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Clothing Design in the Era of Artificial Intelligence

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Abstract

The integration of artificial intelligence (AI) into the fashion industry is driving transformative advancements in design, production, and sustainability. This article explores the synergistic potential of AI and computer-aided design (CAD) systems, focusing on generative design, personalized clothing models, virtual try-on technologies, and sustainable production optimization. Key applications include AI-driven parametric image generation, digital twins of human figures and textiles, and enhanced material simulation. The study highlights the role of datasets like "DeepFashion" in training AI models and addresses challenges such as data scarcity, software compatibility, and intellectual property risks. By restoring a unified 2D-2.5D-3D digital chain, AI enables seamless integration of design and production stages, fostering digital unity in fashion workflows. Experimental results demonstrate high accuracy in AI-generated figures (up to 95% with Stable Diffusion) and significant accuracy in textile material draping through new approach. Despite obstacles, the future of fashion lies in hybrid systems where human creativity is augmented by AI's analytical and generative capabilities, promising improved product quality, reduced costs, and greater consumer satisfaction.

Keywords

Artificial Intelligence (AI), Computer-Aided Design (CAD), Generative Design, Digital Twins, Parametric Modeling, Virtual Reality (VR), 2.5D-3D Conversion, Textile Material Simulation

1. Introduction

The interaction between digital technologies and artificial intelligence (AI) is poised to fundamentally transform artistic and industrial design processes. Machine learning and computer vision address key challenges—from generating design sketches to optimizing sustainable clothing production. AI technologies have become a powerful tool for enhancing human creativity. Historical perspectives [1] indicate that AI's integration into the clothing industry began with automation and process optimization, with early applications focused on quality control and production planning. As technology advanced, the focus shifted toward AI-driven design, reflecting a transition from improving production efficiency to shaping creative products [2].

A primary application of AI lies in image generation. Advanced generative models create visuals ranging from simple sketches to highly realistic photographs. Generative neural networks like Generative AI and Explainable AI [3] produce new content based on continuously evolving datasets, which are increasingly relevant in the fashion industry.

AI already optimizes various aspects of clothing design and fabric pattern creation [4] [5]. Its creative potential often surpasses that of an average designer: an analysis of leading publications on generative image design shows a strong focus on clothing models [6]-[14]. One of AI's major strengths is its ability to generate images using not only textual prompts but also numerical parameters, paving the way for parametric design.

Many tasks once handled by specialists are now automated. However, translating professional expertise into a digital environment through knowledge bases, rules, and algorithms remains a significant challenge. Advanced AI technologies (Grok3, DeepSeek, ChatGPT, etc.) have already reduced the reliance on traditional 3D programs like Clo3D and Style3D. These developments call for a reassessment of current principles and the search for new ways to integrate AI with CAD systems.

2. AI Capabilities and Challenges

AI is revolutionizing the fashion industry by offering innovative solutions for design creation, trend forecasting, and product personalization. Scientific and applied research focuses on exploring AI's potential, as well as its advantages and limitations in these areas.

2.1. Generative Design and Styling of New Clothing Models

Generative adversarial networks (GANs) have become essential tools for clothing design. The Fashion-Aware GAN model generates images that reflect current trends, speeding up the design process and reducing the time needed to develop collections [15]. AI combines different styles, transfers artworks onto clothing surfaces, and experiments with avant-garde shapes, colors, and structures. This enables rapid prototyping and the development of more dynamic design concepts [16].

2.2. Trend Forecasting

AI's ability to analyze vast amounts of visual data underpins its effectiveness in fashion trend forecasting [17]. This is particularly crucial for fast fashion: by processing social media content and search queries, AI predicts trends with up to 78% accuracy [18]. Through analyzing datasets from social media images to sales statistics, algorithms can identify and forecast emerging fashion trends [19] [20].

2.3. Personalization

AI facilitates the creation of personalized designs based on user preferences, both by replicating existing styles and generating entirely new ones through creative synthesis [20]. Recommendation systems and digital assistants [21] further enhance personalization by analyzing purchase histories and individual style choices.

2.4. The Role of Datasets and Computer

Vision Datasets like "DeepFashion" play a crucial role in training AI models [1]. These datasets contain millions of annotated images, categorizing attributes like fabric types, color combinations, silhouettes, and structural details. This enables algorithms to recognize and interpret complex design elements, considering regional consumer preferences.

2.5. Sustainability and Ethical Aspects

AI contributes to sustainability by minimizing the fashion industry's environmental impact. Fabric-cutting optimization algorithms reduce material waste by 15% - 20%, while accurate demand forecasting limits the production of unsold goods [22]. However, the widespread adoption of AI also raises ethical concerns, including job displacement in design and production, intellectual property rights, and the environmental cost of energy-intensive AI model training.

3. Digital Design Challenges

Modern fashion is rapidly moving into the realm of virtual reality (VR) every year, especially during the pandemic period. Thanks to the capabilities of the internet, smart gadgets, smart mirrors, and various IT technologies based on virtual clothing, consumers can try on clothes, assess their style and fit, and order them anytime and anywhere. On the other hand, the creation of new virtual clothing significantly reduces labor and material costs. Brands using 3D design processes and digital clothing development report a 75% reduction in the number of samples and a 50% - 75% reduction in product development time. New demands for mass production Ready-to-Wear (R-t-W) and made-to-measure clothing (M-t-M) are driving active efforts to formalize traditional planning, production, and sales processes, as well as introducing an innovative approach that leverages virtual technology advantages [23]. At the same time, digitalization faces serious challenges in creating digital twins (DT) of the human body and clothing and combining them into a completely new virtual system—"virtual human body-virtual clothing"—due to the diversity of human morphology and the physical properties of fabrics. In line with the virtual design process, this chapter focuses on two key digital twins: the virtual human body and virtual clothing created based on virtual patterns. Further development of digital design depends on addressing the following issues.

3.1. Generation of Digital Twins of Textile Materials

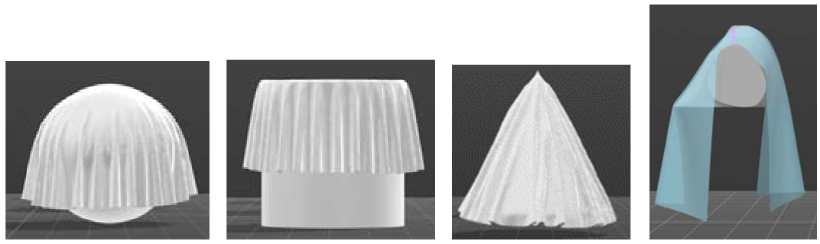
The deformation of textile materials, which is crucial for generating virtual twins, is mainly studied only under the influence of gravitational forces or short-term loads. Traditionally, well-known indicators characterize internal deformation processes under applied mechanical loads, but their number is limited by the availability of existing mechanical equipment and established standards. For example, the 3D software CLO3D allows users to adjust several properties of woven and nonwoven textile materials—such as tensile, shear, and bending resistance—by modifying their digital parameters, which were previously measured in flat fabric samples.

Currently, the generation of virtual textile material twins in this software mainly uses physical and mechanical property indicators (based on the KAWABATA method) and drapability. So, mathematical algorithm of clothing shape modelling in 3D relies on test results from flat textile material samples. These inconsistencies—testing in a flat form versus generating volumetric clothing—affect the predictability of material behavior in a three-dimensional environment. Expanding the range of property indicators included in mathematical models and aligning test methods with real-world conditions are crucial directions in digital textile material science. The importance of sensory properties is also evident, as they provide the opportunity to assess clothing comfort.

Digital twins of textile materials must replicate real situations that may arise with virtual clothing. The capabilities of three-dimensional design software make it possible to model and create new testing schemes that measure unexplored reaction indicators reflecting the interaction of fabric with the human body's surface. The human body's surface has complex contours, and a fabric's ability to conform to these shapes directly impacts the appearance of virtual clothing.

A new approach to evaluating the conformability of textile materials involves modeling the interaction of fabrics with non-developable surfaces, unlike geometric primitives such as cones and cylinders. **Figure 1** shows testing schemes for textile materials in two well-known 3D modeling programs and on a newly developed anthropometric stand that simulates an upper section of the human body's surface. The look of samples produced by existing programs, featuring numerous vertical folds, differs significantly from the actual shape of physical garments (coats, jackets, shirts, dresses, etc.).

From **Figure 1**, it is evident that the new testing scheme changes the spatial shape of the sample: additional factors significantly influence the material's form-shaping process, bringing the appearance closer to real clothing. Clearly, the development of virtual textile material twins will require the exploration of new testing schemes for both single-layer samples and material packages from multilayer clothing.



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

Figure 1. Fabrics virtual test stands. (a) Spherical in CLO3D, (b) Cylindrical in Style3D, (c) Cone in Style3D, (d) anthropometrical stands copied an upper part of human body.

3.2. Generation of Digital Twins of Clothing

The quality of clothing render generation directly depends on accurately reproducing the structural features of pattern details, methods of their connection, types, and quantities of materials used, including frame materials (interlinings, reinforcements). Existing three-dimensional visualization programs (CLO3D, Style3D, and others) produce good results for single-layer garments (dresses, skirts, blouses, shirts, trousers, etc.), but as the number of materials increases, the reliability of clothing renders decreases. Improving the accuracy of generating various types of clothing, differing in their positioning on the figure and volumetric-spatial form, directly depends on the completeness of formalizing the internal content of the pattern construction process: the interconnection of design parameters, the configuration of design lines, and understanding their impact on clothing shape indicators. **Figure 2** presents clothing model renders generated in 3D programs and using AI.

(a) (b) (c)

Figure 2. Images generated by Clo3D (a), Style 3D (b) and Midjourney (c).

From **Figure 2**, the high degree of realism in the AI-generated image is obvious, which significantly enhances the level of trust in it. A key advantage of such images is the ability to generate them without using construction drawings of details, that is, without involving the professional experience of a clothing designer.

3.3. Lack of Predictive Design Decision Scenarios

Algorithms for the preliminary validation of design decisions, concerning not only the appearance of clothing, should restrict and warn designers against potential mistakes. The consequences of such errors can negatively affect the cost-effectiveness and manufacturability of industrial production. New algorithms integrating different stages of design and production could become an effective tool for preventing uneconomical and unjustified decisions. At present, such algorithms have not yet been developed, but the capabilities of AI will undoubtedly accelerate their emergence.

3.4. Absence of Commonly Accepted Quality Assessment Criteria for Virtual Clothing

Standardized criteria are essential for a comprehensive assessment of virtual clothing quality, including fit on an avatar's body, proportionality, and appearance. Currently, the desired quality level and appearance of clothing are determined by the manufacturer, focusing on the selected consumer category. However, this aspect is not yet quantitatively reflected in existing processes and technologies. It is evident that improving quality levels directly depends on the number of design, manufacturing, and subsequent verification procedures performed. To optimize the design decision-making process, it is necessary to develop appropriate criteria, which are currently formulated mainly in descriptive form.

4. Potential Areas of Interaction between AI and Digital Fashion

The modern fashion industry is undergoing radical changes driven by digital technologies. The use of AI opens up the possibility for the complete digitalization of the clothing design process, where all objects will have digital characteristics that can be converted into one another. The structure of an AI prompt can include a verbal description and quantitative parameters of the image. **Figure 3** shows how

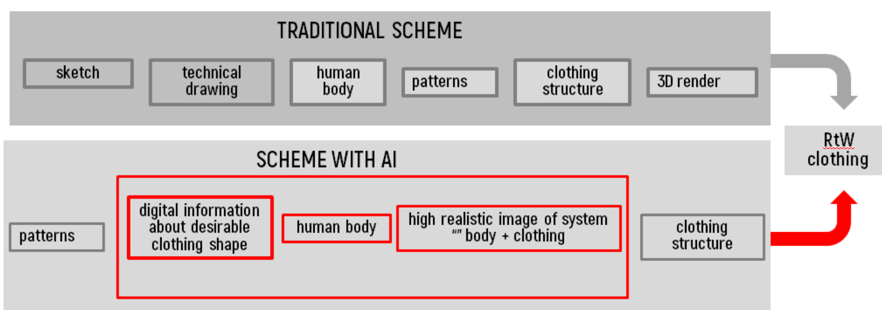


Figure 3. Interaction scheme of AI and CAD.

the traditional scheme can change when using AI to generate realistic images of human figures and clothing at the very beginning of the process, at the concept development stage.

In the traditional design process, the image of the future clothing form is based on the designer's intuition, often stylized, and its correct interpretation by technical specialists and subsequent realization into finished clothing requires considerable attention and compromises. 3D modeling software renders help facilitate this process. Nevertheless, the effectiveness of this approach depends on the coordinated efforts of many specialists.

As shown in **Figure 3**, the AI-driven scheme requires a new digital database containing parameters of the desired clothing form, closely linked to the technical drawings from which the garments will be produced. This database, formalizing the professional experience of pattern designers, should become a fundamentally new step in the industry's future development.

The parameters of the future clothing form depend on many interconnected factors: the values of design allowances, material property indicators, production technology, and appearance requirements. It is clear that the development of such digital databases and reference guides for writing AI prompts should start with mass-produced clothing RtW.

A prime example of such standardized clothing is men's jackets. **Table 1** presents the basic parameters of jackets related to flat technical drawings (allowances for shoulder width, waist and hip half-girths) and the front silhouette. The conversion of the first set of parameters into the second was carried out through numerous physical experiments with jackets of three main fits: slim fit, fit, and regular.

Table 1. Men blazer parameters taken from pattern blocks and used in the prompt for Shedevrum (Yandex, Russia).

Blazer style	Parameters, cm		
	Shoulder width	Chest width	Waist width
1. Ease allowance from prom pattern blocks			
Slim fit	0	5.5	1.7
Fit	1.4	9.6	3.6
Comfort	3	13.7	8.3
2. Projection parameters used in the prompt			
Slim fit	46	40	31
Fit	49	43	35
Comfort	52	47	40

Figure 4 shows images of men's jackets with different silhouettes generated using AI Shedevrum (Yandex, Russia) and the parameters from the second group in **Table 1**.

Figure 4. Images of men blazers generated by digital prompts in AI Shedevrum: left to right—slim fit, fit, comfort.

Figure 4 clearly demonstrates the differences between the jackets and the potential use of the new database for the digitalization of the first stage of the design process—generating the visual concept of the created clothing.

One of the most important directions is the integration of AI with CAD systems to significantly speed up and optimize the process of developing new clothing models, improve quality, and increase design accuracy. The following sections discuss the key aspects of AI and CAD interaction, the benefits of using generative models and analytical algorithms, and some examples of research in this field. **Figure 5** shows the AI and CAD system interaction scheme.

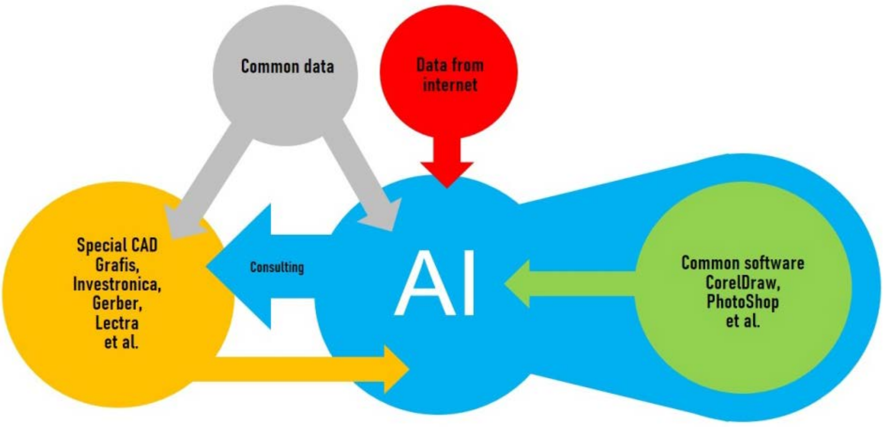


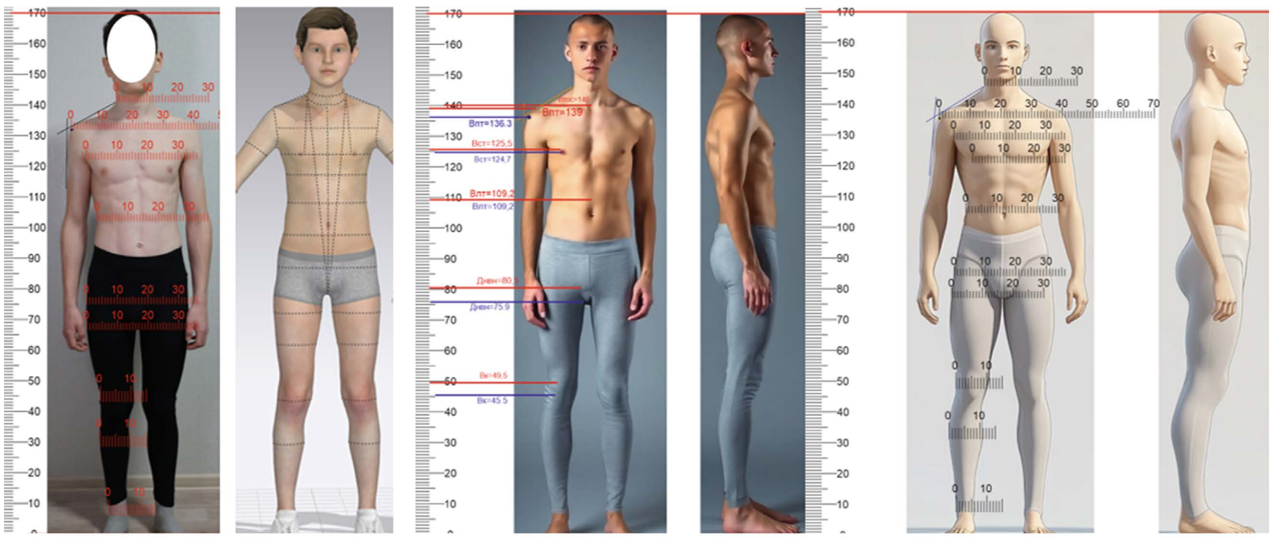
Figure 5. Interaction scheme of AI and CAD.

4.1. Generation of Digital Twins of Human Figures

This issue is particularly relevant for figures that must comply with national standards for clothing design. Typically, the number of dimensional features included in such standards worldwide does not exceed 35 - 40 measurements, but this is insufficient for creating a virtual twin. In addition to linear measurements, horizontal and vertical cross-sections and projection parameters are required to describe the front, side, and back contours. Currently, there are no sufficient anthropometric databases to generate virtual twins covering the entire size range of human figures—from the smallest to the largest.

The accuracy of virtual twin generation in 3D modeling programs is limited by the number of dimensional features (not exceeding 18), while AI-based models achieve an accuracy rate of 87% (Stable Diffusion AI) to 95% (Fusion Brain AI). The accuracy of a human figure's virtual twin significantly impacts the results of virtual clothing simulation, especially for specialized clothing (therapeutic, medical, sports, cosmetic). Expanding the anthropometric database is a crucial factor for leveraging all the advantages of digital technologies and AI. A simple method for verifying the accuracy of a generated image can involve aligning two outlines.

Figure 6 presents an example of generating and verifying the quality of images produced in several programs. **Figure 4** also shows measurement schemes for vertical and horizontal projection dimensions, totaling 32 indicators in this example.



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

Figure 6. Real teenager (a), avatar generated in Clo3D (b) and the images generated by AI: (c) LeonardoAI, (d) Stable diffusion.

For the verification of generated figure images, a mathematical framework has been developed, the results of which can serve as criteria for assessing trust in AI. After measuring N dimensions, each measurement i has expected value E_i. G_i is desired value. The significance (weight) of i-measurement is wi, which have been chosen in accordance with its influencing on virtual try-on or pattern making. Then the formula for the accuracy of image generation can then be determined as:

$$\text{Accuracy} = \left(1 - \sum_{n=1}^{N}\left(wi\frac{/Gi - Ei/}{Ei}\right) \Big/ \sum_{n=1}^{N} wi\right)100\%$$

For the compared images in **Figure 4**, the generation accuracy was, %: Clo3D—71, LeonardoAI—82, StableDiffusion—95.

AI programs are already capable of generating images of individual figures based on a limited number of dimensional characteristics. In the future, AI could be used to create catalogs of standard figures for national standards.

4.2. Scheme 2D-2.5D-3D

The accuracy of figure and clothing generation depends on the quality of the source data, the correctness of algorithm settings, and the structure of prompts in AI. Generating images using AI required the restoration of the complete digital chain for presenting figures, clothing, and "figure + clothing" systems according to the scheme: 2D (CAD)-2.5D (AI)-3D (three-dimensional modeling). 2.5D images combine three views: front, side, and back. The reliability of such clothing images, under which a figure is hidden, depends on the air gaps between the figure and the clothing, the structure of the clothing, the form-shaping properties of the materials, and other factors. The parameters of 2.5D images are necessary for writing prompts containing verbal terms and numerical parameters, and for subsequent image generation using AI.

Referring to the previous example in **Figure 6**, it is important to note that the generation of human body images, as shown in **Figure 6**, faced a significant challenge in their comprehensive quantitative evaluation. Since national standards primarily include measurements taken on the surface of figures (circumferences, arcs, widths, distances) and the heights of anthropometric points, they cannot, except for heights, be used to verify the accuracy of image generation using AI. Contour verification can only be performed using projection measurements, into which the measurements used in the standard must be converted.

A solution to this situation is the use of body scanning results to form a new anthropometric database, as body scanning programs allow obtaining sets of dimensional characteristics (up to 150 measurements), horizontal and cross-sectional data. These databases enable the creation of a 2D-2.5D-3D chain for converting dimensional characteristics into one another. This data chain will allow the creation of criteria for verifying generated images.

Figure 7 shows an example of a 2.5D representation of a standard female figure generated using body scanning, for subsequent verification of its AI-generated image.

A particular challenge is the parametric description of the clothing form when worn on a figure. Due to the complex morphology of the body, the style, and the construction of the garment, air gaps form between them. **Figure 8** shows an example of a horizontal cross-section of the female figure and the blazer at the waistline level.

It is precisely under the influence of air gaps that the final silhouette of the clothing takes shape. To ensure digital consistency in the 2D-2.5D-3D image chain, mathematical patterns are needed to describe the relationship between the parameters of the figure, the clothing, and the air gaps. These relationships are multifactorial.

Figure 8 shows measurement schemes for the torso of the figure and the blazer,

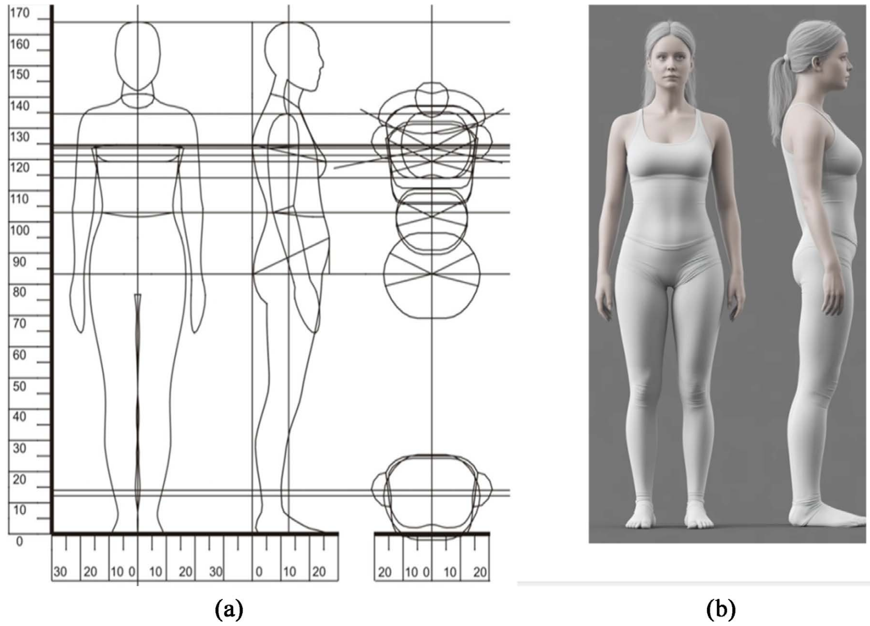


Figure 7. 2.5D images of typical Russian women (a) and its virtual twin generated by Stable Diffusion (b).

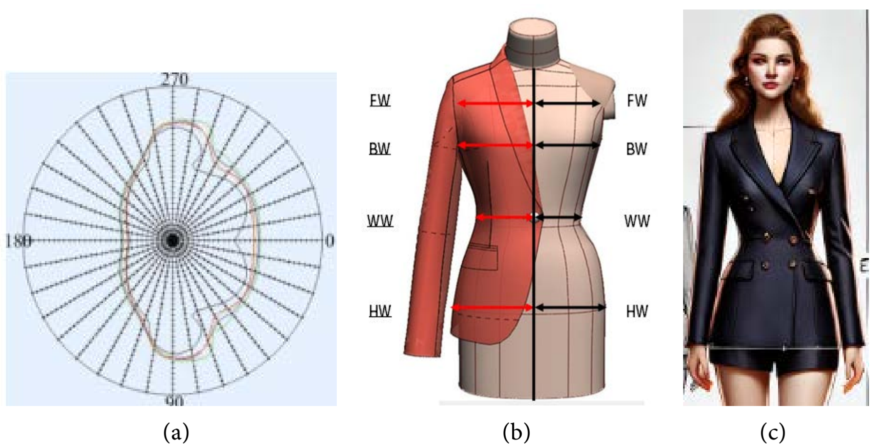


Figure 8. Scheme of parameterization the both elements of 2.5D system: (a) cross-section of system "torso-blazer" on waist level to explore the relations between $\underline{WW}$ and WW, (b) left—women blazer ($\underline{FW}$, $\underline{BW}$, $\underline{WW}$, $\underline{HW}$), right—body torso (FW, BW, WW. HW); (c) stylish blazer generated in Grok3.

the results of which can be included in the prompt for generating the blazer image:

FW—front torso width,

BW—front torso projection of bust girth,

WW—front torso projection of waist girth,

HW—front torso projection of hip girth

$\underline{FW}$—front blazer width,

$\underline{BW}$—front diameter of blazer bust,

$\underline{WW}$—front diameter of blazer waist,

$\underline{HW}$—front diameter of blazer hip.

To describe the air gap, a system of equations can be used, where its value is predicted based on the volumes of adjacent sections—along the bust, waist and hip [24]. The equations in **Table 2** designed to calculate the air gaps that arise between the body torso and a women's blazer, depending on the ease allowances (Eb at the bust line, Ew—waistline, Eh—hip line, and Eah—armhole width) designing in the blazer pattern. The air gaps are projected along rays drawn from the center of cross-sections of bust, waist and hip at angles of 0 degrees (center of bust), 40 degrees (through bust point), 70 degrees (through front corner of the armpit), 120 degrees (through back corner of the armpit), and 180 degrees (center of the back).

Table 2. Equations for calculating of air gaps between women body and blazer along cross-sections on the bust level.

angle, degree	cross-section	equations for calculating of air gaps, cm
0	bust	−0.35Eb − 1.05Eh + 0.66Eah + 4.27
	waist	0.11Eb + 0.17Eh − 0.13Eah + 0.86
	hip	0.77 − 0.12Eh + 0.49Eah + 4
40	bust	0.05Eb + 0.07Eh + 1.3
	waist	0.13Eb + 0.16Eh + 0.9
	hip	0.28Eb + 0.15Eh + 2.9
70	bust	−0.48Eb + 0.38Eh + 4.6
	waist	0.14Eb + 0.28Eh + 1.6
	hip	0.12Eb + 0.02Eh + 1.5
120	bust	−0.03Eb − 0.07Eh + 0.35Eah + 0.7
	waist	−0.26Eb + 0.5Eh + 1.35Eah + 0.8
	hip	0.03Eb − 0.1Eh + 0.55Eah + 0.9
180	bust	−0.29Eb + 0.04Ew + 0.76Eah + 1
	waist	−0.04Eb − 0.61Ew + 2.1Eah + 7.9
	hip	−0.2Eb − 0.2Ew + 1.55Eah + 3.1

Figure 8(c) shows an image of a women's blazer in the 1950s style, generated using two groups of coordinated parameters related to the figure and the blazer and taken from **Table 2**.

4.3. AI and Specialized CAD Systems

The interaction between AI and CAD (Computer-Aided Design) systems represents a new scientific direction. Modern CAD systems for fashion design (e.g., CLO3D, Optitex, Browzwear) provide tools for creating 3D models, simulating fabrics, designing patterns, and visualization. The integration of AI into these systems opens new opportunities for process optimization, enhanced creativity, and cost reduction. Key areas of collaboration between AI and CAD include:

1) Optimization of Simulation Parameters: AI analyzes data on fabrics, garment fit on human bodies, and material properties to improve the accuracy of CAD simulations. Machine learning algorithms predict how fabric will drape on a 3D model, considering factors like density, elasticity, and weight. This reduces the need for physical prototypes. In [1], the "DeepFashion" dataset is used to train models that automatically adjust garment fit in CAD based on body morphology.

2) Personalized Design: AI integrates with CAD to create customized designs for individual users. Based on 3D body scan data, algorithms generate personalized patterns. Recommendation systems suggest design options in CAD, taking into account the customer's purchase history and style preferences [24].

3) Smart Cutting and Sustainable Production: AI optimizes fabric cutting processes by integrating with CAD modules for production planning. Machine learning algorithms analyze pattern geometry and propose layout schemes that reduce waste by tens of percent. AI also forecasts demand for collections, helping designers focus on relevant models and avoid overproduction.

4) Enhanced Material Simulation: Neural networks are trained on fabric property data to improve the realism of CAD simulations. AI predicts fabric wear over time, enabling designers to test the durability of their creations during the design phase.

5) Integration with AR/VR and Digital Twins: AI and CAD collaborate to create virtual fitting rooms and digital collections. Computer vision algorithms allow customers to "try on" clothes in AR, while designers can test models in VR environments.

5. Challenges and Limitations

Several challenges in applying AI should be noted:

Training AI requires large volumes of prepared data (e.g., a unified 2D-2.5D-3D chain, fabric parameters, garment design features, digital body measurements, and clothing patterns), which are often unavailable due to commercial secrecy.

Achieving compatibility between CAD and AI will require significant architectural changes to software.

Risks of copying "others'" designs and infringing intellectual property rights when using generative models raise legal concerns in AI applications.

6. Conclusions

The opportunities opened by AI are not yet obvious to everyone but are immense. Despite existing challenges, further technological advancements and algorithm improvements will significantly expand the capabilities of both traditional and digital production.

1) Parametric Image Generation: The ability to generate parametric images (of clothing, figures, and patterns) is a prerequisite for integrating results with existing databases and CAD systems, unifying all stages under the concept of digital unity. Digital unity in fashion design is a new concept that involves using a single digital platform and a set of prompts to develop images, patterns, and technologies with AI. This approach will integrate all stages of development and production into a unified, interconnected ecosystem where every detail, change, or piece of information about a product is synchronized. CAD systems, enhanced by AI's analytical and generative capabilities, will optimize the design process, predict fashion trends, and create unique digital models.

2) Collaborative Decision-Making: By leveraging multiple AI systems, designers and engineers can make decisions collaboratively, consulting diverse sources of information. This is particularly valuable when making ambiguous decisions. The integration of AI with CAD opens new horizons for creative and production processes.

3) Future Scenarios: The integration of AI with existing CAD systems will enable several scenarios, such as simulating generative reasoning and writing algorithms for the rational application of CAD commands. In the future, closer integration of AI into CAD systems, the development of adaptive interfaces, and increased automation are expected. The future lies in hybrid systems where human creativity is amplified by AI capabilities.

Thus, the continued development of AI technologies and their integration into clothing modeling and design processes open new horizons for the fashion industry. Addressing the identified challenges and actively implementing AI will significantly improve the quality of designed products, optimize production processes, and meet growing consumer demand for personalized and comfortable garments.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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