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AN INTERACTIVE KNOWLEDGE-BASED RECOMMENDER SYSTEM FOR FASHION PRODUCT DESIGN IN THE BIG DATA ENVIRONMENT

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ABSTRACT

In this paper, we originally propose an interactive, knowledge-based design recommender system (IKDRS) for relevant personalised fashion product design schemes with their virtual demonstrations for a specific consumer. This system enables the iterative interaction between virtual product demonstration and the designer's professional knowledge and perception in order to find the best existing design solution, i.e. combination of basic garment elements. To develop this system, the anthropometric data and designer's perception of body shapes are first acquired by using a 3D body scanning system and a sensory evaluation procedure. Next, an instrumental experiment is realised for measuring the technical parameters of fabrics and five sensory experiments are carried out in order to acquire design knowledge. The acquired data are used to classify body shapes and model the relations between human bodies, fashion themes and design factors by using fuzzy techniques. From these models, we set up an ontology-based design knowledge base, including key data and relevant relation models. This knowledge base can be updated in a big data environment by progressively learning from new design cases. On this basis, we propose an interactive, personalised design recommender system. This system works through a newly proposed design process: *consumers' emotional requirement identification – design schemes generation – recommender – 3D virtual prototype display and evaluation – design factors adjustment*. This process can be performed repeatedly until the designer is satisfied. The proposed system has been validated through a number of successful real design cases.

KEYWORDS: interactive knowledge-based design recommender system; sensory evaluation; fuzzy techniques; ontology; design knowledge base

1. Introduction

A recommender system aims to recommend the most suitable items (products or services) to particular users (individuals or businesses) by predicting a user's interest in an item, based on related information about the items, the users and the interactions between them [1]. Since their introduction

by Marko Balabanovic in 1995 [2], recommender systems have been widely developed due to the fast progression of the Internet and big data. The classical recommendation techniques usually include: 1) content-based filtering, aimed at discovering product attributes and relations between products and between customers [3]; 2) collaborative filtering, permitting the exploitation of information about user interaction and transactions, such as product ratings and orders [4]; 3) knowledge-based approach, enabling the generation of advice based on explicit human knowledge about the item assortment, user preferences, and recommendation criteria (i.e. which item should be recommended in which context) [5]; and 4) a hybrid recommender system based on the approaches outlined above [6]. Recently, social network-based approaches have also been greatly developed [7]. These methods are based on the fact that when people are friends, they share certain things in common. Currently, recommender systems have been widely applied in all Internet-related areas, including e-commerce, e-learning, e-library, e-government and e-business services [1].

In the fashion industries (clothing, shoes, jewels and other consumer goods where style holds the primary importance), due to fierce worldwide competition in fashion markets and increasing consumer demands, the realisation of personalised fashion products with low cost and quick reactivity has become a key to success for many enterprises [8]. According to Statista (2018), fashion products (65% garments) constitute the fastest-growing category of online sales, with a rate of 19% for e-retailing as a whole. In this area, recommender systems are mainly developed for e-shopping and related product design because a consumer's emotional preferences, fashion styles and fitting effects constitute the most important elements in the whole textile/apparel value chain. The objective of these systems is to find the most relevant products or design solutions for a specific consumer, optimising fitting effects and fashion preferences.

In this context, the existing work on garment design-oriented recommender systems can be summarised as follows. Wong et al. [9] proposed a decision support tool for fashion coordination through integration of the knowledge-based attribute evaluation expert system and the Takagi–Sugeno Fuzzy Neutral Network (TSFNN). This paper also proposed a fuzzy clustering technique and a new hybrid learning algorithm, combining the PSO and GA techniques, in order to reduce the coordination rules and the training time for the TSFNN. Jung et al. [10] and Ajmani et al. [11] explored different ontology-based fashion design recommender systems. Jung's system applied hybrid collaborative filtering and content-based filtering to discover knowledge about user preference. Ajmani et al. [11] presented a content-based method using probabilistic multimedia ontology. Yang and Xin-Juan [12] presented a case study of an online system that recommends apparel based on rules extracted from decision tree mining and experienced dressing knowledge. Mok et al. [13] proposed a customised garment design recommender system by using an interactive genetic algorithm (IGA) for non-professional users (general customers) to create their preferred garment designs in a user-friendly way. Also, in our previous work, a perception-based design recommender system was proposed by exploiting the relationship between human perception on body shapes and a garment's technical parameters [14].

Previous design recommender systems mainly focus on the technological development of virtual garment assembling, permitting designed products to be fitted to specific models of the human body and/or their relations with the consumers concerned. However, they rarely deal with professional design knowledge, the basic components of fashion products or a consumer or designer's emotions. In fact, experienced designers usually work with their professional knowledge (such as the overall design principles, specific design rules characterising the relations between design factors (fabrics, styles and colours), human body shape perception and fashion themes), as well as previously successful design cases with related parameters and sketches. In this context, the development of designers' knowledge-based, personalised recommender systems is extremely significant because they can effectively help designers and consumers to select the most relevant garment products and personalised garment design by studying a user's preferences and performing personalised

computations. Formalisation and exploitation of professional designers' knowledge will constitute the key issue in the development of such recommender systems.

Human emotions have already been exploited in existing recommender systems. González [15] developed a recommender system by embedding emotional context and explained some results of these new trends in real-world applications through a smart prediction assistant (SPA) platform. Lazemi [16] improved the performance of traditional, user-based collaborative filtering by entering the users' emotional features. Mizgajski [17] set up an efficient recommender system by introducing emotions in order to influence reading choices in the online news industry.

Our study differs from the previous approaches that permitted general users' emotional attributes to be formalised and integrated by focussing on the characterisation of professional fashion design knowledge, in which emotional context is related to the relationship between fashion images, linguistic expressions and a garment's technical parameters. Concretely, we set up an ontology-based design knowledge base for storing complex, structured and unstructured information on fashion design. Ontology [18] enables clarification of the related concepts and relationships in the process of garment design. On this basis, we propose a new interactive knowledge-based design recommender system (IKDRS) for selecting the most relevant personalised garment design scheme. In this system, sensory evaluation techniques [19] are used to extract knowledge from design experts on the relationship between body shapes, design factors (i.e. design style, fabric and colour) and fashion themes, and characterise human body shapes and the fitting effects of new garments. When extracting designer knowledge, the socio-cultural context, fashion trends and individual aesthetic preference should be taken into account. Therefore, a number of emotional and hedonic descriptors have been generated by using some reference images describing related ambiances. For human body shape and garment fitting evaluations, we use the classical quantitative description method for determining the relevant neutral and non-hedonic descriptors. In the garment design process, the proposed system can effectively help young designers and general consumers to quickly rank and select their design schemes or products according to their personalised preferences by computing with the relation models concerned.

Moreover, the proposed system has a feedback mechanism, permitting new data and design cases to be progressively integrated into the knowledge base, which is significant in the big data environment. The continuous use of the recommender system by various designers will enable the obtention of a complete design knowledge-base, representing all design scenarios. The designed garments, as well as the related fitting effects on specific body shapes, can be displayed virtually on the 3D platform and the results can be returned to the system for an automatic adjustment. The design schemes can be evaluated and adjusted repeatedly until they meet designer expectations.

Due to their capacity for interpretation and robustness, fuzzy techniques [20] constitute the main computational tool for the formalisation and modelling of perceptual data and their relationships. In fact, fuzzy logic is particularly consistent with the fashion design process, which is strongly related to the designer's perception and thinking, expressed with uncertain and imprecise keywords. Fuzzy sets can be qualitative and quantitative simultaneously because they are both case-oriented and variable-oriented, due to their allowance for degrees of membership and, thus, for detailed variation across cases. In our past work, Chen et al. [21] optimised the ease allowance (the gap between the human body and garment surface) for personalised garment design by using fuzzy models. Wang et al. [14] modelled the relation among fashion themes, human body measurements and garment styles using fuzzy decision trees and fuzzy cognitive maps, developing a fashion recommender system based on body shapes. However, the existing methods are less efficient when modelling and analysing a design process with more complete and complex design elements (see Fig.6). In the current study, fuzzy sets, fuzzy relations and related operations with newly defined fuzzy nearness degrees have been used for the modelling of the complex relations between body shapes, fashion themes and design factors, due to their capacity for dealing with uncertain and inaccurate data.

Compared with the existing literature, the proposed recommender system brings four original contributions:

1) It enables human knowledge and human emotions on garment design to be extracted, formalised, updated and applied to recommendations. As this system will be implemented by the e-shopping platforms of fashion brand companies, the proposed feedback mechanism can be largely adapted to the big data environment (various connected consumers with time-varying purchasing behaviours and various innovative products), permitting the generation of an efficient and complete knowledge base by integrating new design cases related to continually increasing e-transactions.

2) It can not only rank all existing design schemes but also generate new solutions by finding the most relevant combination of all decomposed basic garment elements.

3) It permits the interaction between virtual product demonstrations (virtual space) and designers' knowledge and perception (real space) and progressively improves the quality of the recommended design scheme by adjusting the concerned relation models (feedback mechanism). Compared with current recommender systems with feedback, mostly aimed at improving the user's rational requirements [22], the feedback mechanism we developed is capable of minimising the difference between the user's requirements (rational verbal criteria) and his/her perception of the recommended product. In an e-shopping environment, the union of a consumer's rational and perceptual criteria is extremely significant for recommending relevant fashion products.

4) Compared with the existing fashion recommender systems, which mostly deal with only one design factor (such as fashion style), the proposed system originally combines all three factors of fashion design (style, colour and material), enabling more complete design solutions to be obtained, which can be easily evaluated by non-professional consumers.

The general principles of the proposed recommender system can be applied to all kinds of garments and adapted to the design of other fashion products. However, for simplicity, in this paper we describe it using the specific case of women's jeans design.

This paper is organised as follows. In Section 2, we give the general structures and related concepts of the proposed design recommender system and the ontology-based design knowledge base. In Section 3, a number of physical and sensory experiments are proposed for acquiring relevant data, describing relations between human bodies, fabrics, garment styles and colours as well as fashion themes. In Section 4, we describe a body classification model and four mathematical models characterising the previous relations using fuzzy techniques. In Section 5, we present the garment design process with the proposed recommendation and feedback mechanism, permitting the knowledge base to be adjusted according to the designer's evaluation of the recommended design scheme (virtual product). In Section 6, we give a real application case for validating the proposed system. Section 7 provides the conclusions.

2. The interactive knowledge-based design recommender system and knowledge base: structures and concepts

In this section, we present the general structures of the proposed recommender system and related garment design knowledge base. The recommender system aims at generating the best design solution, i.e. the best combination of basic design elements from a specific consumer profile. As the key module of the recommender system, the design knowledge base enables the classification of body shapes and models the relations between fashion themes (consumer fashion requirements) and garment factors (fabrics, styles, colours).

2.1. The general structure of the proposed system

In the proposed interactive design recommender system, the input is a user interface permitting the designer to input two categories of parameters (consumer profile), including a specific body shape represented by eight key body dimensions and a specific desired fashion theme. The design knowledge, acquired from designers, is stored in the *Knowledge Base* under the ontology form. An interaction between the consumer profile and *Knowledge Base* enables the generation of a relevant design scheme by using the *Inference Engine* and then displaying it on a 3D virtual platform for the user to determine, by using sensory evaluation, whether this design scheme conforms to the specific human body and the desired fashion theme, or not. If the user is satisfied with the design scheme, she/he will validate it and then deliver it to the production unit for real garment prototyping. Otherwise, the user will provide feedback to the system, allowing the knowledge base to be adjusted by the *Self-Adjusting Engine*, and will then be offered a new, relevant, design scheme.

The proposed interactive design system enables the development of a new working cycle with feedback, i.e. *consumer emotional requirements identification – design schemes generation – recommendation – 3D virtual prototype display and evaluation – design factors adjustment*. This cycle will be executed repeatedly until the user is satisfied, in terms of consumer body shape and desired fashion theme. The knowledge base can become more and more efficient by successively adding new design cases.

2.2. Construction of garment design knowledge base

The main component of the proposed recommender system is the design knowledge for garments, which is built using an ontological form. Ontologies are usually considered as powerful tools for modelling and formalising various knowledge-based systems.

Currently, the majority of ontological models in the apparel field merely involve classification of garment components, related concepts such as garment structure, basic garment components and the complex relations between them. In fact, we can easily generate new design schemes from existing knowledge if we can clearly master the related concepts and relations in the process of garment design by using ontology.

For example, in the design of women's jeans, we acquire and build this ontology with the help of experts and set up the garment ontology model (GOM) by using a 6-tuple as follows:

$$\text{GOM} = (\text{FD_Class}, \text{FD_Relation}, \text{FD_Attribute}, \text{FD_Rule}, \text{FD_Axiom}, \text{FD_Instance})$$

"*FD_Class*" expresses the classes or concepts in garment design, including society entity (e.g. human circumstance, culture, etc.) and product entity (e.g. garment categories, components of garment structure, style elements, etc.). "*FD_Relation*" expresses the relations between concepts, e.g. Women's Garment is a subclass of Garment. "*FD_Attribute*" expresses aspects, properties, features, characteristics, parts, or parameters of various classes in ontology, e.g. Fabric Property is an attribute of Garment. "*FD_Rule*" includes the IF-THEN rules that describe the logical inferences that can be drawn from the previous models. "*FD_Axiom*" removes the conditions in *FD_Rule*, which show whenever implications in garment design are true, e.g. a subclass succeeds all relations of its parent class. "*FD_Instance*" expresses the instance in design ontology.

A tree structure diagram of the garment design ontology is shown in Fig. 1.

In practice, this ontology model could be extended by introducing new concepts, building more complex relations or adding new instances.

Based on the design ontology model, we propose the design knowledge base with a structure of three layers, as shown in Fig. 2.

This knowledge base is organised by following a hierarchical structure. All of the raw data collected in the different databases (human bodies, styles, colours, fabrics) are stored in the data layer. The relevant concepts and the relations between various elements used in the garment design are expressed by an ontology model in the concept layer, in order to create a structured and complete knowledge base for further applications in the whole system. The data in the data layer and the

relations between concepts in the ontology model are analysed quantitatively and modelled in the computational layer by using the five fuzzy models on the classification of body shapes (see Section 4) and the relations of fashion themes with body shapes and design factors (garment styles, colours and fabric properties). The computational layer constitutes the core of the knowledge base.

In addition, the created knowledge base can be automatically adjusted at any time by introducing new knowledge into it.

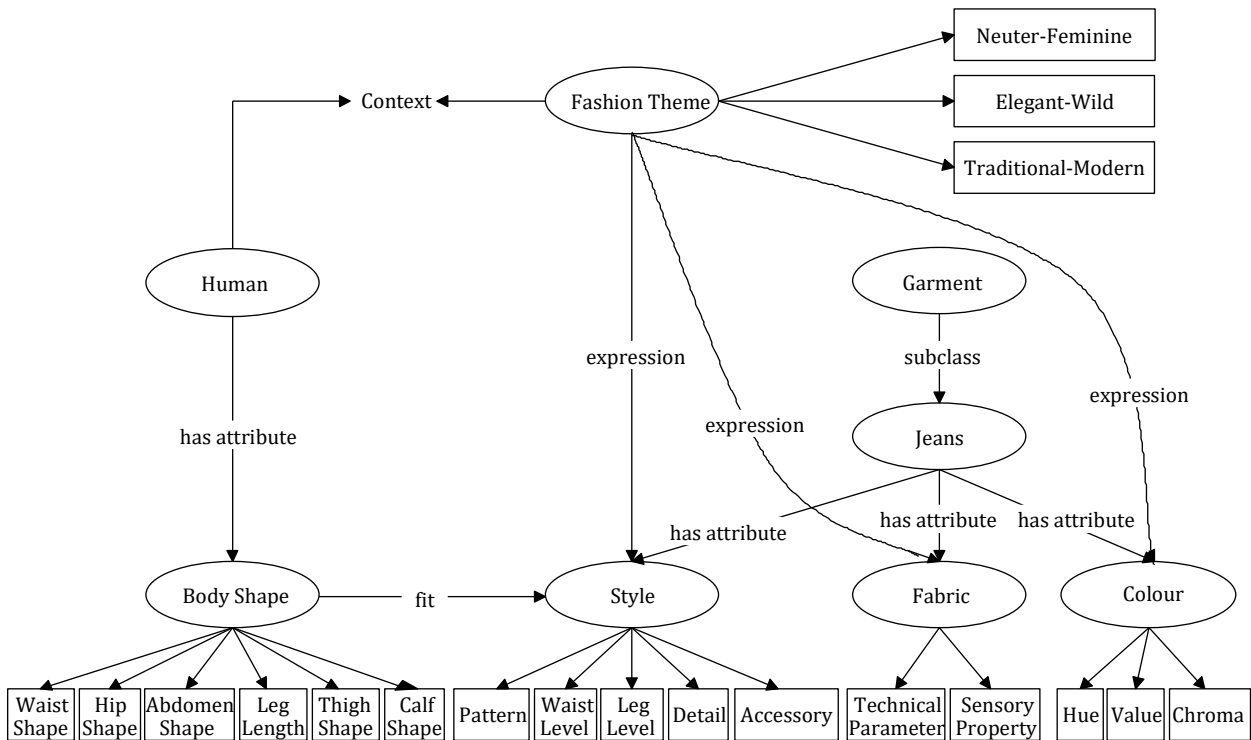


Fig. 1. The tree structure diagram of garment design ontology.

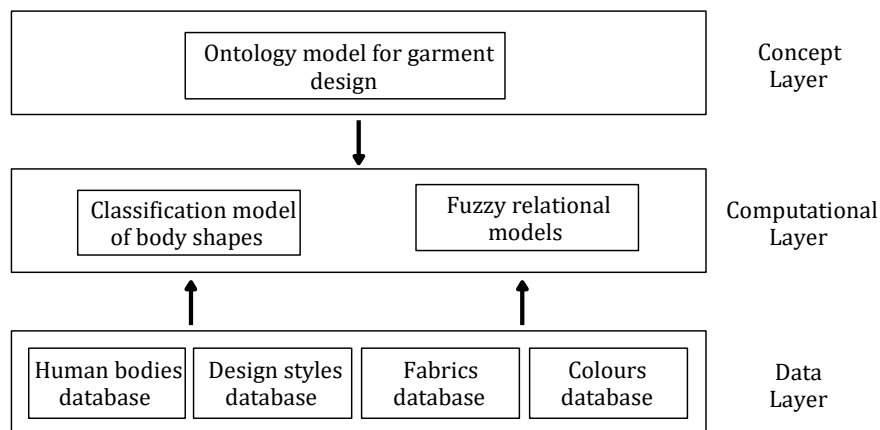


Fig. 2. Hierarchical diagram of the design knowledge base.

3. Acquisition and formalisation of physical and sensory data

The five models of the computational layer of the knowledge base (Fig.2) are built by learning from the data measured with devices or evaluated by experts. Therefore, for this section we designed a number of experiments for collecting relevant data, including human body measurements from a

3D scanner, technical parameters of fabrics and sensory evaluation data on body shapes and garment fits, provided by experienced designers according to their professional knowledge. All the acquired data are mathematically formalised in order to set up models in the following sections.

3.1 Physical measurement experiments

A garment design process requires data obtained from two categories of physical measurements: 1) body measurements characterising the body shapes of consumers; and 2) technical parameters characterising the nature of fabrics. The details of these measurements are given below.

3.1.1. 3D body measurements (Experiment 1)

By using 3D body scanning, a large number of measurements can be generated. However, in practice, only a small number of them are significant for a specific garment design. For example, in a lower garment design (trousers, skirts, etc.), designers only consider the most relevant dimensions, including *Stature (S)*, *Waist Height (WH)*, *Crotch Height (CH)* in the vertical direction and *Waist Girth (W)*, *Hip Girth (H)*, *Abdomen Girth (A)*, *Thigh Girth (T)*, *Calf Girth (C)* in the horizontal direction (see Fig. 3).

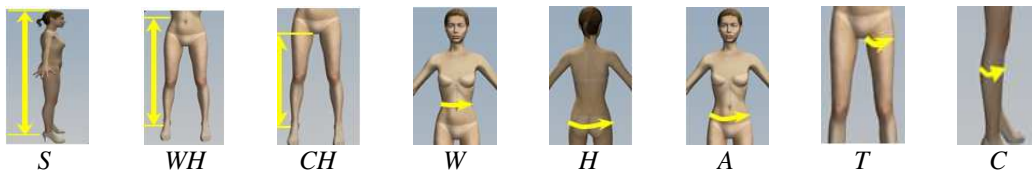


Fig. 3. The 8 body measurements relevant to lower-garment design.

These measurements are called key body dimensions describing the lower body shape [23]. They describe the lower body shapes at six key body positions: *Waist Shape (WS)*, *Hip Shape (HS)*, *Abdomen Shape (AS)*, *Leg Length (LL)*, *Thigh Shape (TS)* and *Calf Shape (CS)*. They permit further studies to be performed, such as body shape classification. The corresponding formalisation is given below.

Let $B = \{b_1, b_2, \dots, b_n\}$ be the set of n representative human bodies. In our experiments, we select 125 body shapes of different types ($n=125$).

Let $BM = \{bm_1, bm_2, \dots, bm_p\}$ be the set of p key dimensions (measurements) of a human body. In the case of women's jeans design, we have $p=8$ and BM can be rewritten as $BM = \{S, WH, CH, W, H, A, T, C\}$.

Let $BP = \{bp_1, bp_2, \dots, bp_q\}$ be the set of q key body positions of a human body. In the case of women's jeans design, we have $q=6$ and BP can be rewritten as $BP = \{WS, HS, AS, LL, TS, CS\}$.

Moreover, in garment design, the differences and ratios of body measurements are generally more significant than BM for classification of human body shapes. According to garment size standards and expert analysis, we generate 15 body characteristic indices as follows: 1) Waist Shape index: $WS = W/S$; 2) Hip Shape indices: $hs_1 = H - W$, $hs_2 = H/W$, $hs_3 = H/S$; 3) Abdomen Shape indices: $as_1 = A - W$, $as_2 = A/W$, $as_3 = A/S$; 4) Leg Length indices: $ll_1 = CH/S$, $ll_2 = WH/S$; 5) Thigh Shape indices: $ts_1 = TG/W$, $ts_2 = TG/H$, $ts_3 = TG/S$; and 6) Calf Shape indices: $cs_1 = CG/W$, $cs_2 = CG/H$, $cs_3 = CG/S$. These body characteristic indices will be used for body shape classification.

3.1.2. Measurement of technical parameters of fabrics (Experiment 2)

Fabric is one of the important factors for expressing fashion themes. In a garment design, selected fabric materials should satisfy the designer's requirements, in terms of appearance, fit and comfort, and the garment manufacturer's technical requirements and functional restrictions. Therefore, it is

necessary to characterise fabrics in terms of their physical, mechanical, aesthetic and sensory properties. The measured physical and mechanical properties of fabrics (e.g. bending, shearing, tensile, surface friction) are called the ‘technical parameters of fabrics’. The corresponding formalisation is given below.

Let $F = \{f_1, f_2, \dots, f_m\}$ be the set of all the m representative fabrics.

Let $TP = \{tp_1, tp_2, \dots, tp_{u_1}\}$ be the set of all the u_1 technical parameters of fabrics.

The u_1 technical parameter values of all the m fabrics in F constitute a matrix, denoted as $TPM = (p_{ij})_{m \times u_1}$ with $i = 1, 2, \dots, m; j = 1, 2, \dots, u_1$.

3.2. Sensory experiments

The purpose of the sensory experiments is to acquire design knowledge on the relations between body shape and garment design elements and between fashion themes and garment design elements, by quantitatively evaluating a set of representative human bodies and virtual, finished garment products.

This panel is composed of r ($=r_1+r_2+r_3$) experienced designers, including r_1 fashion designers (Group 1), r_2 pattern designers (Group 2) and r_3 fabric designers (Group 3), who play different roles in different sensory experiments according to their knowledge structures. Fashion designers who are specialists in garment aesthetics, can effectively control design elements and their combinations. Pattern designers have mastered the knowledge of both human body structures and various garment structures. Fabric designers have a good feeling about fabrics and their relations with design elements. The fashion designers participate in all of the sensory experiments except those on body shapes and fabrics. The garment designers participate in all of the experiments except those on colours and fabrics. The fabric designers only take part in the experiments related to fabrics. In the same experiment, we assume that the importance weights of all the panellists are identical.

3.2.1. Sensory evaluation of body shapes (Experiment 3)

The r_1 panellists in Group 1 are invited to perform this experiment. Before the experiment, the pictures of 3D virtual body shapes are generated for the subjects selected in Experiment 1 (body measurements). In Experiment 3, the body shape at each position bp_i ($i \in \{1, \dots, q\}$) is classified into five sensory classes (*Very Small, Small, Neutral, Large and Very Large*) according to the visual perception on all the 3D human samples generated in Experiment 1. The corresponding numerical scores are -2, -1, 0, 1, and 2, respectively. For each evaluator, each specific body position belongs to one of the five sensory classes.

3.2.2. Sensory evaluation of body shapes and basic styles (Experiment 4)

The aim of this experiment is to characterise the relation between body shapes and basic styles (i.e. the combination of different basic style components). A complete design style is composed of *Basic Style, Details* and *Accessories*. For example, for jeans design, the basic style is composed of the basic style components (i.e. *Pattern, Waist-Level* and *Leg-Level*) and we have *Basic Style* = $\langle \text{Pattern, Waist-Level, Leg-Level} \rangle$. Each basic style component takes one value from a number of style elements. The value of *Pattern* can be one element from $\{\text{Skinny, Slim, Straight, Loose}\}$. *Details* comprises the detailed components, i.e. *Front-Pocket, Back-Pocket, Front-Fly, Side-Seam*, and so on. Each detail component takes one value from a number of detail elements, e.g. the value of *Front-Pocket* takes one element from $\{\text{Crescent, Covered}\}$. The combination of one basic style and detail elements, selected from the six detail components and accessories, constitutes the complete design style, i.e. *Garment Style* = $\langle \text{Basic Style, Details, Accessories} \rangle$. All of the design styles constitute a design styles base. The descriptions of all the elements and their symbols are listed

in Table 1. The elements can be added, deleted and updated according to new fashion trends and user preference.

Table 1
Style, detail, accessory and their symbols

Basic style component	Basic style element	Symbol	Detail component	Detail element	Symbol	Accessories	Symbol
Pattern	Skinny	$PATTERN_1$	Front-Pocket ($DETAIL_1$)	Crescent	$DETAIL_{11}$	no-Accessory	$ACCESSORY_0$
	Slim	$PATTERN_2$		Covered	$DETAIL_{12}$	Lace	$ACCESSORY_1$
	Straight	$PATTERN_3$	Back-Pocket ($DETAIL_2$)	Uncovered	$DETAIL_{21}$	Embroidery	$ACCESSORY_2$
	Loose	$PATTERN_4$		Covered	$DETAIL_{22}$	Fasteners	$ACCESSORY_3$
Waist Level	Low-Waist	$WAIST_1$	Front-Fly ($DETAIL_3$)	Fasteners	$DETAIL_{31}$	Rivets	$ACCESSORY_4$
	Regular-Waist	$WAIST_2$		Buttons	$DETAIL_{32}$	Diamonds	$ACCESSORY_5$
	High-Waist	$WAIST_3$	Side-Seam ($DETAIL_4$)	Hidden	$DETAIL_{41}$	Tassels	$ACCESSORY_6$
Leg Level	Tapered	LEG_1		Exposed	$DETAIL_{42}$
	Regular	LEG_2	Patchwork ($DETAIL_5$)	no-Patchwork	$DETAIL_{51}$		
	Boot-Cut	LEG_3		Patchwork	$DETAIL_{52}$		
	Wide-Bell	LEG_4	Broken-Hole ($DETAIL_6$)	no-Holey Holey	$DETAIL_{61}$ $DETAIL_{62}$		

In Experiment 4, we only consider basic styles because details and accessories are less sensitive to body shapes.

The panellists in Group 1 and Group 2 are invited to perform this experiment. In Experiment 4, the panellists are asked to determine whether a style element is fit for the body positions of a specific body shape and give the corresponding evaluation scores, selected from the set of $\{unfit, neutral, fit\}$ according to the three-points scale method. We denote “*unfit*”, “*neutral*” and “*fit*” by -1, 0, and 1, respectively.

3.2.3. Sensory evaluation of fashion themes and design styles (Experiment 5)

Generally, fashion theme is the value orientation, intrinsic character and artistic characteristics shown from the form and content of a garment. In fashion events, fashion themes are often communicated to the general public through fashion forecasting reports or seminars [24]. In women’s jeans design, three pairs of opposite keywords are usually used for describing fashion themes, i.e. *Fashion Theme* = {*Neuter/Feminine*, *Elegant/Wild*, *Traditional/Modern*} whose ambience corresponds to the images shown in Fig. 4.



Fig. 4. The ambiances associated with the 3 opposite fashion themes.

The aim of this experiment is to characterise the relation between fashion themes and previously mentioned design styles (combinations of basic style elements, detail elements and accessories). The panellists in Group 1 and Group 2 are invited to perform this experiment with the help of the images in Fig. 4. The results of this experiment are obtained by giving the intensity of the relation between

each style element and each fashion theme using the semantic differential method. We use the seven-point scale method for expressing evaluation scores (Fig. 5). Denoted as F_1, F_2, \dots, F_7 , they correspond to the numerical values of -3, -2, ..., 2, and 3, respectively.

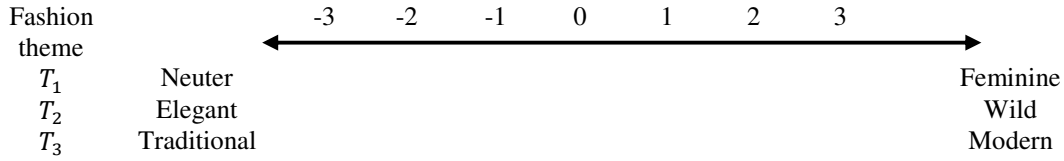


Fig. 5. Semantic differential scales of fashion themes.

3.2.4. Sensory evaluation of fashion themes and colours (Experiment 6)

We know that different colours can express different emotions. In fact, a fashion theme can be regarded as the expression of a scenario or ambience. Therefore, we can directly find out the relation between fashion themes and colour emotions with different colour properties *Hue*, *Value* and *Chroma*. Each colour property is divided into three levels (*low*, *middle* and *high*), according to the colour perception. The aim of this experiment is to characterise the relationship between fashion themes and colours in fashion design with the help of the six images in Fig. 4.

The panellists in Group 1 and Group 3 are invited to perform this experiment. During this experiment, for each level of each colour property, each panellist is asked to give an evaluation score the closest to each fashion theme by using the semantic differential method (seven-point scale: F_1, F_2, \dots, F_7).

3.2.5. Sensory properties of fabrics (Experiment 7)

The r_3 panellists in Group 3 perform the sensory evaluation of fabrics. The sensory properties can be described by several pairs of opposite keywords, i.e. $SP = \{Soft/Hard, Smooth/Rough, Wrinkle-Resistant/Crumply, Cool/Warm, Draped/non-Draped\}$. Before the tests, all the fabric samples are conditioned for a minimum of 24 hours under standard atmospheric conditions ($20 \pm 2^\circ\text{C}$ temperature and $65 \pm 2\%$ relative humidity), and the panellists are asked to wash and dry their hands with a non-moisturising soap and paper towel provided [25].

During the experiment, all samples are laid on a large, clean table in a laboratory under the above conditions. For each descriptor (e.g. *Soft*), the panellists are invited to first select three typical fabrics (two extreme samples, e.g. the softest and the hardest, and one medium sample). They then compare the remaining fabric samples against these three typical samples and give them evaluation scores according to the seven-points scale method (seven-point scale: F_1, F_2, \dots, F_7). In the whole evaluation process, the panellists can achieve the tests by combining real touch and vision.

3.2.6. Relationship between fashion themes and sensory properties of fabrics (Experiment 8)

This relationship means the extent to which one fabric is relevant to a specific fashion theme. In fact, the sensory properties describing fabrics, obtained in Experiment 7, are strongly related to the fashion themes.

All of the r panellists are invited to perform this experiment. During this experiment, for each fashion theme and each sensory property, each panellist is asked to evaluate which level of the fashion theme is the most relevant to each level of sensory property (using seven evaluation levels). This evaluation is carried out with reference to the representative fabric samples and the image describing the related fashion theme (Fig. 4). One example of evaluating the relationship between the fashion theme “*Elegant-Wild*” and the sensory property “*Soft-Hard*” by one panellist is given below (see Table 2, the most relevant level of fashion theme to each level of “*Soft-Hard*” is represented by using “ \checkmark ”).

Table 2

Example of evaluating the relationship between the fashion theme and the sensory property

	Extremely Elegant	Elegant	A Little Elegant	Neutral	A Little Wild	Wild	Extremely Wild
Extremely Soft				✓			
Rather Soft				✓			
A Little Soft		✓					
Neutral			✓				
A Little Hard					✓		
Rather Hard						✓	
Extremely Hard							✓

In Table 2, we find that the “*elegant*” ambience can be enhanced if the fabric is a little soft and the level of “*wild*” can be increased with the level of fabric hardness. However, there is no influence on this fashion theme if the fabric becomes *rather soft* or *extremely soft*.

4. Modelling of design knowledge

In this section, the details of the five mathematical models in the knowledge base are proposed, based on the previously measured and evaluated data. First, we set up the body shape classification model using body measurements according to their sensitivity to designer perception. Next, we set up four models characterising the relations between various design factors (design styles, fabric properties and colours) and fashion themes, according to the results of sensory experiments.

These relations are schematically illustrated in Fig. 6.

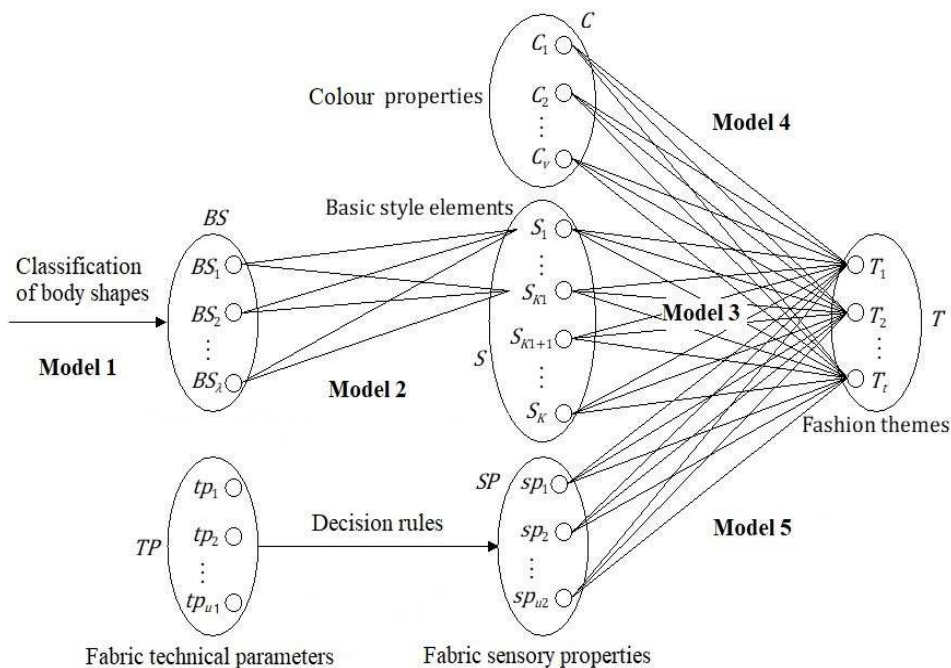


Fig. 6. The five models characterising the relations of the design knowledge base.

As described in Section 3, the involved linguistic variables (body shapes, design factors and fashion themes) and their relations in Fig.6 are usually described using perceptual and emotional keywords that are complex and uncertain. Therefore, to model this knowledge base, we express these

linguistic variables by using a number of fuzzy sets and then analyse their complex relations using fuzzy operations.

According to the classical definition in [26], a fuzzy linguistic variable is defined by a quintuple denoted as $(X, T(X), U, G, M)$, where X expresses the name of the linguistic variable, $T(X)$ is the set of its linguistic values, U is the universe of discourse, G is a syntactic rule which generates the values in $T(X)$ and M is a semantic rule which relates each linguistic value X to its meaning, $M(X)$; $M(X)$ denotes a fuzzy subset of U .

By adding mood operators to primary terms, we obtain the linguistic values describing the design knowledge, such as “very large” and “a little small”. For a linguistic variable, the calibration to its universe of discourse and linguistic values, as well as the choice of the mood operators are based on the sensory evaluation results given by each evaluator according to his/her personal perception and experience.

In our study, we first identify the universe of discourse according to the predefined evaluation levels and then select the proper mood operators and linguistic values. Next, the fuzzy subsets on the universe of discourse are constructed for expressing the above linguistic values, in which the semantic rule M corresponds to the defined fuzzy membership functions.

4.1. Classification model for lower body shapes (Model 1)

This model is used to set up a supervised model permitting body measurements to be classified according to the designers’ perceptions of human body shapes.

First, we acquire accurate data on various dimensions of all the selected human bodies (virtual human models) by using the 3D body scanner (Experiment 1) and transform these measured body dimensions into body characteristic indices for all of the body positions (input data), according to the method presented in Section 3.1.

Next, the selected virtual human models are evaluated by a number of designers according to their perceptions and experiences (output data) (see Experiment 3). The main idea of this classification model is to extract rules characterising the relationship between the above input and output data.

The linguistic variable X is “body shape” and the set of linguistic values $T(X)=\{C_1(\textit{Very Small}), C_2(\textit{Small}), C_3(\textit{Neutral}), C_4(\textit{Large}), C_5(\textit{Very Large})\}$ (considered to be standard evaluation levels) expresses the five evaluation scores in Experiment 3. The corresponding equivalence values are $-2, -1, 0, 1, \text{ and } 2$, respectively.

For simplicity, we consider that these five fuzzy linguistic values take triangular membership functions (having the property of “bilateral symmetry where the middle value is higher than the bilateral ones”) and centred on the five standard evaluation levels (e.g. the membership degree of $C_2(\textit{Small})$ is 1 for its equivalence value -1 and 0 for its left and right neighbours -2 and 0). These fuzzy linguistic values are denoted as $C_1=TFN(-2,-2,1)$, $C_2=TFN(-2,-1,0)$, $C_3=TFN(-1,0,1)$, $C_4=TFN(0,1,2)$, $C_5=TFN(1,2,2)$ (see Fig. 7).

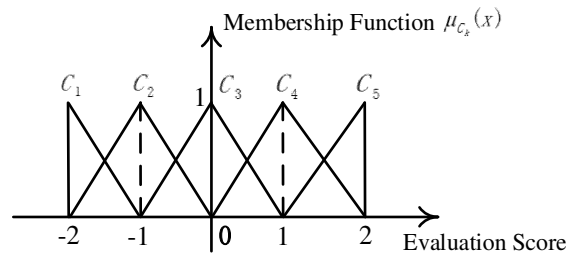


Fig. 7. The membership functions of evaluation levels on relevancy of body positions.

We assume that r_{ik} represents the number of people among the r_1 panellists who give the evaluation level C_k ($k=1, \dots, 5$) on the relevancy of the i -th ($i=1, \dots, q$) body position.

The evaluation results of all the panellists can be expressed by a fuzzy distribution:

$$E_i=(r_{i1}/r_1 \ r_{i2}/r_1 \ r_{i3}/r_1 \ r_{i4}/r_1 \ r_{i5}/r_1)=(e_{i1} \ e_{i2} \ e_{i3} \ e_{i4} \ e_{i5}) \quad (1)$$

E_i is a fuzzy number, whose membership function $\mu_{E_i}(x)$ is a triangle or polygonal (quadrilateral or pentagonal) function, which takes the points $(-2,0)$, $(-2,e_{i1})$, $(-1,e_{i2})$, $(0,e_{i3})$, $(1,e_{i4})$, $(2,e_{i5})$ and $(2,0)$ as vertexes (some points could be coincident).

By learning from the data acquired in Experiment 1 and Experiment 3, we set up a Radial Basis Function (RBF) neural model characterising the relationship between body characteristic indices and human perception E_i 's at any given body position. For example, at hip position ($i=2$), we take the three characteristic indices ($hs_1 \ hs_2 \ hs_3$) as inputs and the corresponding output is a fuzzy distribution $E_2=(e_{21} \ e_{22} \ e_{23} \ e_{24} \ e_{25})$ defined over the five standard scores C_1, \dots, C_k . For each body position bp_i , the human perception $E_i=(e_{i1} \ e_{i2} \ e_{i3} \ e_{i4} \ e_{i5})$ predicted from the previous neural model should be adjusted so that $\sum_{j=1}^5 e_{ij} = 1$.

In order to obtain a concise interpretation of the predicted human perception at each body shape, we define the *Fuzzy Nearness Degree* of the distribution of evaluation data E_i on the body position bp_i , to the previously defined standard evaluation levels C_k 's, according to Equation (2).

$$r(E_i, C_k) = \frac{\int_{-2}^2 [\mu_{E_i}(x) \wedge \mu_{C_k}(x)] dx}{\int_{-2}^2 [\mu_{E_i}(x) \vee \mu_{C_k}(x)] dx} \quad (2)$$

Evidently, E_i is closer to C_k if $r(E_i, C_k)$ is larger and it satisfies the following three properties for all fuzzy nearness degrees:

- (a) $0 \leq r(E_i, C_k) \leq 1$, and $r(E_i, C_k) = 1 \Leftrightarrow E_i = C_k$;
- (b) $r(E_i, C_k) = r(C_k, E_i)$;
- (c) $r(E_i, C_k) \leq r(E_i, C) + r(C, C_k)$, C is a fuzzy number defined on the interval $[-2, 2]$.

For each body position bp_i , we use the closest C_k to express E_i .

The combinations of all standard evaluation levels for all the body positions constitute the set of all possible body shapes. From this, each body shape can be expressed by one q -dimensional body shape vector bs :

$$bs = (C_{i_1}(bp_{p_1}) \ C_{i_2}(bp_{p_2}) \ \dots \ C_{i_q}(bp_{p_q})) \quad (3)$$

where $C_{i_k}(bp_{p_k})$ expresses the level of the body position bp_k , $i_1, i_2, \dots, i_q \in \{1, 2, 3, 4, 5\}$.

One example of body shape model is described below. From a specific human body, denoted as $body_2$, we obtain her measurements expressed in the following vector:

$$\text{measure}_{body_2} = \begin{matrix} S & WH & CH & W & H & A & TG & CG \\ (166.6 & 105.0 & 76.3 & 66.0 & 91.6 & 77.6 & 55.0 & 32.7) \end{matrix}$$

By converting these body measurements into body characteristic indices, then computing the corresponding body shape vector using the previous model, we obtain:

$$bs_{body_2} = \begin{matrix} WS & HS & AS & LL & TS & CS \\ (C_2 & C_4 & C_3 & C_3 & C_4 & C_3) \end{matrix}$$

The lower body shape of $body_2$ is $(WS^{(S)} \ HS^{(L)} \ AS^{(M)} \ LL^{(M)} \ TS^{(L)} \ CS^{(M)})$, meaning that the waist shape is small, and both the hip shape and thigh shape are large, whereas the abdomen shape, leg length and calf shape are all medium. According to these results, we can easily characterise any body shape from its body measurements and classify a group of body shapes.

4.2. Modelling the relationship between body shapes and basic design styles (Model 2)

This model is used to find the set of the most relevant styles to a specific body shape. First, we set up the relational matrix $R(BS, D_j)$ between all the possible body position shapes (BS) of the human body set B and the j -th basic style elements (D_j) by using the evaluation scores. The linguistic variable X is the "relationship between body shapes and basic design styles", and the set of linguistic values $T(X) = \{A_1(\text{unfit}), A_2(\text{Neutral}), A_3(\text{fit})\}$ expresses the three standard evaluation scores in

Experiment 4. For processing the difference between evaluators, we use three triangular fuzzy sets A_1, A_2, A_3 to express these evaluation scores (see Fig. 8).

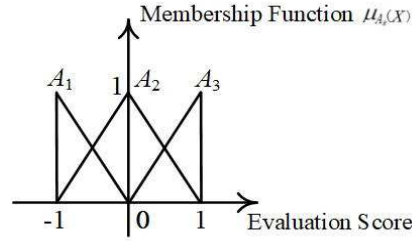


Fig. 8. Fuzzy membership functions of the three evaluation scores.

We assume that $r_{ij}^{(k)}$ is the number of people (among all the r panellists) giving the evaluation score k ($k \in \{-1, 0, 1\}$) on the relevancy of the j -th ($j \in \{1, \dots, K_1\}$) basic style element to the i -th ($i \in \{1, \dots, \lambda\}$) possible type of body shape. The set of the K_1 ($K_1=11$) basic style elements, corresponding to all the combinations in Table 1, is:

$$\{ \underset{D_1}{PATTERN_1}, \underset{D_2}{PATTERN_2}, \underset{D_3}{PATTERN_3}, \underset{D_4}{PATTERN_4}, \underset{D_5}{WAIST_1}, \underset{D_6}{WAIST_2}, \underset{D_7}{WAIST_3}, \underset{D_8}{LEG_1}, \underset{D_9}{LEG_2}, \underset{D_{10}}{LEG_3}, \underset{D_{11}}{LEG_4} \}$$

The set of the λ types of possible body shapes correspond to all of the combinations of the five evaluation scores (from *very small* to *very large*) at the six body positions (*waist, hip, abdomen, thigh, calf*).

$$BS = \{ WS^{(VS)}, WS^{(S)}, WS^{(M)}, WS^{(L)}, WS^{(VL)}, HS^{(VS)}, HS^{(S)}, HS^{(M)}, HS^{(L)}, HS^{(VL)}, AS^{(VS)}, AS^{(S)}, AS^{(M)}, AS^{(L)}, AS^{(VL)}, LL^{(VS)}, LL^{(S)}, LL^{(M)}, LL^{(L)}, LL^{(VL)}, TS^{(VS)}, TS^{(S)}, TS^{(M)}, TS^{(L)}, TS^{(VL)}, CS^{(VS)}, CS^{(S)}, CS^{(M)}, CS^{(L)}, CS^{(VL)} \}$$

From the set BS, we find that there are five body types at each of the six body positions and the total number of body types is 30 ($\lambda=30$). For a specific body shape vector $bs = (C_{i_1} C_{i_2} \dots C_{i_6})$ (Eq.3), we define a $(6 \times \lambda)$ -dimensional body shape matrix BODY in order to interpret more clearly the position of bs related to all the possible body shapes in BS. The matrix BODY is defined by:

$$BODY = \begin{pmatrix} ws & 0 & 0 & 0 & 0 & 0 \\ 0 & hs & 0 & 0 & 0 & 0 \\ 0 & 0 & as & 0 & 0 & 0 \\ 0 & 0 & 0 & ll & 0 & 0 \\ 0 & 0 & 0 & 0 & ts & 0 \\ 0 & 0 & 0 & 0 & 0 & cs \end{pmatrix}_{6 \times \lambda}$$

Where ws, hs, as, ll, ts and cs are 5-dimensional unit vectors in which the element corresponding to the index C_{i_j} of bs is 1 and the others are 0 ($j=1, \dots, 6$).

For the body shape *body_2*, we have $ws = (0 \ 1 \ 0 \ 0 \ 0)$, $hs = (0 \ 1 \ 0 \ 0 \ 0)$, etc.

The evaluation results of all the panellists can be expressed by a fuzzy distribution:

$$G_{ij} = (r_{ij}^{(-1)}/r \ r_{ij}^{(0)}/r \ r_{ij}^{(1)}/r) = (g_{ij}^{(-1)} \ g_{ij}^{(0)} \ g_{ij}^{(1)}) \quad (4)$$

G_{ij} is a fuzzy number, whose membership function $\mu_{G_{ij}}(x)$ is a triangle or polygonal (quadrilateral or pentagonal) function, which takes the points $(-1, 0)$, $(-1, g_{ij}^{(-1)})$, $(0, g_{ij}^{(0)})$, $(1, g_{ij}^{(1)})$, and $(1, 0)$ as vertexes.

We define the *Fuzzy Nearness Degree* of the distribution of evaluation data G_{ij} on the j -th basic style element D_j related to the i -th type of possible body shapes, to the previously defined standard evaluation levels (scores) A_k 's according to Equation (5).

$$r(G_{ij}, A_k) = \frac{\int_{-1}^1 [\mu_{G_{ij}}(x) \wedge \mu_{A_k}(x)] dx}{\int_{-1}^1 [\mu_{G_{ij}}(x) \vee \mu_{A_k}(x)] dx} \quad (5)$$

Evidently, $r(G_{ij}, A_k)$ can be maximised if G_{ij} is the closest to A_k (i.e. the best evaluation score of the j -th basic style element relating to the j -th body shape type).

The relationship between all of the λ ($=30$) possible types of body shapes and the j -th basic style element D_j can be expressed by a $(\lambda \times 3)$ -dimensional fuzzy relational matrix $R(BS, D_j)$:

$$R(BS, D_j) = \begin{pmatrix} r(G_{1j}, A_1) & r(G_{1j}, A_2) & r(G_{1j}, A_3) \\ r(G_{2j}, A_1) & r(G_{2j}, A_2) & r(G_{2j}, A_3) \\ \vdots & \vdots & \vdots \\ r(G_{\lambda j}, A_1) & r(G_{\lambda j}, A_2) & r(G_{\lambda j}, A_3) \end{pmatrix} \quad (j=1, 2, \dots, K_1) \quad (6)$$

where K_1 is the total number of all basic style elements.

The relational matrix $R(bs, D_j)$ of the j -th basic style element to a specific body shape bs can be obtained by using the composition operation of the $(6 \times \lambda)$ -dimensional body shape matrix BODY and $R(BS, D_j)$, i.e.:

$$R(bs, D_j) = \text{BODY} \circ R(BS, D_j) \quad (7)$$

The elements of the (6×3) -dimensional fuzzy matrix $R(bs, D_j)$ represent the fuzzy nearness degree of a specific basic style element D_j relating to a specific body shape bs at the six body positions. It is necessary to set up a data fusion model to obtain the overall relevancy of D_j to bs and make recommendations according to the results of the overall relevancy for all of the basic styles.

For this purpose, we define the relevancy degree $\rho(bs, D_j)$ of a basic style element (D_j) to the specific body shape bs by using the following fuzzy composition operation:

$$\rho(bs, D_j) = W_B \circ R(bs, D_j) \circ L_B \quad (8)$$

where W_B is the weight vector of importance for all six body positions and is determined by the designer (user of the recommender system) using the analytic hierarchy process (AHP).

L_B is the vector of the numerical equivalence values of the three evaluation scores A_1 , A_2 and A_3 (see Fig. 9), i.e.:

$$L_B = (\text{equiv}(A_1) \quad \text{equiv}(A_2) \quad \text{equiv}(A_3)) = (-1 \quad 0 \quad 1)$$

As each basic style s_1 is composed of three elements belonging to the pattern style component, waist style component and leg-opening style component, respectively (see Table 1), we get $s_1 = (\text{Pattern}_x, \text{Waist}_y, \text{Leg}_z)$ with $(\text{Pattern}_x \in \text{PATTERN}, \text{Waist}_y \in \text{WAIST}, \text{Leg}_z \in \text{LEG})$ and $x \in \{1, 2, 3, 4\}$, $y, z \in \{1, 2, 3\}$.

The relevancy degrees of these three style elements corresponding to the body shape bs can be computed by $\rho_x = \rho(bs, \text{Pattern}_x)$, $\rho_y = \rho(bs, \text{Waist}_y)$, and $\rho_z = \rho(bs, \text{Leg}_z)$. We obtain the relevancy degree of the basic style s_1 to the body shape bs by computing their average, i.e. $f_{xyz} = (\rho_x + \rho_y + \rho_z) / 3$.

Given a threshold Td , we ultimately obtain a set of the most relevant styles to a specific body shape that satisfies $f_{xyz} \geq Td$.

4.3. Modelling the relationship between fashion themes and design styles (Model 3)

This model is used to obtain the set of the styles most relevant to a specific fashion theme. The approach of modelling is almost the same as that of Section 4.2. We first obtain the relational matrix $R(s, T_j)$ characterising the relation between a specific style (s) and the j -th fashion theme (T_j) by using seven-level evaluation scores given by all the evaluators (i.e. F_1, F_2, \dots, F_7) in Experiment 5 (Section 3.2.3). For a specific fashion theme (T_j), we define the relevancy degree $\rho(s, T_j)$ of a design style (s) to a specific fashion theme by using the following fuzzy composition:

$$\rho(s, T_j) = W_S \circ R(s, T_j) \circ L_S \quad (9)$$

where W_S is the vector of the style elements in the design style s and L_S is the vector of the numerical equivalence values of the seven evaluation scores F_1, F_2, \dots, F_7 , i.e.:

$$L_S = (\text{equiv}(F_1) \text{ equiv}(F_2) \dots \text{equiv}(F_7)) = (-3 \ -2 \ -1 \ 0 \ 1 \ 2 \ 3) \quad (10)$$

From this, we obtain the relevancy degrees of all the design styles to a specific fashion theme. According to these relevancy degrees, we obtain the set of the most relevant styles to a specific fashion theme.

4.4. Modelling the relationship between fashion themes and colours (Model 4)

This model is used to obtain the set of the most relevant colours to a specific fashion theme. According to Experiment 6, we establish the relational matrix $R(C, T_j)$ between all the colour properties (C) and the j -th fashion theme (T_j). Similar to Model 2, we obtain the relevancy degrees of all the colours to a specific fashion theme and then obtain the set of the most relevant colours to a specific fashion theme.

4.5. Modelling the relationship between fashion themes and fabrics (Model 5)

In this section, we set up the relation between fashion themes and fabrics by using rough sets. From Experiment 2, we acquire the data of the u_1 fabric technical parameters $tp_1 \sim tp_{u_1}$ (e.g. bending, shearing, tensile). From Experiment 7, we obtain the evaluation scores of each sensory property of all the m fabrics in F (the set of the representative fabrics). We set up a decision system by taking the fabric technical parameters as conditional attributes and the sensory properties of fabrics as decision attributes. From this decision system, we obtain a number of generalised decision rules on the relationship between the technical parameters and sensory properties of fabrics.

According to Experiment 8, for each evaluator, we obtain a judgment (relevant or irrelevant) on the relationship between each sensory property level and each fashion theme level. From these evaluation results, we obtain the fuzzy relational matrix $FRM(sp_l, T_j)$ of the sensory property sp_l (e.g. softness, smoothness) to the fashion theme T_j .

According to Model 5 and the previous decision system, we obtain the set of the most relevant fabrics to a specific fashion theme.

5. Garment design process with the recommender system and feedback mechanism

In this section, we provide a systematic fashion theme-driven personalised garment design process for a specific human body by using the proposed knowledge-based recommender system. This design process is realised by a series of interactions between the designer, the knowledge base and virtual product demonstration. It can be expressed by a cycle of *consumer emotional requirements identification – design schemes generation – recommendation – 3D virtual prototype display and designer's evaluation – design factors adjustment*. The knowledge base, i.e. the five relational models presented in Section 4, can be updated by progressively integrating the designer's evaluations on recommended design schemes.

5.1. Recommendation of fashion design using the proposed knowledge base

We denote the k^* -th evaluation level of the j -th fashion theme T_j as $T_j^{(k^*)}$ ($k^* \in \{1, 2, \dots, 7\}, j \in \{1, 2, \dots, t\}$, where t is the total number of all the fashion themes). The purpose of this recommendation is to obtain the best design schemes related to $T_j^{(k^*)}$ for a specific human body.

In the general process of garment design, a fashion designer first selects a set of suitable styles according to the body shape of a specific consumer and the desired fashion theme. Then, he/she selects the fabrics most relevant to the selected styles (not considering the colour of the fabrics) based on the desired fashion theme. Next, she/he identifies the most relevant colours of the fabrics related to the desired fashion theme. The proposed recommendation procedure includes the following 6 steps:

Algorithm 1:

Step 1: Identifying the body shape bs of a specific consumer according to Model 1 of the knowledge base.

Step 2: From Model 2 of the knowledge base, identifying the set $S_1^R(bs)$ of relevant basic styles related to the specific body shape bs .

Step 3: Expanding $S_1^R(bs)$ to the set of relevant styles $S_2(bs) (\subset S)$ (S is the set of all the styles) by adding detail and accessory elements. Finding the set $S^R(T_j^{(k^*)})$ of the most relevant styles related to $T_j^{(k^*)}$ from $S_2(bs)$ according to Model 3. The styles that are the most relevant to $T_j^{(k^*)}$ are not unique.

Step 4: According to Model 5 of the knowledge base, identifying the set of fabrics the most relevant to $T_j^{(k^*)}$, denoted as $F^R(T_j^{(k^*)})$, of which each element corresponds to a numbered fabric in the fabrics base. The fabrics the most relevant to $T_j^{(k^*)}$ are not unique.

Step 5: Let C' be the set of colours of all the relevant fabrics in $F^R(T_j^{(k^*)})$. From Model 4 of the knowledge base, identifying the set $C^R(T_j^{(k^*)})$ of the most relevant colours of C' to $T_j^{(k^*)}$.

Step 6: Identifying the set of the relevant design schemes:

$$DS = S^R(T_j^{(k)}) \times F^R(T_j^{(k)}) \times C^R(T_j^{(k)}) \\ = \{(s, c, f) : s \in S^R(T_j^{(k)}), f \in F^R(T_j^{(k)}), c \in C^R(T_j^{(k)})\}$$

The best design schemes will be selected from this set by a user. In practice, there are strong correlations between the sets of selected styles, fabrics and colours. Some combinations will enhance their relevancy degrees related to a specific level of the desired fashion theme but some others

cannot do that. For simplicity, we will neither aggregate these three sets, to generate a unique relevancy degree, nor make an overall ranking but just show all of the relevant design schemes of *DS* to the designer, who will make his/her final decision according to personal preference.

In some personalised design scenarios, the designer first selects the relevant fabrics and colours according to the desired fashion theme and then identifies the suitable styles according to the body shape of the specific consumer. In this context, the inference procedure is carried out according to the following steps: Step 4 – Step 5 – Step 1 – Step 2 – Step 3 – Step 6.

The recommendation procedure can be expressed by using the proposed garment ontology in Section 2.1. An example is shown in Fig. 9.

All of the children nodes of “*Human*” and “*Fashion Theme*” in this figure vary with the specific body shape and specific desired fashion theme. Ultimately, the recommendation procedure enables the generation of all the relevant design schemes, to be evaluated by the designer.

It is possible to use only one or several components of the proposed system for fashion design by activating the corresponding models. For example, if we hope to only recommend suitable fabrics for a specific fashion theme, we only activate Model 5.

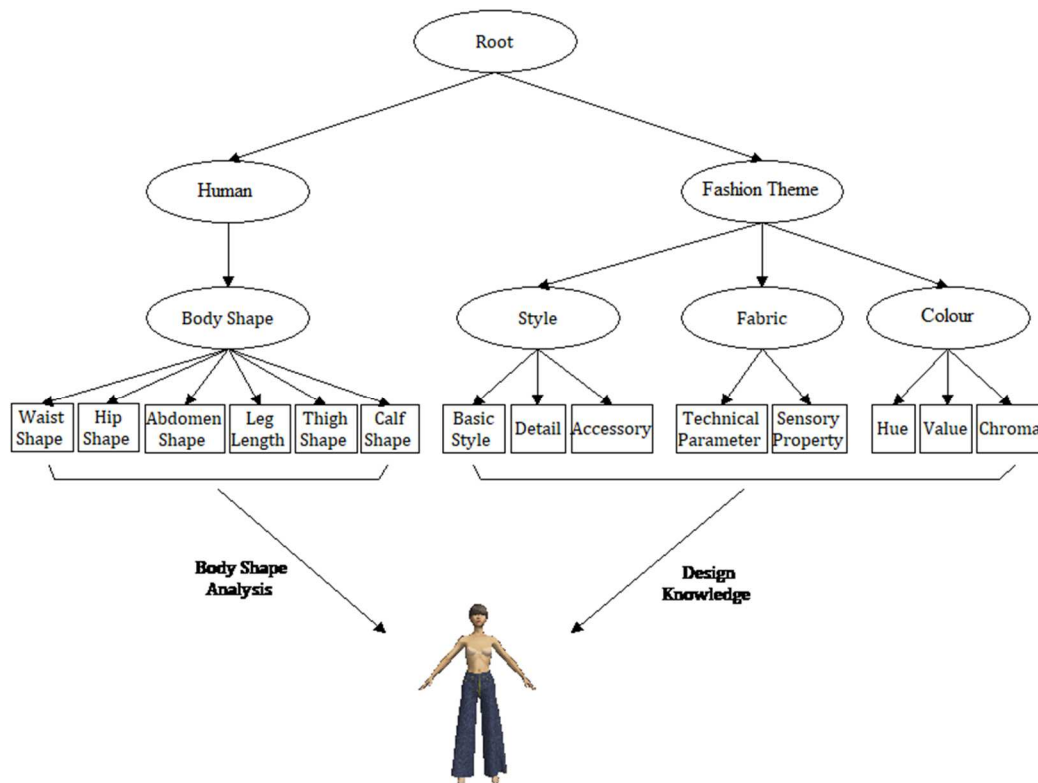


Fig. 9. Ontology for the proposed recommendation procedure.

5.2. The design process with designer evaluation and feedback mechanism

The recommended design scheme (fabric, colour, style) will be evaluated by a designer on a virtual fitting related to the personalised consumer’s body shape. This design process is shown in Fig. 10.

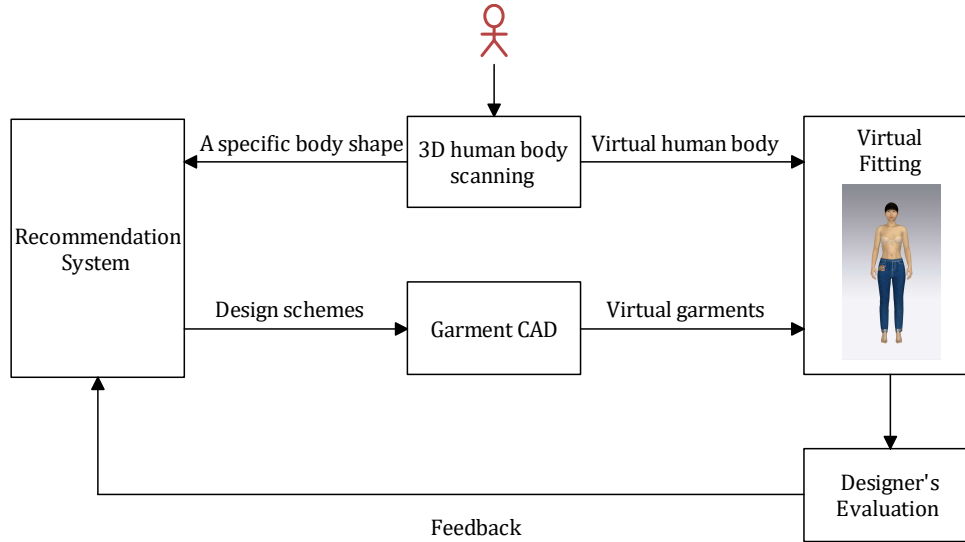


Fig. 10. The flow chart of the evaluation and feedback.

During the evaluation, the designer observes the 3D virtual product, generated by the garment CAD software according to the elements of the recommended design scheme. This observation concerns the virtual fitting in static views from different angles (front, back, left, right, down, up, etc.) and dynamic display. In our study, the designer will evaluate the recommended garment product in the two following aspects:

- (1) Evaluation of the relevancy of the recommended design scheme related to garment fitting, i.e. the three basic style components (*Pattern*, *Waist*, *Leg-Opening*) by using the corresponding basic style elements (4 levels for *Pattern*, 3 levels for *Waist* and 4 levels for *Leg-Opening*) (see Table 1);
- (2) Evaluation of the relevancy of the recommended design scheme related to the desired fashion theme level by using seven levels (see Fig.5).

The proposed feedback mechanism permits the automatic adjustment of the design knowledge according to a user's (designer or consumer) evaluation results and recommends a new design scheme. The process can be executed repeatedly until the user is satisfied. The knowledge base will be definitively modified if this adjustment is confirmed by a number of other designers with the same design objective and fashion theme.

According to the two previous designers' evaluations, we first propose the self-adjusting algorithm related to the garment fitting deviation. In this case, we only need to adjust the relational matrix $R(BS, D_j)$ (see Section 4.2) since the relevancy of all the possible body shapes to each basic style is only determined by the corresponding relational matrix.

For simplicity, we only give the self-adjusting algorithm for one basic style component. Assume the evaluation values (levels) of the current recommended design scheme of *Pattern*, *Waist-Level*, *Leg-Opening-Level* to be p_{i_0} , w_{j_0} , and l_{k_0} , respectively, for a specific human body and the expected level of *Pattern* to be p_{i_1} ($i_1 \neq i_0$) with the levels of *Waist-Level* and *Leg-Opening-Level* remaining unchanged. According to the computation of the model (Model 2), the relevancy degree of the design style $(p_{i_0} \ w_{j_0} \ l_{k_0})$ related to the body shape is larger than the threshold Td . If we hope that the recommended result is moved to level p_{i_1} of *Pattern*, then the relevancy degree of the design style $(p_{i_1} \ w_{j_0} \ l_{k_0})$ related to the body shape should be greater than Td . Meanwhile, the other elements in the relational matrix concerned should be changed at a minimal level. In fact, for a specific body shape bs , we only need to adjust the specific relational matrix $R(bs, D_j)$. On this basis, we present the following procedure for *Pattern*. The other design factors can be processed in the same way.

Algorithm 2:

Step 1: For a specific body shape bs (the body shape matrix is $BODY$), compute the initial relational matrix and the relevancy degree of bs to each Pattern element (level) p_j ($j \in \{1, 2, 3, 4\}$).

According to Eq.7, we obtain an initial relational matrix:

$$R^0(bs, D_j) = BODY_{6 \times \lambda} \circ R(BS, D_j)_{\lambda \times 3} = (r_{uv}^{(j)})_{6 \times 3} \quad (11)$$

According to Eq.8, we obtain the initial fuzzy nearness degree r_j^0 of the level p_j of Pattern ($j \in \{1, 2, 3, 4\}$) related to bs .

Step 2: Setting up the adjustment model for the relational matrix $R(bs, D_j)$.

A new relational matrix $R^1(bs, D_j) = (r_{uv}^{(j)})_{6 \times 3}$ can be computed by:

$$\begin{aligned} \min \quad & \|R^1(bs, D_j) - R^0(bs, D_j)\| \\ \text{s.t.} \quad & f_{i_1 j_0 k_0} \geq Td \end{aligned} \quad (12)$$

where $f_{i_1 j_0 k_0}$ is the relevancy degree of the design style ($PATTERN_{i_1}$ $WAIST_{j_0}$ LEG_{k_0}) to bs .

For this complex optimisation problem, we solve it by using a Genetic Algorithm (GA) under an appropriate number of iterations. The corresponding fitness function is defined by:

$$\text{fitness} = 1 / \left[\sum_{u=1}^6 \sum_{v=1}^3 (r_{uv}^{(j)} - r_{uv}^{(j)})^2 + \lambda (f_{i_1 j_0 k_0} - Td)^2 \right] \quad (13)$$

where λ is a penalty coefficient.

Finally, we obtain an approximate optimal solution $R^t(bs, D_j)$.

Step 3: Updating the knowledge base.

The new relational matrix $R^t(BS, D_j)$ (integration of the change of $R^t(bs, D_j)$ for one single body shape bs into the overall matrix $R(BS, D_j)$) is taken as a temporary knowledge on the relationship between body shapes and Pattern and will be used in the current recommendation. This has no impact on the other recommendation cases. The permanent knowledge base, i.e. the former matrix $R(BS, D_j)$, will be definitively modified only when several designers confirm the change of $R(bs, D_j)$ in different cases.

Step 4: According to the new knowledge base $R^t(BS, D_j)$, the system recommends a new design style.

Step 5: The self-adjustment algorithm stops until designer satisfaction. Otherwise, the algorithm returns to Step 2, to repeat the procedure again.

Next, we propose the self-adjusting algorithm adapted to the expected level of fashion theme. Taking fabric recommendation as an example, the algorithm we proposed is capable of adjusting the deviation of the fashion theme level, computed from the recommended design scheme, related to the designer's expectation. The other design factors can be solved in the same way.

For a given level of the fashion theme T_j , the recommender system can generate a relevant fabric according to Model 5. However, the current fashion theme level of the recommended fabric,

identified by a set of fabric sensory properties $sp_l(l=1, 2, \dots, u_2)$, may not conform to the designer's expectation. In this case, it is necessary to adjust the established knowledge base, i.e. all the corresponding relational matrices $FRM(sp_l, T_j)$ ($l=1, 2, \dots, u_2$).

For a specific fashion theme T_j ($j=1, 2, \dots, t$), we assume that the fashion theme level of the recommended fabric, calculated from Model 5, is i_0 ($1 \leq i_0 \leq 7$) and the expected fashion theme level is i_1 ($1 \leq i_1 \leq 7$). The aim of the adjustment is to generate a new fabric corresponding to i_1 level of the fashion theme T_j . In this case, the relevancy degree related to the i_1 level of T_j is greater than those at the other levels. Meanwhile, we hope that the distribution of the relevancy degrees of the recommended fabric related to all levels of T_j is changed at a minimal level. On this basis, we propose a self-adjusting algorithm according to the same principle as the previous one.

If several fashion themes are considered simultaneously by the fashion designer, the system will recommend a list of relevant design schemes (styles, fabrics, colours) for each of them. Then, an intersection operation will be carried out for all of the lists computed from all the fashion themes, in order to obtain the final list of design schemes.

6. An application case in garment design

To validate the proposed knowledge-based design recommender system, we applied it to the design of women's jeans for a specific body shape and multiple fashion theme levels. The aim is to validate 1) whether the system can offer suitable design schemes for a specific body shape and specific fashion themes, and 2) whether the system can improve the design schemes via the feedback mechanism.

The input data for this case are given below.

(1) Target population: young women aged 18–25 in Central China.

(2) The desired fashion theme levels.

We propose eight design objectives in the fashion requirements, i.e. eight combinations of levels for three fashion themes, as follows:

FT1: $T_1 = \text{"a little Neuter"}$, $T_2 = \text{"a little Elegant"}$, and $T_3 = \text{"Neutral"}$

FT2: $T_1 = \text{"Neuter"}$, $T_2 = \text{"Elegant"}$, and $T_3 = \text{"Traditional"}$

FT3: $T_1 = \text{"Neuter"}$, $T_2 = \text{"Elegant"}$, and $T_3 = \text{"Modern"}$

FT4: $T_1 = \text{"Neuter"}$, $T_2 = \text{"Wild"}$, and $T_3 = \text{"Traditional"}$

FT5: $T_1 = \text{"Neuter"}$, $T_2 = \text{"Wild"}$, and $T_3 = \text{"Modern"}$

FT6: $T_1 = \text{"Feminine"}$, $T_2 = \text{"Elegant"}$, and $T_3 = \text{"Traditional"}$

FT7: $T_1 = \text{"Feminine"}$, $T_2 = \text{"Elegant"}$, and $T_3 = \text{"Modern"}$

FT8: $T_1 = \text{"Feminine"}$, $T_2 = \text{"Wild"}$, and $T_3 = \text{"Modern"}$

In the proposed system, we assume that all the basic styles are related to body shapes, and fabric properties and colours are only related to fashion themes but have no impact on body shapes and design styles. Therefore, in a design scheme, the fabric and colour are only determined by a specific fashion theme.

Next, we give an example of jeans design related to a specific design objective (**FT1:** $T_1 = \text{"a little Neuter"}$, $T_2 = \text{"a little Elegant"}$, and $T_3 = \text{"Neutral"}$) for two specific human bodies (*body_1* and *body_2*).

For each human body, we apply the recommendation procedure (Algorithm 1) given in Section 5.1 and obtain the following results. For simplicity, we recommend only one style, fabric and colour for each human body.

Step 1: By using Model 1, we transform the body measurements of *body_1* and *body_2* into body shape vectors and obtain:

$$\begin{aligned} \text{measure}_{body_1} &= \begin{matrix} S & WH & CH & W & H & A & TG & CG \\ (165.2 & 101.4 & 72.6 & 67.2 & 88.8 & 75.9 & 49.0 & 33.6) \end{matrix} \\ \text{measure}_{body_2} &= \begin{matrix} S & WH & CH & W & H & A & TG & CG \\ (166.6 & 105.0 & 76.3 & 66.0 & 91.6 & 77.6 & 55.0 & 32.7) \end{matrix} \\ bs_{body_1} &= (C_2 \quad C_3 \quad C_3 \quad C_3 \quad C_3 \quad C_3), \quad bs_{body_2} = (C_2 \quad C_4 \quad C_3 \quad C_3 \quad C_4 \quad C_3) \end{aligned}$$

Therefore, the lower body shape of *body_1* is $(WS^{(S)} \quad HS^{(M)} \quad AS^{(M)} \quad LL^{(M)} \quad TS^{(M)} \quad CS^{(M)})$ and the lower body shape of *body_2* is $(WS^{(S)} \quad HS^{(L)} \quad AS^{(M)} \quad LL^{(M)} \quad TS^{(L)} \quad CS^{(M)})$.

Step 2: The sets of relevant basic styles related to these two specific body shapes, denoted as $S_1^R(bs_{body_1})$ and $S_1^R(bs_{body_2})$, are computed by using Model 2. Hence:

$$\begin{aligned} S_1^R(bs_{body_1}) &= \{s_1^{(1)}(bs_{body_1}), s_1^{(2)}(bs_{body_1}), s_1^{(3)}(bs_{body_1})\}, \text{ where} \\ s_1^{(1)}(bs_{body_1}) &= (\text{Straight, High-Waist, Regular-Leg}) \\ s_1^{(2)}(bs_{body_1}) &= (\text{Straight, Regular-Waist, Regular-Leg}) \\ s_1^{(3)}(bs_{body_1}) &= (\text{Straight, High-Waist, Boot Cut-Leg}) \text{ and} \\ S_1^R(bs_{body_2}) &= \{s_1^{(1)}(bs_{body_2}), s_1^{(2)}(bs_{body_2}), s_1^{(3)}(bs_{body_2})\}, \text{ where} \\ s_1^{(1)}(bs_{body_2}) &= (\text{Straight, High-Waist, Regular-Leg}) \\ s_1^{(2)}(bs_{body_2}) &= (\text{Loose, Regular-Waist, Boot Cut-Leg}) \\ s_1^{(3)}(bs_{body_2}) &= (\text{Straight, Regular-Waist, Regular-Leg}) \end{aligned}$$

Step 3: The recommended styles are computed by using Model 3.

The recommended style to *body_1* is:

style_1 = (Straight, Regular-Waist, Regular-Leg, Crescent Front-Pocket, Uncovered Back-Pocket, Front-Fly with Fasteners, Hidden Side-Seam, no-Patchwork, no-Holey, Lace, Diamonds).

The recommended style to *body_2* is:

style_2 = (Straight, High-Waist, Regular-Leg, Crescent Front-Pocket, Uncovered Back-Pocket, Front-Fly with Fasteners, Hidden Side-Seam, no-Patchwork, no-Holey, Lace, Diamonds).

Step 4: The recommended fabrics are computed by using Model 5.

The recommended fabric *fabric_1* to *body_1* and *fabric_2* to *body_2* are the same, i.e.
fabric_1 = *fabric_2*.

Step 5: The recommended colours are computed by using Model 4. Therefore:

$$\text{colour}_1 = \text{colour}_2 = (\text{low-Hue, low-Value, high-Chroma}).$$

Step 6: By aggregating the previous results, we obtain the most relevant design schemes for these two body shapes as follows:

For *body_1*, the recommended design is *design_1* = $\langle \text{style}_1, \text{fabric}_1, \text{colour}_1 \rangle$. For *body_2*, the recommended design is *design_2* = $\langle \text{style}_2, \text{fabric}_2, \text{colour}_2 \rangle$.

By visualising the virtual products corresponding to the recommended design schemes (Fig.11), the evaluator (the above-mentioned designer) makes an evaluation of virtual fitting effects and expression quality of the fashion theme on the two specific body shapes.

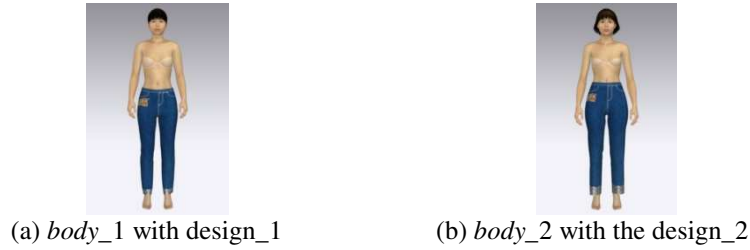


Fig. 11. Virtual display of the recommended results for various human bodies.

By using the evaluation procedure, the designer is satisfied by the design scheme for *body_1*, but considers that the level of the fashion theme “*Traditional-Modern (T₃)*” of the designed style for *body_2* is “*a little Traditional*” instead of “*Neutral*” (user’s expectation). Therefore, the designed style for *body_2* needs to be adjusted according to the expected level for the fashion theme *T₃* by using Algorithm 2.

(1) Computing the initial relational matrix $R(bs_{body_2}, D_j)$ and the relevancy degree f_{xyz} of bs_{body_2} to each style.

From Model 1, we obtain

$$BODY(body_2) = \begin{pmatrix} ws & 0 & 0 & 0 & 0 & 0 \\ 0 & hs & 0 & 0 & 0 & 0 \\ 0 & 0 & as & 0 & 0 & 0 \\ 0 & 0 & 0 & ll & 0 & 0 \\ 0 & 0 & 0 & 0 & ts & 0 \\ 0 & 0 & 0 & 0 & 0 & cs \end{pmatrix}_{6 \times 30}$$

where $ws = (0 \ 1 \ 0 \ 0 \ 0)$, $hs = ts = (0 \ 0 \ 0 \ 1 \ 0)$, $as = ll = cs = (0 \ 0 \ 1 \ 0 \ 0)$.

By using the AHP method, we obtain:

$$W_B = \begin{matrix} \text{waist} & \text{hip} & \text{abdomen} & \text{leg} & \text{thigh} & \text{calf} \\ (0.1332, & 0.2530, & 0.4663, & 0.0434, & 0.8329, & 0.0722) \end{matrix}$$

$$R^0(bs_{body_2}, D_1) = \begin{pmatrix} 0.2421 & 0.5615 & 0.7995 \\ 0.5006 & 0.8943 & 0.3972 \\ 0.3972 & 0.7147 & 0.3139 \\ 0.3972 & 0.8943 & 0.5006 \\ 0.3139 & 0.7147 & 0.3972 \\ 0.3139 & 0.7147 & 0.3972 \end{pmatrix}, \dots$$

$$f_{322} = 0.9359, f_{333} = 0.9189, f_{432} = 0.8675, f_{323} = 0.8547, \dots$$

(2) Let the threshold *Td* be 0.9, we ultimately obtain a new style design scheme as follows:

style_3 = (Straight, High-Waist, Regular-Leg, Crescent Front-Pocket, Uncovered Back-Pocket, Front-Fly with Fasteners, Hidden Side-Seam, no-Patchwork, no-Holey, Lace).

Having introduced the new style *style_3* into the system, the evaluation of the corresponding virtual display shows that the former levels of the fashion themes *T₁* and *T₂* are unchanged and the

level of the fashion theme T_3 is moved to “ F_3 ” (*Neutral*), meaning that the adjusting procedure is efficient. After one adjustment, this system can successfully provide a satisfactory design scheme to the designer.

Next, we discuss the statistical performance of the proposed design system for the whole population. We take 10 various body shapes from the target population. By combining these body shapes with the previous eight fashion theme levels (design objectives), we generate 80 design cases and apply the proposed working cycle of *design – recommendation – virtual product display – evaluation – adjustment*. For these different cases, we obtain the overall statistical results for all design cases of successful recommendations according to the consumers’ evaluations (see Table 3).

Table 3
Averaged rates of satisfaction for all cases of successful recommendations

	1st recommendation	2nd recommendation	3rd recommendation	Accumulated rate of satisfaction
Without knowledge updating	66.25%	16.25%	8.75%	91.25%
Knowledge updating once	82.50%	8.75%	3.75%	95.00%
Knowledge updating twice	91.25%	3.75%	3.75%	98.75%

From Table 3, we find that the rates of satisfaction are rather high for all design cases. Most of the successful design schemes are obtained just after performing the first recommendation without knowledge adjustment. The adjustment procedure can effectively improve the rate of satisfaction for the second and third recommendations. The successive updating of the design knowledge base can clearly improve the quality of the recommendations. From these results, the capacities of recommendation and knowledge learning in the proposed system can be validated effectively.

For a further validation of the proposed recommender system, we compare its averaged rate of satisfaction for 50 representative jeans design schemes (associated with different body shapes and fashion themes), extracted from the previous 80 cases, with those of two other fashion recommender systems ([13,14]), which use IGA algorithms and fuzzy decision trees, respectively. For making a relevant comparison, we have to remove the functionality of feedback in the proposed system (this enables the rate of satisfaction to increase from 66% to 91% (with three recommendation rounds)) and focus on style recommendation only. This is because the other fashion recommender systems cannot process either the user’s perceptual feedback or all design factors (style, colour and material) together.

According to the evaluations given by the 10 previous consumers with various body shapes, we obtain the distributions of the numbers of successful design schemes (accepted by consumers) at different levels of satisfaction rates, generated by the three recommender systems, respectively, in Table 4 and the overall comparison of averaged rates of satisfaction in Table 5.

Table 4
Numbers of successfully recommended design schemes at different consumer satisfaction levels (statistics for 50 design schemes)

Levels of satisfaction rates (%)	(0, 30]	(30, 40]	(40, 50]	(50, 60]	(60, 70]	(70, 80]
IGA-based system	3	3	9	17	18	0
Fuzzy decision tree-based system	2	2	5	23	9	9
The proposed interactive knowledge-based system without feedback	0	0	3	25	10	12

Table 5
Comparison of three fashion recommender systems for fashion style (statistics for 50 design schemes)

	Averaged rate of satisfaction	Lowest rate of satisfaction	Highest rate of satisfaction	Standard deviation of rates of satisfaction
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IGA-based system	59.80%	30.00%	70.00%	0.1143
Fuzzy decision tree-based system	62.40%	30.00%	80.00%	0.1209
The proposed interactive knowledge-based system without feedback	66.20%	50.00%	80.00%	0.0914

From Table 4 and Table 5, we can see that the performance of the proposed system is better than the other two, with higher consumer satisfaction rates and more stable results (lower standard deviation). Moreover, if we introduce the feedback mechanism with human evaluation, the rate of satisfaction on the proposed system can be quickly increased to 91% (see Table 3).

7. Conclusion

In this paper, we propose a new designer-oriented recommender system to support personalised fashion design. It will be implemented by various fashion brands on their e-shopping platforms. In contrast to the existing systems in the same category, the proposed system is based on the professional knowledge of designers and can effectively deal with consumer and designer emotions and interactions between the virtual display of the recommended design scheme, designer perception and design knowledge. It cannot only recommend existing design schemes but also automatically generate new design solutions by making optimised combinations of basic design elements. The main component of this system is the design knowledge base, composed of five mathematical models characterising relations between consumer body shapes, fashion requirements and design factors. In this knowledge base, the classically separated design knowledge is structured and formally represented by an ontology model, allowing the generation of feasible design schemes.

Based on designer evaluation, the proposed system provides a feedback and self-adjustment mechanism, which can adjust the knowledge base automatically, according to the users' perceptual feedback, and be adapted to the big data environment relating to continually increasing e-transactions of brand companies. In this context, the proposed design system is directly involved in the new design process of personalised garment products. The new design process is strongly associated with human-machine interactions and supported by the resources of the professional design knowledge base, which will be progressively enhanced by learning from new design cases.

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