Introduction
Multi-style features determine the diversity of wearing so that the traditional fixed size garments are unable to meet the requirements of the garment fit.1 The characteristics of garment fitness also put forward higher requirements to garment comfortability.2 With regard to consumers’ increasingly individualized wearing demand, strict quality requirements will be a chance to promote the pursuit of high-end consumption psychology going on in spending to bring about the transformation of seller’s market to buyer’s market.

With the rapid transformation of the fashion industry, big data-driven technology presents an efficient and aggressive development momentum, which penetrates into the traditional industry and spreads to the field of garment customization.4 At the same time, traditional business processes has defined big data as the means of establishing and enforcing how garment customization surmount technical barriers to continuous integration for the new products, new services, new models, and new formats in the traditional industries.5 The application of garment customization is becoming more and more wider, which leads to the strong demand for diversified data such as the body size, the type of personalized, and high-end consumer demand provides a huge customized space.6 In terms of application, the garment customization needs to be based
on a flexible data processing and control architecture that can seamlessly integrate multiple cloud computation to achieve high-speed data acquisition, processing, and communication. It also needs to build the customized database of local customer storage and indexing, which performs with customized data resources fully and effectively that can be shared between the consumers and the customized team, resulting in improved performance over previous existing account scheme.

**Literature review**

*Impact of big data on garment customized platform*

Spiess et al. have contributed a way of integrating big data insights with intellectual processes related to interact with consumers to ultimately improve the customer experience. They build accurate key big data formula, predict customer behavior, and evaluate which factors influence the customer most. Their approach can be used, for example, to improve the efficiency of user tailoring. Zerbino et al. explored the relationship between big data and customer relationship management, and found that big data could require several changes to adopt an explorative approach toward customer relationship management by defining a mandatory operation direction through pilot tests. Chen et al. have presented the practical implementation methods of intelligent apparel system, and applied in medical emergency response, emotional care, disease diagnosis, and real-time tactile interaction. In addition, mobile healthcare cloud platform is constructed by the use of mobile Internet, cloud computing, and big data analytics to provide pervasive intelligence for smart clothing system. Chen and Luo designed a novel method that investigated a large-scale clothing data set from online shopping. It was also pruning and extracting images of popular clothes and user transaction history. The approach can discover the representative characteristics of popular clothing style elements and gain valuable insight into clothing consumption trends and available clothing characteristics. Matzen et al. exploit the rich trove of data to predict fashion and style trends. They proposed a framework for visual discovery at scale, analyzing clothing and fashion across millions of images of people around the world for several years. Based on the large-scale data set of photos of people annotated with clothing attributes, visually consistent style clusters were presented to capture useful visual correlations by using the data set to train attribute classifiers via deep learning.

*The application of garment customization*

Hahn et al. have presented an approach to garment customization using low-dimensional linear subspaces. Their method interprets the simulation data as offsets from a kinematic deformation model in order to construct a pool of low-dimensional bases. It can reproduce diverse and detailed folding patterns with only a few basis vectors. Their experiments demonstrate the feasibility of subspace clothing try-on and indicate its potential in regard to the efficiency of garment customization. Chen et al. present an approach of simulating realistic folds and wrinkles for wet garments. A simplified saturation model is adopted to modify the masses, and a nonlinear friction model derived from previously reported is used in the real-world measurements. After that, a wrinkle model based on imperfection sensitivity theory was proposed to simulate wet garments. Park has presented the working pants patterns through the computerized 3D virtual clothing simulation system. They verify the effects of the 3D simulated clothing by comparing the result to the images of material object. Through the comparison between the developed working pants and the real working pants, the virtual simulation image of working pants is similar to the real image, which has remarkable similarity.

*Summary of research review, application, and gap areas review*

The previous garment customization was adapted to cope with the limitations of a single design. With big data, it can be understood and accomplished in many different modes to capture real-time order plan, and predict customer behavior to ultimately understand the factors which could influence the customization before product manufacturing. The method also can discover the representative and discriminative characteristics of popular clothing style elements based on big data.

From the above, there seems a strong demand for user interaction of composite big data prediction in garment customization. Based on the development and application of big data, customized design has rapid responsibility of the change for the requirements of diversified production. This study addresses these gap areas in garment customization with big data. The research gap observed based on the literature review is that the practical feasibility of integrating big data and garment customization for enabling consumer demand-oriented clothing customization has been attempted by few researchers. From this point of view, this research project has been carried out.

*Garment customization compatibility prediction*

*An improved penetrative customization model*

The diversity of garment styles provides broad development space for garment customization, including advanced clothing customization and large-scale work clothing customization. Therefore, garment customization needs
to meet people’s different requirements such as high-end customization, fast fashion collocation, and mass customization. In order to meet the requirements of personalized garment customization, interactive garment customization mode would be powerful to satisfy garment consumer and optimization design of clothing. In this mode, the garment customization based on stable cross-holdings and optimization analysis of data shares, in which big data provides opportunities for pattern analysis, rational decisions, and recommendations. In addition, the mode establishes the information exchange between consumers and designers, the basic mode of garment customization is shown in Figure 1. It shows that big data can be obtained through the interaction between consumers and the apparel customization process, and big data is used as the carrier to analyze and feedback the apparel customization results.

In such interactive customization mode, garment customization model was presented, and its supporting process to customized design under big data was analyzed in detail. It propose information service to give to push away voluntarily, information intellectual screen service and individualized information customization person who serves operational mode. Product family development strategy based on big data platform adapts to the product mode of garment customization, and is better. Based on this, garment customization has become an important manufacture mode. The traditional clothing customization mode has many limitations, such as the inability to form economies of scale, hindering the popularity of clothing customization to the public. Machine learning is an effective method to realize mass customization of clothing. The interactive garment customization mode based on machine learning improves the applicability and operability of garment customization.

Learn compatibility and personalized styles for garment customization

We present our unsupervised approach to learn compatibility and personalized styles, and estimate of garments using currently available big data. We transformed garment matching into a problem of selecting a subset from a large candidate data set that maximizes compatibility and versatility, which helps reduce complexity and speeds up the development cycle. To ensure an accurate garment matching for the customer, garment customization has been transformed from manual evaluation to big data prediction. This method solves the shortcomings of manual evaluation, such as unable to accurately locate, slow detection speed, low detection accuracy, and uniform detection results.

Unlike previous efforts to supervision by manually creating matches, we propose an improved key-frame extraction method based on unsupervised clustering, and establish the algorithm of retrieve boundaries detection based on garment attributes. When we train the garment model on a pool of attributes marked as disjoint images, our model runs on the basis of inference prediction to solve the bipartite matching problem with incomplete attribute weights in garment customization process. The mirror garment model is learned from hundreds of thousands examples created by 2D projections of multiple shapes generated from big database, corresponding to a reference size that can be deformed into various shapes. Individual characteristics are the main parameters of garment modeling, where the texture is additional matching points that controls the attributes elaborately to the model. The mirror garment model represents a wide range of costume matching, also suitable for fitting. In future work, we will generalize the predictive garment models to take advantage of the ability of the expanded database with big data.

Search method by query and attribute manipulation

We take advantage query and attribute manipulation to test the effectiveness of the search. Therefore, the custom module directly recommends the corresponding garment according to the user’s dressing habit. We first crawled more than 30,000 fashion images from online shopping websites and removed these product with descriptions of less than four words, resulting in over 20,000 images. Then, we split them into 17,048 images for training, 1,265 for validation, and 2,536 for testing. The mirror personal model is fitted with the recommended clothing to obtain a fitting simulation results. For each point on the mirror model, we calculate the key points of intelligent clothing customization, and use big data to learn the user’s clothing and accessories model to reduce the loss.

According to the customized image $I$, $k_i(i, j)$ is the activation amount of unit $j$ in the last convolution layer at position $(i, j)$. After using the global average pool, $f_i = \sum_{j} k_i(i, j)$ represents the $t$-th dimension feature of image $f$. If given the parameter $a$, the cosine distance
between the image inserted $x$ and attribute inserted $y^a$ represents the probability that the parameter $a$ exists in the image. Substitute $f_i$ into the cosine distance we get

$$d(x,y^a) = \sum_{n} y_n^a x_n = \sum_{n} y_n^a \sum_{j} y_{I_i,j} f_i$$

$$= \sum_{n} y_n^a \sum_{i,j} k_i(i,j)$$

$$= \sum_{i,j} \sum_{n} y_n^a y_{I_i,j} k_i(i,j)$$

(1)

The fitting model can be considered that there are two levels of integration, which combine the modeling of body posture with the modeling of garment.\textsuperscript{20} The first layer generates nude models through big data prediction, and the second layer generates clothing and accessories models, which is compositional in outputting normal based on displacement and color mapping. The first layer is the mirror model, which is based on the deformation of the model in the large database. The hierarchical representation is separate because it allows for the application of independent formulation modules to the body and clothing.

We can see that the activation map indicates where the federated embedding model used to identify a property. Dress images are often paired with accessories and aligned in front view with a solid color background. Based on this, for the specific attribute $a$ and its positive training data $P_m$, we generate an activation map $B_m$ for the average EAAMs of all images in $P_m$. We call it the property activation mapping of $m$

$$B_m = \frac{1}{|P_m|} \sum_{i \in P} \sum_{j} y_{I_i,j} k_i(i,j)$$

(2)

Since we have trained visual semantic embedding, if the user wants to change one property while keeping the others, the baseline method will use the query image and query attribute to sort the database image according to the cosine distance. Based on this, the matching image gets high score in query attributes and is similar to user requirements. For the retrieval image $X_q$ and the retrieval attribute $Y_p$, the attribute feedback retrieval task of finding image $X_c$ is defined as

$$X_c = \arg \max_x \left( X_q + Y_p - Y_n \right) \cdot X$$

(3)

To overcome retrieval compatibility issues, we found that users may unconsciously delete similar description attributes of similar products when retrieving attributes. Since the attributes found in garment types describe the same features, we perceive the implicit negative attribute $Y_n$ and use it to search image $X_c$

$Y_n = \arg \max_y Z^D(X_q)$

(4)

$X_c = \arg \max_x \left( X_q + Y_p - Y_n \right) \cdot X$

(5)

Where $D$ is a patch extracted from $Y_p$, $Z^D(X_q)$ is tuning parameters to adjust the $D$’s sub-network, and $Y_n$ is the higher resolution version of $D$’s attribute.

Based on shoppin100k data set, top-k retrieval precision results are presented in Figure 2 for different garment attributes. By contrast with the above different methods, our method achieved the good performance, getting 56.3% Top-30 accuracy. In the process of query $X_q$, negative attributes are deleted and detected negative attributes are subtracted from query embedding to avoid two visually contradictory attributes damaging retrieval performance. Equation 5 indicates that since the subspace network is not trained by the above classes, we use multimodal rule and automatic negative attribute detection to predict whether $X_q$ has attributes in concept $D$. In this case, The performance of our method without localization shows that using the global characteristic graph to learn feature specification may add noise features, thus affecting the matching accuracy.

**Operational factors affecting garment customization integration**

**Big data factors identified through custom practice**

The analysis and application of garment customization relies on accurate and sufficient big data.\textsuperscript{6} The source of the data is from a massive database of users, so it needs to connect the database to the garment data set. Then based
on machine learning training process, it can combine mass production with personalized customization perfectly. Since facing a lot of personalized customers and products, custom process is simpler than the traditional production workflow. In addition, in contrast to previous prediction tools, big data is especially useful for the analysis of large data sets in real time with high accuracy, which use the database for storing the raw data from the survey form and as a method of reporting the information for customization application.

In Figure 3, big data can establish the basis for personalized recommendation, accurately predict the human model, and analyze the concentration trend, dispersion degree, and correlation of data. After the normal distribution test, the big data of clothing customization is descriptive analyzed through standard deviation, variance, mean value and coefficient of variation, and then the graph data are standardized to extract feature size and feature vector of human model.

The big data analysis of the garment customization will conduct descriptive analysis of the data after completing the test of normal distribution by means of standard deviation, variance, average, and coefficient of variation. According to this, it needs to standardize the figure data, extract two types of data including the characteristic size and eigenvector of the human model. At the same time, user interaction conducts inductive grouping determine factor model, which enabled the virtual fitting to fast real-time display through high-speed processing capacity. After the data analysis is true and effective, the corresponding functional relationship between the virtual sample data and other main data can be determined.

**Optimization of garment customization process based on different observation sets**

The garment customization module is interactive between the integrated statistical processing based on user customization, which is a way of interactive information processing on the strength of big data. Symmetry of information will exert a favorable influence on both parties, namely operators and consumers in the garment customization, which can input data information and operation instructions via PC terminal or mobile phone client. We selected 16,000 women clothing images with multiple extracted feature attributes, and split these 16,000 images into 13,200 for training and 2800 for testing. The 13,200 training images together with another 17,048 authentic images form the training set. The 2800 test images are combined with 2536 authentic images as the test set. The remaining images are further split into seven testing set with acquiescent apriori (a1), apriori with counterparts (a2), apriori with influence filtering (a3), apriori with influence priority (a4), prioritizing by rulesize (a5), rule generation including duplicate data (a6), and making confident predictions (a7). The algorithm processes the received instructions immediately to provide accurate and reliable information for the prediction results of the observation data set, and then match the results with the minimum loss through iteration.

The results for predictions made with varied observation sets are shown in Figure 4. We can see that the overall change in matching accuracy over the entire range of tested values is about 25%, which is less than we expect. Meanwhile, it shows the importance of clothing customization objects and training models, in which fitting process has some synergies with the mediation model. When we increase the size of the observation set, we see an increase in the matching accuracy (a7), as the prediction of clothing customization decreases. We can also observe that when the training set is very small or empty, the performance of the observation set (a3) is not so well, which may be due to the lack of information from other data sets to distinguish the correct choices. In observation set a5, when only a small number of unique
Table 1. The compared result by the baseline greedy algorithm with the iterative greedy algorithm.

| Objective | Optimal obj. (%) | Time |
|-----------|------------------|------|
| Optimal   | 41.3             | 128.8s |
| Baseline greedy | 30.2             | 36.1s  |
| Ours      | 34.9             | 56.2s  |

subsets are observed, this may lead to a decrease in accuracy, and when situational heuristic information is added in this process, it will inevitably lead to more accurate prediction. Our method models both high-level matching attributes and low-level local features, so it is robust to adjust the retrieval scope and boundary. As a result, its performance is far superior to all other methods. As a result, its performance is better than other prediction methods of clothing customization.

We compare our iterative greedy algorithm with the baseline greedy algorithm\(^2\) and run the algorithms on the same single Intel I7-6700 3.40Ghz machine. In order to verify that our iterative method is closer to the optimal solution in garment customization, we created a garment experiment with \(N=12\) candidates and \(T=3\) selections in each layer in which the scale of this experiment is only limited by the true optimal solution.

Table 1 shows that our algorithm obtain target optimal function value of 85%, apparently higher than the baseline greedy algorithm at 73%. Depending on the realistic scale of the experiment, using brute force to solve the clothing customization match needs about 2 \(\times\) our run-time in the clothing data set. In addition, brute force solutions are difficult and take more than an hour per customization, but our solution only takes 180 s.

Conclusion

Machine learning can play an increasing role in garment applications. Our work explores garment customization based on machine learning. The proposed method provides new insights in terms of both effectively optimization for personalized design, as well as generative learning of garment customization prediction. We adopt a novel unsupervised training method, which optimizes the configuration of various data sets, and provides the corresponding dressing coordination according to the user’s dressing habit. Experiments and analysis show that our model outperforms the others. Future work will explore ways to optimize the query and attribute manipulation for garment customization.

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