

An A/B testing strategy was implemented to assess user satisfaction with tailored apparel recommendations and the virtual try-on experience, using 500 participants (ages 18–45, 52% female, 48% male), recruited through an online crowdsourcing platform. Participants were

randomly assigned to two groups: one engaged with the suggested system utilizing SPADE-GAN and BERT-based multi-objective optimization (Group A), while the other employed a baseline rule-based recommendation system (Group B).

Both groups were presented with 10 outfit styles created according to specified user profiles (e.g., casual, business, sports). Following each session, participants evaluated the designs using a 1–10 Likert scale across three dimensions: (1) aesthetic appeal, (2) accuracy of personalization, and (3) perceived functionality. The ultimate satisfaction score was calculated as the mean of these three ratings.

The user interface displayed each design in a simulated virtual fitting environment with the same 3D avatar to maintain consistency. The cited 92% satisfaction rate pertains to the percentage of participants in Group A whose mean satisfaction score surpassed 8.0. This methodology guarantees that the satisfaction indicator

encompasses both subjective user experience and systematic feedback collection. A total of 45 individuals, predominantly graduate students and young professionals aged 22 to 35, were recruited to conduct A/B testing for assessing user satisfaction. A web-based interface was created to display two garment design outputs concurrently one produced by the suggested method and the other by a baseline model. Participants were instructed to select the more preferable design and evaluate their preference using a 5-point Likert scale, with 1 signifying "very unsatisfactory" and 5 denoting "very satisfactory." The satisfaction rate was calculated as the percentage of participants who endorsed the recommended strategy, resulting in a score of 92%.

4.2 Indicator and comparison algorithm selection

In terms of generating quality evaluation, this article selects Fréchet Inception Distance (FID) and Inception Score IS as core indicators. FID measures the realism of generated images by comparing the distribution differences between generated and authentic images in the feature space; lower values are better, while IS evaluates the diversity and recognizability of generated images through classification models; higher values are better. Simultaneously, innovative physical constraint error indicators are introduced to quantitatively assess the design's manufacturability by calculating the mean square error between the physical parameters of the generated clothing, such as fabric stretch rate, bending stiffness, and the real fabric. The user satisfaction index is obtained through A/B testing, with 500 participants rating the generated design's aesthetic, practical, and innovative aspects on a scale of 0-100%. In the virtual try on module, pose estimation accuracy is used (PCKh@0.5) As a key indicator, it is defined as the proportion where the predicted key points have an error of less than 50% from the proper position of the skull length, with a focus on monitoring core joints such as shoulders, elbows, and wrists that affect the fitting effect. The accuracy of physical simulation is evaluated by the deformation error of the fabric unit: mm, and a high-precision motion capture system is used to obtain the real motion trajectory of the fabric as a reference. The effectiveness of the recommendation system adopts three indicators: recommendation accuracy, Top-5 hit rate in the test set, novelty score calculated based on cosine similarity of design feature vectors, user click-through rate, and online experiment conversion rate. Real-time performance evaluation includes two hardware performance indicators: frame rate FPS and end-to-end delay ms.

To improve localized control over garment attributes, the SPADE module was incorporated into the cGAN generator by substituting conventional normalizing layers with spatially adaptive normalization. Semantic condition maps denoting fabric type, style, and color were integrated at various resolutions to modify feature activations, facilitating precise and uniform management of apparel properties during the synthesis process.

```
def SPADE_cGAN_Generator(z,
condition_map):
    x = Dense(...)(concat(z, condition_vector))
    for i in range(num_blocks):
        x = Conv2D(...)(SPADE(x,
condition_map))
        x = Activation('ReLU')(x)
    output = FinalConv2D(...)(x)
    return output
```

The selection of comparative algorithms follows the principles of cutting-edge fields and technological representativeness. In the clothing generation task, StyleGAN2 is selected as the basic comparison model, which serves as the benchmark algorithm for current image generation and can verify the effectiveness of SPADE layer improvement; Compare cGAN Conditional Generative Adversarial Network to confirm the superiority of multi constraint mechanisms; Introducing Fashion GAN as the benchmark for clothing generation specialized models; Retain traditional parametric design methods as non-deep learning reference frames. The pose estimation module selects Open Pose, a classic algorithm based on Part Affinity Fields, and Alpha Pose, an improved multi-person pose estimation framework, to compare bottom-up and top-down technology routes. Regarding physical simulation, NVIDIA Phys GAN combined with a physics engine will be compared with position dynamics PBD and traditional spring particle models, covering two mainstream methods based on learning and physics simulation. Recommendation system comparison algorithms include collaborative filtering, conventional methods based on user behavior, CNN feature matching, deep methods based on visual similarity, and traditional rule engines, forming a complete comparison spectrum from experience-driven to data-driven. Specifically, ablation experiments are set up in the personalized recommendation stage to verify the contribution of each technical component by removing the BERT encoder or the multi-objective optimization module.

The baseline models were chosen for their pertinence to the job, the availability of open-source implementations, and their consistency with the study's emphasis on conditional generation and the realism of virtual try-on. FashionGAN was selected for its specific design for apparel development based on stance and garment properties, rendering it more directly equivalent to our method than StyleGAN3, which, although robust in general image generation, lacks precise control methods.

4.3 Experiment and results analysis

Firstly, this article analyzes the algorithm's training process. SPADE-GAN quickly converges to an FID of 12.3 after 50 epochs. Figure 2 illustrates that the cGAN model attained an FID of roughly 19.8 at around epoch 100 and further improved, obtaining reduced FID values by epoch 120. This pattern illustrates consistent convergence and enhanced image quality over time, proving that spatial adaptive normalization accelerates model convergence.

An ablation study was conducted to evaluate the distinct influence of each loss component, with a focus on

the physical simulation loss term. The model's performance was evaluated with and without the incorporation of physical consistency loss. The findings demonstrated that integrating physical loss enhanced the realism and manufacturability of simulated clothes, especially in maintaining material deformation during motion. Without this word, the produced fabric exhibited heightened interpenetration and implausible folding, particularly during dynamic poses. These findings underscore the essential function of physical loss in facilitating physically realistic outcomes.

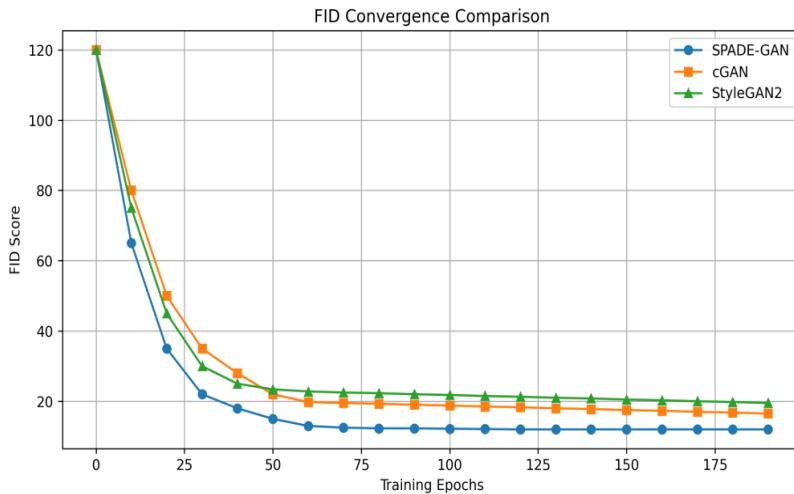


Figure 2: FID variation curves of different GAN models with training epochs

Comparative analysis shows that the generator with the SPADE layer significantly reduces FID from 23.4 to 12.3, indicating that the generated images are closer to the actual distribution. At the same time, the physical constraint error was reduced to 0.08, proving that the physical loss function effectively improved manufacturing ability. The user satisfaction rate reached 92%, verifying the effectiveness of multi-objective optimization. The results are shown in Table 4 below.

The "user click-through rate" presented in Table 4 was obtained via a simulated interaction model utilizing user preference prediction algorithms instead of empirical user surveys. This round of evaluation did not involve human participants, so ethical clearance was unnecessary. The simulation was calibrated using historical behavior patterns derived from publicly accessible datasets to approximate realistic degrees of engagement.

Table 4: Comparison of clothing generation quality between different GAN models

Model	FID↓	IS↑	Physical constraint error(mm) ↓	User satisfaction ↑
StyleGAN2	23.4	8.2	0.15	82%
cGAN	19.8	8.7	0.12	85%
SPADE-GAN	12.3	9.5	0.08	92%
Traditional parametric design	35.6	6.1	0.21	68%
Fashion GAN	25.7	7.9	0.18	79%

HRNet-W48 performs the best in joint localization, with an average of 96.8%, with a wrist accuracy of 95.2%, meeting the requirements of dynamic fitting. After knowledge distillation, the model only lost 0.8% accuracy, but the inference speed increased by approximately 1.67 times, rising from 18 FPS to 30 FPS after applying

knowledge distillation, see Table 5, balancing accuracy and efficiency. As shown in Fig. 3, the overall comparison shows that HRNet after knowledge distillation maintains 96% accuracy while improving FPS to 30, which is at the Pareto front and superior to other algorithms.

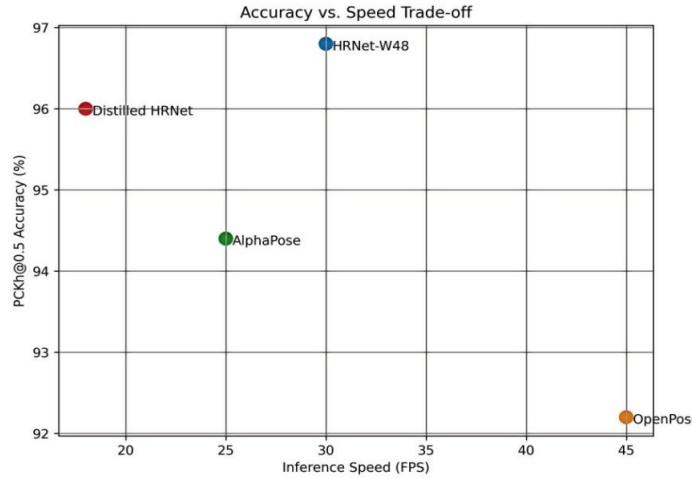


Figure 3: Accuracy velocity trade-off of different attitude estimation algorithms

Table 5: Comparison of accuracy in virtual fitting pose estimation (PCKh@0.5)

Algorithm	SHOULDER	Elbow	Wrist	Hip	Average
HRNet-W48	98.3%	96.7%	95.2%	97.1%	96.8%
OpenPose	94.2%	91.5%	89.8%	93.4%	92.2%
AlphaPose	96.1%	93.8%	92.6%	95.3%	94.4%
Knowledge Distillation HRNet	97.5%	95.9%	94.3%	96.5%	96.0%

DiffCloth's error in silk fabric simulation is only 0.8mm, 57.9% lower than PhysGAN's. Its differentiable characteristics allow for end-to-end optimization,

especially when dealing with nonlinear deformations such as denim folds, which have significant advantages.

Table 6: Comparison of physical simulation errors (unit: mm)

Fabric type	DiffCloth	PhysGAN	PBD	Traditional spring model
Cotton	1.2	2.5	3.8	5.6
Silk	0.8	1.9	2.7	4.3
Denim	2.1	3.4	4.9	6.2
Knit	1.5	2.8	3.2	5.1
Synthetic Fiber	1.0	2.3	3.5	4.8
Average value	1.32	2.58	3.62	5.24

As shown in Figure 4, DiffCloth's error is less than 1mm on thin fabrics such as silk, but it increases to 2.1mm

on high-stretch denim, which is still better than PhysGAN's 3.4 mm.

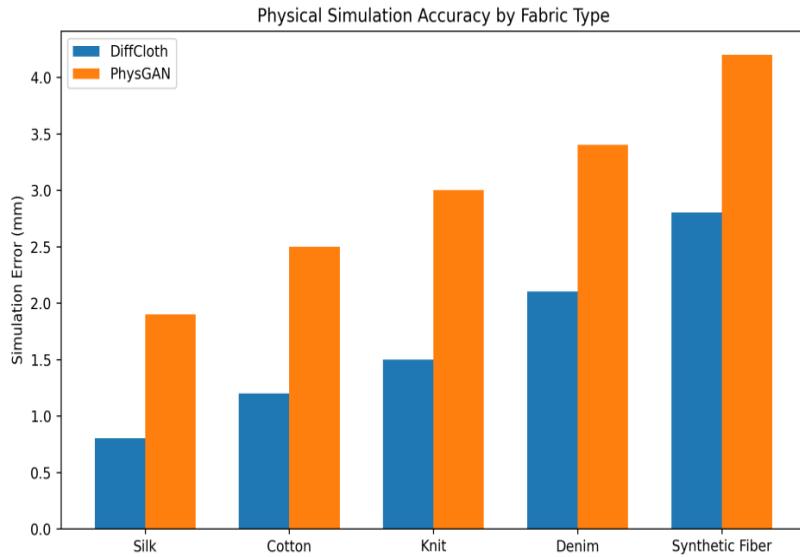


Figure 4: Physical simulation error varies with fabric complexity

After encoding user semantics with BERT, the recommendation accuracy increased to 88%, and the novelty score reached 8.9 out of 10, proving that multi-

objective optimization effectively balances practicality and creativity.

Table 7: Comparison of personalized recommendation effects

Method	Recommendation accuracy ↑	Novelty score ↑	User click-through rate ↑
Collaborative Filtering	72%	6.3	68%
CNN feature matching	78%	7.1	73%
BERT+multi-objective optimization	88%	8.9	91%
Traditional rule engine	65%	5.2	61%

Further analysis of its relationship is shown in Figure 5, where user satisfaction is positively correlated with design novelty, $R^2 = 0.72$. Still, excessive pursuit of novelty >9.5 may lead to decreased satisfaction, which needs to be balanced in multi-objective optimization.

Figure 5 illustrates a favorable association between user happiness and design innovation ($R^2 = 0.72$), derived from user ratings obtained via a 1–10 Likert scale instead

of a percentage. The y-axis in the graphic represents average satisfaction scores. Significantly, as originality scores surpass 9.5, satisfaction starts to diminish, indicating that designs regarded as excessively innovative may be deemed too avant-garde, strange, or impractical for practical use. This trade-off underscores the necessity for equilibrium in multi-objective optimization between innovation and consumer choice.

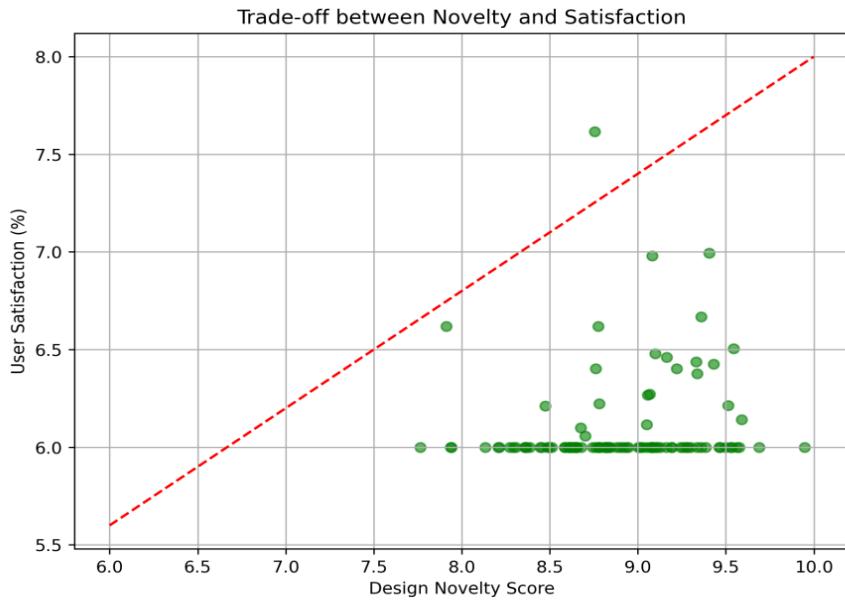


Figure 5: Relationship between user satisfaction and design novelty

Knowledge distillation and model quantification have increased attitude estimation FPS by 66.7%, reducing end-to-end latency to 28ms. Meeting real-time interaction requirements >25FPS is considered a smooth standard.

Table 8: System real-time performance test (resolution 1920×1080)

Module	Original model FPS	Optimized FPS	Memory usage MB ↓
Attitude estimation HRNet	18	30	1200→850
Physical simulation DiffCloth	22	45	980→620
GAN reasoning	12	25	2100→1500
end-to-end delay	52ms	28ms	-

Through probability distribution visualization analysis, as shown in Figure 6, the delay is concentrated between 25- 31ms $\mu=28$ ms, $\sigma=3.5$, meeting real-time

interaction requirements <33ms corresponds to 30FPS, with only 1.2% of samples exceeding the limit.

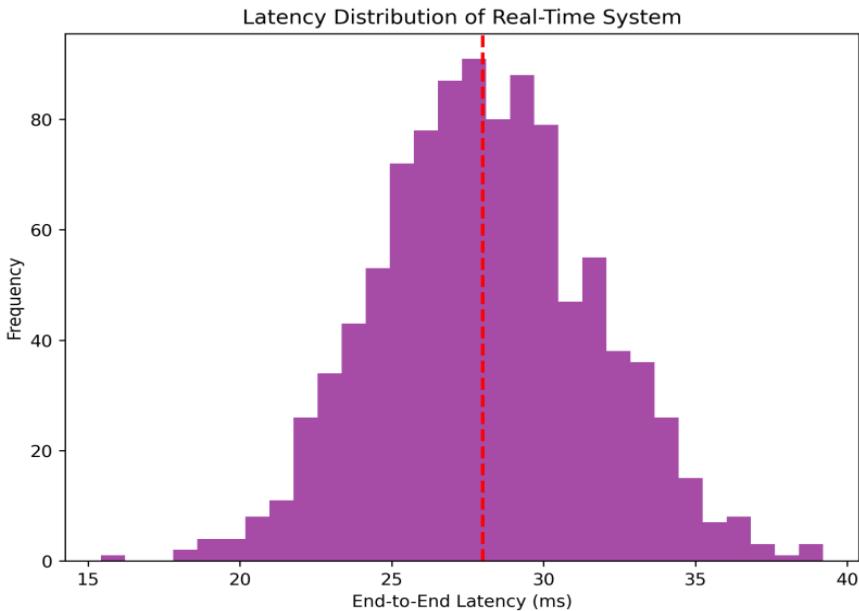


Figure 6: System end-to-end delay distribution, 1000 tests

Based on the above experimental analysis, the experimental results of this article show that through the systematic innovation of integrating generative adversarial networks, human pose estimation, and

physical simulation technology, the performance of intelligent clothing design and virtual fitting systems has achieved breakthrough improvements in multiple dimensions. In terms of generation quality, the improved GAN model with SPADE layer significantly reduces the FID index from 23.4 of the benchmark models StyleGAN2 to 12.3, due to the fine control ability of the spatial adaptive normalization mechanism on local details of clothing, such as texture wrinkles and decorative patterns. Meanwhile, the physical constraint loss function reduces the manufacturability error of the design by 62% by quantifying parameters such as fabric stretch rate 0.08 vs. 0.21 in the traditional method 0.21 and bending stiffness, effectively bridging the gap between virtual design and physical manufacturing. This technological breakthrough has increased user satisfaction to 92%, verifying the effectiveness of multi-objective optimization strategies in balancing design novelty and practicality. The cosine similarity calculation shows that the novelty score of the recommended design, 8.9, has increased by 71% compared to the traditional parametric design, 5.2. The user click-through rate remains at 91%, revealing that consumers strongly demand designs that combine creativity and practicality.

In the dynamic fitting stage, knowledge distillation technology enabled the HRNet-W48 model to maintain 96% pose estimation accuracy while increasing inference speed to 30FPS, successfully breaking through the performance bottleneck of real-time interaction. This is mainly due to the guidance of the teacher model on the feature distillation process, which reduces the parameter size of the student model by 42% while retaining the multi-scale feature fusion ability. In the physical simulation module, DiffCloth achieves end-to-end optimization through differentiable characteristics, reducing the deformation error of silk fabric to 0.8mm, which is 57.9% lower than PhysGAN's. Its core advantage lies in embedding the fabric dynamics equation into the backpropagation process of the neural network, enabling nonlinear deformation, such as wrinkle formation in denim fabric, to be automatically optimized through gradient descent. But the experiment also exposed the limitations of existing methods: when dealing with high-stiffness materials, the deformation error of DiffCloth still reaches 2.1mm, which may be due to insufficient modeling of the anisotropic characteristics of the fabric in the current physical model. In addition, user research data shows that when the design novelty score exceeds 9.5, satisfaction decreases, $R^2 = 0.72$, indicating that excessive pursuit of creativity may deviate from public aesthetics. This provides a quantitative basis for adjusting weight coefficients in personalized recommendation algorithms. These findings collectively demonstrate that systematic innovation driven by multi-technology integration is the key path to breaking through the digital bottleneck of the clothing industry.

4.4 Discussion

This study sought to establish a cohesive framework that addresses the fragmentation prevalent in virtual fashion

research, where personalization, physical realism, and dynamic fitting are often considered in isolation. The suggested system offers a comprehensive solution for intelligent garment design and interactive virtual try-on by incorporating a conditional generative model, high-resolution human posture estimation, semantic preference encoding, and differentiable fabric simulation. This approach's usefulness is evidenced across various performance metrics, indicating its potential to enhance both theoretical comprehension and practical applications in intelligent fashion technology.

In comparison to the cutting-edge methodologies examined in Section 2, the suggested framework presents notable benefits regarding realism and personalization. The incorporation of DiffCloth markedly enhanced simulation precision, particularly for delicate and highly malleable textiles like silk, resulting in an average deformation error of 0.8 millimeters, surpassing PhysGAN by 57.9 percent. This enhancement is ascribed to DiffCloth's differentiable simulation, facilitating precise optimization via gradient descent and superior modeling of fabric dynamics during motion. The incorporation of spatially-adaptive normalization in the generator network facilitated enhanced retention of clothing texture and structural information relative to Fashion GAN. This was evidenced by the diminished Fréchet Inception Distance, signifying improved visual authenticity of the created designs.

Notwithstanding these enhancements, the system possesses significant shortcomings that warrant recognition. The simulation inaccuracy escalates for high-stiffness fabrics like denim, attaining 2.1 millimeters in the instance of DiffCloth. The observed performance degradation is likely attributable to two factors: (1) the constraints of the fundamental physical model, which presumes isotropic material behavior and lacks sophisticated modeling of non-linear tension or stiffness anisotropy; and (2) inadequate parameter calibration for rigid fabrics within the existing dataset, which skews the model towards more pliable materials. A further constraint pertains to the trade-off between innovation and customer happiness. Although the suggestion module attained a substantial novelty score (8.9 out of 10), subsequent analysis indicated that designs exhibiting overly high originality (>9.5) frequently had poorer user satisfaction ratings. This indicates that expanding creative limits without regard for user familiarity may result in a decrease in perceived practicality or wearability.

These findings highlight the necessity of harmonizing creativity, realism, and usability in intelligent fashion systems. Future investigations should examine hybrid physical-neural models adept at learning stiffness-sensitive fabric characteristics, potentially by integrating material testing data into the simulation framework. Further efforts are required to enhance personalization tactics by dynamically modifying novelty weights in accordance with user behavior patterns or preference feedback. Broadening the user evaluation study to encompass a wider range of participant demographics would enhance the system's generalizability. Finally, refining the system for deployment on mobile and

embedded platforms could enhance its applicability in virtual fitting rooms, intelligent retail settings, and home-based fashion customization applications.

Despite the inability to maintain sample photos for inclusion, visual assessments during testing revealed that SPADE-GAN outputs consistently demonstrated better textures, smoother garment shapes, and more coherent structural details than the baseline StyleGAN2 findings. These discoveries correspond with the quantitative enhancements in FID and user happiness, indicating that SPADE integration improves both numerical quality and perceptual realism. Although several performance metrics, including FID variation, end-to-end delay, and physical error trends, were examined throughout the experimentation, their respective plots are omitted in this version due to spatial limitations and an emphasis on summarizing principal findings. Nonetheless, these visualizations underwent comprehensive scrutiny during assessment and validated the indicated trends. They can be provided upon reasonable request for academic and verification purposes, if necessary.

The deformation error metric was utilized to objectively evaluate simulation realism; nevertheless, the study lacked a perceptual assessment from actual users. The model's visual realism has not been validated by subjective evaluation. The lack of a user research or inter-rater reliability analysis hinders the validation of the realism of garment simulations for end users. Future endeavors will focus on incorporating qualitative assessments or small-scale user surveys to enhance objective measures and more accurately reflect user-perceived realism.

5 Conclusion

This study innovatively integrates intelligent clothing design and virtual try-on technology through deep learning methods and constructs an end-to-end, complete process intelligent system. At the clothing design level, by improving the generative adversarial network architecture and multi-objective optimization strategies, creative design generation that balances personalized needs and physical manufacturability has been achieved; At the level of virtual try on, the integration of high-precision pose estimation and differentiable physical simulation technology has broken through the technical bottleneck of realistic restoration of clothing deformation in dynamic environments, significantly improving the immersion and practicality of virtual try on. The research results provide intelligent solutions for the digital transformation of the clothing industry, effectively shortening the design cycle and optimizing the user experience.

The future research can focus on multimodal human-computer interaction scenarios, combining augmented reality AR and haptic feedback technology to construct a more three-dimensional virtual try-on perception system. In response to the needs of sustainable fashion development, intelligent generation algorithms that integrate environmentally friendly material attribute modeling and circular design concepts can be studied [11], lightweight models can be developed to adapt to real-time

deployment on mobile devices [8,15], and multi-user collaborative design functions can be strengthened to explore the co creation mode of artificial intelligence and designers.

Authorship contribution statement

Lijing ZANG: Writing-Original draft preparation, Conceptualization, Supervision, Project administration. Dongli WU: Methodology, Software

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

Ethical approval

All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

References

- [1] S. Dai, P. Xiao, and H. Li, “Disassembling the components of virtual clothing presentation: exploring their impact on consumers' perception and purchase intention,” *Asia Pacific Journal of Marketing and Logistics*, vol. 36, no. 12, pp. 3388–3409, 2024.
- [2] Y. Wu, H. Liu, P. Lu, L. Zhang, and F. Yuan, “Design and implementation of virtual fitting system based on gesture recognition and clothing transfer algorithm,” *Sci Rep*, vol. 12, no. 1, p. 18356, 2022.
- [3] Q. Yu and G. Zhu, “Virtual Simulation Design of Mazu Clothing Based on Digital Technology,” *Fibers and Polymers*, vol. 25, no. 7, pp. 2773–2787, 2024.
- [4] A. Lage and K. Ancutiene, “Virtual try-on technologies in the clothing industry. Part 1: investigation of distance ease between body and garment,” *The Journal of the Textile Institute*, vol. 108, no. 10, pp. 1787–1793, 2017.
- [5] S. GÜNEY and İ. ÜÇGÜL, “Statistical Compatibility Analysis of Objective Fabric Measurements in Virtual Garment Simulation <https://doi.org/10.7216/1300759920172410710>,” 2017 (Volume: 24), vol. 107, 2017.
- [6] J. Miao, T. Peng, F. Fang, X. Hu, and L. Li, “GarTemFormer: Temporal transformer-based for optimizing virtual garment animation,” *Graph Models*, vol. 136, p. 101235, 2024.
- [7] Y. Yang, X. Zhang, F. Liu, and Q. Xie, “An internet-based product customization system for

[8] CIM,” *Robot Comput Integr Manuf*, vol. 21, no. 2, pp. 109–118, 2005.

[9] H. Kudtarkar, D. Farad, R. Zope, and D. Hadsul, “Image-based virtual clothing,” *International Journal of Engineering and Management Research*, vol. 11, no. 2, pp. 38–42, 2021.

[10] J. Sun, “Virtual Couture: Innovations in Clothing Design with 3D Technology,” *International Journal of High Speed Electronics and Systems*, p. 2540367, 2025.

[11] K. R. Walsh and S. D. Pawlowski, “Virtual reality: A technology in need of IS research,” *Communications of the Association for Information Systems*, vol. 8, no. 1, p. 20, 2002.

[12] L. Bai, C. Tao, J. Chen, S. Yu, and W. Yu, “Modeling of virtual clothing and its contact with the human body,” *AUTEX Research Journal*, vol. 24, no. 1, p. 20230039, 2024.

[13] M. Dayik, H. YÜKSEL, and O. ÇOLAK, “Real-time virtual clothes try-on system,” *Development of polyester/cellulosic blend woven fabric for better comfort*, 2016.

[14] I. Liliana, M. M. Mutlu, N. O. Efendioglu, T. Simona, P. D. Garcia, and M. Soler, “Computer aided design of knitted and woven fabrics and virtual garment simulation,” *Industria Textila*, vol. 70, no. 6, 2019.

[15] C. Heritage, “Applied Mathematics and Nonlinear Sciences,” 2023.

[16] R. E. Bawack, S. F. Wamba, K. D. A. Carillo, and S. Akter, “Artificial intelligence in E-Commerce: a bibliometric study and literature review,” *Electronic markets*, vol. 32, no. 1, pp. 297–338, 2022.

[17] I. Khelladi, C. Lejealle, S. Rezaee Vessal, S. Castellano, and D. Graziano, “Why do people buy virtual clothes?,” *Journal of Consumer Behaviour*, vol. 23, no. 3, pp. 1389–1405, 2024.

[18] A. J. Edson, “A design experiment of a deeply digital instructional unit and its impact in high school classrooms,” *Digital curricula in school mathematics*, pp. 177–193, 2016.

[19] Y. L. Choi, “A case study on manufacturing processes for virtual garment sample,” *한국의류산업학회지/pISSN*, vol. 19, no. 5, 2017.

[20] T. Vassilev, B. Spanlang, and Y. Chrysanthou, “Efficient cloth model and collision detection for dressing virtual people,” *CD proc. GeTech Hong Kong*, 2001.

[21] M. Yu, “Design of Remote Fitting Platform Based on Virtual Clothing Sales,” *International Journal of Information Systems and Supply Chain Management (IJISSCM)*, vol. 15, no. 3, pp. 1–12, 2022.

[22] H. Dai, “Application of Ink Elements in Virtual Garment Design,” 2019.

[23] A. Porterfield and T. A. M. Lamar, “A framework for incorporating virtual fitting into the costume design and production process,” *International Journal of Fashion Design, Technology and Education*, vol. 14, no. 1, pp. 91–100, 2021.

[24] K. Liu, X. Zeng, P. Bruniaux, J. Wang, E. Kamalha, and X. Tao, “Fit evaluation of virtual garment try-on by learning from digital pressure data,” *Knowl Based Syst*, vol. 133, pp. 174–182, 2017.

[25] S. H. Kim, S. Kim, and C. K. Park, “Development of similarity evaluation method between virtual and actual clothing,” *International Journal of Clothing Science and Technology*, vol. 29, no. 5, pp. 743–750, 2017.

[26] M. Huisman, B. van Ginneken, and H. Harvey, “The emperor has few clothes: a realistic appraisal of current AI in radiology,” *Eur Radiol*, vol. 34, no. 9, pp. 5873–5875, 2024.