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Article

Tailoring Garment Fit for Personalized Body Image Enhancement: Insights from Digital Fitting Research

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Abstract: In the context of the Fashion Apparel Industry 4.0, a transformative evolution is directed towards the Online Apparel Mass Customization (OAMC) strategy, which provides efficient and personalized apparel product solutions to consumers. A critical challenge within this customization process is the determination of sizes. While existing research addresses comfort evaluation in relation to wearer and garment fit, little attention has been given to how garment fit influences the wearer's body image, which is also an important purchase consideration. This study investigates the impact of garment fit on the wearer's body scale perception using quantitative research design. A digital dataset of avatars, clothed in varying sizes of T-shirts, were created for the body scale perception experiment, and an Artificial Neural Network (ANN) model was developed to predict the effect of T-shirt fit on body image. With only a small number of garments and body measurements as inputs, the ANN model can accurately predict the body scales of the clothed persons. It was found that the effect of apparel fit on body image varies depending on the wearer's gender, body size, and shape. This model can be applied to enhance the online garment shopping experience with respect to personalized body image enhancement.

Keywords: online apparel mass customization; body image perception; computer-aided design; artificial neural network; garment fit

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1. Introduction

The global expansion of fashion e-commerce, propelled by widespread Internet and smartphone usage, is anticipated to reach a value of 906 billion U.S. dollars by 2024, surging to over 1.36 trillion U.S. dollars by 2028 [1]. However, this expansion also poses challenges, notably, a high return rate of online apparel orders. In the U.S. market, the return rate of online apparel products has reached 24.4% in 2023, primarily attributed to size and fit issues [2,3]. Consumers today are facing the challenges of navigating through mass-customization products while still finding their demands for fit and style unmet. Many of them are turning to customization products for more tailored options and better shopping experiences [4–7]. This demand leads to the rise of Online Apparel Mass Customization (OAMC). OAMC generally refers to a kind of service that allows consumers' involvement, through a system or website, to customize apparel features including fabric, patterns, fit, and other design details [8,9]. This strategy could satisfy individuals' demands for personalized products at an acceptable price by being manufactured on a mass-production platform [10].

Industry 4.0 has great potential to bring transformative evolution to OAMC by engaging digital technologies, automation, and data exchange [10]. By leveraging data analytics and machine learning algorithms, OAMC platforms could provide data-driven personalization services and enhance consumer experiences. In the past few years, many efforts have been made to automatically generate garment patterns based on human body measurements, three-dimensional models, and parametric formulas [11–13]. However, these efforts mainly focus on how garments physically fit the human body, not on how garments enhance the body image.

When consumers shop for apparel products, they seek not only physical fit, but also psychological comfort, particularly body image enhancement and confidence building. With the boom in social media, concerns about body image dissatisfaction have grown worse due to increased social exposure and comparison [14,15]. Consumers nowadays have more urgent needs for body image enhancement than ever.

Although previous research identified some body ratios [e.g., body mass index (BMI), waist–hip ratio (WHR), and volume–height index (VHI)] and garment measurements which are potentially related to body image perception [16–22], no systematic quantitative relationship has been established to provide effective guidelines for customized apparel pattern making for body image enhancement.

In order to better quantify the impact of garment fit on the body image, this established a large dataset of perceived body image, rated according to Thompson and Gray's Contour Rating Scale [23], of male and female digital avatars wearing T-shirts in different garment fit levels and developed an AutoGluon's deep Learning Neural Network model to map the inter-relationship between body image perception, garment fit levels, and the wearer's body metrics. The model can be applied for consumers to choose or designers to tailor the right fitting for body image enhancement.

2. Theoretical Framework and Hypotheses

In contemporary society, the ideal female physique is often depicted as a curvaceous, yet slender hourglass shape [24,25]. Conversely, there has been a consistent preference for males to have a muscular physique to have masculinity, which urges males to seek a lower body fat with a higher muscular rate [25]. People who are not satisfied with their body image tend to make efforts to approximate their ideal body scales, whether through exercise, dieting, or seeking external assistance such as clothing. The inter-relationship between body metrics, clothing design elements, and perceived body image are conceptually illustrated in Figure 1. This research is focused on how clothing interacts with the wearer's body in changing their perception of body image.

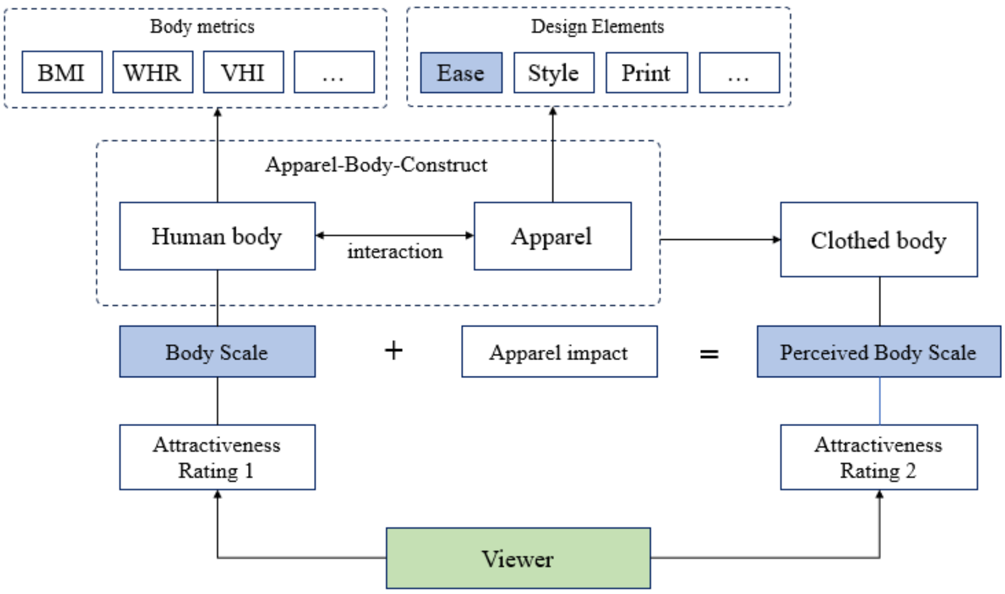

Figure 1. Conceptual relationships between the human body, apparel, and perceived body image in terms of perceived body scale and attractiveness.

2.1. Body Metrics Affecting Body Image Perception

Body image was originally defined as a person's subjective picture of their own body [26]. Although the perception of the ideal body image keeps changing throughout human history, the pursuit of the ideal body image has never stopped.

A lot of previous research has been carried out to identify the physical cues to body image perception and attractiveness. The waist–hip ratio (WHR) and body mass index (BMI) were found to be the most important factors for human body attractiveness, especially for females [20–22], as they are strong indicators of physical health and fertility [27]. Later on, Fan et al. [18] proposed to replace BMI with VHI as the most important and direct visual determinant of physical bodily attractiveness, as BMI can be misleading for people with lower body fat and higher muscular rate, like athletes [27,28].

2.2. Impact of Apparel on Body Image Perception

Considered as the "second skin" or the "second nature" of a human body, apparel could alter the wearer's body image and social image. In 1998, DeLong [29] proposed the model of apparel–body-construct, and stated that the perception of the clothed body appearance is the interaction of apparel, the human body, and the environment. People use apparel to camouflage their bodies to create a more ideal body image by concealing unsatisfying body features and highlighting the desirable body features [30,31].

Fit, as one of the most important apparel elements to consumers, encompasses complex properties related to human body measurements and ease [27,32]. In fashion product development, ease refers to the amount of extra room that allows for mobility, comfort, and appearance enhancement [33,34]. The amount of ease is usually measured by comparing the difference between the garments' circumference and the wearer's body [35].

In 2003, Fan et al. [17] conducted an experiment on the body image perception of three Chinese male models wearing different sizes of white T-shirts and showed that the effect of garment ease on body image perception is different for people with different body builds. Subsequently, a backpropagation neural net model was established to map the nonlinear relationship between BMI, bust girth, ease of T-shirts, and perceived body sizes [19]. It was found that for thin males, the effect of garment ease on body size perception is relatively small, for tall males with a large chest girth, wearing larger size T-shirts would make them look bigger, and for males with a high BMI (obese), wearing a too tight or too loose T-shirt would both cause overestimation of body size. Although this research was the first of its kind, the human models (only three males), garment type (only one type), and number of viewers for rating the body size perception involved in the investigation were very limited.

2.3. Hypotheses

Past research indicated that factors such as human body metrics and garment fit have an impact on body image perception. Moreover, the effect of garment fit appears to vary depending on individual body metrics for males. The effect of garment fit on female body image perception has not been investigated at all. More comprehensive research is needed to map the relationship between body features, garment ease, and perceived body image for both genders with a larger dataset and more participants.

Drawing from the existing literature, it can be anticipated that the effect of garment fit varies on individual body metrics like obesity levels and height. Moreover, gender differences may contribute to distinct effects on body perception due to the body natures and societal expectations. Based on the theoretical backgrounds, the following hypotheses are proposed:

Hypothesis 1. *The perceived body scale can be predicted based on garment ease allowance and a few basic body metrics of the wearer.*

Hypothesis 2. *The impact of garment fit may differ depending on the gender of the wearer.*

Hypothesis 3. *The impact of garment fit may differ depending on the body scale of the undressed body.*

3. Materials and Methods

This study employed a quantitative research design to investigate the impact of garment fit on perceived body scales. The independent variables consisted of the wearer's fundamental body measurements and the garment ease allowance value, while perceived body scales served as the dependent variables. White T-shirts were selected as experimental garments due to their widespread usage and simplistic design, effectively minimizing their impact on perceived body scales aside from fit levels. To ensure control over the independent variables, a digital dataset of avatars dressed in white T-shirts of varying sizes was created using commercial computer-aided design (CAD) software. Subsequently, the avatars were rated for perceived body sizes using a 3D reference scale, developed from Thompson and Gray's Contour Rating. The collected data was then employed for artificial neural network training.

3.1. 3D Human Body Dataset and Size Classifications

The 3D avatar dataset in this research was based on the data of 25 male and 33 female bodies originally scanned with a TC2 whole-body scanner. All scan files were modified, repaired, and converted into 3D avatars following a procedure shown in Figure 2, using three commercial computer-aided design software (viz. MeshLab version 2021.05, Maya version 2019, and CLO3D version 6.2). Thereafter, the avatars were imported into a computer-aided design software called TG3D Studio version 2021 to automatically extract the key body measurements, including height, shoulder width, bust girth, waist girth, hip girth, and shoulder width. Furthermore, the volumes of the avatars were measured in 3Ds MAX software version 2023 and were used to calculate the volume–height index (VHI) as defined by Fan et al. [18], viz.

$$\mathrm{VHI} = \mathrm{V}/\mathrm{H}^2 \tag{1}$$

where V is the volume of the whole body including the head and H is the total height of the body including the head.

The means and standard deviations of body dimensions of female and male avatars are listed in Table 1 below.

Table 1. Details of female and male avatars' body dimensions.

Gender	Body Measurements	Mean	SD
Female	Height (cm)	167.32	6.84
	Shoulder Width (cm)	43.84	3.41
	Bust Girth (cm)	101.58	13.52
	Waist Girth (cm)	84.26	14.65
	Hip Girth (cm)	109.78	14.59
	VHI (L/m^2)	27.55	7.17
	WCR (Waist-to-Chest Ratio)	0.83	0.05
	WHR (Waist-to-Hip Ratio)	0.76	0.05
Male	Height (cm)	177.47	7.21
	Shoulder Width (cm)	48.56	3.32
	Bust Girth (cm)	106.76	9.91
	Waist Girth (cm)	98.72	13.62
	Hip Girth (cm)	105.43	8.52
	VHI (L/m^2)	27.99	4.43
	WCR (Waist-to-Chest Ratio)	0.92	0.05
	WHR (Waist-to-Hip Ratio)	0.93	0.07

For rating the body image perception of 2D figures, the 2D schematic contour rating scale, developed by Thompson and Gray has been widely used [20]. In order to provide a better reference for the visual assessment of 3D body images, Thompson and Gray's 2D contour rating scale was converted into a 3D rating scale using CLO3D. Figure 3 shows the converted 3D version of the body size scales and the VHI value of each avatar in the scale.

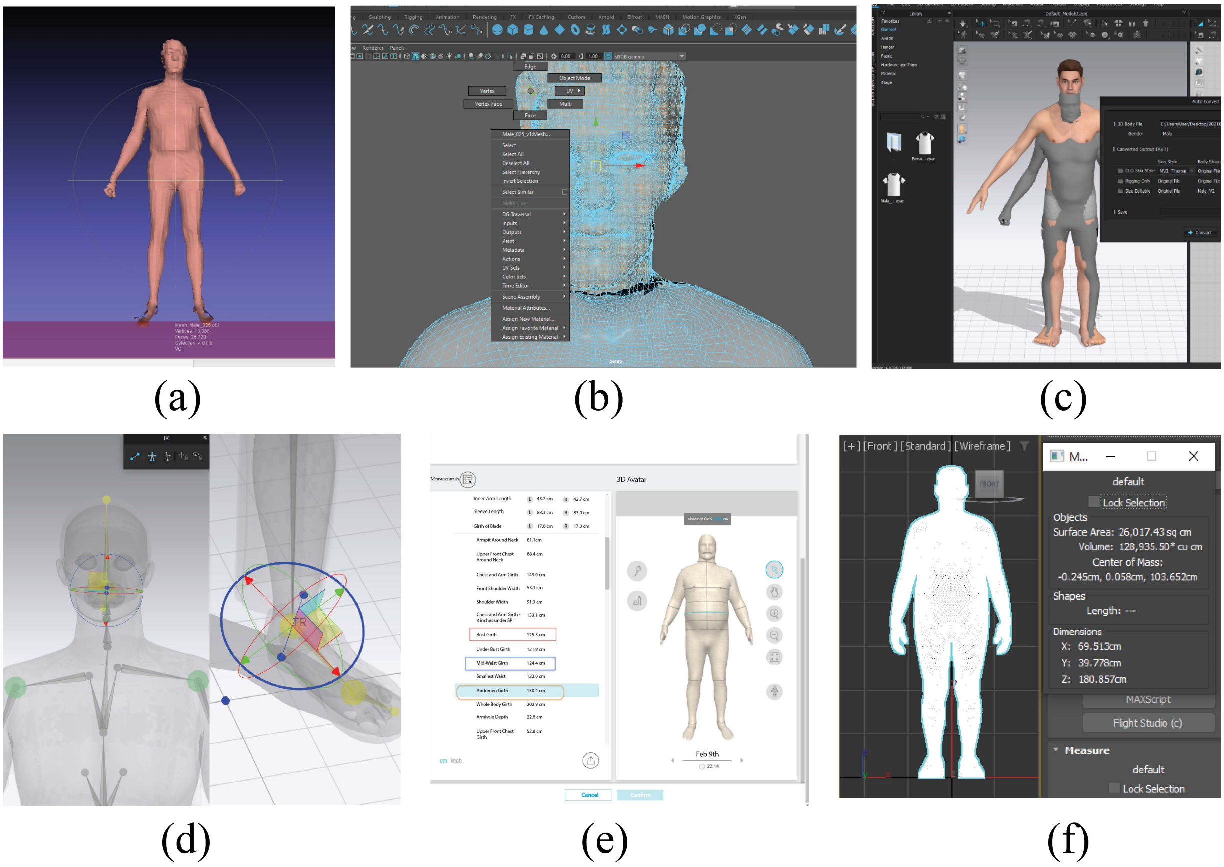

Figure 2. 3D avatar development process: (**a**) Convert body scan files into .obj files in MeshLab; (**b**) Modify and repair the incomplete surfaces of the scan files in Maya; (**c**) Convert the scan files into editable .avt files in CLO 3D; (**d**) Manually adjust joints of avatars in CLO 3D; (**e**) Extract key body measurements in TG3D Studio; (**f**) Measure the volume of the avatars in Autodesk 3Ds Max.

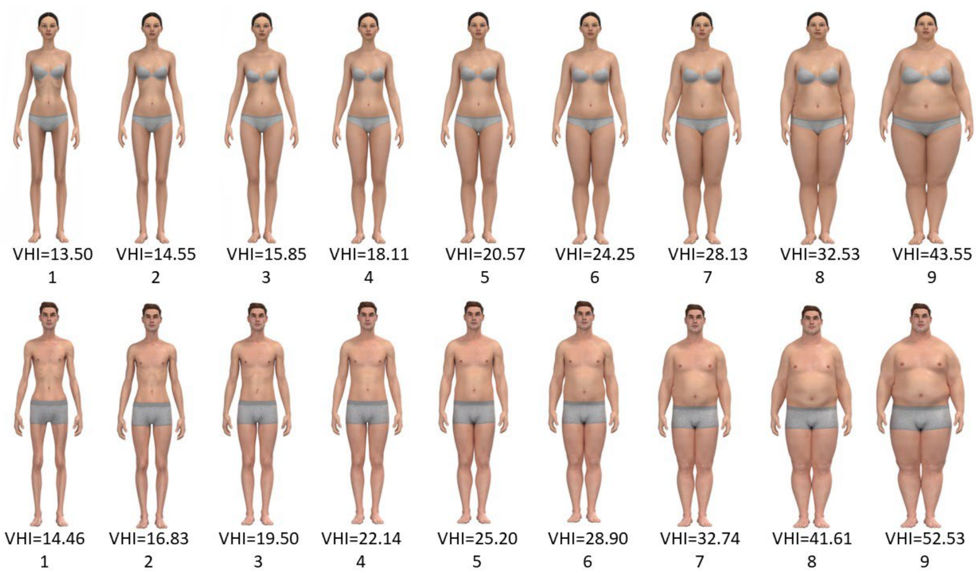

Figure 3. The converted 3D version of Thompson and Gray's Contour Rating Scale.

3.2. 3D Apparel Dataset

Apparel items of different sizes were designed to dress the human avatars through the virtual fitting function in CLO3D. In developing an apparel sizing system to cover the body size range of the avatars, the bust girth was selected as the core measurement for both male and female avatars. The avatars were categorized into 6 groups based on their bust girth, with an interval of 10 cm. The median measurement of each group was taken as the reference body measurement for the next step of patternmaking. Under each size group, three fit levels (tight, medium, and loose) were designed to create different levels of fit, with ease allowance ranging from 3 cm, 10 cm, and 17 cm, respectively. Using this sizing system, 36 T-shirt patterns were made for male and female avatars using CLO3D. An example of the T-shirt pattern is shown in Figure 4. Table 2 presents the sizing system and the bust girth measurements of each fit level.

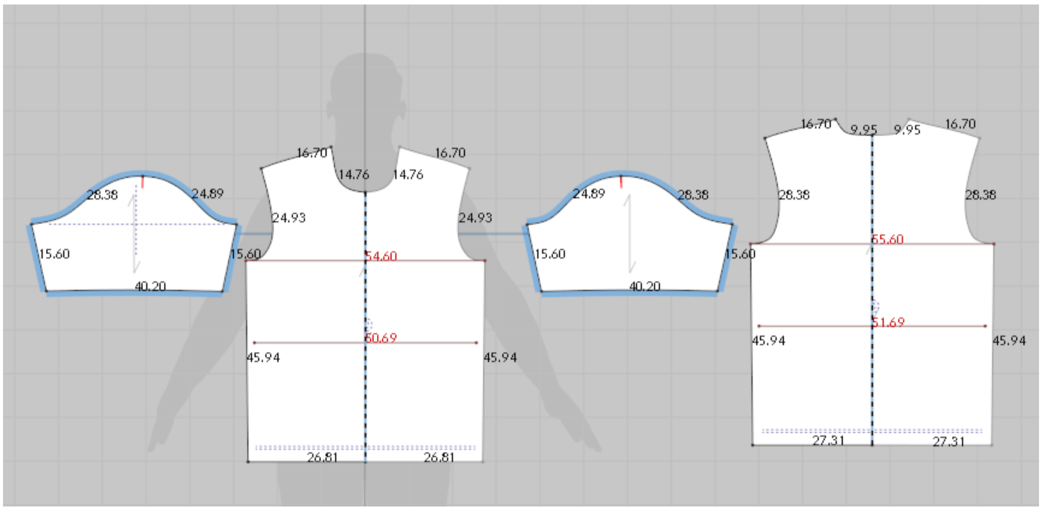

Figure 4. T-shirt pattern example. The highlighted measurements are the bust and waist girths of the T-shirt.

Table 2. Size groups and fit level designs for male and female sizing systems (cm).

Gender	Group	Median Bust Girth (cm)	T-Shirt Bust Measurement (cm)		
			Tight	Medium	Loose
Male	Group 1	88.7	91.7	98.7	105.7
	Group 2	100.2	103.2	110.2	117.2
	Group 3	110.4	113.4	120.4	127.4
	Group 4	117.8	120.8	127.8	134.8
	Group 5	130.0	133.0	140.0	147.0
	Group 6	140.7	143.7	150.7	157.7
Female	Group 1	90.2	93.2	100.2	107.2
	Group 2	100.5	103.5	110.5	117.5
	Group 3	110.1	113.1	120.1	127.1
	Group 4	118.3	121.3	128.3	135.3
	Group 5	134.8	137.8	144.8	151.8
	Group 6	143.4	146.4	153.4	160.4

3.3. Avatar Fitting and Image Preparation

To prepare for the visual assessment of body image, each avatar was dressed in T-shirts at different fit levels. Based on the sizing system described in the above section, each avatar was fitted with three adjacent groups of T-shirts. Figure 5 shows an example of fitting options of an avatar from Group 4. This customized fitting system provides a diverse spectrum of fitting options with an ease allowance range of about −10 to 30 cm for all avatars. For avatars situated within Group 2 to Group 5, each avatar was dressed in 9 different fit levels of T-shirts. As for avatars in Group 1 or Group 6, they only have 6 fit levels as there are no smaller/larger groups.

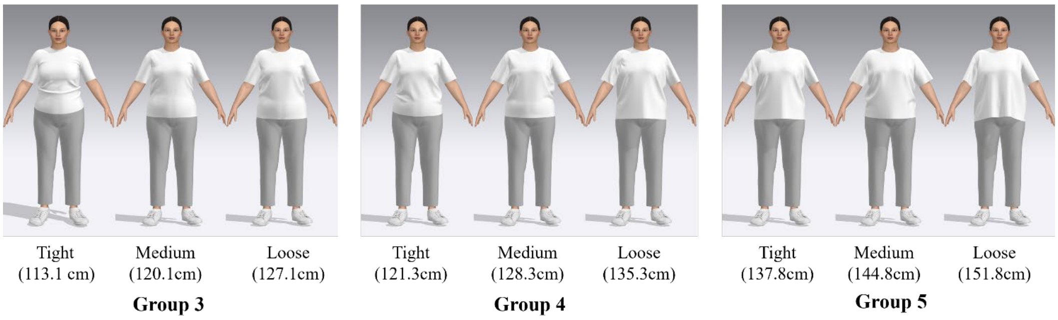

Figure 5. Example of the same avatar wearing garments in different fit levels.

In order to better assess the body size perception of dressed avatars, both standing and walking posture front views were rendered in a uniform image size of 900 × 900 pixels. Figure 6 provides examples of male and female avatars in two rendered poses. Eventually, 504 images were rendered for female avatars, and 444 images were rendered for male avatars for experiment preparation.

Figure 6. Rendered avatars in standing and walking postures.

3.4. Rating Body Size Perception of Dressed Avatars

The body size perceptions of the dressed avatars displayed on a computer screen were rated by a total of 38 viewers, primarily college students from Hong Kong SAR, aged between 20 to 35. Before rating the dressed avatars, all participants were required to pass through the training section. In the training section, participants were first shown the 3D version of Thompson and Gray's contour rating scale to familiarize the process and scale range of body size perception, then rated the 3D figures in the Thompson and Gray's contour rating scale in random order until they correctly rated all example figures. When rating the dressed avatars, each image remained on the screen for 3 s before disappearing, then the participants were asked to compare the dressed body images with the contour rating scales and give the closest rating to the image. Once the rating was given, the participants would see crosshairs on the center of the screen to reposition their line of sight before viewing the next image. This process was repeated until all images were rated. For both male and female avatars, four rounds of ratings were conducted, the first and third rounds for the front-view in standing posture, and the second and fourth rounds for the front-view in walking posture.

3.5. Artificial Neural Network Application and Feature Analysis

To map the impact of garment fit levels on body size perception, artificial neural network modeling was applied. Artificial neural networks are efficient in learning and modeling the relationships between input and output data, especially when they are nonlinear or complex [36,37]. Our methodology encompassed the utilization of an open-source automated machine learning (AutoML) framework, named AutoGluon-Tabular, developed by Erickson et al. in 2020 [38]. The architecture of the artificial neural network section is shown in Figure 7. It used an optimized feedforward network architecture to handle diverse types of values in tabular datasets. The artificial neural network model could be represented as the function:

$$y = f(x_1, x_2, \ldots, x_n) \tag{2}$$

where y represents the perceived body size from the experiment above, and x represents pivotal parameters of size for the rendered images. We will explain the input x in more detailed results and analysis later.

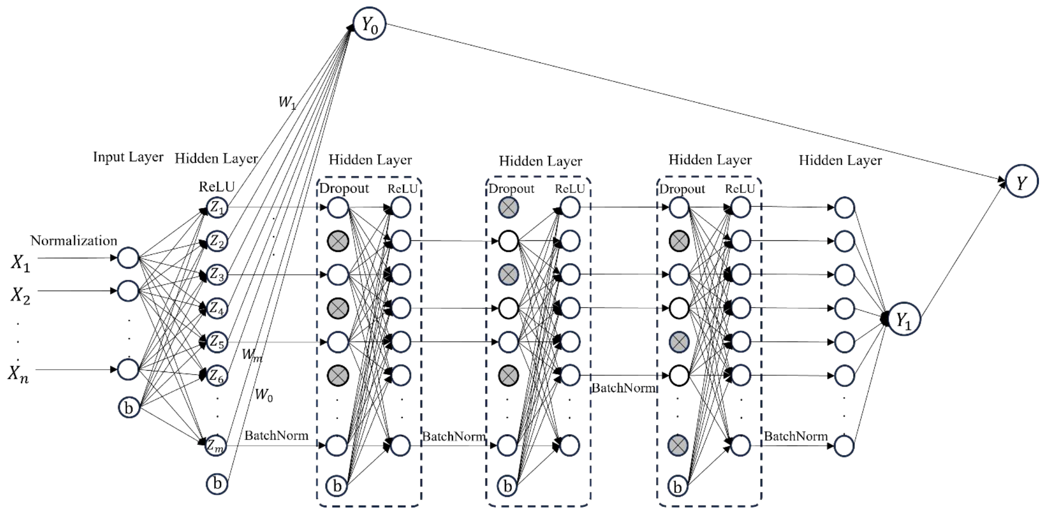

Figure 7. AutoGluon's Neural Network architecture.

The input tabular data in the .csv file was first normalized into similar scales for input to speed up the training process, then fed forward to the hidden layers, in which each neuron calculates a weighted sum of its inputs and activates them with the activation function of Rectified Linear Unit (ReLU). The ReLU function is defined as follows:

$$f(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases} = \max\{0, x\} \tag{3}$$

ReLU has been one of the most widely applied activation functions in neural networks due to its computational simplicity and superior training performance [39,40]. It also benefits neural network training in the vanishing gradient problem by working as a gradient blocker for negative inputs to block the backpropagation of small gradients which may prevent weight from changing values and stop the neural network from further training [41].

The hidden units and output units may have biases, and those biases are treated as other weights. The output vector of the first hidden layer is both fed to a 3-layer feed-forward network as well as directly connected to the output Y_0 via a linear shortcut path. This shortcut path structure could help to avoid performance degradation and vanishing gradient problems when adding more layers [42]. The final output Y can be presented as:

$$Y_0 = wz \tag{4}$$

$$Y_1 = g(x) \quad (5)$$

$$Y = Y_1 + Y_0 = g(x) + wz \quad (6)$$

The 3-layer feed-forward network contains three steps for each layer: (1) batch normalize to improve the training speed and stability by recentering and re-scaling the layer's inputs [43]; (2) dropout: a regularization method which randomly drops neurons during the training process by the probability of p, and all forward and backward connections with the dropped neurons are temporarily removed to construct a smaller new "thinned" network architecture to prevent the prediction model from overfitting. When testing, the effect of averaging the prediction of all these "thinned" networks can be approximated by using a single un-thinned network with smaller weights [44]; (3) calculates the weighted sum of inputs with the activation function of Rectified Linear Unit (ReLU).

The prediction model was trained using body size ratings obtained from our experimental data. The k-fold cross-validation technique was used to evaluate the model. K-fold cross-validation is a resampling approach which uses different portions of data to train and test a model in different iterations, where k refers to the number of groups that a given data sample is to be split into [45]. In this research, the collected data is randomly shuffled and split into 4 equal subsets, or 4 folds. The evaluation process was then repeated four times, with each iteration using one of the four folds (25%) of data as a test set and the rest three folds (75%) as a training set, using the key features of avatars and apparel items as input and the average of perceived body scales for output.

4. Results and Discussion

4.1. Data Processing and Noise Removal

In data analysis, it has come to our attention that disparities exist in how individuals perceive avatar body scales. Although all viewers passed the body scale training practice before starting rating dressed avatars, their rating behavior tended to be different. To address this scenario, the rating scores of each participant were standardized and rescaled to give a general body scale perception to the dressed avatars. Other than the standardization and rescaling process, an additional refinement was executed to remove the extreme values for each image rating score group. The five highest and five lowest ratings were removed to avoid the influence of stochastic noise that might be caused by misoperation, such as pressing the adjacent buttons on the keypad while rating the images.

4.2. Impact Factors on Human Body Scale Perception

Many factors potentially contribute to the perception of human body size, encompassing attributes such as body volume, body height, bust girth, waist girth, hip girth, and proportions derived from the above measurements including VHI, WHR, and Waist–Chest Ratio (WCR). However, adding more variables does not necessarily mean that the prediction model will have a better performance. Adding redundant variables might reduce the model's generalization capability, increase the overall complexity, and elongate the training time. To enhance the predictive model's parsimony without compromising its predictive efficacy, the Pearson Correlation Coefficient (PCC) analysis and feature importance analysis were undertaken to gain an overview of the variables. The AutoGluon-Tabular framework was used to process the feature importance analysis and train the models with all-feature subsets and reduced-feature subsets for the assessment of predictive performances. In the data processing phase, since the human body images have been standardized to a uniform size when rendering in the CLO3D environment, it is necessary to incorporate the relational dimensions of horizontal measurements including shoulder width, bust girth, waist girth, and hip girth, in proportion to the overall body height. The new variables are denoted as shoulder width/height, bust girth/height, waist girth/height, and hip girth/height.

Figure 8 showcases the PCC results; these visualizations reveal that the basic body measurement variables, including bust girth/height, shoulder width/height, waist girth/height, hip girth/height, and VHI are highly correlated to each other, especially for female bodies.

In this case, the VHI value could be used as a representative descriptor instead of other body measurements for body scale descriptions.

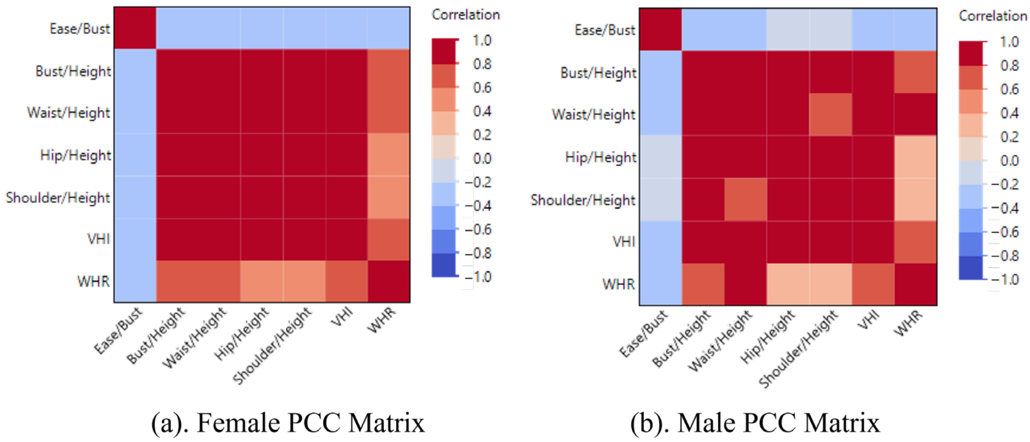

Figure 8. Female and Male PCC Matrix.

Figure 9 presents the feature importance analysis results of individual attributes to the output of prediction models for females and males. The importance score of a feature represents the performance drop when the model makes predictions on a perturbed copy of the data with this feature's value randomly shuffled. For a certain feature, the higher the importance score is, the more important it is to the model's performance. Notably, VHI emerges as the paramount determinant across all variables for both genders. For male avatars, the contribution of WCR is the fifth most important among all features, exerting a more pronounced impact on prediction outcomes compared to females. This phenomenon can be attributed to the direct correlation between WCR and obesity levels. The WCR value is less connected to body shapes for male avatars than to female avatars. Furthermore, the metric of the ease/bust girth ratio also has a larger contribution to the male prediction model, which underscores the potential for garment fit levels to have a more significant influence on the enhancement of body size perception within the domain of menswear.

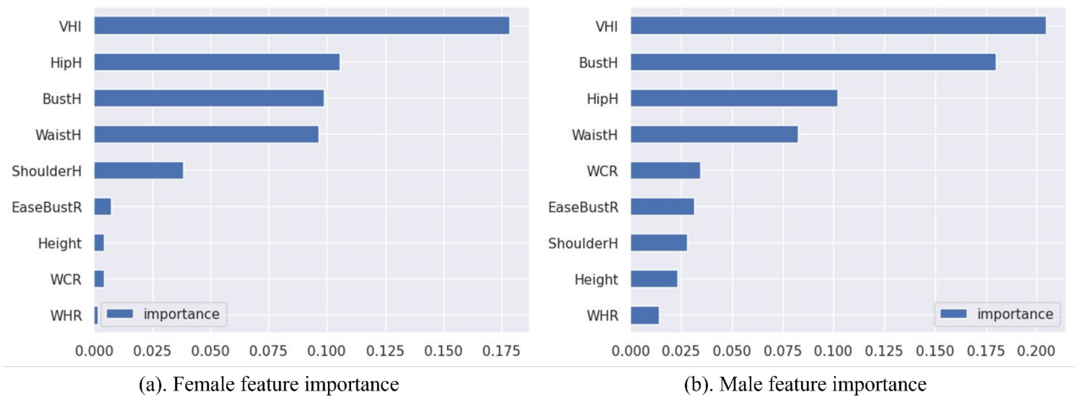

Figure 9. Female and male feature selection analysis.

Utilizing our three-dimensional dataset, we constructed regression models for females and males VHI, expressed by Equations (7) and (8), respectively. Figure 10 illustrates the comparison between the observed and predicted volume–height index (VHI) values based on these regression equations. Using these regression models, the VHI value could be predicted using basic body measurements without requiring three-dimensional body scanning technologies for real-world application.

$$\mathrm{VHI_{female}} = 0.8868 - 0.1533 * \mathrm{Height} + 0.0877 * \mathrm{BustGirth} + 0.1274 * \mathrm{WaistGirth} + 0.2527 * \mathrm{HipGirth} + 0.1125 * \mathrm{ShoulderWidth} \quad (7)$$

$$\mathrm{VHI_{male}} = 4.3383 - 0.1829 * \mathrm{Height} + 0.0957 * \mathrm{BustGirth} + 0.0899 * \mathrm{WaistGirth} + 0.2367 * \mathrm{HipGirth} + 0.2484 * \mathrm{ShoulderWidth} \quad (8)$$

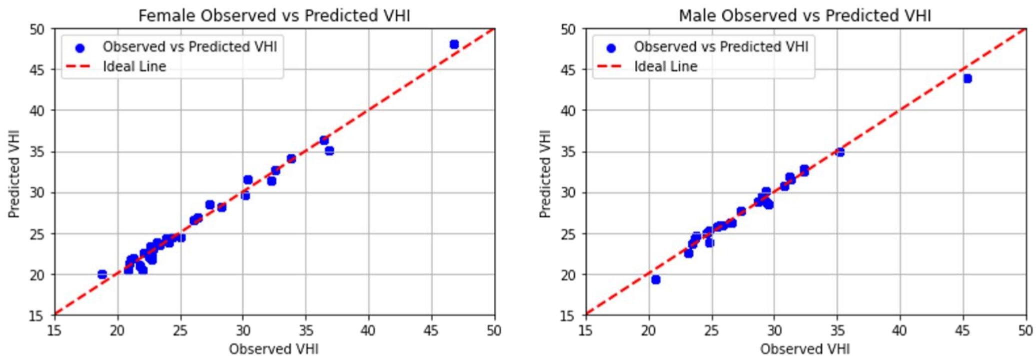

Figure 10. Comparison between the observed and predicted VHI values.

Based on the assumption that VHI could be used as a representative descriptor of an avatar's body image in terms of size perception instead of using multiple complicated body dimension variables including bust girth/height, shoulder width/height, waist girth/height, and hip girth/height. To further simplify the model for training and visualization, we choose VHI, WCR, ease/bust, and height as the simplified features, as they are not correlated and could give a relatively comprehensive description of the human body image, especially the upper body. Two prediction models were trained to evaluate the difference for verification.

The first prediction model used all four body dimension ratios (bust girth/height, shoulder width/height, waist girth/height, hip girth/height) together with VHI, WHR, WCR, ease/bust ratio, and avatar height as input features. By contrast, the second prediction model used VHI to substitute the four related body dimension ratios while retaining WCR, ease/bust girth, and avatar height as input features. The training and subsequent assessment of the two prediction models' k-fold cross-validation (k = 4) results are presented in Table 3. The R^2 score, or the coefficient of determination, emerged as the chosen metric to encapsulate the predictive efficacy of the models, as articulated by Equation (9):

$$R^2 = 1 - \frac{\sum_{i=1}^{m} (X_i - Y_i)^2}{\sum_{i=1}^{m} (\overline{Y} - Y_i)^2} \quad (9)$$

Table 3. Prediction model comparison between all features versus the reduced feature prediction models.

Gender	Body Features	Fold 1 (R^2)	Fold 2 (R^2)	Fold 3 (R^2)	Fold 4 (R^2)
Female	Horizontal measurements, VHI, WHR, WCR, Ease/Bust, and height	0.98	0.99	0.99	0.98
	VHI, WCR, Ease/Bust, and height	0.96	0.98	0.96	0.95
Male	Horizontal measurements, VHI, WHR, WCR, Ease/Bust, and height	0.91	0.92	0.94	0.92
	VHI, WCR, Ease/Bust, and height	0.90	0.93	0.93	0.88

This matrix can be interpreted as the proportion of the variance in the dependent variable that is predictable from the independent variables [46].

The evaluation results showed that the prediction model, using a reduced number of features, could achieve a similar R^2 value with a very small loss as that of the prediction model using all body dimension ratios, sometimes even increasing the model performance by simplifying the prediction model (Male Fold2). This result suggests the feasibility of substantial variable reduction by adopting a streamlined set of factors, specifically encompassing VHI, WCR, ease/bust girth, and body height, as the principal determinants in explicating body size perception. This result supported Hypothesis 1.

4.3. Body Scale Perception Prediction Model

According to the PCC analysis and feature importance analysis results, the final prediction models selected VHI, WCR, ease/bust girth, and body height as the pivotal input parameters. In this section, for Equation (2), a total of n = 4 pivotal input parameters are used, namely x_1, x_2, x_3, and x_4. The new function is represented as:

$$y = f(x_1, x_2, x_3, x_4) \tag{10}$$

where y represents the perceived body size, ranging from 1 to 9; x_1 stands for the VHI value, ranging from 20.5 to 45.5 (L/m^2) for females, from 18.5 to 50.5 (L/m^2) for males; x_2 denotes the WCR value, ranging from 0.70 to 0.95 for females, from 0.80 to 1.05 for males; x_3 stands for the height, ranging from 1.50 to 1.85 m for females, from 1.65 to 1.95 m for males; x_4 stands for the ease/bust girth ratio, ranging from -0.1 to 0.4 for both genders.

For each value taken (x_1, x_2, x_3, x_4), the prediction model could estimate the possible rating result from the population. By sampling equidistantly in feature space (x_1, x_2, x_3, x_4), we plotted the prediction results with a partial dependency plot (PDP) to show the potential relationship between garment fit, human body features, and body scale perceptions. The partial dependency plot (PDP) could show the marginal effect one or two features have on the predicted outcome of a machine learning model [47].

Figure 11 visualizes the female and male prediction models and underscores the differential impact of garment fit levels, denoted by the ease/bust girth ratio, on the two genders' body perceptions. The *y*-axis shows the perceived body scale difference compared to the nude body scale, and the error bars present the value changes caused by height changes. Both genders were separated into three groups of VHI, representing the body scale 4 to 5 (slim), 5 to 7.5 (regular), and 7.5 and above (obese). Figure 11 provides a strong support for Hypotheses 2 and 3. For females, there is a notable tendency to underestimate the perceived body scale when dressed, and the influence of garment fit appears to be less pronounced compared to males, which echoes the results of the feature importance analysis. There is a subtle increment in perceived body scale with larger ease allowances, hinting at a milder impact. In this context, the WCR wields a greater influence, especially for female bodies with a VHI under 37.5. These bodies experience a significant WCR-driven impact on the perceived body scale, with those possessing a lower WCR more likely to be underestimated. Contrary to some fashion theories suggesting that wearing oversized garments could visually decrease body scale, our findings suggest that the primary function of oversize garments may lie in concealing unwanted body parts rather than reducing perceived body scale. Emphasizing the chest-to-waist ratio could potentially offer a more effective solution for this purpose.

Turning to males, the perceived body scale is largely affected by garment fit levels, particularly among individuals with a lower VHI. Among slender males with a VHI falling within the range of 18.5 to 20.5, the perceived body scale increases significantly with the ease/bust ratio when the WCR is smaller than 0.99. For small VHI males with a WCR exceeding 0.99, the perceived body scale increases with the garment ease/bust ratio from -0.1 to 0.2 and plateau after 0.2. Similarly, for regular-scale males with a VHI between 20.5 to 30.5, the perceived body scale increases with the ease/bust ratio when the WCR is smaller than 0.99, and for a WCR surpassing 0.99, the perceived body scale slightly increases with the ease/bust ratio from −0.1 to 0.2 then slightly decrease. As for the large-size males with VHI between 30.5 to 50, the impact of garment fit is minimal if the WCR is larger than 0.99. For those large-scale males whose WCR is below 0.99, a garment ease/bust ratio between −0.1 to 0.2 emerges as optimal for underestimating the wearer's body scale. This finding suggests that strategically wearing loose-fitted garments could significantly help slender males to create a stronger body image, potentially enhancing their confidence and self-perception to fit social expectations. Additionally, for obese males, wearing more close-fitted garments could help to reduce their perceived body scales.

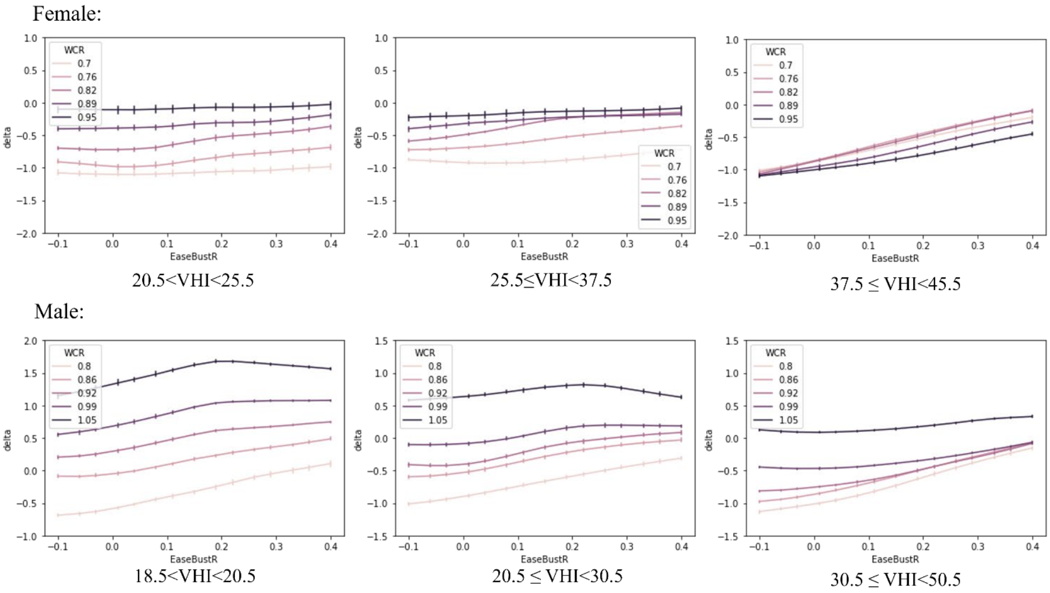

Figure 11. Prediction model of female and male perceived body scales (y: perceived size difference compared to nude body, x: proportion of ease allowance versus bust girth).

Based on the prediction models, it is clear that the effect of garment ease is different depending on the wearer's gender, original body size, and WCR. When determining garment ease allowance for customized apparel design, it is imperative to recognize that the trajectory of desired body enhancement is multifaceted. The mere pursuit of a decrease or increase in body size perception does not unequivocally signify an enhancement or detriment to body image perception. For individuals who have concerns related to obesity, the underestimation of body size might be their predominant objective, while for individuals characterized by a petite physique or those exhibiting marked underweight, enlarging their body scale could emerge as an effective strategy to enhance their body images.

5. Conclusions

Due to the diversity of fashion design elements, the countless combinations have made it extremely challenging to quantitatively explore their impact on human body image. This study attempts to explore one dimension of this multidimensional space—the fit of garments—on human body perception using CAD software and AutoGluon-Tabular, an ANN framework. The practice has shown that utilizing CAD software for avatar measurement extraction, apparel pattern development, 3D model simulation, and image rendering extraction can significantly reduce the consumption of labor and materials while obtaining a more controllable and diverse digital database. On the other hand, the use of ANN has greatly facilitated the exploration towards the impact of design elements for prediction model training. By learning patterns from existing data, ANN enables the prediction of previously unseen variables, facilitating extrapolation beyond the scope of the experiment and enhancing our understanding with limited data. This research methodology can be extended to investigate the influence of various factors such as garment silhouette, color schemes, and print patterns on body image perception to build up the coordinate system of fashion design elements and body image. Such a system would be valuable for guiding aesthetic-driven fashion product development and providing personalized recommendations for consumers.

After mapping and interpreting the prediction model in this study, we found that garment fit impact varies based on individual body measurements. Particularly, male wearers exhibit a more pronounced influence of garment fit than female wearers, and the fit of garment is not the only factor that could impact the perceived body scale. The obesity and WCR of the wearer are also important factors. This study addresses a notable gap in the literature by investigating the impact of garment fit on perceived body scales, especially for females.

For practical implications, the prediction model offers potential application in OAMC systems. While T-shirts were chosen for their simplicity and commonality, the underlying principles of how garment fit affects body image perception may also be appliable to other basic style tops such as shirts, blouses, and outwear. Manufacturers can predict consumers' VHI values from basic measurements and adapt the model to determine optimal ease allowance for garment designs based on consumers' preferences. Beyond its application in OAMC, this prediction model could also benefit online shopping in product and size recommendation. By leveraging our prediction models, online retailers can provide personalized recommendations and tailored fit options. This approach helps to satisfy their desire to reconstruct an ideal body image that aligns with their expectations while ensuring physical comfort when wearing the garments. Moreover, a nuanced understanding of garment fit can contribute to the development of sustainable fashion practices. By optimizing clothing production to minimize the waste associated with returns and maximize consumer satisfaction, fashion companies can move towards more environmentally friendly practices, fostering a more responsible and ethical fashion industry.

However, this research acknowledges certain limitations. One of the limitations is the use of convenient samples. The recruited participants were mostly college students, which does not fully represent consumers' attitudes to the mass market. Other limitations include the apparel category selection and design element application. The focus solely on the upper body of male and female avatars within the chosen apparel category constrains the breadth of inquiry. Future investigations might delve into the interplay between clothing and the lower body or the entirety of the body, and incorporate additional design elements, such as colors and silhouettes, to enhance the evaluation's comprehensiveness. Additionally, exploring the impact of avatars under diverse body shapes could provide more comprehensive insights about apparel's impact on body image enhancement.

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