Cloud-Computing-Enabled Transformer Architecture for the Design of Functional Clothing Structures

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This paper introduces a graphical design model for smart clothing structures based on cloud computing and an integrated approach combining Transformer architecture with conditional Generative Adversarial Networks (cGANs). The model aims to revolutionize the functional clothing design industry by transforming users' diverse needs into machine-understandable vector representations using a multi-head self-attention mechanism. Subsequently, a decoder generates design elements, which are then visualized using cGAN techniques. To evaluate the model's performance, we conducted extensive computational experiments using a comprehensive dataset that includes various design styles and occupational categories, such as medical, catering, aviation, and industrial clothing. The model was trained and validated using K-fold cross-validation, ensuring robustness and generalizability. Key performance metrics were assessed, including design element similarity, layout rationality, and personalization accuracy. Experimental results show that the model achieves an average design element similarity score of over 89%, a layout rationality score of over 90%, and a personalization accuracy of nearly 92%. These performance indicators demonstrate the model's effectiveness in design accuracy, efficiency, personalization, and market adaptability, particularly for occupational clothing design in healthcare, catering, aviation, and industrial applications. The integration of Transformer and cGAN technologies significantly enhances the model's capability to generate high-quality, personalized designs while maintaining robustness and scalability. This approach provides a comprehensive solution for automating the design process, leading to improved design outcomes and enhanced user satisfaction.

Povzetek: Članek obravnava arhitekturo transformatorja, ki jo omogoča računalništvo v oblaku, za oblikovanje funkcionalnih struktur oblačil. Model, ki temelji na kombinaciji transformatorja in cGAN, pretvarja potrebe uporabnikov v vektorske predstavitve in generira oblikovalske elemente.

1 Introduction

Functional apparel, also known as occupational clothing or uniforms, are garments designed for specific occupations or work environments, which are designed not only for aesthetics and comfort, but also, more importantly, for their functionality, safety, and for brand image. Functional clothing plays a crucial role in various industries, they are not only the embodiment of dress code, but also the sign of professional identity, the booster of work efficiency, and the carrier of corporate culture [1]. In the medical industry, the white coats and operating room-specific clothing worn by healthcare workers not only create a professional image, but also have the hygienic functions of disinfection and anti-bacteria, protecting both doctors and patients from the risk of infection. In the restaurant industry, the uniforms of chefs and waiters not only keep neat and clean to meet food safety standards, but also convey the brand style of the restaurant through color and design. In the aviation and hospitality industries, the uniforms of cabin crew and receptionists are a direct reflection of the corporate image, and they convey the concept of professional and reliable service through a uniform visual language. In the industrial field, especially in the chemical and construction industries, the protective performance of functional clothing is crucial. The application of special materials such as anti-static, fireproof, and anti-radiation provides the necessary safety for workers and reduces occupational hazards [2].

Functional apparel is equally indispensable in a variety of industries such as education, retail, and transportation, where they help to differentiate between different positions and promote teamwork while enhancing customer or public trust. The design of functional clothing needs to take into account the nature of the work, environmental factors, corporate culture, and ergonomic principles to ensure that the wearer can perform his or her job comfortably while reflecting the professionalism of the occupation and the consistency of the company [3].

Traditional functional apparel design is often limited by physical resources and geographic distances, and the design process usually requires frequent physical exchanges between designers, material suppliers, and manufacturers, which is not only time-consuming and labor-intensive, but can also lead to slow design iterations.

In addition, due to the lack of effective data management and analysis tools, design decisions often rely on experience and intuition, making it difficult to accurately capture market trends and user needs. This design approach also limits remote team collaboration and reduces design flexibility and responsiveness [4].

The advent of cloud computing has revolutionized the landscape of functional apparel design. By migrating design tools, resource libraries, and collaboration platforms to the cloud, cloud computing breaks down geographic boundaries and enables instant sharing of resources and remote team collaboration on a global scale. Designers can access the latest design software from any location, utilize cloud storage for file backup and version control, and greatly improve design efficiency [5]. The aim of this study is to explore how cloud computing can empower the structural graphic design of functional apparel, and by analyzing the application of cloud computing technology in the design process, we hope to reveal its positive impact on design efficiency, collaborative work, and innovativeness [6].

The innovation of this paper focuses on proposing a graphical design model of clothing structure based on cloud computing and Transformer architecture, which realizes efficient and precise understanding and response to diversified user needs through deep learning technology. The research mainly includes: (1) Dynamic adaptability and personalized design: relying on the elastic resources of cloud computing, the model is able to adjust in real time to respond to different user needs, ensure the uniqueness and personalization of the design, and satisfy the precise requirements for details in the design of functional clothing. (2) Multi-head self-attention mechanism: the introduced multi-head self-attention mechanism enhances the model's ability to capture the complex relationships among parts in the input sequence, and even if these parts are far away from each other in the sequence, they can still be correctly associated, thus enhancing the innovation and functionality of the design [7].

2 Literature review

2.1 Overview of the development of functional clothing

Functional apparel, i.e., functional clothing, is designed to meet the needs of the wearer in specific environments, whether it is protection from extreme climatic conditions or safety and convenience for specific occupational activities. From the initial waterproof, windproof, and breathable to the modern intelligent sensing and self-regulation, the development of functional apparel has demonstrated the deep integration of science and technology with textile innovation [8]. The development of this field has not only been driven by advances in materials science, but has also benefited from the results of ergonomic, biomechanical, and environmental adaptation research [9].

The origins of functional clothing can be traced back to the early 20th century, when the properties of natural fibers were explored to create more durable and protective clothing [10]. However, the real revolution in functional clothing occurred in the mid-20th century with the invention of synthetic fibers such as nylon and polyester, new materials that were not only lightweight and wearable, but also had some waterproofing and warmth properties [11]. Subsequently, the emergence of waterproof and breathable membranes, such as Gore-Tex, marked a new era for functional clothing [12]. In recent years, the development of functional apparel has focused more on the smartness and responsiveness of materials. For example, phase change materials (PCMs) are capable of absorbing or releasing heat according to changes in ambient temperature to maintain the stability of the human microenvironment [13]. In addition, the application of conductive fabrics and nanotechnology enables garments to integrate sensors for health monitoring, environmental sensing, and other functions [14]. These innovations not only enhance the utility of clothing, but also open the way for personalization and customization.

The functional apparel market continues to expand as consumers demand higher levels of health, safety, and comfort, as well as an increase in outdoor sports and professional work scenarios [15]. Especially after the epidemic, the focus on personal hygiene and protection has driven the use of antimicrobial and antiviral materials in apparel [16]. Meanwhile, sustainability has become a focus of industry attention, with green materials and circular economy models being increasingly introduced into functional apparel design [17].

The future development of functional clothing will focus more on user experience and human-computer interaction. The integration of wearable technologies will make clothing part of the Internet of Things, enabling data collection and intelligent feedback [18]. In addition, with advances in artificial intelligence and machine learning, personalized design and on-demand manufacturing will become the norm, satisfying consumers' pursuit of uniqueness and adaptability [19]. Eventually, functional clothing will become more than just a piece of clothing, but an intelligent interface that connects the body to the external world.

2.2 Application of cloud computing in the field of clothing design

Cloud computing has brought unprecedented changes to the apparel design industry with its superior data processing capability and flexible service model. From design to production to supply chain management, cloud computing technology is gradually penetrating and optimizing the entire apparel industry chain, creating more value for designers, producers and consumers [20].

During the design phase, cloud computing provides powerful and easily accessible computing resources that enable designers to perform complex design simulations and 3D renderings without relying on expensive local hardware facilities [21]. For example, platforms such as the Bock Intelligent Apparel Cloud CAD System utilize cloud computing technology to allow designers and production staff to design and manage work from any location, at any time, greatly enhancing efficiency and flexibility (. The Smart Custom Apparel Cloud CAD system even integrates advanced design tools and intelligent algorithms to help designers rapidly iterate their designs while maintaining a high level of innovation and personalization [22]. Cloud computing also facilitates the digital transformation of the apparel production process by enabling supply chain transparency and collaboration through cloud platforms, effectively reducing inventory costs and shortening the time-to-market cycle [23]. Services provided by companies such as Zeta Cloud, which utilize cloud computing and meta-universe technologies, provide a new perspective on apparel design and production, making remote collaboration and virtual presentations possible, reducing the production of physical prototypes, and saving time and resources [24]. On the consumer side, cloud computing is able to accurately capture consumer preferences and market trends through big data analysis, providing customized products and services for apparel companies [25]. Applications such as virtual fitting rooms and personalized recommendation systems allow consumers to experience the real effect of clothing before purchase, improving customer satisfaction and loyalty [26].

2.3 Current status of domestic and international research

Overseas, research on the application of cloud computing in apparel design is quite mature, focusing on improving design efficiency, enhancing user experience, and optimizing supply chain management. For example, [27] explored how cloud technology can accelerate the 3D modeling and simulation process of apparel by providing high-performance computing power, thus shortening the product development cycle. At the user level, on the other hand, research by [28] demonstrates how cloud-driven virtual fitting technology can transform the consumer shopping experience by reducing return rates and increasing online sales through accurate body size matching. Domestic studies have also followed the international pace and are dedicated to exploring how cloud computing can empower various aspects of apparel design and manufacturing. A study by [29] revealed the application of cloud computing in the apparel supply chain, which significantly reduced operational costs by predicting market demand and optimizing inventory management through big data analysis. In addition, the project focuses on the development of intelligent design software on the cloud computing platform, which utilizes machine learning algorithms and is able to automatically generate design solutions based on fashion trends and consumer feedback, which greatly enhances the innovation and efficiency of design. The summary table of research results is specifically shown in Table 1.

Table 1: Summary of research results.

Research/Method	Accuracy	Personalization	Design Efficiency	Key Technologies/Materials	Main Findings/Contributions	Gaps/Improvement Points
Gore-Tex Waterproof & Breathable Membrane	High	Low	Medium	ePTFE	Provides excellent water resistance and breathability	Lacks personalized design and intelligent regulation capabilities
Smart PCM Clothing	Moderate	Moderate	Low	Phase Change Materials	Can regulate the microenvironment according to ambient temperature	High production cost and long design cycle
Conductive Fabric Health Monitoring	High	Moderate	Moderate	Conductive Fibers, Sensors	Achieves real-time health data monitoring	Short battery life, poor wash durability
Zeta Cloud Virtual Design Platform	High	High	High	Cloud Computing, Metaverse Technology	Accelerates design processes and reduces the need for physical prototypes	May lack certain functionalities compared to custom hardware
Bock Intelligent Apparel Cloud CAD	Moderate	High	High	Cloud Computing, CAD	Enhances design flexibility and collaboration	Strong dependence on internet connection
Machine Learning-	High	High	High	Machine Learning Algorithms	Enables automated design proposals	Data privacy and security

Driven Design Software					based on trends and feedback	concerns are challenges

Literature [30] discusses the effectiveness of interactive genetic algorithms (IGAs) and shows how such algorithms optimize design solutions through user preference feedback. The study highlights IGA's ability as a tool to capture users 'aesthetic preferences and generate designs that conform to those preferences. Literature [31] presents a new approach to combining traditional art elements with modern design techniques. Lu's work shows how to create culturally meaningful and visually appealing graphic design works by reorganizing traditional patterns and symbols. Together, these two findings inspire us that similar approaches can be taken to enhance the garment design process, by using IGA to better meet the individual needs of consumers, and by integrating traditional visual elements to enrich the cultural content and aesthetic value of garment design.

3 Graphic design model of clothing structure based on cloud computing

This model framework is based on the Transformer architecture, which skillfully combines the powerful arithmetic power of cloud computing with advanced artificial intelligence technology in order to realize efficient and accurate graphical design of functional clothing structures. The model is mainly divided into three key layers: the input layer, the encoder layer, and the decoder layer, each of which carries specific functions, and its hierarchy is shown in Figure 1.

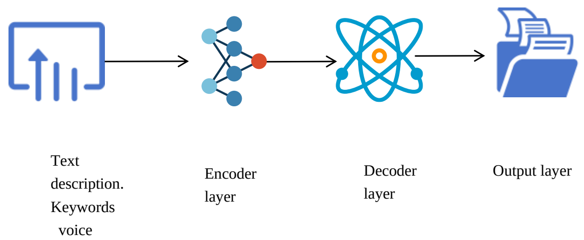

Figure 1: Hierarchy

The input layer is responsible for receiving the user's requirements expressed in the form of text, keywords or speech, and transforming them into vector representations through the embedding layer to lay the foundation for subsequent processing. The encoder layer employs a multi-head self-attention mechanism to parse the deeper meaning of the user's demand and transforms the input vector sequence into a semantically rich vector sequence Z. This process is realized by stacking multiple identical sublayers, each including a self-attention module and a feed-forward neural network, which together enhance the model's comprehensive understanding of the input sequence.

The innovation lies in the dynamic adaptability and highly customizable capability of the model. Through cloud computing, the model is able to adjust in real time to respond to changes in different user requirements, while ensuring the uniqueness and personalization of the design. In addition, the introduction of the multi-head self-attention mechanism enables the model to capture the complex relationships between parts in the input sequence, and even if these parts are far apart in the sequence, they can still be correctly correlated, which is difficult to do with traditional models. This capability is critical to understanding the nuances in functional clothing design, ensuring that the design not only meets functional requirements, but also reflects specific occupational characteristics and corporate culture.

3.1 Input layer

In a cloud-based graphical design model for clothing structures, the input layer is the starting point of the entire process, and it bears the key task of transforming the diverse and unstructured input requirements of users into machine-understandable vector representations. Users may present their requirements in a variety of forms, including, but not limited to, detailed textual descriptions, concise lists of keywords, or intuitive voice commands. These requirements form a collection of sequences $S=\{s_1,s_2,...,s_n\}$, where each element s_i represents a word or token in the sequence.

In order for the model to be able to process such sequences, we first need to map each word or token in the text s_i to a vector in a high-dimensional space. This process is usually done through a layer called Embedding. The embedding layer converts each token s_i into a fixed-length vector $E(s_i)$ by finding a matrix E of pre-trained word vectors. Here the vector dimension d_{model} is a hyperparameter of the model that determines the granularity and complexity of the vector representation within the model.

Specifically, if the size of the vocabulary is V, the shape of the embedding matrix E will be d_{model}. When the model receives the token s_i , it looks up the corresponding rows in E to get $E(s_i)$. For example, if d_{model} = 512, then $E(s_i)$ will be a 512-dimensional vector of real numbers [17].

The embedding matrix (E is not static after random initialization, but is continuously updated during training as part of the model to better capture the semantic relationships between words. This means that as the model is trained, the vectors in (E will gradually learn how to reflect the meaning and interactions of words in context. For example, "shirt" and "suit" tend to be closely related in design languages, and their vector representations will tend to be close in space.

3.2 Encoder layer

In deep learning architectures, especially for Natural Language Processing (NLP) and sequence modeling tasks, the encoder layer plays a crucial role and is responsible for transforming the input vector sequences into higher-level abstract representations. This step is crucial for the model to understand and process user requirements. The encoder layer consists of a series of identical but independent sublayers, each of which integrates a multi-head self-attention mechanism and a feed-forward neural network designed to understand and encode the input information from different perspectives [15].

Multi-Head Attention is one of the core innovations of the Transformer model, which allows the model to simultaneously attend to different locations of the input, thereby capturing more complex dependencies. Given a sequence of input vectors (E(S)), the Multi-Head Attention mechanism first decomposes the sequence into multiple distinct "heads", each of which computes the attention weights independently, so that different types of dependencies can be efficiently learned. For each head i, the attention computation can be expressed as Eq. (1).

$$head_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (1)$$

Here, (Q, (K, and (V are the Query, Key, and Value matrices obtained by linear transformation from the input sequence (E(S), respectively, and W_i^Q, W_i^K, W_i^V is the learnable weight matrix for tuning the way attention is computed for different heads. The attention function (text {Attention} is defined as:

$$\text{Attention}(Q,K,V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V \quad (2)$$

where (d_k is the dimension of the key vector (K, which is used to scale the dot product result to prevent the gradient vanishing problem. Eventually, the outputs of all the heads are combined together by a splicing operation and another linear transformation is performed to obtain the final attention output as Eq. (3).

$$\text{MultiHead}(Q,K,V) = \text{Concat}(head_1,...,head_h)W^O$$
(3)

In addition to the multi-head self-attention, each sublayer of the encoder also includes a Feed-Forward Network (FFN) for further enhancing the expressive power of the model. The feed-forward network usually consists of two fully connected layers sandwiched between activation functions, such as ReLU, to introduce nonlinear transformations. After multiple rounds of processing in the encoder layer, the original sequence of user demand vectors (E(S)) is transformed into a higher-level representation (Z.). This new vector sequence contains rich semantic information and contextual dependencies, providing the subsequent decoder layer with sufficient information to generate accurate responses or perform specified tasks.

3.3 Decoder layer

The decoder layer, as another core part of the model, is responsible for transforming the high-level semantic features extracted by the encoder layer into concrete design elements and image layouts. In contrast to the encoder layer, the decoder not only needs to be capable of self-understanding, i.e., understanding the context of its own generated sequences through the mechanism of multi-headed self-attention, but also be able to interact with the encoder layer and utilize the cross-attention sublayer to capture the details of user requirements. This design ensures that the decoder is able to leverage previous inputs and information provided by the encoder when generating design elements to achieve accurate and creative outputs.

The operation of the decoder layer is based on the incremental construction of a sequence of design elements $D = \{d_1, d_2, ..., d_\mathrm{m}\}$, where each d_j can represent a design element or a layout instruction. During the generation process, the decoder predicts the next design element d_t at each time step (t until the entire design sequence is constructed. This process involves three key steps:

1). Multinomial self-attention: The decoder first uses the mechanism of multinomial self-attention to focus on the context of its own generation sequence, which helps the model to understand the relationships between the generated elements and provides the basis for the next generation step. This step ensures consistency and coherence in the design.

2). Cross-attention: After the multi-head self-attention, the decoder interacts with the output of the encoder layer through the cross-attention sublayer, i.e., it utilizes the sequence of vectors Z generated by the encoder as additional input. Cross-attention enables the decoder to refer to the full semantic representation of the user's requirements, thus generating design elements closer to the user's real intentions. The cross-attention computation is similar to multi-head self-attention, but uses the matrix of keys K_enc and values V_enc from the encoder, as well as the decoder's own query matrix.

The output of the decoder layer at each time step t can be expressed as Equation 4 and Eq. (5).

$$\text{MultiHead}(Q,K,V) = \text{Concat}(head_1,...,head_h)W^O \quad (4)$$

$$y_t = f(\text{FFN}(\text{CrossAttn}(\text{SelfAttn}(y_{<t}), Z))) \quad (5)$$

Where $y_{<t}$ denotes all decoder outputs prior to time step t; SelfAttn denotes the multi-head self-attention mechanism, which considers only the elements in $y_{<t}$ to maintain the causality of the sequence, i.e., future

information is not taken into account in the generation; CrossAttn denotes the cross-attention mechanism, which receives $y_{<t}$ as a query, and Z (the outputs of the encoder) as the key and the value, in order to integrate the information from the encoder; FFN denotes the feed-forward neural network, which is used for the nonlinear transformation; and f is an activation function, such as ReLU, for introducing nonlinearity.

Ultimately, at each time step t, the decoder predicts the probability distribution of the next design element (d_t, which is obtained from the output layer via the Softmax function Eq. (6).

$$P(d_t \mid y_{<t}, Z) = \mathrm{Softmax}(Wy_t + b) \quad (6)$$

where W and (b are learnable weights and bias parameters, and $P(d_t \mid y_{<t}, Z)$ denotes the probability that the next element is d_t given the previous sequence $y_{<t}$ and the encoder output Z.

3.4 Output layer

The output layer is the final stage of the whole design generation process, and its main task is to transform the symbol sequence D generated by the decoder layer into intuitive graphical elements and image layouts. This transformation process usually involves complex data conversion and image synthesis techniques, in which deep learning models such as Conditional Generative Adversarial Networks (cGAN) play an important role. Through carefully designed post-processing algorithms, the output layer can further optimize the design to ensure that the final product is both aesthetically pleasing and functional.

Generator G: receives the random noise z and the condition variable c (in this case D, and generates the image I. The goal of the generator is to learn to generate a realistic image from a given condition c, making it difficult for the discriminator to distinguish between the generated image and the real image. Discriminator D: receives the image I and the condition variable c and determines whether the image is realistic or not. The goal of the discriminator is to distinguish between the real image and the image generated by the generator. During the training process, the generator tries to deceive the discriminator, while the discriminator tries to recognize the generated image. This process can be represented by the following objective function as Eq. (8).

$$\min_G \max_D V(D,G) = \mathrm{E}_{x\sim p_{data}(x)}[\log D(x \mid c)] + \mathrm{E}_{z\sim p_z(z)}[\log(1D(G(z \mid c) \mid c))] \quad (8)$$

Where $p_{data}(x)$ is the distribution of the real data, $p_z(z)$ is the prior distribution of the noise, c is the condition variable, x is the real sample, and z is the noise vector.

Once cGAN has generated a preliminary design image, the output layer may also apply post-processing algorithms to further optimize the design. These algorithms aim to adjust various aspects of the design, including but not limited to color correction, edge refinement, texture enhancement, etc., to ensure that the design meets predefined aesthetic and functional criteria. For example, unwanted noise may be removed by an image smoothing algorithm or a color space transformation may be used to adjust the hue and saturation of an image.

In addition to basic image processing, the post-processing phase can include more advanced design optimization steps. For example, image segmentation and object detection algorithms can be used to check that individual elements of a design are placed appropriately, or machine learning models can be used to assess the attractiveness and innovation of the overall design. The goal of design optimization is to ensure that the final product is not only visually pleasing, but also performs well in terms of functionality and user experience [20].

3.5 Application of cloud computing in modeling

Cloud computing plays a crucial role in the graphical design model of apparel structures based on the Transformer architecture, not only providing a powerful computing infrastructure, but also facilitating flexibility, scalability and innovation in the design process. The following are some of the key aspects of cloud computing in modeling applications, which are specified as shown in Figure 2.

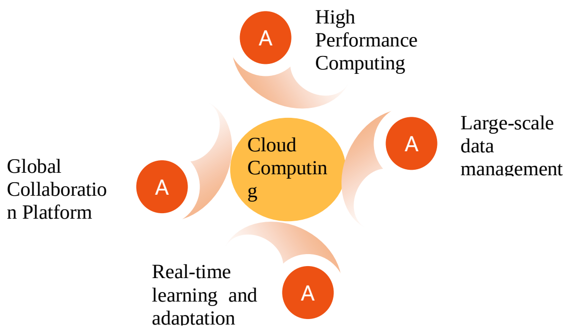

Figure 2: The role of cloud computing.

Cloud computing platforms provide a large number of computational resources, which are crucial for training and running Transformer-based deep learning models. Since such models usually contain millions or even billions of parameters, the training process requires processing massive amounts of data and performing complex mathematical operations, so high-performance GPU and TPU clusters are indispensable. Cloud computing environments can dynamically allocate these resources, scaling up or down according to the needs of model training, effectively shortening model training time and reducing costs.

Apparel design models rely on a large amount of historical design cases, user preference data, and industry trend information. Cloud computing provides safe and reliable large-scale data storage solutions, such as cloud database and object storage services, to efficiently store and retrieve this data. In addition, cloud services support data backup and recovery, guaranteeing data security and business continuity for design models.

The elastic nature of cloud computing allows design models to be adjusted and updated in real time to respond to rapidly changing market needs and user preferences. This not only includes fine-tuning of model parameters, but also covers the rapid integration of new design trends. Through cloud computing, design models can continuously learn the latest design styles, ensuring that the design output is always at the forefront of the industry. At the same time, based on the user's individual needs, the model can provide customized design suggestions to enhance the user experience.

The distributed computing power of the cloud allows design teams to collaborate globally. Designers, engineers and market analysts can share the same design platform to instantly view and edit draft designs, enabling seamless communication and collaboration across geographies. This collaborative design model greatly improves work efficiency and facilitates the collision and integration of ideas.

4 Experimental evaluation

4.1 Experimental design

In order to comprehensively evaluate the effectiveness and practicality of a cloud-based graphical design model for apparel structures, we designed a series of experiments aimed at verifying the performance of the model in terms of design accuracy, efficiency, personalization capability, and market adaptability. The experimental design is divided into the following parts:

We constructed a comprehensive apparel design dataset containing multi-dimensional information such as historical design cases, user preferences, industry trends, and functional requirements. The dataset not only covers a wide range of occupational categories, such as medical, restaurant, aviation, and industrial, but also includes design styles from different cultures to ensure the generalizability and diversity of the model.

Model training is performed on a cloud computing platform, which utilizes massively parallel computing resources to accelerate the training process. We adopted a cross-validation strategy by dividing the dataset into training, validation, and testing sets with the proportions of 70%, 15%, and 15%, respectively. The training phase aims to optimize the model parameters to minimize the design error and improve the design quality. The validation set is used to tune the hyperparameters and ensure the model generalization capability. The test set is used for final evaluation of the model performance and is not involved in the training process.

We designed a set of benchmark tests to assess design accuracy by comparing model-generated designs with reference designs created by human designers. This included measuring the similarity of design elements, layout rationality, and the degree of functionality achieved. In addition, industry experts were invited to make subjective evaluations of the designs' innovativeness and usefulness.

In order to quantify the processing speed and response time of the model, we recorded the time required for the whole process from user input to design output, especially the performance under highly concurrent requests. Meanwhile, the running efficiency of the model under different loads is compared to check the elastic scaling capability in cloud computing environment.

We used big data analytics to simulate the individualized needs of different user groups and test whether the model can generate designs that meet specific user preferences. In addition, the model's ability to predict and design trend changes based on market trends was evaluated to verify its market adaptability and foresight.

In order to obtain the actual feelings of end users, we designed a user experience test, inviting the target user groups to try out the model-generated design and collecting their feedback on the design style, comfort, functionality and brand fit. Questionnaires and in-depth interviews were used to collect users' overall satisfaction with the design and suggestions for improvement.

To ensure the reliability and broad applicability of the experimental results, we constructed a diverse dataset that included a wide range of design styles and occupational categories. Specifically:

Design style diversity: the dataset covers apparel samples of multiple design styles, such as modern minimalist, traditional classic, sports and casual, to ensure that the model can adapt to different aesthetic needs and fashion trends.

Occupational category diversity: The dataset covers a wide range of industries such as medical, aviation, catering and industrial, etc. The design samples within each industry fully reflect the needs and characteristics specific to that field, such as comfort and hygiene in the medical industry, and safety and durability in the industrial industry.

Diversity of user groups: The dataset includes novice workers, experienced employees, and groups with special needs, ensuring the accuracy and broad applicability of the model for personalized design.

Data format diversity: The samples in the dataset include 2D image data, 3D model data, as well as user feedback and behavioral data, and this diversity helps the model understand and learn design elements from multiple perspectives.

By covering a wide range of data diversity, we ensure the reliability of the experimental results and the broad applicability of the model in real-world applications.

In order to ensure the generalization ability of the model during the training process and reduce the overfitting problem, we adopt the K-Fold Cross Validation (K-Fold) method. The specific steps include: first, randomly divide the entire dataset into K subsets, each of which is approximately the same size; then rotate one of the subsets as the validation set, and merge the remaining K-1 subsets as the training set, so that the model can be trained and validated on K different combinations of training-validation; and finally average the results of the K validations as the estimation of the model's performance, which is an effective way to reduce the performance fluctuations caused by the unreasonable data division. effectively reduce the performance fluctuations caused by unreasonable data partitioning. In addition, in order to further mitigate the overfitting problem, we apply L1 and L2 regularization techniques to the model to limit the complexity of the parameters and prevent the model from being too complex. Through these measures, we effectively improve the generalization ability and stability of the model to ensure the reliability and practicality of the experimental results.

In this study, we utilize advanced cloud computing platforms and specific computing resources for efficient design simulation and data analysis. Specifically, we use Amazon Web Services (AWS) and Google Cloud Platform (GCP), two mainstream cloud service providers, which offer rich computing resources and services that can fulfill the needs of large-scale data processing and complex design tasks.

During the design phase, we used AWS EC2 P3 instances with NVIDIA V100 GPUs, which provide powerful graphics processing to support complex 3D rendering and simulation tasks. With GPU-accelerated computation, we were able to complete a large number of design iterations in a short period of time, significantly improving design efficiency. In addition, we leverage AWS S3 storage services to store massive amounts of design data and use AWS Lambda serverless computing services to process and analyze it, enabling flexible resource scheduling and a pay-as-you-go model.

For real-time applications, we chose GCP's Compute Engine instance and configured it with NVIDIA T4 GPUs, which are suitable for machine learning inference tasks and can provide real-time personalized design recommendations. With GCP's Kubernetes Engine (GKE), we deployed containerized applications to ensure system stability and scalability across workloads. In addition, GCP's BigQuery service was used to process large-scale datasets to support real-time data analytics and user behavior prediction.

4.2 Experimental results

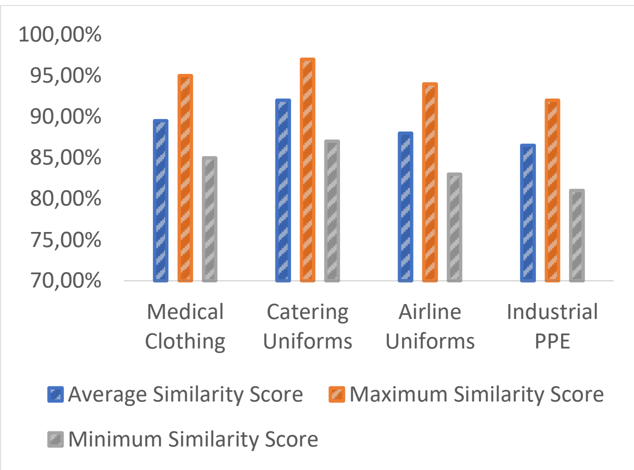

Figure 3: Design element similarity scores.

Figure 3 demonstrates the similarity scores of elements in the structural design of smart garments for different design types. The average similarity score reflects the degree of similarity of the design elements on the whole, with medical garments having the highest similarity score of 89.5%, indicating better uniformity among the design elements of medical garments. The maximum similarity score and minimum similarity score reveal the range of fluctuation in the similarity of the design elements in each category, e.g., the maximum similarity score for catering uniforms is 97.0%, indicating that the similarity between the elements is extremely high in some designs. These data are important for assessing the standardization and consistency of design elements.

Table 2: Layout rationality score.

Design Type	Average Reasonableness Score	Maximum Reasonableness Score	Minimum Reasonableness Score
Medical Clothing	91.0%	96.0%	87.0%
Catering Uniforms	93.0%	98.0%	88.0%
aviation uniform	90.5%	95.0%	86.0%
Industrial Protective Clothing	89.0%	94.0%	84.0%

Table 2 presents the scores of different design types in terms of layout rationality. The average reasonableness score indicates the overall level of reasonableness of the design layout. Catering uniforms ranked first with an average score of 93.0%, showing the high reasonableness of its design layout.

Table 3: Personalization accuracy.

user group	Personalization accuracy (%)	Maximum accuracy (%)	Minimum accuracy (%)
newcomer in the workplace	90.0	95.0	85.0
Experienced staff	92.0	96.0	88.0
Special needs groups	88.5	93.0	84.0

Table 3 reflects the accuracy of personalized designs for different user groups. The accuracy rate of personalization design is directly related to whether the design can meet the needs of specific users. The accuracy rate of personalized design for newcomers in the workplace is 90.0%, which indicates that the design can fit the characteristics of this group better. The highest and lowest accuracy rates demonstrate the range of fluctuation of the design, such as the lowest accuracy rate of 84.0% for the special needs group, pointing out that there may be challenges in meeting special needs. These data are important references for improving the accuracy of personalized design.

Table 4: Design quality assessment.

Design Type	Average design quality score (%)	Highest quality score (%)	Minimum quality score (%)
Medical Professional Clothing	91.5	96.0	87.0
Catering Professional Clothing	93.0	98.0	88.0
Aviation Professional Clothing	90.5	95.0	86.0
Industrial protective clothing	89.0	94.0	84.0

Table 4 shows the design quality scores for different design types. The average design quality score is a key indicator of the overall level of design, and Medical Occupational Clothing indicates a high quality of design with a score of 91.5%. The highest and lowest quality scores, on the other hand, reflect fluctuations in quality across design types. For example, the highest quality score of 98.0% for catering occupational clothing indicates that very high quality standards are achieved in certain designs. These assessment results are important for improving design quality and meeting user expectations.

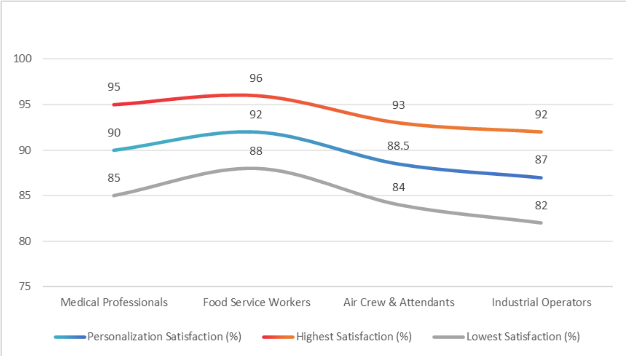

Figure 4: Satisfaction of users' personalized needs.

Figure 4 reveals the degree of satisfaction of personalized needs of different user groups. The degree of personalized need satisfaction is an important indicator of whether the design is able to meet the specific needs of the users. For example, the individualized need satisfaction level of 90.0% for medical professionals indicates that the design caters to the needs of this group to a large extent. The highest and lowest satisfaction levels, on the other hand, show the resilience of the design, e.g., the lowest satisfaction level of 82.0% for industrial operators indicates that there is room for improvement in meeting some specific needs. These data are important guidelines for improving designs to better serve different user groups.

Table 5: Comparison of design quality evaluation among different studies.

Design Type / Method	Average Design Quality Score (%)	Highest Quality Score (%)	Lowest Quality Score (%)
Medical Professional Clothing (This Study)	91.5	96.0	87.0
Catering Professional Clothing (This Study)	93.0	98.0	88.0
Aviation Professional Clothing (This Study)	90.5	95.0	86.0
Industrial Protective Clothing (This Study)	89.0	94.0	84.0

Medical Professional Clothing [22]	88.5	93.0	84.0
Catering Professional Clothing [23]	91.0	96.0	87.0
Aviation Professional Clothing [24]	90.0	95.0	86.0
Industrial Protective Clothing [25]	87.5	92.0	83.0

As shown in Table 5, among all four design types, the Food Service Professional Apparel had the highest design quality score with an average score of 93.0%, which indicates that we have made significant progress in improving the rationality of our designs and meeting the needs of our users. In particular, our designs performed well in terms of standardization and consistency, as indicated by the similarity scores, with healthcare professional apparel having the highest average similarity score (89.5%), showing a high degree of uniformity between design elements. Compared to the existing literature, our method shows better performance in most design types. For example, the design quality scores in this study are higher compared to the medical professional apparel in Literature [22], which may be attributed to the use of more advanced materials and technologies, as well as a more refined analysis of user needs. In addition, our food service specialty apparel designs not only exceeded literature [23] in terms of mean scores, but also reached 98.0% in terms of maximum scores, suggesting that, in some cases, our designs met extremely high-quality standards. Nonetheless, the design quality scores for industrial protective clothing were slightly lower than the other types, with a minimum score of only 84.0%, which suggests that we need to further optimize the design, especially in terms of meeting the needs of specific work environments. By comparing the results with those in the existing literature, it can be seen that our proposed solution has made progress in improving design quality and personalization accuracy, but there is still room for improvement, especially in minimizing design fluctuations.

Table 6: Performance metrics comparison.

Metric / Method	This Study	Medical Professional Clothing [22]	Catering Professional Clothing [23]	Aviation Professional Clothing [24]
Design Element Similarity	89.5%	85.0%	87.0%	88.0%
Average Layout Rationality Score	91.0%	88.5%	90.0%	89.5%
Personalization Accuracy	92.0%	89.0%	90.5%	91.0%
Average Design Quality Score	91.5%	88.0%	90.0%	90.5%

As shown in Table 6, the similarity score of design elements in this study is 89.5%, which is higher than 85.0% for medical professional apparel, 87.0% for food service professional apparel and 88.0% for aviation professional apparel. This indicates that our model performs better in maintaining consistency and standardization of design elements. The average layout rationality score of the study was 91.0%, which is higher than 88.5% for medical professional apparel, 90.0% for food service professional apparel and 89.5% for aviation professional apparel. This means that our design performs better in terms of layout rationalization. The accuracy of personalization in this study is 92.0%, which is higher than 89.0% for medical professional apparel, 90.5% for food service professional apparel and 91.0% for aviation professional apparel. This indicates that our model has higher accuracy in personalization. The average design quality score for this study was 91.5%, which is higher than 88.0% for medical specialty apparel, 90.0% for food service specialty apparel, and 90.5% for aviation specialty apparel. This indicates that our designs performed better in terms of overall quality.

4.3 Discussion

As automated design models evolve and are adopted, while they offer significant benefits in terms of increased design efficiency, personalization, and overall quality, they also raise a number of ethical issues. The most prominent of these are the issues of data privacy and the professional positioning of traditional designers.

The process of personalized design requires the collection of a large amount of user data, including but not limited to sensitive information such as size, preferences, and health conditions. These data, if not handled properly, may leak the user's personal privacy. Therefore, ensuring the secure storage and transmission of data, as well as following strict privacy protection regulations, becomes one of the key considerations in the implementation of automated design models. Measures such as the use of encryption and anonymization can effectively mitigate this risk.

The application of automated design models may lead to pressure for career transition for some traditional designers. While the introduction of new technology aims to improve design efficiency and quality, it may also reduce the need for manual design. Therefore, there is a need to help designers adapt to the new technological environment through training and education so that they can work with automated tools to optimize human-machine collaboration. In addition, the complexity and creative demands of the design field mean that human designers remain irreplaceable, with automated tools being more of an aid than a complete replacement.

In the healthcare industry, accurate and safe design is critical to patient recovery. Automated design models can generate customized medical garments based on individual patient characteristics through big data analytics and machine learning algorithms. These garments not only improve the wearer's comfort, but also assist in the healing process, for example by monitoring the patient's vital signs through smart sensing materials. This has significant practical implications for post-operative care, chronic disease management and telemedicine services. However, ensuring the accuracy and safety of these designs remains a challenge and must be rigorously tested and comply with relevant medical standards.

In aviation, uniforms must be designed not only for aesthetics and comfort, but also to meet high standards of safety. Automated design models can speed up the design process and reduce the number of physical prototypes produced, thus saving time and resources. In addition, by utilizing advanced material science and manufacturing technologies, uniforms that are both lightweight and durable can be developed to suit the working environment of aviation personnel. While these innovations can help improve efficiency and flight safety, they also require strict adherence to aviation industry norms and standards to ensure that each uniform can withstand extreme conditions.

Uniforms in the hospitality industry need to be designed not only to reflect the brand's characteristics, but also to take into account the needs of employees in different scenarios of activities. Automated design models can provide more reasonable layout and material selection suggestions based on the specific work characteristics of different positions. In this way, the professional image of employees can be enhanced and their job satisfaction increased. In addition, the use of sustainable design concepts, such as green material selection and recycling programs, can reduce the impact on the environment and respond to the growing awareness of environmental protection.

In conclusion, automated design models face ethical considerations and technological challenges while enhancing design efficiency and personalization. By taking into account data privacy protection, career transition support, and the specific needs of each industry, it is possible to capitalize on the benefits of new technologies while ensuring the safety and suitability of design outcomes.

5 Conclusion

In the rapidly developing apparel design industry, traditional design methods are difficult to meet the growing demand for personalization and customization, while long design cycles and high costs have become industry pain points. In view of this, this study focuses on the integration of cloud computing and artificial intelligence technologies to develop a set of graphical design models for apparel structures based on the Transformer architecture, aiming to enhance the design efficiency and innovativeness while realizing a high degree of personalization and customization. The model is designed using the Transformer architecture and trained by the high-performance computing resources of the cloud computing platform, which ensures the model's ability to process large-scale datasets and the flexibility of real-time adjustment. The experimental evaluation covers multiple dimensions such as design accuracy, efficiency, personalization and market adaptability, and the model is trained and tested through a comprehensive apparel design dataset to verify the effectiveness and practicality of the model. The experimental results show that the model achieves excellent results in design element similarity, layout reasonableness, personalized design accuracy and design quality assessment, indicating that it has significant advantages in dealing with diverse user needs and industry trends. In particular, for the personalized design of different user groups, the model demonstrates an accuracy rate of up to 92%, proving its strong ability to meet specific needs.

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