Thèse en cotutelle avec
l'Université technique d'Iasi (Roumanie) et l'Université de Soochow (Chine)

Développement d'un Système Intelligent d'Aide à la Création de Vêtements Personnalisés pour des Personnes à Morphologie Atypique par Exploitation de Connaissances

Development of an Intelligent Knowledge-Based Personalized Garment Design Support System for People with Atypical Morphology

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pour obtenir le grade de Docteur de l'Université de Lille
Discipline: Automatique et Productique
Soutenue le 20/04/2018 devant la commission d'examen

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Développement d'un Système Intelligent d'Aide à la Création de Vêtements Personnalisés pour des Personnes à Morphologie Atypique par Exploitation de Connaissances

Résumé

Ce projet de recherche de doctorat vise à développer un nouveau ***Système d'Aide à la Conception de Vêtement Personnalisé*** (PGDSS en Anglais) pour les ***personnes à morphologie atypique (***PWAM en Anglais***)***. Ce système nous permet de développer rapidement des vêtements adaptés à leurs besoins ***fonctionnels, expressifs et esthétiques (***FEA en Anglais***)*** et à leurs morphologies atypiques. Afin de réaliser le PGDSS proposé, deux sous-systèmes sont développés: un ***Système de Recommandation de Mode Personnalisée (***PFRS en Anglais***)*** et une ***Plate-Forme Virtuelle de Prototypage de Vêtement 3D/2D (***VGPP en Anglais***)***. Le PFRS est conçu pour sélectionner les solutions de vêtement personnalisées les plus pertinentes en termes de couleur, de tissu et de style, tandis que le ***VGPP*** permet de créer rapidement des vêtements virtuels en fonction de leurs critères de conception (profils de produits), de les ajuster ensuite. Le ***PGDSS*** proposé peut être entièrement utilisé en ligne, il est alors connecté à une plate-forme E-commerce de vêtement. Mais il peut aussi être connecté à un système de fabrication de vêtements automatique hors ligne.

Le ***Système de Recommandation de Mode Personnalisée*** proposé a été développé en établissant une série de modèles qui ont pour but d'évaluer quantitativement les besoins du consommateur et de caractériser les relations entre les espaces des besoins du consommateur et les paramètres de conception. Différentes connaissances acquises et différents outils de calcul intelligents ont été utilisés pour réaliser ce système. Ces outils comprennent l'évaluation sensorielle, la modélisation par les techniques du flou, l'apprentissage automatique, etc. Un profil de produit de vêtement personnalisé est alors généré à l'issue de ce système.

La ***Plate-Forme Virtuelle de Prototypage de Vêtement 3D-2D (VGPP)*** proposée a été développée afin de générer des modèles de vêtements personnalisés en fonction du profil de produit offert par le PFRS. De nouvelles technologies numériques 3D ont été utilisées pour personnaliser un vêtement pour toute morphologie atypique. Les patronages 2D et les vêtements 3D générés par ce processus seront fournis selon les exigences du consommateur.

Les facteurs de conception pour les vêtements personnalisés ont été identifiés et analysés dans ma recherche de doctorat. Les nouveaux produits générés par le système proposé répondront aux exigences et aux fonctions spécifiques imposées par les personnes à morphologie atypique en termes d'ergonomie, de biophysique, de psychologie, d'esthétique, de confort et de commodité. Le système proposé est capable d'offrir des designs à forte personnalisation à un faible coût pour un marché de vêtement dont la demande est en hausse. Ce qui fait la distinction avoir les produits existants du marché est que nous prenons en compte l'ensemble des exigences de ce type de consommateur par un produit entièrement personnalisé.

Keywords: *Morphologie Atypique; Intelligence Artificielle; Évaluation Sensorielle; Apprentissage Automatique; Réalité Virtuelle; Système Basé sur les Connaissance; Prototypage 3D; Système de Recommandation.*

Development of an Intelligent Knowledge-Based Personalized Garment Design Support System for People with Atypical Morphology

Abstract

This PhD research project aims at developing a new ***Personalized Garment Design Support System (PGDSS)*** for ***People with Atypical Morphology (PWAM)***. This system enables to quickly develop garments adapted to their special Functional, Expressive and Aesthetic (FEA) needs and atypical morphologies. In order to realize the proposed ***PGDSS***, two subsystems are developed: the ***Personalized Fashion Recommendation System (PFRS)*** and ***Virtual 3D-to-2D Garment Prototyping Platform (VGPP)***. The ***PFRS*** is developed for selecting the most relevant personalized garment design solutions in terms of color, fabric and style, while the VGPP enables designers to quickly create virtual garments according to their design criteria (product profiles) and visualize them in order to adjust design parameters. The proposed ***PGDSS*** can be fully used online. It can be further connected to a garment e-shopping platform or an offline automatic garment manufacturing system.

The proposed ***Personalized Fashion Recommendation System (PFRS)*** has been developed by establishing a series of models for quantitatively assessing consumer's needs and characterizing relations between the spaces of consumer's needs and design parameters. Different knowledge acquisition and intelligent computational tools have been used to realize this system. These tools include sensory evaluation, fuzzy modeling, machine learning etc. A personalized garment product profile is generated by using this system.

The proposed ***Virtual 3D-to-2D Garment Prototyping Platform (VGPP)*** has been developed in order to generate personalized garment patterns based on the product profile offered by the PFRS. New digital 3D technologies have been used to customize a garment for any atypical morphology. The 2D patterns and 3D garments will be provided according to the consumer's requirements.

The design factors for personalized garments have been identified and analyzed in my PhD research. The new products generated by the proposed system will meet the specific demands and functions imposed by people with atypical morphology in terms of ergonomics, biophysics, psychology, aesthetics, comfort and convenience. The proposed system is able to offer more personalized designs at low-cost level for highly customized garment market.

Keywords: *Atypical Morphology; Artificial Intelligence; Sensory Evaluation; Machine Learning; Virtual Reality; Knowledge-Based System; 3D Prototyping; Recommendation System*

Dezvoltarea unui Sistem Inteligent de Proiectare Personalizată a Produselor de Imbrăcăminte pentru Persoane cu Morfologie Atipică

Rezumat

Prezentul proiect de cercetare doctorală are ca scop dezvoltarea unui nou ***Sistem de proiectare personalizată a produselor de îmbrăcăminte (PGDSS)*** pentru ***Persoanele cu morfologie atipică (PWAM)***. Acest sistem face posibilă crearea rapidă a produselor de îmbrăcăminte care corespund nevoilor speciale ale acestei categorii de consumatori, atât din punct de vedere funcțional, expresiv și estetic (FEA), cât și al morfologiilor atipice. Pentru a obține acest PGDSS au fost concepute două subsisteme: ***Sistemul de recomandare a modei personalizate (PFRS)*** și ***Platforma virtuală de transformare 3D-2D generatoare de prototipuri vestimentare (VGPP)***. ***PFRS*** este creat pentru a selecta cele mai relevante soluții de proiectare a îmbrăcămintei personalizate ținând cont de culoare, material și stil, în timp ce VGPP permite designerilor să creeze în timp scurt produse de îmbrăcăminte virtuală, conform propriilor criterii de proiectare („profilul produsului”) și să vizualizeze produsul vestimentar pentru a putea regla parametrii de design. ***PGDSS*** propus poate fi utilizat în întregime în spațiul virtual. Mai mult decât atât, poate fi conectat la o platformă virtuală de achiziție a îmbrăcămintei sau la un sistem automat de producție a îmbrăcămintei care nu este conectat la internet.

Sistemul de recomandare a îmbrăcămintei personalizate propus (PFRS) a fost creat prin stabilirea unei serii de modele cu scopul de a evalua cantitativ nevoile consumatorului și de a caracteriza și stabili legătura dintre „spațiul nevoilor consumatorului” și parametrii de proiectare. Pentru a realiza acest sistem au fost folosite diferite instrumente de colectare a datelor și de calcul inteligent. Aceste instrumente includ evaluarea senzorială, modelarea fuzzy, învățarea automatizată etc. Prin utilizarea acestui sistem se obțin datele (profilul) unui produs de îmbrăcăminte personalizat.

Platforma virtuală de conversie 3D-2D generatoare de prototipuri vestimentare (VGPP) a fost dezvoltată pentru a genera tipare personalizate pentru produsele de îmbrăcăminte, pornind de la profilul generat de PFRS. Noile tehnologii digitale 3D au fost aplicate pentru a personaliza produsul vestimentar pentru orice profil atipic. Tiparele 2D și îmbrăcămintea 3D pot fi puse la dispoziție, în concordanță cu cerințele consumatorului.

Factorii de design ai îmbrăcămintei personalizate au fost identificați și analizați în această cercetare doctorală. Noile produse generate de sistemul propus vor satisface cerințele și funcțiile specifice impuse de persoanele cu morfologie atipică în termenii parametrilor ergonomici, biofizici, psihologici, de estetică, confort și facilitare. Sistemul propus poate oferi mai multe modele personalizate la prețuri mici, satisfăcând astfel cererea de produse de îmbrăcăminte cu un grad ridicat de personalizare.

Cuvinte cheie: *Morfologie Atipică; Inteligen□ă Artificială; Evaluare Senzorială; Învă□are Automatizată; Realitate Virtuală; Sistem Bazat Pe Cunoa□tere; Crearea De Prototipuri 3D; Sistem De Recomandare.*

基于知识系统和人工智能技术的个性化特体人群服装设计支持系统

摘 要

在服装个性化定制的大背景下，本研究针对服装设计知识的抽象性和主观性，利用感性工学和人工智能技术，对基于知识的服装设计过程进行了系统的研究。总结和分析了服装设计的各项要素、服装设计的知识特点和层次、以及基于知识的服装设计规则的建模，构建了以特体人群（PWAM）为目标设计对象的个性化服装设计支持系统（PGDSS），并以衬衫为例进行了实证分析。

本文提出的个性化服装设计支持系统（PGDSS）主要解决了针对特殊体型人群（PWAM）的个性化服装款式自动生成、个性化服装纸样设计，及其与现有服装智能制造平台的对接。该系统能够快速自动设计出满足特殊体型消费者功能需求、审美需求和个性展示需求（FEA）的服装。该系统包含两个子系统：个性化服装推荐系统（PFRS）和三维虚拟服装立裁平台（VGPP）。个性化服装推荐系统（PFRS）能够根据消费者的个性需求生成服装产品档案，包括产品的颜色、面料和服装款式。三维虚拟服装立裁平台（VGPP）能够根据个性化服装推荐系统（PFRS）生成的服装产品档案生成服装纸样。本文提出的个性化服装设计支持系统（PGDSS）能够通过互联网平台实现全程可视化，并且可以进一步与服装电子商务平台和现代服装智能制造系统对接。

针对个性化服装推荐系统（PFRS），本研究通过感官评估方法，将设计师的抽象的设计知识进行了获取、表征、量化和规则化，并通过模糊逻辑、机器学习等人工智能算法，构建了消费者需求和设计参数之间的数学模型，实现了服装款式的智能化、个性化推荐。本研究通过不同的服装CAD软件架构了三维虚拟服装立裁平台（VGPP），并在此基础上提出了针对特殊体型的三维虚拟立体裁剪方法，建立了从三维服装到二维样板的服装纸样设计方法，大大提高了特体人群的服装纸样设计精度和效率。本研究以特体人群衬衫设计为例，对个性化服装设计支持系统进行实证分析，结果证明本研究提出的方法与系统具有比较良好的应用价值与操控性能。

本研究将人工智能技术和知识系统技术引入服装设计领域，主要贡献在于系统提出了服装设计专家知识的获取与表征方法、基于知识的个性化服装设计系统、在设计交互过程中专家认知与消费者认知统一方法。在知识系统上建立了可交互式推荐系统。研究成果不仅可以用于针对特殊体型的衬衫设计，也可在扩充了相应的专家知识和设计规则以后用于其他体型和服装的设计。本研究的成果对服装设计的个性化、感性化、智能化、快捷化有着重要的指导意义。

关键词：特殊体型；人工智能；感官评估；机器学习；虚拟现实；知识系统；三维建模；推荐系统

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List of Abbreviation

2D: Two Dimensional
3D: Three Dimensional
AHP: Analytical Hierarchy Process
ALGD: Anatomical Landmarks for Garment Design
BCSA: Basic Color Sensory Attribute
BSIS: Body Shape Image Space
BSRA: Body Shape Related Recommendation Attributes
CDKB: Color Design Knowledge Base
CIS: Color Image Scale
CIW: Color Image Words
CR: Color Range
CRS: Color Recommendation System
FASS: Fashion Style Space
FAST: Fabric Assurance by Simple Testing Systems
FEA: Functional, Expressive and Aesthetic
FNIS: Fuzzy Negative-Ideal Solution
FPIS: Fuzzy Positive-Ideal Solution
FRA: Fabric Related Recommendation Attributes
FSKB: Fabric Selection Knowledge Base
FSPS: Fabric Sensory Property Space
FSS: Fabric Selection System
FSS: Fabric Selection System
Fuzzy AHP: Fuzzy Analytical Hierarchy Process
GCM: Garment Components Module
GDSM: Garment Design Space Module
GSDKB: Garment Style Design Knowledge Base
GSRS: Garment Style Recommendation Subsystem
GSRS: Garment Style Recommendation System
KES: Kawabata Evaluation Systems
KFM: Key Fit Measurements
NIS: Negative Ideal Solution
PD&D: Product Design and Development
PD&P: Product Design and Production
PDPS: Physically Disabled People with Scoliosis
PFRS: Personalized Fashion Recommendation System
PGDSS: Personalized Garment Design Support System
PIS: Positive Ideal Solution
PWAM: People with Atypical Morphology
RB1-FS: Fashion Style Related Garment Design Rule Base
RB2-BS: Body Shape Image Related Garment Design Rule Base
RB3-F: Fabric Sensory Property Related Garment Design Rule Base
RBRM: Rule-Based Recommendation Module
RTW: Ready-To-Wear
RUM: Rule Updating Module
SCD: Successful Cases Database
SCDM: Successful Cases Database Module
SCP: Shaping Controlling Points
TFN: Triangular Fuzzy Number
TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution
VGPP: Virtual 3D-To-2D Garment Prototyping Platform

General Introduction

Elderly people and people with disabilities constitute a social group with atypical morphologies. Apparel products (garments, shoes, accessories) influence the daily life quality of this group. Having and wearing appropriate clothing can effectively meet the functional, expressive, and aesthetic requirements of consumers. General apparel products, which do not take into account special requirements of ***People with Atypical Morphology (PWAM)*** will significantly reduce the quality of life and social participation of this group. These special requirements exist at different levels: fabric design, aesthetic design, easy-to-wear consideration, ease allowance and movements.

Making adapting ***ready-to-wear (RTW)*** garments is strongly required for ***PWAM***, but the current design solutions for adapted garments not only take more time for production and delivery but also lead to bad aesthetic effects and uncomfortable feeling. There is a huge gap between the supplied products in the mass market and the demands from the customers. The traditional garment design process and related design knowledge, developed for normal body shapes cannot fully meet the requirements for the deformed morphologies. Finding a tailor seems a good solution but it is not available for all consumers. In this situation, the main goal of my PhD research is to find personalized garment design solutions to ***PWAM*** by selecting relevant fabrics and proposing appropriate garment constructions and other related issues.

Based on the investigation of consumer's behaviors of ***PWAM***, we find that there are three problems faced by them during their garment purchasing: garment design, garment fit and garment shopping. The problem of garment design is that it is difficult for them to find appropriate garment styles adapted to their atypical morphologies. The problem of garment fit is that the ease allowance given by current garments cannot be well controlled. The problem of garment shopping is that the disabled people have more inconvenience for physically trying on products in a classical garment shop.

In a traditional design process for ***PWAM***, designers should take into consideration of the requirements regarding ***Functional, Expressive, and Aesthetic (FEA)*** aspects. However, perceptual data in these aspects are evolutionary. Also, different design elements, such as color, fabric and garment style are strongly related to the fashion trend, which is dynamically changing with time. New design rules and materials (such as functional fabrics, color therapy...) related to the design of ***PWAM*** can be continuously created and influences the garment design process. In this changing environment, the traditional design process, strongly related to designers' subjective knowledge and experience, is rather limited and cannot ensure a very high consumer satisfaction. In this condition, traditional garment design process cannot fulfill the personalized requirements for ***PWAM***.

In my PhD research, we propose an intelligent fashion recommendation system for ***PWAM***, in order to solve the fashion related issues faced by this group. The proposed fashion recommendation is a design support system for both designers and consumers when designing personalized garment for ***PWAM***. The proposed system is capable of helping designers to understand dynamically changing requirements of consumers, designing and prototyping ***FEA*** oriented personalized garments for ***PWAM***.

Currently, there exist a great number of recommendation systems, which have been applied in different scenarios. However, a number of drawbacks exist when applying them to personalized garment design.

1) The existing systems uniquely consider one aspect of the fashion design (fabric, color, and garment style…), without giving a comprehensive frame with all the related design elements.

2) Designers' (fashion designer and pattern designer) and consumers' knowledge and experience are not systematically taken into account. In a real personalized garment process, the knowledge and experience are the important factors to the success of the design case.

3) The time-varying requirements of consumers cannot be completely identified.

4) The current CAD-based personalized garment design process cannot be connected to an automatic garment manufacturing system, which will limit its capacity of industrial exploitation.

5) The current recommendation systems are mostly closed systems and cannot dynamically integrate new design rules and design materials from open resource.

In order to solve these drawbacks, we propose a dynamic system in my study which is capable of processing evolutionary consumer perceptual data on fashion requirements and integrating new design rules from the open resource. Designers' knowledge and experience can be continuously learned and utilized to support the recommendation process.

This system has two functions: automatic garment recommendation and virtual prototyping. The process of the proposed recommendation system starts with 3D scanning and several sensory evaluations procedures of consumers on colors, fabrics and styles. These measured and evaluated data constitute the inputs of the system. The output of the system is the final personalized garment product. All the processes can be presented to the consumer through an online platform, which ensures the collaborative design with interactions between designers and consumers. The proposed system can be connected to both an e-shopping platform for providing ***PWAM*** with more convenient design service, and an automatic manufacturing system of the company with simplified operational processes.

This thesis is structured as follows (see Figure 0-1). **Chapter 1** introduces the problems faced by ***PWAM*** and related garment design solutions. In **Chapter 2**, the general framework and working process of the proposed personalized garment design support system are presented.

Chapter 3 describes related knowledge acquisition tools and computational tools used to realize the proposed system. **Chapter 4** and **5** gives related experiments for setting up the proposed system. The implementation with different cases is also presented in order to explain the working process of the proposed system. Finally, a conclusion is provided in **Chapter 6**.

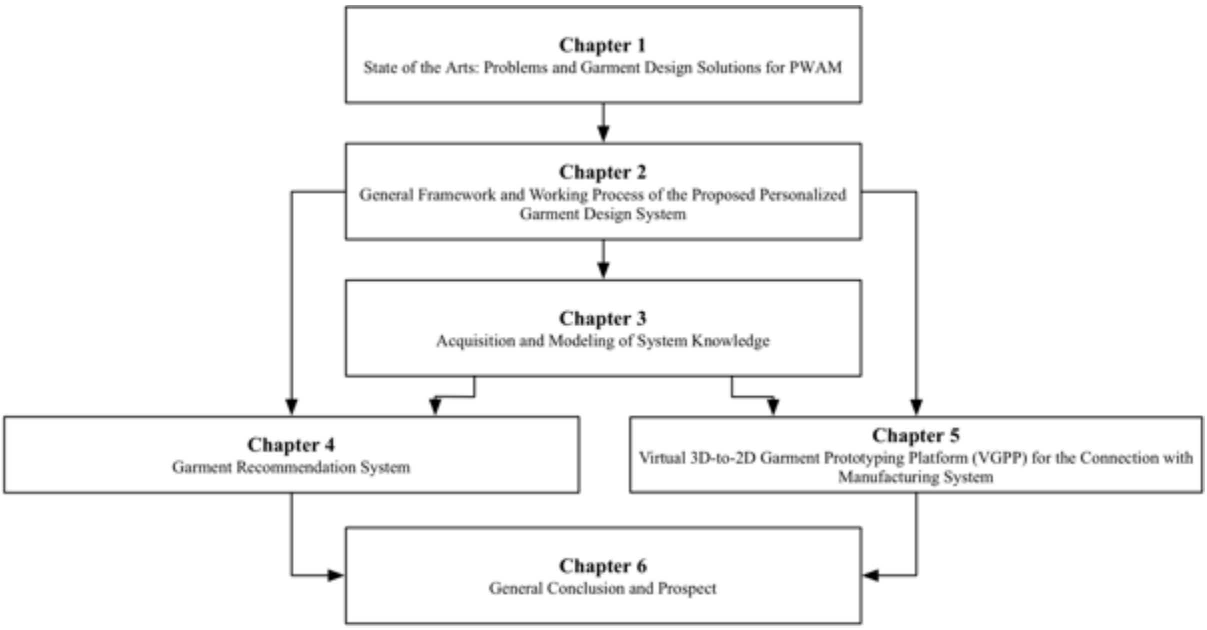


Figure 0-1: Organization of the chapters of this PhD Thesis.

Chapter 1 State of the Arts: Problems and Garment Design Solutions for *PWAM*

This chapter introduces the problems faced by ***PWAM,*** related garment design theory and solutions. A brief principle of the proposed intelligent knowledge-based ***PGDSS***, which is developed based on these design theory and solutions, is also presented.

1.1 Fashion Related Issues Faced by *PWAM*

1.1.1 Atypical Morphology and Fashion

1.1.1.1 *PWAM* Have Problem to Find a Suitable Garment

Each social group has its own expectations on how its group members dress in different situations. The way of dressing depends on the social group and the willingness of the individual to adapt to the social environment's expectations [1]. Clothing has both a functional value and a symbolic value to the human being [2]. There are innumerable ways of dressing, there are certain dress codes depending on in which country, society, social status, Circumference and group we find ourselves [3]. With the way we dress we communicate things about us as individuals e.g. our personality, what we stand for, to which group we belong, etc. [4]. People have more clothes than they actually need for protection of the physical body. Everyone enjoys wearing clothes that are comfortable, pleasant to the eyes, and give them a feeling of self-confidence. However, to find suitable clothes is a problem for quite a lot of individuals. It is a very widespread problem, which can affect anyone, all depending on their figures, the supply of clothes in the stores, and the individual's demands [4]. Especially, the categories of individuals with atypical morphology are facing more difficulties in finding suitable garment [5]. These individuals are the elderly, impaired, and/or disabled people [6].

1.1.1.2 Problems Faced by *PWAM* to Find a Suitable Garment

There is a gap between the stores' supply and the demands from the customers [6]. The more the figure diverges from the standard one, the more difficult it is to find suitable clothes in retail stores. Customers are demanding a more flexible market that can provide them with suitable garments. There are several factors preventing ***PWAM*** from finding a satisfied garment: size problem, aesthetic design and functional requirements [7].

(1) Garment fitting

PWAM have unique figures, which do not always fit into the standard sizes that are available in the stores [8]. These problems are caused by their deformed body part, such as over fat, too slim, too short, too tall [9].

At technical level, the current market is able to offer ***PWAM*** with garments made according to their desires and body figures with more automatic equipment and software [10]. However, the process for adapting the general patterns to various atypical morphologies is still difficult due to a large number of repeated garment try-on tests and non-explicit knowledge in this special design process.

(2) Aesthetic design

For the physically disabled/impaired individual, the attractiveness of clothing is very important [11]. They expect that the observer can notice that he/she is well-dressed and the disadvantage or disfigurement on the body shape can be visually masked by the garment [7]. The disabled person does not want to appear different from others in his social group, irrespective of his age, sex or financial Circumferences [12]. The choice of clothing is a highly individual experience for an impaired, disabled or disfigured person. It is therefore very important that an individual is free to choose clothes according to his/her own style and personal priorities. However, current designs for ***PWAM*** ignore the aesthetic requirements of this group.

(3) Functional requirements

There are some functional requirements of ***PWAM*** when selecting a garment because they might have problems of agility and incontinence [6]. If the wearer's agility is low, the garment has to be designed accordingly, with the right opening and technical solutions needed for helping him/her to get rid of the convenience. The goal of these functions is to make it possible for all individuals with disability/impairments to dress themselves by using various technical solution and aids.

For all individuals it is of great importance that the garment has the appropriate design, material, fastenings, and technical solutions. Clothing can also be designed in a way that it facilitates the dressing intellectually by making a clear difference between front/back, left/right, and up/down. Some individuals have the problem when they shop for clothes, since they are not able to easily get into the store or the fitting room. They might not be able to try the garment on before they buy it due to lack of space in the fitting room or lack of assistance.

1.1.1.3 Discussion on garment design elements related to *PWAM*

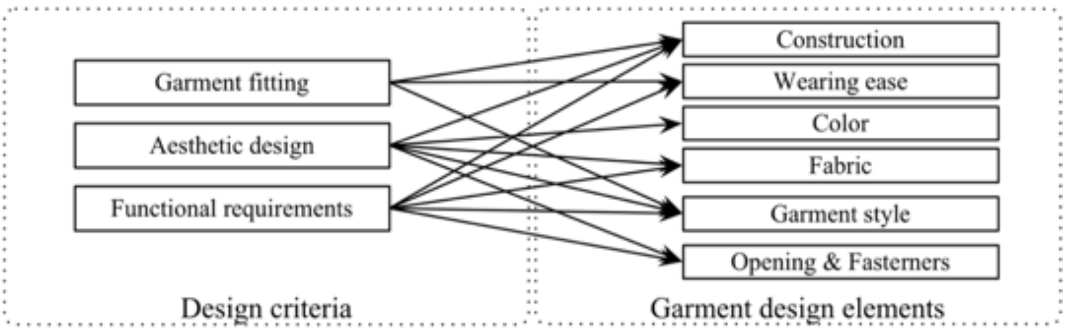


Figure 1-1: Garment design elements analysis regarding design criteria for *PWAM*.

The previous problems encountered by ***PWAM*** in choosing a satisfied garment lead to the formalization of the design criteria or requirements in the garment design process. In order to design a suitable garment for this group, the relationship between garment design elements and these design criteria will be established (see Figure 1-1).

(1) Construction

Garment construction is the general structure of a garment, which cuts the garment into several fabric pieces [13]. The final product obtained by assembling the garment pieces should fit the shape of a human body. The structure of the garment on the wearer will influence the ease allowance and harmony with the covered body parts. In the garment design of ***PWAM***, garment construction will influence the size, aesthetic design and function of a garment.

(2) Ease allowance

Ease allowance is the difference between the body's measurement and the inside garment's measurement [14]. Garment fit is largely related to ease allowance. For example, if the garment has a width of 102cm at the bust level while the bust girth of the wearer is 88cm, the ease allowance in this case is 14cm over the bust. Ease allowance should be determined by the measurement and functional requirements of the ***PWAM***.

(3) Color

Color is one of the most influential factors of aesthetic design for a garment [15]. It greatly controls the design emotion of a garment. Inappropriate color of a garment will draw public attention to the ***PWAM***, which will make them psychologically uncomfortable.

(4) Fabric

The color and texture of a piece of fabric influences the aesthetic design of a garment [16]. Physical properties, such as thickness, will influence of the function of a garment [17]. ***PWAM*** have more requirements about fabrics than normal people. For example, the problem of incontinence leads to the selection of fabrics very good at moisture management and vapor absorption.

(5) Garment style

Garment style is composed of style lines and details such as collar, button stand, pockets etc. It will influence the garment appearance, aesthetic design of a garment and garment functions.

(6) Opening and fasteners

Openings and fasteners for clothing are both functional and decorative [18]. Certain types of snap fasteners, for example, feature a decorative cap that resembles a round button, yet requires no buttonhole. Toggle-fastenings offer an alternative to zippers that occasionally jam or break. Fasteners can help reinforce a section of a garment and add structural integrity [19]. Opening and fasteners should fulfill the requirement of aesthetic design and garment function of ***PWAM*** [20].

1.1.2 Analysis of Fashion Requirements of ***PWAM***

In order to analyze the fashion requirements of ***PWAM***, an online questionnaire was distributed to a group of PWAM and their professional caregivers. Then, the problems faced by ***PWAM*** were analyzed. The related design elements were discussed in order to find the garment design solutions for this group.

1.1.2.1 About the interview

(1) Subject

Overall, a group of 90 people answered the questions via email. 70% of them are ***PWAM*** and the rest 30% are professional caregivers for ***PWAM***. All the involved ***PWAM*** are female. These ***PWAM*** were aged between 20 and 74 years.

(2) Interview design

The questionnaire has been designed regarding the design elements summarized in Section 1.1.1.3 (fabric, garment style, fitting…). Besides, the lifestyle and problems encountered in different shopping scenarios are also interviewed. The questionnaire was designed with the help of the medical experts in Eurospine (a European society for diseases related to spine). All the interviewees answered the questionnaire via email. The designed questionnaire is attached in ***APPENDIX 1***.

1.1.2.2 Analysis of the Consumer Behavior of ***PWAM***

Through the results collected from the involved ***PWAM*** and their professional caregivers, there are five fashion related aspects concerned by ***PWAM***.

(1) Problems related to auxiliary tools

The answers from the interview indicate that: (1) auxiliary tools are commonly used by ***PWAM***, (2) there are different auxiliary tools used by ***PWAM***, and (3) auxiliary tools put forward some requirements related to the fabrics used in the garments of ***PWAM***.

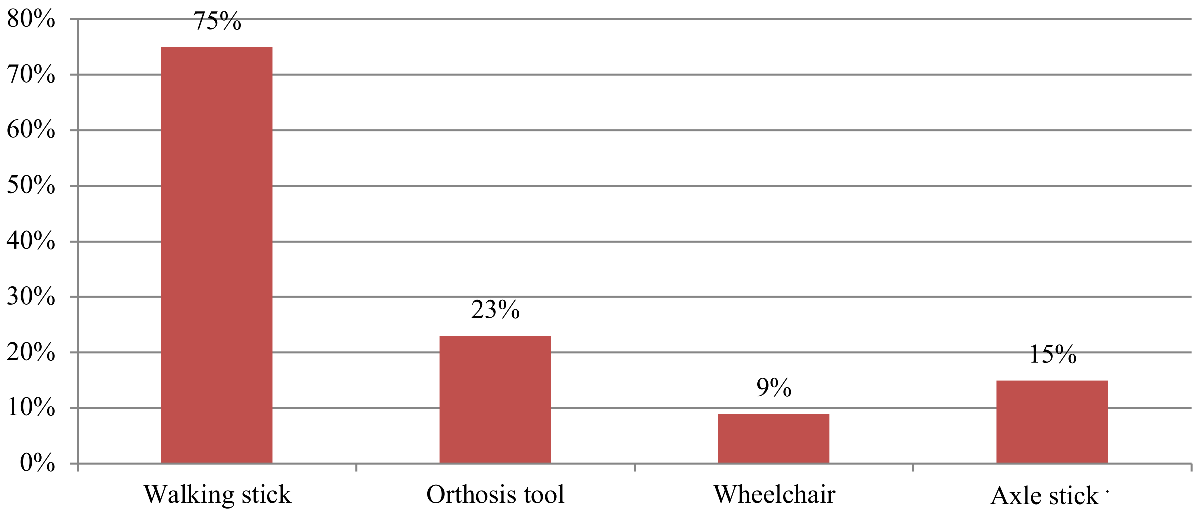


Figure 1-2: Multiple choices of auxiliary tools used by PWAM.

Figure 1-2 presents multiple choices of auxiliary tools used by ***PWAM***. "Walking stick" and "Orthosis tool" are the most commonly used auxiliary tools used by ***PWAM***. 75% of ***PWAM*** use walking stick and 23% of them use orthosis tool.

For the interviewees, ***PWAM*** really need some special fabric properties due to the use of different auxiliary tools (Figure 1-3). 55% of them consider that *"Moisture management"* is very important, 36% of them believe that *"Sweat absorption"* is significant, 33% of them vote for *"Abrasion performance"*, 29% of them for *"Easy to wash"*, and 21% of them for *"Wrinkle-free"*.

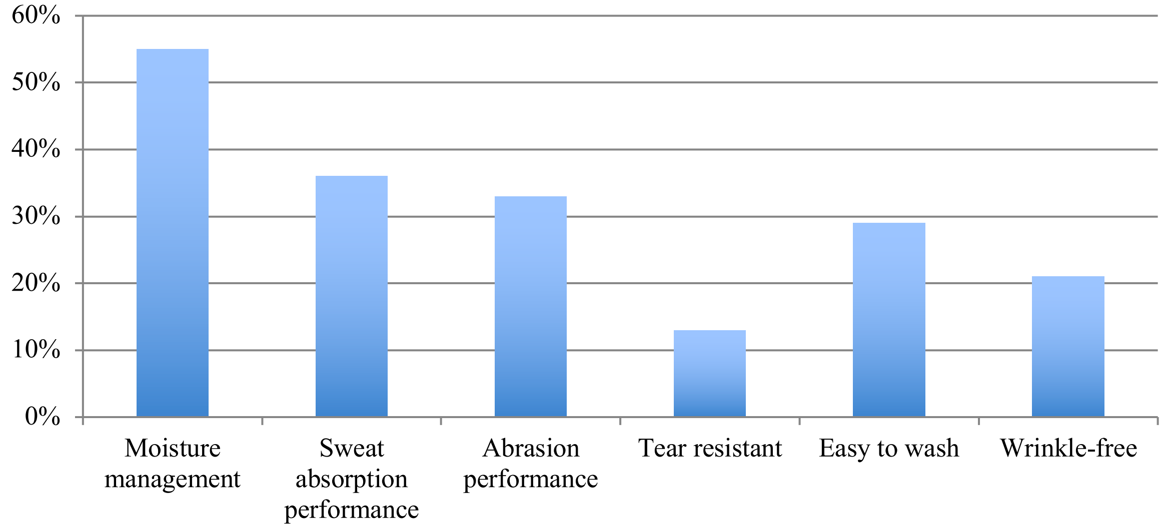


Figure 1-3: Specific fashion requirements of *PWAM* on auxiliary tools.

(2) Requirements related to garment perception

Two questions were asked to the interviewees about ***PWAM***'s preference and perception in terms of garment category.

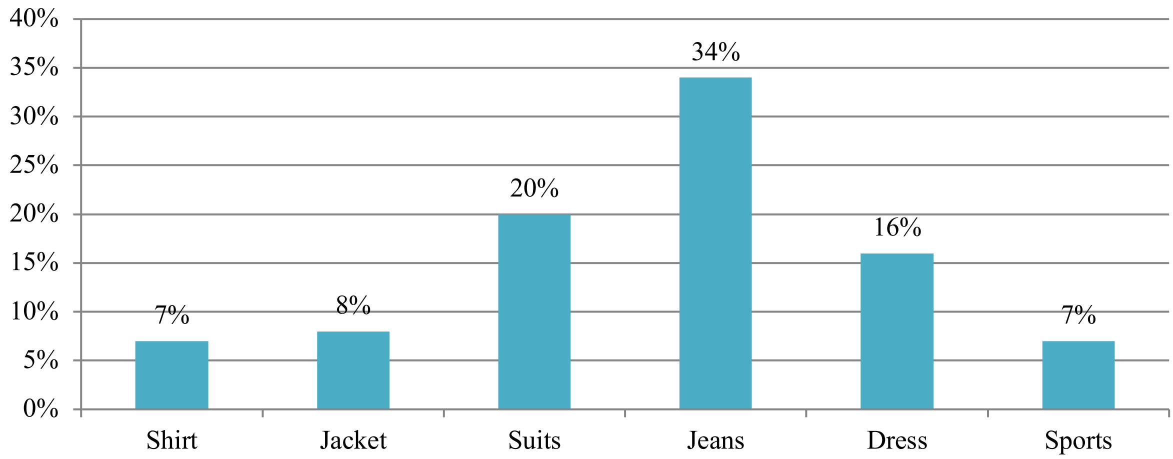


Figure 1-4: Answers of "What kind of garment category do you think inconvenient for *PWAM*?"

Figure 1-4 presents the results of "What kind of garment category do you think inconvenient for ***PWAM***?" 34% of the interviewees consider that jeans are very inconvenient. Suits and dress are also regarded as very inconvenient for ***PWAM***. Shirt, jacket and sportswear are considered to be more convenient for ***PWAM***.

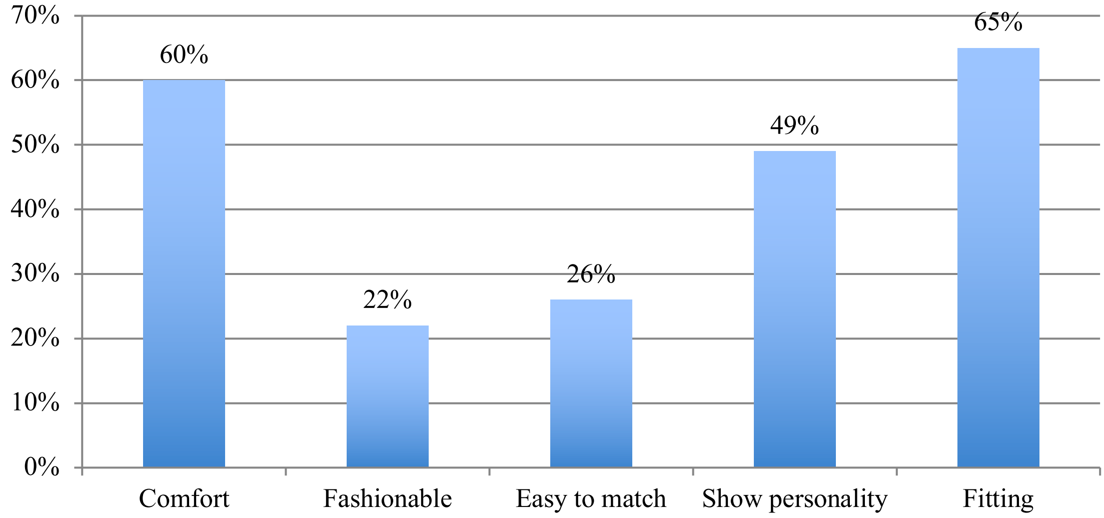


Figure 1-5: Answers of "What is the expectation of *PWAM* for garment?"

Figure 1-5 presents the garment expectations of ***PWAM***. 65% of the interviewees believe that "fitting" is very important for ***PWAM***. 60% of them select "comfort". The capacity of "Show personality" or not is also concerned by 49% of the interviewees.

(3) Requirements related to dressing and undressing

The requirements of dressing and undressing, and fasteners preference of ***PWAM*** about clothing is also researched.

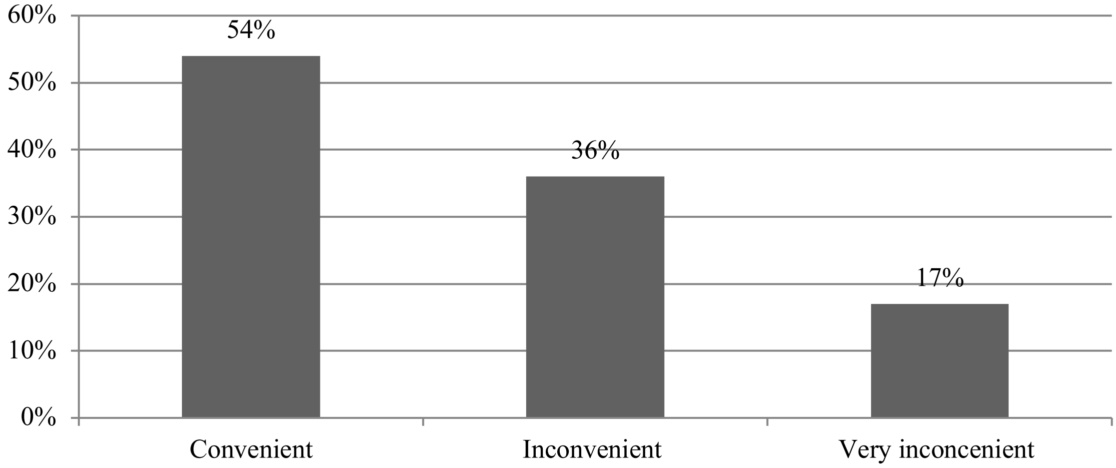


Figure 1-6: Answers of "Is the dressing and undressing activity convenient or not with your current garment?"

54% of the interviewees consider that the current garment design is convenient for the dressing and undressing activity. The rest of them think that current garment design is not so convenient for the dressing and undressing activity. The general satisfaction of dressing and undressing is not high enough.

In order to find out a solution to improve the convenience of the dressing and undressing activity, we carried out a research on preference of fasteners. Figure 1-7 presents the result. According to the interview, the most preferred fastener for ***PWAM*** is zipper, with a percentage of 78%. 60% of the interviewees believe that button is also convenient for ***PWAM***. Ties are the most unsatisfied fastener type.

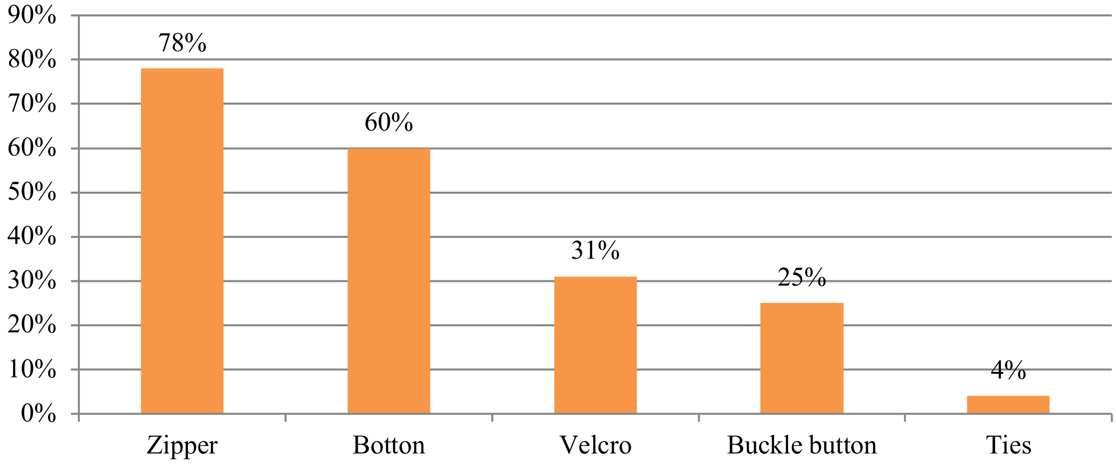


Figure 1-7: Answers of "What kind of fasteners can help you improve the dressing and undressing?"

(4) Requirements related to scoliosis

As an atypical morphology, scoliosis has an influence on fashion design. In order to investigate the problems caused by scoliosis, two questions were asked to the interviewees.

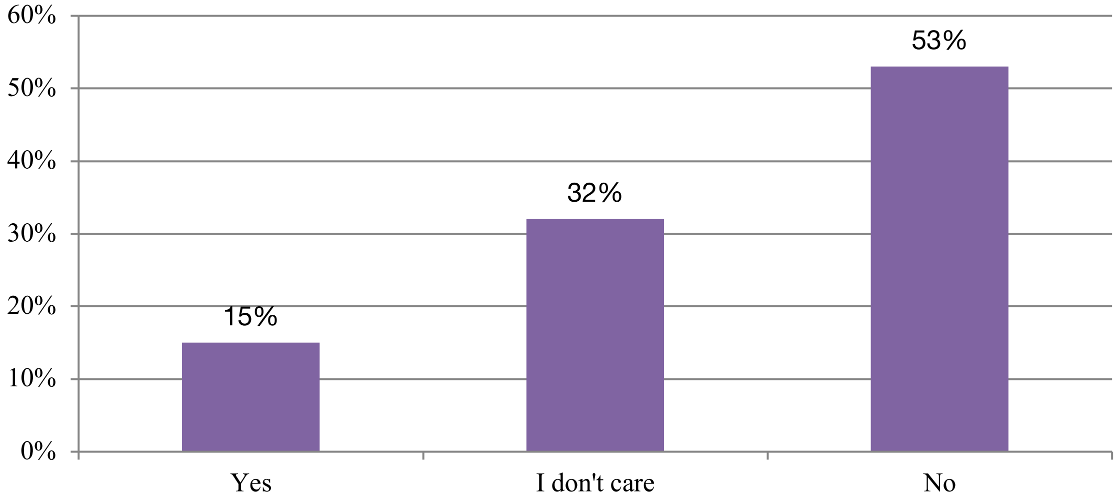


Figure 1-8: Answers of "Do you think *PWAM* like that other people pay more attention to their scoliosis?"

Figure 1-8 presents the result on the question "if ***PWAM*** like to be paid attention by the public". Most of the ***PWAM*** don't like to be paid a lot of attention by others. Extra attention from the public will make them psychologically uncomfortable. In the design process, designers should make more efforts to reduce visual deformations caused by scoliosis.

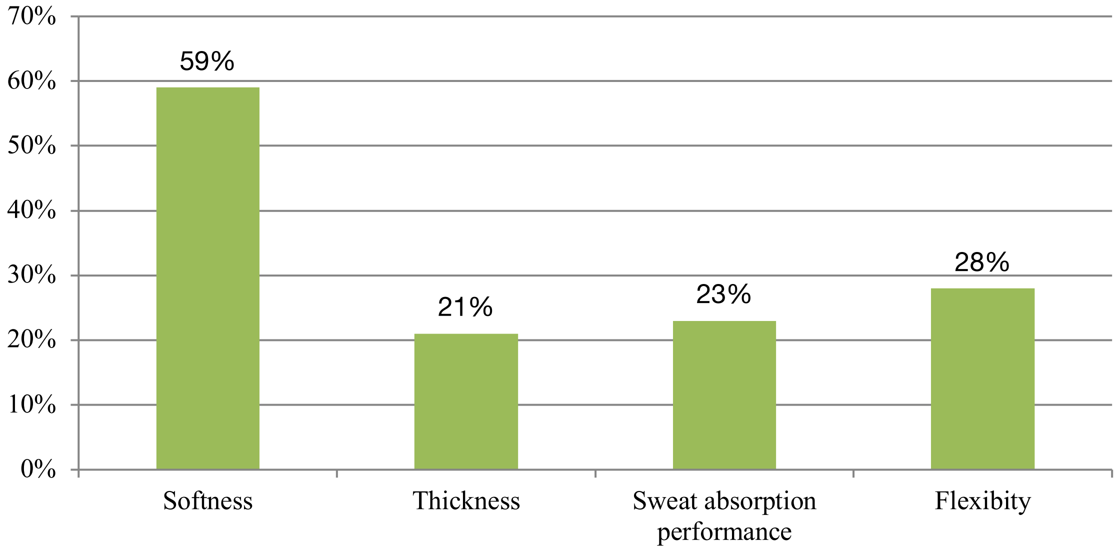


Figure 1-9: Answers of "Is there any special requirement about the garment fabric due to the use of auxiliary tools?"

Figure 1-9 presents the specific requirements of the garment fabric caused by scoliosis. 59% of the interviewees believe that ***PWAM*** require soft fabrics. Flexibility is also concerned by 28% of the interviewees. Thickness and sweat absorption performance in fabrics also affect the satisfaction of garments designed for ***PWAM***.

(5) Requirements related to fashion shopping

Fashion shopping is also a problem faced by ***PWAM*** due to the disability of movement. Two aspects on ***PWAM***'s fashion shopping have been studied in my PhD research: (1) shopping modes: there exist several modes of garment shopping for ***PWAM***, including shopping mall, e-commerce, chain store, supermarket, tailors, homemade; and (2) the general satisfaction of the current mode of shopping.

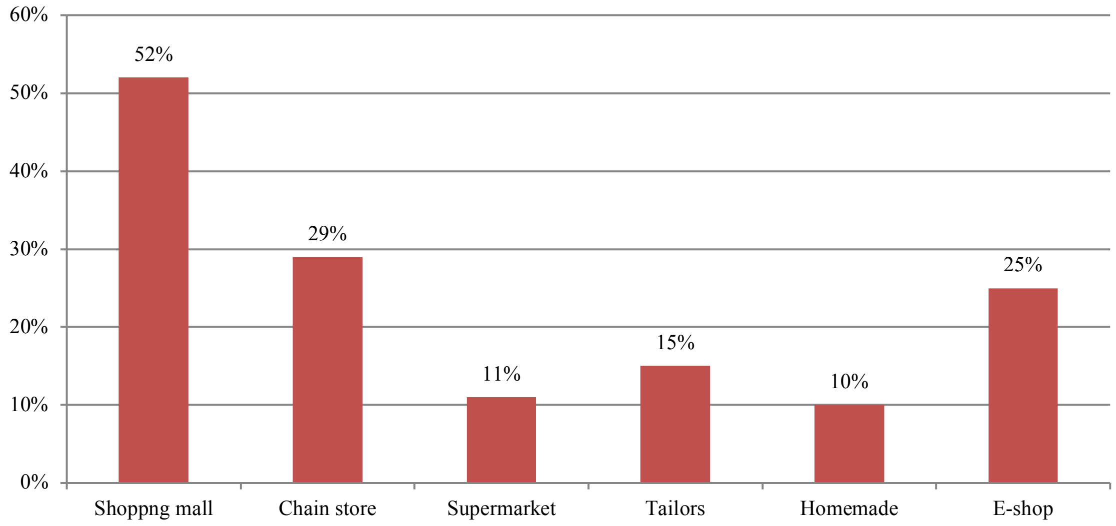


Figure 1-10: Answers of "Where will *PWAM* usually go to buy clothes?"

Figure 1-10 presents the current places offered to ***PWAM*** for garment purchasing. From the collected data, it can be found that, most of ***PWAM*** will carry out their garment purchasing in shopping malls and fashion chain stores. E-shop is a new trend for fashion shopping but it is not so popular for ***PWAM***.

Figure 1-11 presents the general satisfaction of ***PWAM*** on fashion shopping modes. This result indicates that their satisfaction degree is not very high. Therefore, garment shopping mode for ***PWAM*** should be further improved.

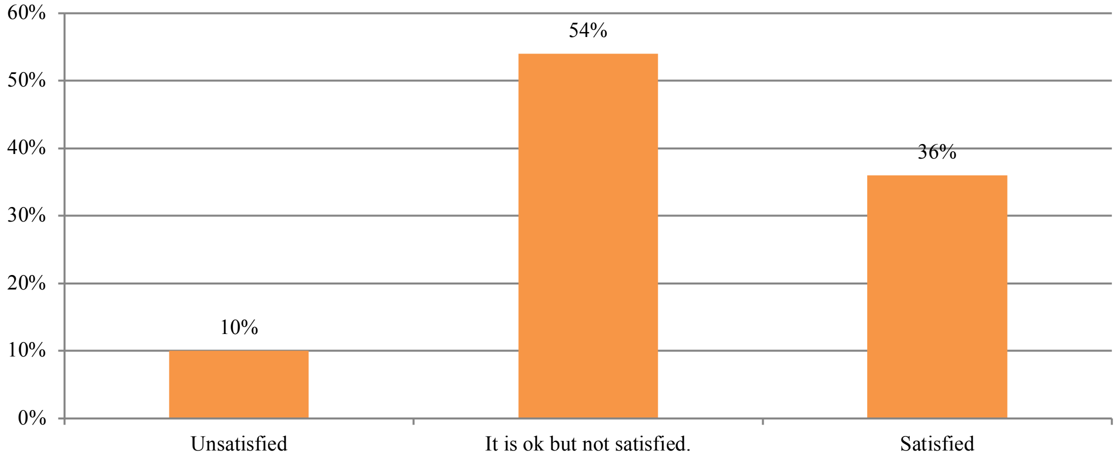


Figure 1-11: Answers of "Can *PWAM* easily buy satisfied garment from their fashion shopping places?"

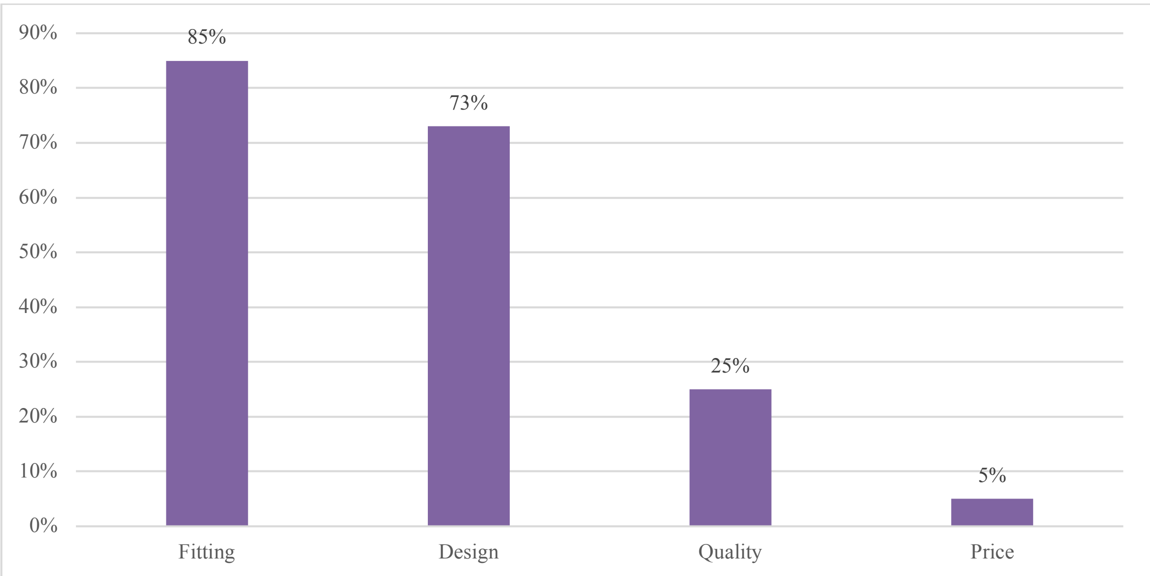


Figure 1-12: Answers of "What is the most dissatisfied factor of *PWAM* about e-shopping?"

Figure 1-12: Answers of "What is the most dissatisfied factor of ***PWAM*** about e-shopping?" Different factors influencing e-shopping for ***PWAM*** were also investigated. Most of ***PWAM*** have no e-shopping experience because of the garment fitting issues. Also, adapted design should be realized for e-shopping platform. E-shopping seems to be an effective way for helping ***PWAM*** to get rid of their moving restrictions but the fitting issue and design should be considerably improved.

1.1.2.3 Summary of special garment design issues for *PWAM*

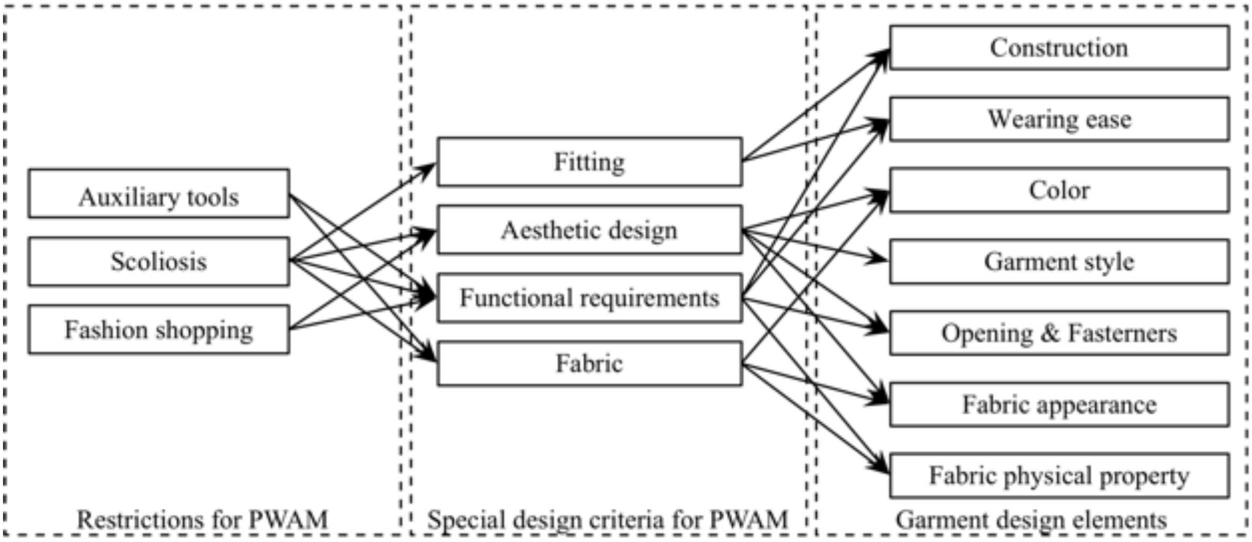


Figure 1-13: Restrictions for *PWAM*, special design criteria and concerned design elements.

In this section, based on the previous analysis, the special requirements for garment design of ***PWAM*** will be summarized along with their real restrictions and garment design elements. Figure 1-13 presents the relationship between these elements.

(1) Restrictions for ***PWAM***

There are three main restrictions for ***PWAM*** which can effectively affect the garment design criteria. They are auxiliary tools, scoliosis and fashion shopping.

Most ***PWAM*** will use auxiliary tools, such as walking stick and orthosis tool. These tools usually have direct contact with human body and garment. Specific design criteria, related to functional requirements for garments and fabrics, are provided by these auxiliary tools. For example, functional requirements of the garment, such as the ease allowance, should be considered. If there is too much ease allowance at the contact part between the auxiliary tool and garment, too much fold will be created between the human body and auxiliary tools. These folds will stick to the skin and make ***PWAM*** uncomfortable. Also, the general shape of the garment will be affected due to these extra folds. Extra requirements are also related to fabric. Secretion of sweat will happen between the human body and auxiliary tools, especially in summer. Fabric should have good moisture management and sweat absorption.

Scoliosis breaks down the traditional garment design rules, in both aesthetic design and garment fitting. Due to the scoliosis, some specific properties related to garment function (such as symmetry) and fabrics are also required by scoliosis. New fashion design rules, related to textile design, garment fitting and aesthetic design should be generated to fulfill the requirements caused by scoliosis.

Fashion shopping for ***PWAM*** is also a restriction caused by scoliosis. Current garment design and prototyping technologies are not able to ensure the consumer satisfaction for ***PWAM*** through e-shopping. More efficient e-shopping systems are required by integrating more appropriate garment fitting and design solutions.

(2) Special design criteria for ***PWAM*** and related design elements

Generally, at fashion level, there are four aspects of special design criteria for ***PWAM***: garment fitting, garment aesthetic design, garment function design and fabric selection. Garment fitting is one of the most concerned design aspects related to the garment products for ***PWAM***. To improve garment fitting, garment construction should be carefully designed with suitable values of allowances. New garment prototyping technology should be proposed to ensure a good garment fitting.

Garment aesthetic design is also concerned. There are two aspects of garment aesthetic design for ***PWAM***. Designers should use appropriate design elements to: (1) reduce the visual deformations caused by scoliosis and (2) show the personality for ***PWAM***. To fulfill this requirement, new design rules should be studied, such as design of garment style, fabric, color etc.

Some special functions of garment are required by ***PWAM***, including special garment construction, well defined ease allowances, opening and fasteners, and fabric physical property. These functions will further improve the comfort of ***PWAM***.

Fabrics should be specially selected due to the scoliosis and auxiliary tools. Some key physical properties of fabrics for ***PWAM***, such as softness and moisture management, should carefully be determined.

At fashion design level, two categories of restrictions faced by fashion designers in the fashion design process for ***PWAM*** can be found at garment fashion design and garment prototyping. For garment fashion design, the restrictions cover: fabric selection, color design, opening and fasteners verification, garment style design (collars, cuffs, hems...). For garment prototyping, the restrictions cover: garment construction and ease allowance.

1.2 Garment Design Solution for *PWAM*: Fashion Design for Improvement

In fashion design, the human body and clothing create an isolated system [2]. Fashion design is the design of the relationship between the human body and clothing [21]. In this relationship, the human body is the main object of the design [9]. The morphology of human body will influence the shape of clothing [22]. Clothing provides function (convenience and comfort) and decoration for the human body [23]. For ***PWAM***, the function and decoration of the clothing should be emphasized [24].

In this section, the function of clothing decoration will be discussed. Fashion has the function of improvement of visual images of human morphology. There are two principles of the improvement: emphasis (for advantages) and reparation (for shortcomings).

1.2.1 Fashion Design for Improvement

The improvement function of fashion design is developed to realize an ideal visual image of human body [25]. Different design elements, such as shape, color, texture, will be used for the improvement [26].

1.2.1.1 Physical and psychology improvement

The improvement includes two aspects: physical improvement and psychology improvement [26]. The physical improvement aims at increasing the wearer's satisfaction of the human body, while the psychological improvement tries to enhance the wearer's personalized perception about clothing acceptance.

Physical improvement will help to improve the visual image of the wearer [27]. Physical improvement deals with the relationship between the human body and clothing, and permits to adjust the visual image of the human body to a desired "ideal" state [27]. The direction of this kind of improvement is very clear. For example, when designing the collar for a consumer, if he/she is too fatty and his/her neck is relative short (Figure 1-15 A), open collar should be chosen to reduce the visual extension in the horizontal direction (Figure 1-15 B). On the contrary, if he/she is too slim and his/her neck is relative long (Figure 1-15 C), stand collar should be chosen to reduce the visual extension in the vertical direction (Figure 1-14 D).

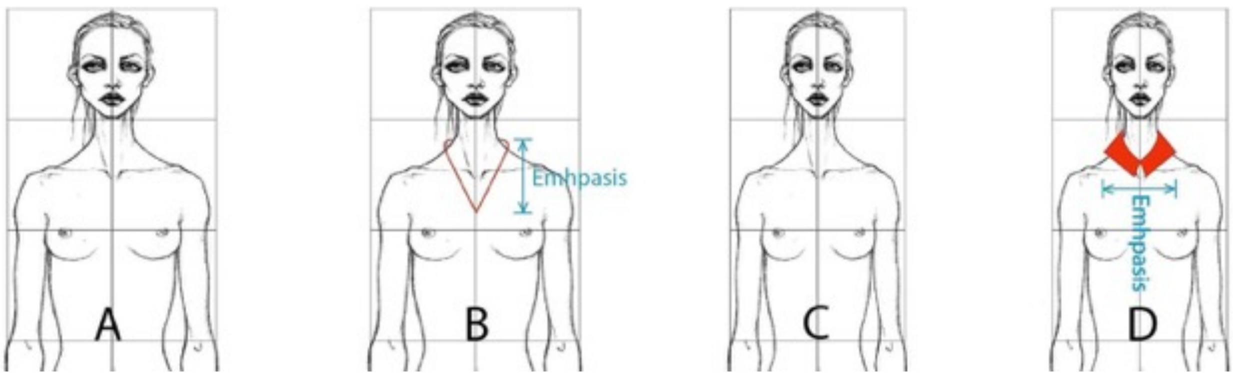


Figure 1-14: An example for physical improvement by using different collar.

Psychological improvement is based on the result of physical improvement [27]. A global satisfaction of the wearer should be considered. In this condition, in order to maximize psychological improvement, different physical improvements should be controlled by using designer's experiences. The final design should a compromise between the consumer's satisfaction and designer's aesthetic expression.

1.2.1.2 Attention Shift

Attention shift is the main principle for design of improvement [28]. Each garment has a "design focus", which is the most striking part of the garment. In fashion design, there are several methods to create the "design focus". Figure 1-15 presents an example for different "design focuses" of a shirt. These "design focus" can be the emphasis of color, texture, shape, and position, respectively.

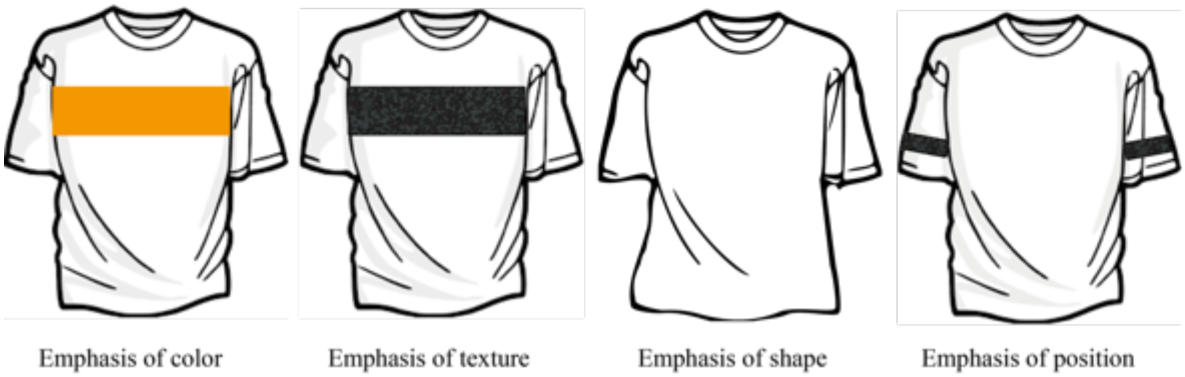


Figure 1-15: An example of different "design focuses" of a T-shirt.

Normally, people turn to pay attention to the morphology of the ***PWAM*** if the garment is not appropriately designed. By emphasizing some specific parts of a garment, the vision of the general public on ***PWAM*** can be shifted in order to mask their physical deformations. In this condition, the visual image of scoliosis will be greatly reduced. Anyway, this emphasis should be consistent with the personality of the ***PWAM***. Extra or inappropriate emphasis will also make ***PWAM*** feel uncomfortable.

1.2.2 Strategies of Fashion Design for Improvement

There are five different principles of fashion design and four different elements permitting to apply these principles. The five principles are emphasis, rhythm, unit, balance and scale and proportion. The four different elements are texture, color, line and form [29]. We take these principles as fashion orientations to be developed and then the design elements as ingredients for realizing these principles. Each design will incorporate all of these different principles, as it is only through a cohesive usage of all principles and design elements that successful and eye-catching designs can be created. Strategies of fashion design for improvement should follow these principles.

(1) Emphasis and Color

The principle emphasis refers to the part of the design to which the eye is instantly drawn [30]. This emphasis element can be anything. The element of color is frequently used for emphasis, such as using contrasting colors. Color is a very frequently used element as everyone has their own favorite color. Color is also used to express a specific mood.

(2) Rhythm

The rhythm principle refers to repeated applications of an specific item [31]. A designer can repeat the same element in a design, such as lines, colors or details, in order to form a pattern [31]. In general, a designer's complete collection usually has a specific rhythm within all the pieces, by using a repeated element in different ways, such as application of a repeated silhouette in some of items of one collection.

(3) Fabric Hand

Fabric hand refers to the nature of the used fabric. It covers different aspects, such as softness, thickness, surface hand feeling, draping performance, etc. Selecting an appropriate fabric is very important for a successful design. For different design criteria, fabric hand requirements will be different [32].

(4) Proportion, Scale and Balance

The principle of proportion and scale ties into the balance principle. The proportion of a design is important to achieve a balance [33]. A person would look very funny with an oversized head, just as a dress would look odd if it had huge sleeves. The two elements, the head and the sleeves, are out of proportion with the rest of the look. It is important to make all designs to scale so that the proportion of each piece is correct. Proportion also refers to a balance as a design can be symmetrical or asymmetrical. Asymmetrical balance can be quite striking, but each piece needs to be properly proportioned or a person will look lopsided.

(5) Lines

The element of the style lines refers to the outline or silhouette of the design [34]. There are many accessories and items that can be used to create different lines [34]. One very well-known example of a line is the A-line. The A-line can use belts or fitted waists. From the waist, the skirt flares out creating an “A” shape.

(6) Unity

The principle of unity refers to making all elements of a design in a harmonic orientation. A design that has unity will have a sense of completeness while a design that does not achieve unity will leave the viewer wondering if the design is finished [35]. Accessories are often used to add unity to a design.

(7) Shape and Form

The element of shape and form refers to the visual impact of a design [33]. This is one of the first issues that a person can identify from a design. The form refers to the complete shape of a design or garment. The main goal of the shape is to complement or fit a specific body type. The shape and form can emphasize specific areas of the body while downplaying other less desirable areas. The shape tends to vary with current fashion trends.

1.2.3 Garment Fashion Design Rules for the Improvement *PWAM*

1.2.3.1 Color and Fashion Design Improvement

Color is the most attractive design element of a garment [36]. Compared with shape, color can be more easily recognized by human eyes [15]. Normally, when people stay far from an object, only the color information can be received by eyes. Only when the observer goes close to the object, the texture and shape of the object can be received by eyes [37].

Take ***Physically Disabled People with Scoliosis (PDPS)*** as an example, using appropriate color combination, visual illusion can be created to improve the visual image of scoliosis. For example, straight vertical stripes with bright color can emphasize the visual image of "straight" (Figure 1-16). In this case, color draws the attention of the public, which corresponds to the principle of "Attention Shift", as discussed in Section 1.2.1.2.

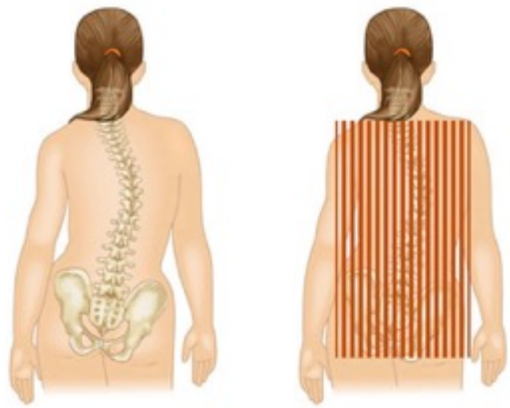


Figure 1-16: An example of different "design focuses" of a T-shirt.

1.2.3.2 Fabric and Fashion Design Improvement

There are different fabrics used in a piece of garment, including outer fabric, liners, and accessories fabrics. An outer fabric will decide the texture of a garment. Fabric selection should be combined with the desired garment shape. For example, if the silhouette of a designed garment is not conventional, the selected fabric should have good shaping properties. The problem of over slim will happen with scoliosis for ***PWAM***. For this group of people, knitted fabric should be avoided because it will make the wearer look slimmer [38]. There are always some deformations on the shoulders of ***PWAM***. In this condition, fabric with special texture can be used to design more details on the shoulders of ***PWAM***.

1.2.3.3 Fashion Details and Fashion Design Improvement

Fashion details of a garment will determine the garment style. For each detail, its size, shape, color should be carefully designed [2]. These details include collar, hem, cuff… For ***PWAM***, fashion details should be emphasized on the placket, collar and shoulder. For example, Figure 1-

17 presents several design cases using decorations on the collar and visible placket with color contrast to improve the visual image of ***PDPS***.

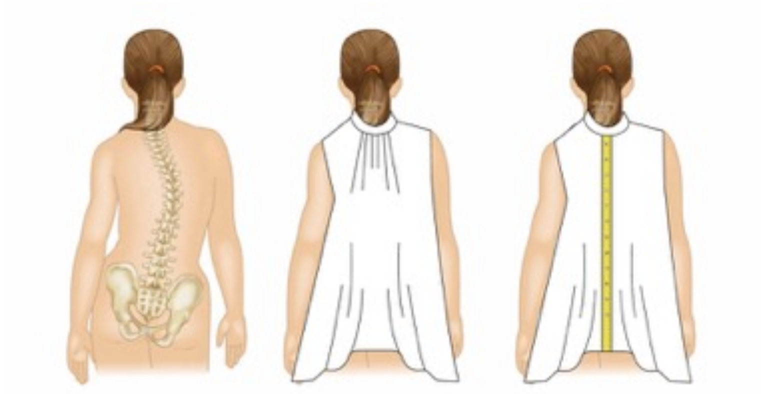


Figure 1-17: Some examples for fashion details design of shirt for *PDPS*.

1.3 Garment Fit Solution for *PWAM*: Virtual Garment Prototype

Garment prototype is used to generate garment patterns with defined garment construction and ease allowance [39]. A pattern is the actual copy of different parts of a garment that is made by cutting board paper after sketching on it [39]. According to this pattern, cloth is cut and then the garment is made. In this section, different garment prototyping methods will be analyzed in order to find the best solution for ***PWAM***.

1.3.1 Traditional Garment Prototyping

The modern garment prototype method is based on a traditional 3D-to-2D draping process [40]. Garment patterns are obtained by flattening fabric pieces from a 3D physical mannequin using fabric-draping process [41]. Using this method, garment block patterns, as the foundation of traditional 2D-to-3D method are developed [41]. Using traditional 2D-to-3D method, garment patterns are generated by the extension and sizing of garment block patterns. With the development of computer-aided design, the traditional 2D-to-3D method can be operated in a virtual environment.

1.3.1.1 Traditional 3D-to-2D Prototyping Method

In the traditional 3D-to-2D garment prototyping method, garment pattern pieces are generated from a 3D physical mannequin using fabric-draping process [14]. The draping process is frequently used by designers for quickly generating the form of a garment by mouldings, cutting and pinning fabric to a mannequin or individual [42]. Style lines and construction details of the drape are carefully marked and removed step by step [43]. Fabric pieces with the construction and style details are generated. Darts will be generated at the same time in the previous steps. The fabric pieces are then laid to be flat and traced over a pattern paper [44]. The pattern is finalized by adding directional marks such as grain lines, notches, buttonholes, correct seam and hem allowances and facings [45].

Figure 1-18: Process of traditional 3D-to-2D garment prototyping (garment draping).

Traditional 3D-to-2D garment prototyping (garment draping) includes two important processes: fashion draping and ease allowance definition [10]. These processes are usually done with muslin (an inexpensive, unbleached, loosely woven cotton) to resolve any design and fitting issues of a garment before cutting the pattern in real fabric [46]. However, it is important to drape using a fabric that has similar drape characteristics (the way it falls and folds) as the real fabric of the finished garment. Muslin comes in a variety of weights, and inexpensive synthetic fabrics can also be used in fitting and draping for apparel design [47]. The draping process will be performed by fashion designers in different body parts i.e. front bodice, back bodice, front skirt, and back skirt. Normally, only the right side of the garment (when worn) will be draped, unless the apparel design is asymmetrical.

1.3.1.2 Traditional 2D-to-3D Prototyping Method

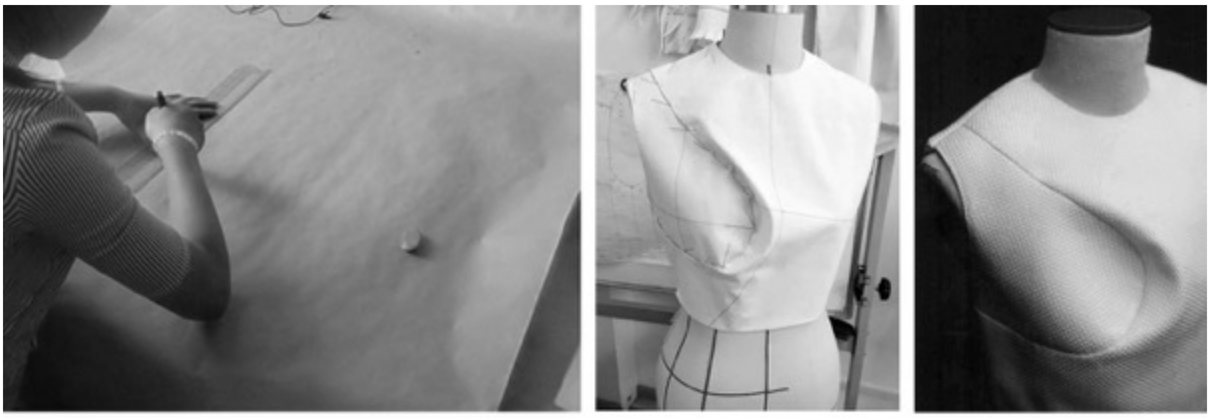


Figure 1-19: Process of traditional 2D-to-3D garment prototyping

In the traditional 2D-to-3D garment prototyping method, 2D garment patterns are sketched manually on the paper based on the measurements of the wearer [41]. Figure 1-19 presents the process of traditional 2D-to-3D garment prototyping. Using traditional 2D-to-3D garment prototyping method, all the necessary information will be defined directly on the paper, such as notches, buttonholes, correct seam and hem allowances and facings. This set of garment patterns will be later assembled through a real sewing procedure to produce realistic garment sample. Then, based on the real garment sample, designers will validate the proposed 2D garment patterns and then modify them on the paper. This process will be repeated for several times until the desired design is obtained.

1.3.1.3 Virtual 2D-to-3D Prototyping Method

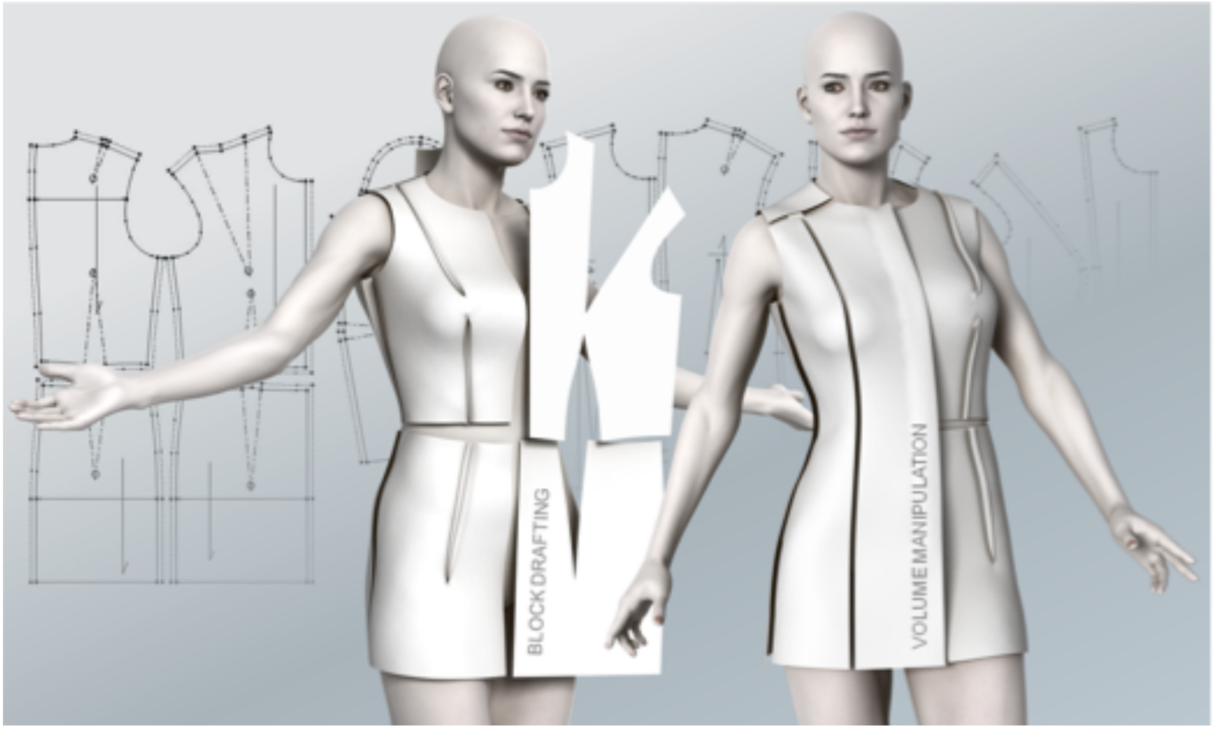


Figure 1-20: Process of virtual 2D-to-3D garment prototyping.

Virtual 2D-to-3D garment prototyping is realized based on the development of computer-aided design technology [48]. The general method and principle of virtual 2D-to-3D garment prototyping follow that of traditional 2D-to-3D garment prototyping method [49]. Different from traditional 2D-to-3D garment prototyping method, all the process of virtual 2D-to-3D garment prototyping will be performed in a virtual environment [39]. Virtual 2D-to-3D garment prototyping ensures fast validation of the pattern within a very short time. It can be done automatically based on the tools of virtual 2D-to-3D garment pattern design software. Virtual 2D-to-3D garment prototyping method greatly reduces the cost and time of pattern design and ensures a fast design validation. Figure 1-20 presents the process of virtual 2D-to-3D garment prototyping.

1.3.2 Virtual Garment Prototype: Virtual 3D-to-2D Method

The virtual 3D-to-2D garment prototyping method is based on the 3D scanning and 3D virtual simulation technology [48]. It occurs in the last three or four years. As a novel garment prototyping method, it draws a lot of attention from both fashion designers and pattern designers.

1.3.2.1 3D Scanning and Human Body Surface Modeling

The 3D body scanning technology is developed and applied in clothing industry for human body measurements and clothing fitting [14]. The three most used applications are described below [50]:

(1) Human body measurements

The 3D body scanning technology can ensure quick and consistent extraction of body measurements and generate customized fit [51]. As well as linear measurements, scanning can easily extract a vast number of data types and measurements related to shapes, angles, and relational data points. An accurate 3D representation of a garment and its relationship with the wearer's body morphology can be captured while minimizing visual distraction. The extracted measurements and the virtual picture constitute the foundation for individual pattern construction.

(2) Human digital data mining

Due to the fast and automatic human body measurements with the 3D scanning technology, the data on the human body surface can be collected more efficiently [39]. These collected data can be further applied to various human body data mining tasks, such as human morphology classification.

(3) 3D human body modeling

The 3D body scanning technology enables to generate a set of discrete cloud points describing the human body surface. By using an existing surface modeling software, all these cloud points can be gathered to form a continuous 3D surface. The obtained 3D human body surface in a virtual space can be further applied for simulating the 3D virtual fitting effects of a virtual garment on its body surface.

1.3.2.2 General Principle of the Virtual 3D-to-2D Prototyping Method

By using the 3D laser body scan, surface reconstruction and virtual reality technology, the virtual 3D-to-2D prototyping method emerges as a new solution to personalization service in fashion industry [52]. The general process of Virtual 3D-to-2D prototyping follows that of the traditional 3D-to-2D prototyping method in a virtual environment [14].

Using the virtual 3D-to-2D prototyping method, a personalized garment is prototyped directly on a 3D human body model surface in order to develop the corresponding garment patterns [53]. By using the virtual 3D-to-2D prototyping method, the process of garment product design and development can be changed in order to generate personalized design solutions satisfying the wearer's garment design requirements.

Compared with the traditional design methods, such as the traditional 3D-to-2D and 2D-to-3D prototyping methods, the virtual 3D-to-2D prototyping method is more adapted to atypical morphologies because general design rules cannot be available for this population. Also, designer's idea can be more easily realized in a 3D visualized space. However, this method is relatively less accurate than the traditional methods. In this situation, the accuracy of design can be enhanced by combining the two design software systems: the virtual 3D-to-2D method and virtual 2D-to-3D method. The former can be used for generating initial patterns and latter for visualizing the virtual garment fitting effects and making adjustments on the initial patterns.

Moreover, the current virtual 3D-to-2D garment prototyping has been focused on the development of a 3D garment directly on the scanned body. However, due to the diversity of ready-to-wear garment styles, 3D garment simulation requires not only high-level technical support of the software, but also an experienced designer to manually perform the design process. It is difficult to extract systematic design rules for designing ready-to-wear products of all kinds of styles using the virtual 3D-to-2D design method. To avoid this problem, we propose to first develop personalized garment block patterns using a virtual 3D-to-2D design method. These garment block patterns can be further extended to accurate 2D garment patterns for generating ready-to-wear products of desired styles. In this way, time, labor and technical expenses can be largely reduced. For example, we recently developed a garment block design method by defining a set of landmarks along with corresponding ease allowance controlling lines on the scanned body surface [39]. Using the surface reconstruction technology, a personalized garment block pattern can be obtained. However, the precision of the design effect largely depends on the quantity of defined landmarks. The ease allowance of each landmark should be given manually, which is also rather complex. Thus, a more efficient 3D-to-2D design method is required for garment block generation.

1.3.3 The proposed *Virtual 3D-to-2D Garment Prototyping Platform (VGPP)*

In my PhD research, a ***Virtual 3D-to-2D Garment Prototyping Platform (VGPP)*** is proposed for simulating personalized ready-to-wear products for ***PWAM***. The proposed platform is based a virtual 3D-to-2D prototyping process and several garment CAD software. The proposed design process begins with designing a personalized garment block first, which can be further extended into a garment style for the desired ***ready-to-wear (RTW)*** product. The personalized garment block can be realized by using the proposed virtual 3D-to-2D prototyping method, which drapes the shape of the garment block on the scanned human body directly, in a 3D virtual environment. The extension and sizing of the garment block pattern into desired ready-to-wear garment patterns is carried out in a 2D environment using the classic methods.

Garment block, regarded as a primary design of the ***ready-to-wear (RTW)*** product, has all the essential elements of a garment such as the construction, opening, darts, controlled ease, without extra style information [39]. Compared with the style of the ***ready-to-wear (RTW)*** products, which is rather subjective, an agreement for the general shape of a garment block can be easily reached by designers without too many conflicts between them. In this study, the research domain is mainly on the introduction of the development of a sleeveless garment block, which can be fast applied to the atypical morphology. Design and construction of the sleeves are not involved in the proposed design method. In fact, by detecting the circumference of different armhole curves on the obtained garment block body, sleeves can be easily obtained by using the 2D classic pattern design method. This will certainly reduce the complexity of the proposed design method.

An evaluation session is performed by both designers and consumers, based on the designed virtual garment obtained from the proposed method. For adjusting unsatisfied design effects, design knowledge and experience of designers will be used in order to provide improved solutions. Using this method, the concept of knowledge-support design is applied so as to enhance consumers' satisfaction.

1.4 General Notions of Recommendation Systems

A traditional design process largely depends on the experience of the designer. Therefore, consumer requirements cannot be fully satisfied in the design process. In this condition, the recommendation system is proposed in my PhD research in order to complete the experience of the designer with additional design knowledge.

A recommendation system is an information filtering system that seeks to predict the "rating," "preference," or "relevancy" that a user would give to an item or social element not yet considered, using a model built from the characteristic of an item or the user's social environment [54]. Recommendation systems are decision support systems that will help both the designer and consumer to quickly obtain the desired product [55]. In this section, the existing recommendation systems along with their application in clothing industry will be analyzed.

1.4.1 Existing Recommendation Systems and Their Application in Clothing Industry

Recommendation systems have become increasingly popular in recent years, and are utilized in a variety of areas including movies, music, news, books, research articles, search queries, social tags, and products in general [56]. There are also recommendation systems for experts, collaborators, jokes, restaurants, garments, financial services, life insurance, and online social networks [57].

These systems are mainly classified into three categories: 1) the content-based filtering approach, aimed at discovering product attributes and relations between products and between customers, 2) the collaborative filtering approach, aimed at exploiting information about user interaction and transactions, such as product ratings and orders, and 3) the hybrid approach, which combines the previous two. Recommendation systems have been developed in different economic sectors, such as e-shopping, web searching, education, and tourism [58].

Recommendation systems have attracted much attention in the clothing industry for realizing personalized garment design, including personalized fashion styles and colors and optimized fit between body shapes and garments. Both fashion designers and garment consumers can benefit from these systems in terms of identifying a new product that is the most relevant to a customer's personalized requirements in fashion, fit and comfort.

An intelligent fashion design system was developed by integrating a cognitive model, the multi-criteria decision field theory, with a genetic algorithm to model the personalized style preferences, and trying to account for the contextual effects occurring in multi-criteria decision making and getting a fast prediction of the costumer's fashion style decision in the meantime. For example, a recommendation system that supports online garment selection based on the customer's tastes was proposed by Sekozawa using the analytical hierarchy process [59]. L.C. Wang proposed a design style recommendation system integrating professional fashion designer's knowledge and human perceptions on human bodies, fashion themes, garment styles and their relations [59]. J.J Zhang developed a consumer-oriented intelligent jeans recommendation system based on market forecasting and social network, which is more robust and interpretable owing to its capacity of treating uncertainty in the recommendation process [60].

1.4.2 Personalized Fashion Recommendation System and Fashion Big Data

A personalized fashion design support system deals with personalized consumer requirements. These requirements including the ***functional, expressive, and aesthetic (FEA)*** aspects, which constitute the input of the recommendation system [32]. In the recommendation process, different categories of design elements will be processed using different pre-defined design rules. Then design elements in different categories will be recommended and integrated into the final product form, which constitute the final output of the recommendation system. These design elements include fabric, color, garment style, garment construction, garment opening and fasteners.

The core of the recommendation is the pre-defined design rules. These design rules are based on the designer's' knowledge and experience, corresponding to consumers' requirements. There are two different types of design rules in my PhD research: popular fashion design rules and specific design rules for PDPS discussed in Section 1.2. Popular fashion rule is strongly related to current fashion trends. These fashion trends are created by fashion institutes, color trend forecast agencies, fashion blogs, and social networks. Data related to fashion trends is created very fast and always dynamically changing. Specific design rules for PDPS are developed based on the theory of fashion design for improvement. These rules developed from this theory are unlimited. New design elements from the open resource will help to generate new design rules, such as the new functional fabric developed by institutions. Besides, consumers' requirements are always evolutionary. There are different fashion data types related to personalized garment recommendation. These data are evolutionary and occurring at an unprecedented rate. In this condition, the personalized fashion recommendation system for ***PWAM*** should be able to deal with recommendation in big fashion data environment. This constitutes one of the main research focuses in the proposed system.

1.5 Foundation of a *Personalized Garment Design Support System (PGDSS)* for *PWAM*

In my PhD research, we propose a ***Personalized Garment Design Support System (PGDSS)*** for ***PWAM***, based on consumer's fashion requirements and scanned consumer's body morphological data. There are two subsystems in the proposed system: 1) the ***Personalized Fashion Recommendation System (PFRS)***, and 2) the ***Virtual 3D-to-2D Garment Prototyping Platform (VGPP)***. The ***Personalized Fashion Recommendation System*** aims at selecting the best fashion design solution (color, fabric, garment style) for a specific consumer, while the ***Virtual 3D-to-2D Garment Prototyping Platform*** enables to realize garment pattern design for this consumer and visualize the corresponding fitting effects.

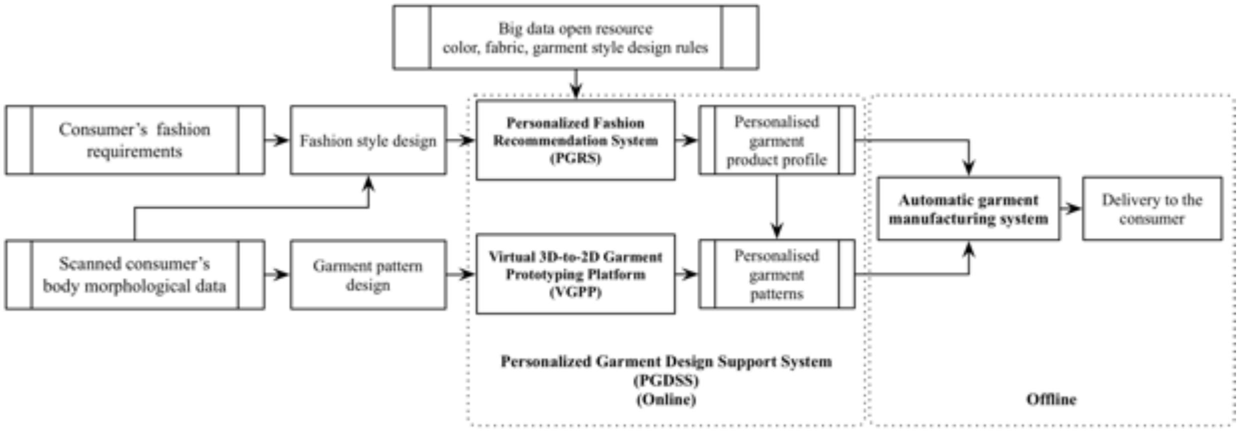


Figure 1-21: Brief principle of the proposed *Personalized Garment Design Support System* (*PGDSS*).

The proposed ***PGDSS*** (see Figure 1-21) starts with a collaborative design process for fashion recommendation. Consumer's fashion requirements and scanned consumer's body morphological data will be processed by the ***PFRS*** in order to generate a personalized product profile for a specific consumer. Then, the information of the product profile will be processed by the ***VGPP***. First, a virtual 3D-to-2D garment prototyping process will be performed. After this step, a set of personalized garment patterns of the recommended garment will be generated. This set of garment patterns along with its product profile will be further transmitted to a garment manufacturing system (classical or automatic) for generating real prototypes. The final garment product will be simulated and delivered to the consumer.

From the point of view of consumers, the proposed system can effectively reduce current inconveniences of ***PWAM*** in fashion shopping. From the point of view of textile professionals, this system is critical for reducing the product design and production cost and increasing the decision-making quality. This section only presents the brief principle of the proposed ***PGDSS***. More details about its functions and related concepts will be presented in Chapter 2. Chapter 3 will describe the related knowledge and data acquisition techniques and computational tools for realizing the proposed system.

1.6 Conclusion

In this chapter, we first introduced the state of the art of fashion related issues faced by ***PWAM*** and concerned garment design concepts and principles, such as the theory of fashion design for improvement and 3D virtual garment prototyping. Next, we extensively discuss the drawbacks of the current garment design methods for ***PWAM***. Based on this analysis, we propose to develop an intelligent knowledge-based personalized garment design support system in order to help designers and ***PWAM*** develop personalized garment products rapidly and effectively. The development of this knowledge-based personalized garment design support system constitutes the main axis of my Ph.D. work. Its details will be further presented in the following chapters.

Chapter 2 General Framework and Working Process of the Proposed *Personalized Garment Design Support System (PGDSS)*

In this chapter, the general framework and working process of the proposed ***Personalized Garment Design Support System (PGDSS)*** is presented. Brief introductions on each of its subsystems are also given together with the involved concepts.

2.1 General Framework of the Proposed System and Related Principles

2.1.1 General Framework and Working Process of the Proposed *Personalized Garment Design Support System (PGDSS)*

As described in Section 1.5, the Inputs of the proposed system are: (1) consumer's fashion requirements, and (2) scanned consumer's body morphological data. All these input data will be first processed by ***PFRS*** in order to generate a personalized garment product profile (including color, fabric and garment style information).

The inputs on consumer's fashion requirements are composed of three categories: color related inputs, fabric related inputs and style related inputs. Three subsystems of the ***PFRS***: ***Color Recommendation System (CRS)***, ***Fabric Selection System (FSS)*** and ***Garment Style Recommendation System (GSRS)***, will process these three categories of inputs respectively. Different design elements, such as color, fabric and garment style will be generated through the PFRS, and formulate a personalized garment product profile.

Then, the data in the product profile will be further processed by the ***VGPP*** along with the scanned consumer's body morphological data. First, the scanned consumer's body morphological data will be used to create a virtual mannequin. Based on this virtual mannequin of the consumer, a virtual 3D-to-2D garment prototyping process will be performed. The working process of the ***VGPP*** starts with simulating a personalized garment block for the consumer. An evaluation is also performed by the designer and consumer based on the virtual garment block. The final satisfied garment block will be extended and graded in order to reach the desired garment patterns as described in the product profile. This set of personalized garment patterns along with its product profile will be further transmitted to a garment manufacturing system (classical or automatic) for generating real prototypes. The final garment product will be simulated and delivered to the consumer.

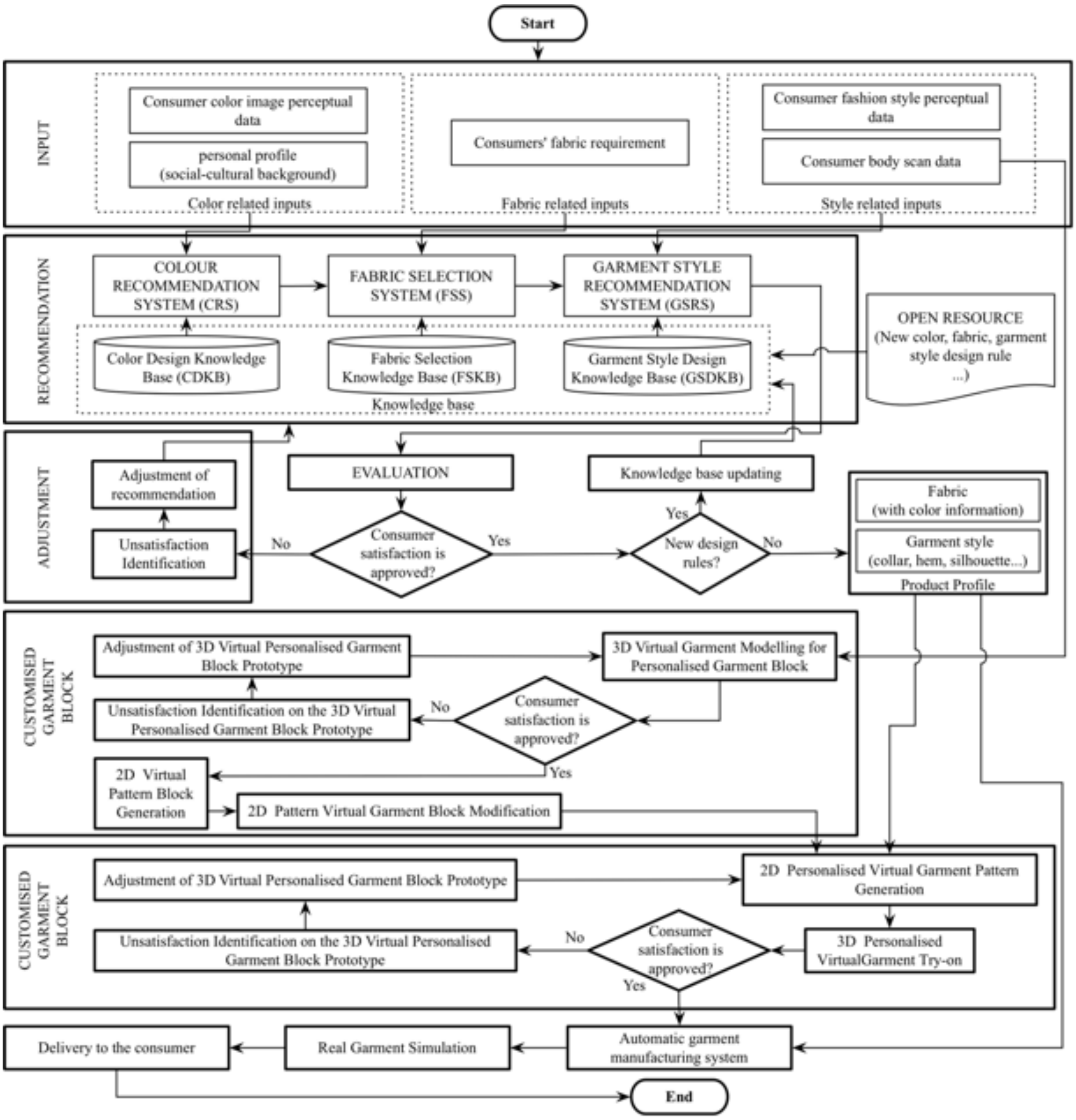


Figure 2-1: General framework and working process of the proposed Personalized Garment Design Support System.

In order to realize the proposed system, three knowledge bases: ***Color Design Knowledge Base (CDKB)***, ***Fabric Selection Knowledge Base (FSKB)***, and ***Garment Style Design Knowledge Base (GSDKB)***, have been predefined in order to support the concerned three recommendation subsystems of the ***PFRS*** respectively. Related design rules (color design rules, fabrics selection rules, and garment style design rules) are formalized and stored in these knowledge bases. Moreover, new design rules extracted from the open resource (fashion trend reports, fashion magazines…) can be integrated into these knowledge bases, and then enhance the recommendation accuracy of the proposed system.

The working process of the ***PFRS*** is a collaborative design process between the designer and the consumer, which follows a sequence of ***Design–Display–Evaluation–Adjustment***. There is an evaluation session after the generation of the personalized garment product profile. If the consumer is not satisfied with the proposed design, he/she will be requested to point out the unsatisfied elements. Based on the feedback of the consumer, the system will adjust the proposed design automatically. This process will be repeated until the consumer is satisfied. In this situation, the system will detect if there is a new design rule to be generated or not. New design rules will be integrated into the related knowledge base, which will be used to enhance the success of the whole system in the future.

The proposed ***PGDSS*** is a knowledge-based dynamic recommendation system enables automatic fashion design for ***PWAM***. It can be fully integrated into an e-commerce platform. A fast validation of the design solution can be realized by the proposed system. Consumers can fully participate in the whole design process. Information exchange can then be strengthened between designers and customers in the decision-making process.

2.1.2 Knowledge Integration and Collaborative Design

The core of the proposed Personalized Garment Design Support System is the knowledge bases and collaborative design process. Knowledge and experience of the designers are extracted in order to form related design rules supporting the working process of the proposed system. The collaborative design process enables interactions between designers and consumers for proposing new design solutions. Such interactions ensure the success and working efficiency of the proposed system.

Traditionally, a fashion design process largely depends on the knowledge and experience of the involved designer. Different design knowledge will be utilized by this designer regarding different design criteria, such as current fashion trend, the customer's requirements, and his/her personalized design expressions. It can be concluded that knowledge and experience of the involved designer plays an important role in the fashion design process.

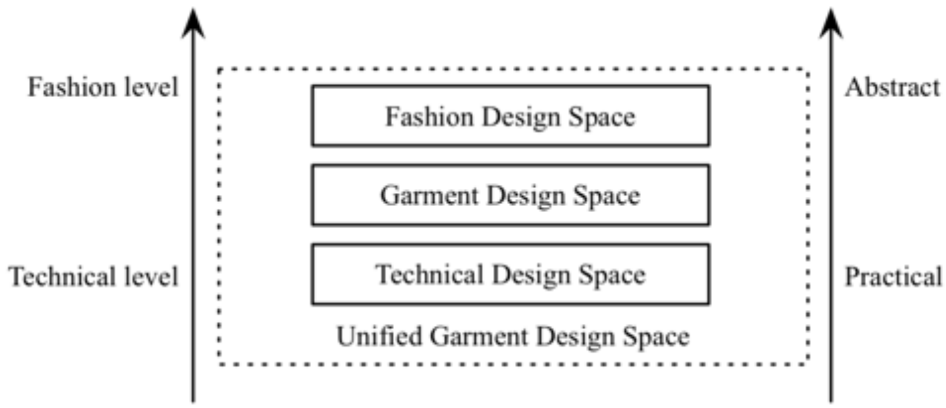


Figure 2-2: The conceptual structure and features of the unified garment design space.

The proposed ***Personalized Garment Design Support System (PGDSS)*** follows the traditional fashion design process. Different design knowledge, regarding different stages of the garment design and development, will be extracted and integrated into the proposed system.

In my research, a classification of the knowledge based on the design process is carried out in order to integrate knowledge into different subsystems. By analyzing the personalized garment design process, we identify three spaces, namely fashion design space, garment design space and technical space, used for building up a unified garment design space. The relationships among these spaces can be from technical level to fashion level, from practical to abstract, as described in Figure 2-2.

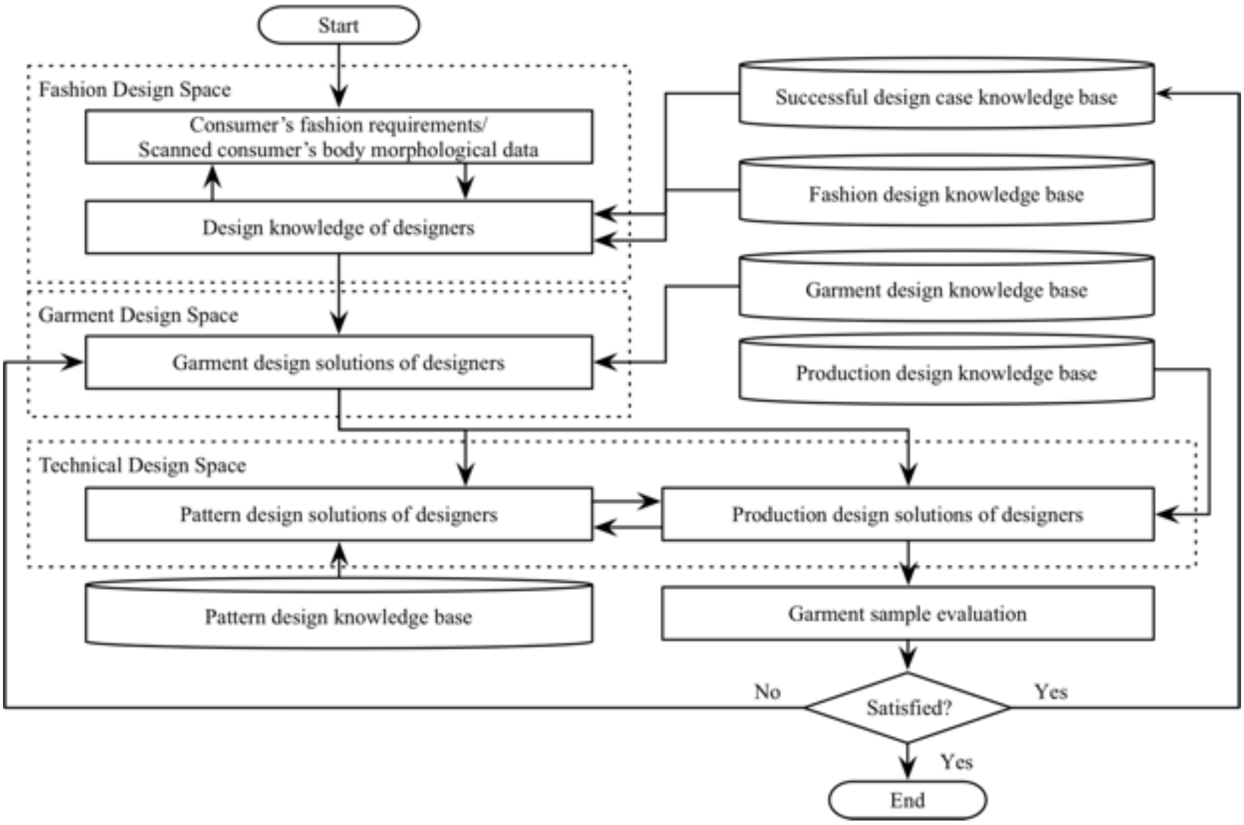


Figure 2-3: Different stages of a general garment development process and the related knowledge bases.

The different stages of a general garment development process and related knowledge bases are described in Figure 2-3. Traditionally, at the beginning of the garment development process, consumer's fashion requirements and scanned consumer's boy morphological data should be analyzed by designers using their professional knowledge in order to obtain fashion design solutions. In this interactive communication process, a proposed design solution can be fully controlled by the perception of the customer and designer. Except for the professional knowledge obtained from designer's experience, a number of successful design cases meeting specific requirements of different consumers can also provide references and inspirations for further generating relevant design solutions (patterns, color, fabrics, accessories, …). Using the virtual garment generated from the selected design solution, an evaluation will be performed by the consumer. If the customer is not satisfied with the visualized virtual garment, the corresponding design solution will be adjusted. If the customer is satisfied with the final result, the data on the consumer's body shape and body measurements, as well as his/her personalized requirements alone with the selected design solution will be stored into the Successful design case knowledge base, which can be used to similar new cases in the future.

2.2 *Personalized Fashion Recommendation System (PFRS)*

For a specific consumer, the proposed ***PFRS*** deals with his/her personalized fashion requirements related to PEA and permit to select the most appropriate design elements of the desired garment product. These design elements include: color, fabric and garment style. The recommended/selected design elements form a final personalized garment product profile of the consumer.

There are three subsystems existing in the proposed ***PFRS***: ***Color Recommendation Subsystem (CRS)***, ***Fabric Selection System (FSS)*** and ***Garment Style Recommendation System (GSRS)***. The working flow of the ***PFRS*** is ***CRS-FSS-GSRS***.

2.2.1 *Color Recommendation System (CRS)*

2.2.1.1 Research Background of *Color Recommendation System*

Strongly related to the visual image of a garment, color is one of the major attributes that affect consumer's perception of a garment [61]. Normally, in the process of color design, several single color combinations, known as color range (Figure 2-4-b), will be determined by designers [62]. ***Color range (CR)*** of a product plays important roles in beautifying the product, improving the competitiveness and satisfaction grade of the good, and enhancing the efficiency of the designer's work [63]. As the most visually impactful part of a garment, color has a direct impression on consumers, which makes it one of the key elements determining the value property of a garment in commodity circulation in the market [64]. Recently, consumers' personalized demands on fashion products have become more and more increasing. Both designers and consumers are requiring a fast and efficient color recommendation. In response to this situation, color research institutes, color trend forecast agencies, fashion blogs, social networks are creating and promoting color recommendation related information to both designers and consumers.

Explosion of color recommendation related data is occurring at an unprecedented rate. These data can be generally classified into two groups: consumers' color image perceptual data and color trend data. Color trend data normally refers to the most "trendy" ***color image words (CIWs)*** and their related ***CR***s (see Figure 2-4-b). ***CIW***s describe the color symbolism of expected ***CR***s. These data are widely concerned by both designers and consumers. In the real design/recommendation process, in order to shorten product life cycles, the color trend information should be quickly received and applied to color design/recommendation [65]. However, in practice, both consumers' color image perception and color trend are dynamical and quickly vary with time and socio-culture [63]. The data concerned by color recommendation are diversified, complex, and massive [66]. It is very difficult (or impossible) to manage these data using traditional data processing methods. In fact, color recommendation can be regarded as a decision-making problem in an open resource or big data environment.

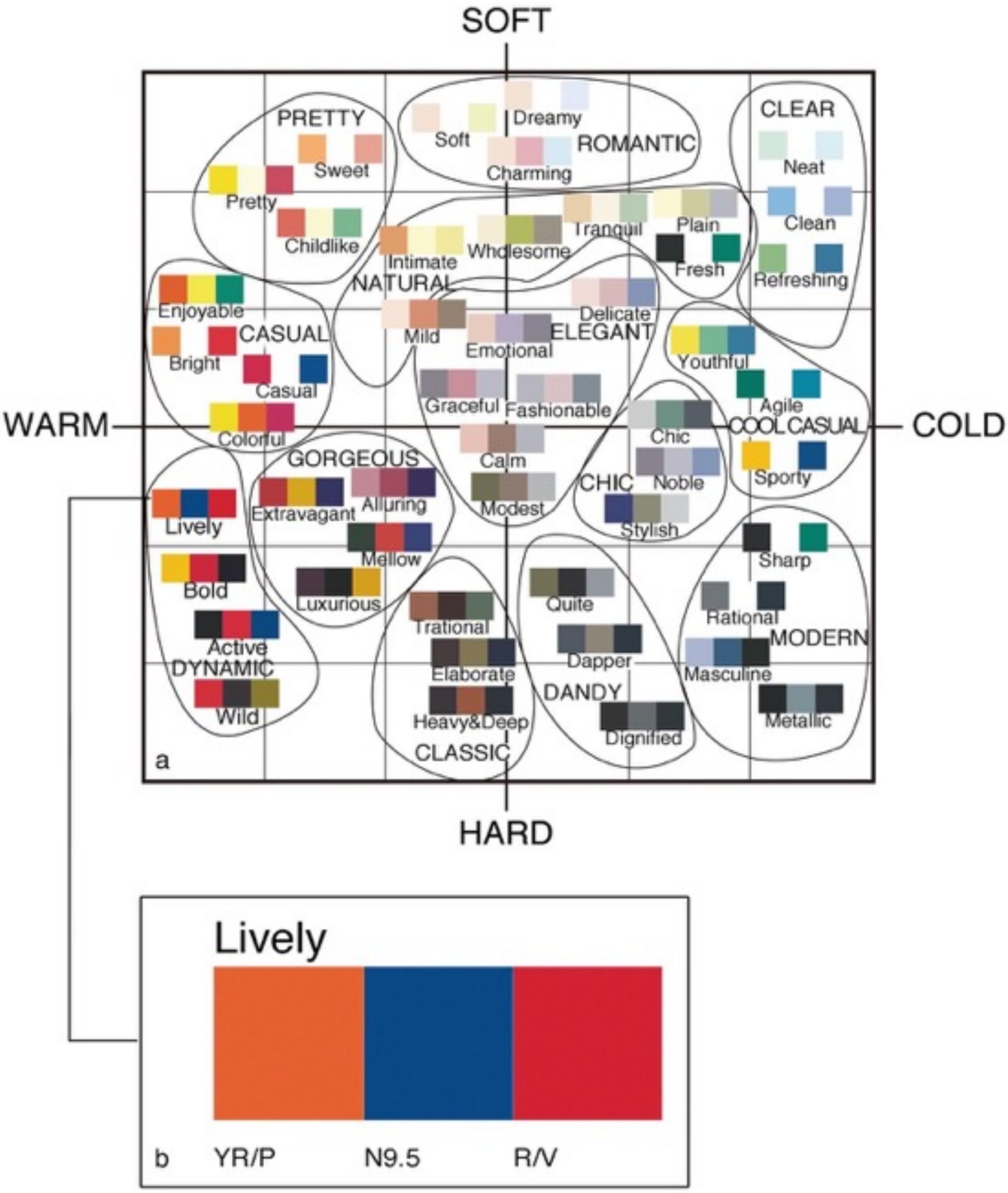


Figure 2-4: Color Image Scale developed by Kobayashi: (a) 180 *CIW*s, their corresponding *CR*s and measurements in a 2D *CIS*; (b) *CR*s, their descriptive *CIW*s and physical color properties.

Traditionally, in the process of personalized ***product design and development (PD&D)***, a recommendation of an appropriate ***CR***, starts by offering the consumer a few ***CIW***s of expected finished products [37]. Then, the consumer's color image perception represented by the ***CIW***s will be analyzed by designers using their knowledge and experience and referring to the current color trend [67]. After several interactions between consumers and designers, the final optimized ***CR*** can be determined. This ***CR*** will be further applied to determine the final visual presentation of the desired product. In practice, there are always differences between designers and consumers on understanding and description of color symbolism when using ***CIW***s [36]. These perceptual differences are caused by the cross-cultural background and linguistic gaps of involved designers and consumers [15]. The traditional method is strongly related to the professional level of the designers, which is not only time consuming but also cannot ensure a stable accuracy of the color recommendation results.

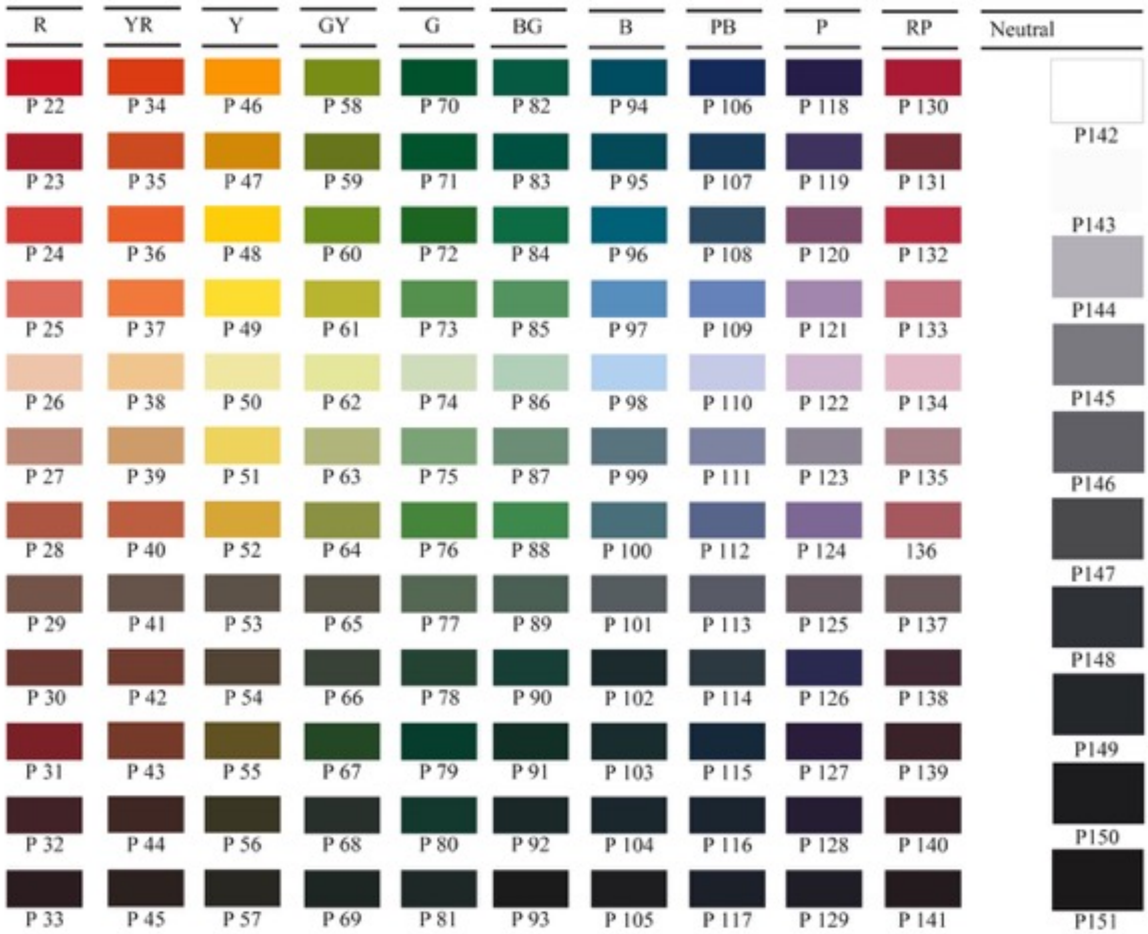


Figure 2-5: 130 Colors used in my PhD research include 120 chromatic colors and 10 achromatic colors.

To solve this problem, there are some researches focusing on automatic color recommendation. For example, Meier proposed a color design system for automatic ***CR*** generation based on several color rules [68]. Cohen developed an automatic recolor method for a given color palette through an optimization process for human-machine interactions [68]. However, there are still some drawbacks in the current color recommendation systems. First, none of these systems can ensure stable recommendation accuracy. Second, understanding of consumers' color image perceptual data is rather weak. Third, related design/recommendation rules are very restricted and easily influenced by the cross-cultural backgrounds of involved designers and consumers. Fourth, these systems do not enable to dynamically process color recommendation-related information. For example, evolutionary consumers' perception on the latest color trends cannot be quickly integrated into these systems. To solve these problems, a dynamical color recommendation process, capable of dealing with perceptual data of consumers' time-varying color images without being affected by cross-cultural factors, and processing the latest color trend information, is required by both designers and consumers.

Color recommendation systems are based on the study of color image perception. In these researches, products with single color and ***CR***s are evaluated and symbolized by ***CIW***s using fuzzy set theory or the Kansei engineering-based expert system. ***Color Image Scale*** is a study about color image perception established by Kobayashi [37]. In ***Color Image Scale***, same format with the standard color trend, 180 ***CIW***s related to mood, lifestyle and taste are selected to describe over 2000 ***CR***s (see Figure 2-4-a). These ***CR***s are determined by 130 basic colors, including 120 chromatic colors and 10 achromatic colors (see Figure 2-5). As a classic color resource used by designers and manufacturers from different countries, ***Color Image Scale*** is a widely used systematic database that has proved to be mature and reliable. However, in Kobayashi's ***Color Image Scale***, color image perception of the involved 180 ***CIW***s is measured in a 2D ***CIS*** (Abscissa: *Soft–Hard*, Ordinate: *Warm–Cold*), which is not sufficient to measure rich emotions of the color image perception of human beings. In this study, a new multidimensional ***CIS*** will be defined. ***CIW***s and ***CR***s of Kobayashi's ***Color Image Scale*** will be re-characterized in the proposed ***CIS***. These ***CIW***s and ***CR***s will be applied as the initial database of the proposed color recommendation system. Further, referring to color trends, these ***CIW***s and ***CR***s of the proposed system will be updated.

Based on the existing work, we propose a knowledge-based color recommendation system that can recommend the most appropriate ***CR*** for industrial products. The proposed system is an open system, which is capable of dynamically dealing with consumers' color image perceptual data and integrating the latest color trend. Color design rules are extracted by designers using their professional knowledge through a series of human evaluation experiments. Using these rules, ***CIW***s developed by Kobayashi can be identified in a novel multidimensional ***CIS*** defined by a set of ***Basic Color Sensory Attributes (BCSAs)***. In the same way, color trend from an open resource will be evaluated by designers and integrated into the proposed system. ***BCSA***s applied in my PhD research are carefully selected for an easy understanding by consumers. For example, "*Warm–Cold*", can effectively avoid linguistic confusion. Also, the recommendation process is based on case-based machine learning, realized by similarity measurement. Successful recommendation cases of the proposed system are stored in a predefined ***Successful Cases Database (SCD)***. This ***SCD*** includes consumer's socio-cultural data (gender, religion and education background and other cross-cultural background factors), color image perceptual data measured in the ***CIS*** regarding ***BCSA***s and satisfactory color recommendation results. Data of a new consumer will be compared with the ***SCD*** in order to find the most similar case. The corresponding ***CR*** of this case will be reused by the system as a recommendation result. Through interactions with the consumer on evaluation of satisfied and unsatisfied attributes of the recommended ***CR***, a feedback mechanism is established for generating new recommendations. New design cases will be retained in the proposed ***SCD*** in order to increase the accuracy of recommendations.

The novelties of the color recommendation system with case-based learning include the following aspects: (1) Compared with the current research results, the input of the consumer is simplified by using a set of ***BCSA***s that are easily recognized by non-specialists without professional knowledge. (2) A multidimensional ***CIS*** is established to provide more possibilities for expressing the rich emotions and perceptions of human beings. (3) As a case-based learning system, real-time recommendations can be realized, permitting to avoid cross-cultural factors. (4) The proposed system is an open resource-based system, capable of progressively integrating new recommendation rules (new ***CIW***s and related ***CR***s) from successful applications for improving the quality of coming recommendations.

2.2.1.2 Working Process of the Proposed Color Recommendation System

In this study, a knowledge-based color recommendation system is proposed. Design knowledge on designer's color image perception is used to support the recommendation process. Describing ***CR***s in a database, 180 ***CIW***s are identified in a novel ***CIS*** by group sensory evaluations of designers. Consumers' color image perception will be analyzed in the ***CIS*** to select the most similar ***CIW***s concerning consumers' color image perception, using similarity measurements. Consumers' evaluation on satisfaction of the recommended color range will be performed in terms of the basic color physical properties (*hue, lightness and purity*). According to the evaluation results, these color parameters can be further modified or defined. When a recommended ***CR*** is satisfied by the consumer, the pair of the corresponding ***CR*** and consumer profile (cross-cultural information, the color image perception measured in the ***CIS***) will be retained in the ***SCD*** for being recommended to those having similar consumer profiles.

When a new user uses the proposed color recommendation subsystem, he/she needs to input the following required information: personal profile and color image perception data. These two parts constitute the retrieved new case for being compared with the existing cases in the ***SCD*** in order to find the most relevant case according to a predefined similarity degree.

If the biggest similarity degree between the retrieved new case and the existing cases in the ***SCD*** is higher than a predefined threshold, the corresponding case in the ***SCD*** is then considered as the target case and it will be re-used for recommendation. The corresponding satisfactory ***CR*** of the target case will be presented as recommendation result to the new user. If the user is satisfied with this result, the recommendation process will stop. If there is no target case in the ***SCD*** meeting the required threshold or the new user is not satisfied with the recommended color of the target case, the corresponding color design rules or knowledge will be updated.

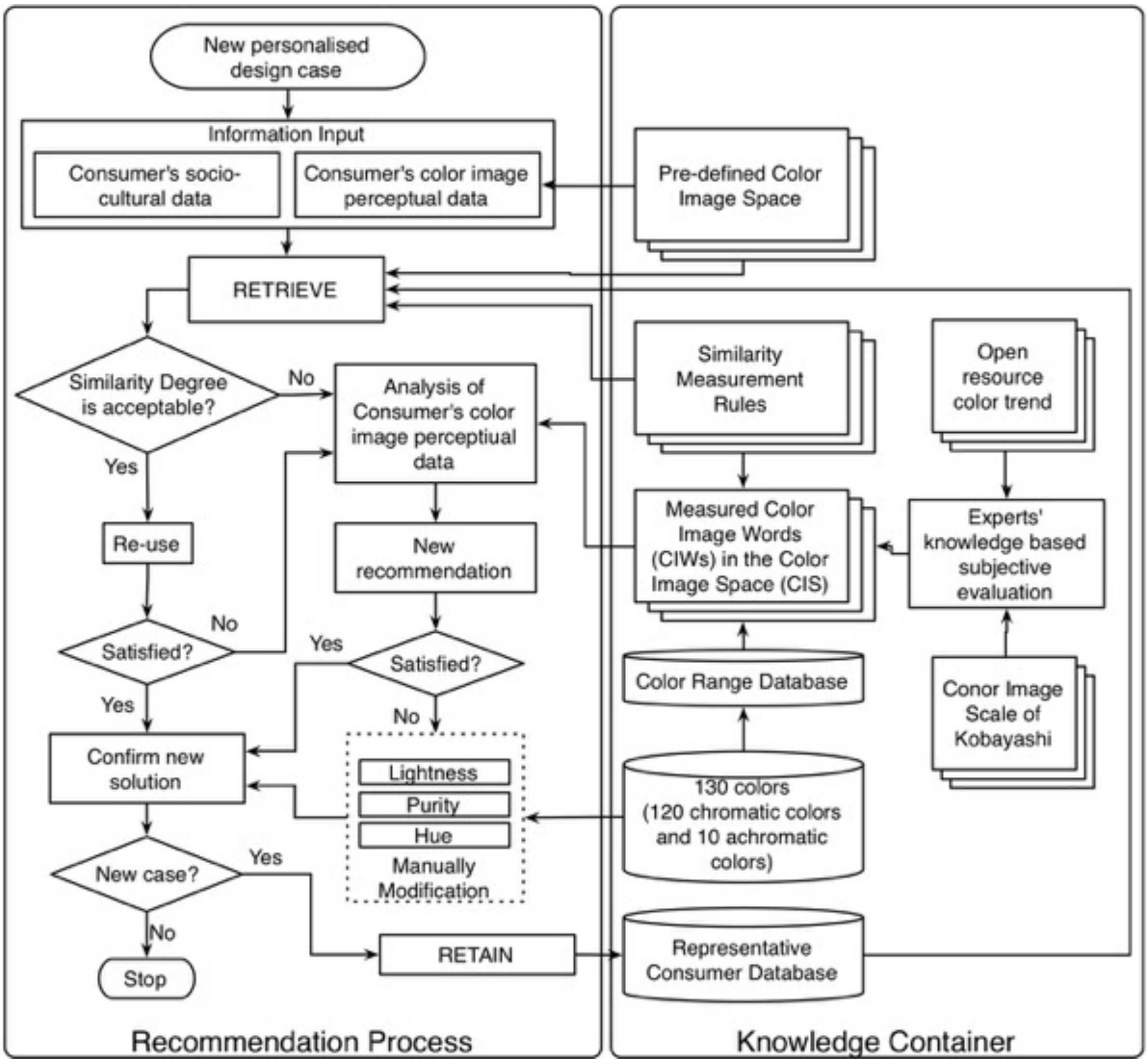


Figure 2-6: Working flowchart of the proposed color recommendation system.

The color design knowledge updating process starts by computing the similarity degree of the color image perception of the new user related to the color image perception of the ***CIW***s initially identified by designers. The most similar ***CIW*** and its corresponding ***CR*** will be provided as a new recommendation. Initially, these ***CR***s are taken from a ***Color Range Database***, developed from the research result of Kobayashi (See Figure 2-4). If the user is satisfied with the new recommendation, the process will stop. Otherwise, the user will be requested to provide a comment on the recommended ***CR*** in terms of lightness, purity and hue, or choose a color directly from the color database shown in Figure 2-4. Users are free to add or delete colors based on the recommended ***CR***. This process is based on the basic parameters of color and can be easily understood and performed by the user. Referring to the latest color trend, the proposed ***Color Range Database*** can be updated with new ***CR***s and their descriptive CIWs through a knowledge-based human evaluation process performed by designers.

The procedure of ***Recommendation – Display - Evaluation – SCD*** *adjustment* will be performed by the user several times until a satisfactory result is obtained. After acceptance of a recommendation result, it will be retained in the ***SCD*** as a new case-based learning rule, enhancing the recommendation accuracy of the proposed system.

2.2.1.3 Related Concepts the Proposed System

The proposed case-based machine-learning recommendation system includes four main subsystems: *retrieve, re-use, adaptation* and *retain*. A set of knowledge-based design rules, similarity measurements rules and a database are applied to support these subsystems. These rules and database constitute a knowledge container to support the whole process (see Figure 2-6).

(1) *CIS* and related *BCSA*s

A novel ***CIS*** is defined as a color image perception measurement system for acquisition of human perceptual data for both designers and consumers. Compared with the classical ***CIS***, the proposed multidimensional ***CIS*** is capable of expressing rich emotions, ensuring knowledge extraction from designers and perceptual data acquisition from consumers. The proposed ***CIS*** comprises several ***BCSA***s that have been chosen from a wide range used in the related literature. The feature recommendation process has been conducted through interactions with a number of experts. The selected ***BCSA***s are in the form of word-pairs, such as *"Cold–Warm"*, that can be easily understood by both designers and consumers without professional design knowledge.

(2) *CIW*s and *CR*s

In my PhD research, a ***Color Range Database*** is proposed initially based on ***CR***s developed by Kobayashi. These ***CR***s constitute the recommendation results of the knowledge-based recommendation process. ***CIW***s are applied to describe these ***CR***s. The relationship between ***CR***s and their corresponding descriptive ***CIW***s will be dynamically updated in the recommendation system based on the feedback of the user. Color image perceptions of ***CIW***s are characterized in the proposed ***CIS*** regarding ***BCSA***s by designers through a human evaluation process. Professional knowledge and experience will be extracted to support this characterization process.

As a dynamical system, the proposed ***Color Range Database*** can be updated in two situations. The first one is that, when a consumer is initially not satisfied with the recommendation result and finally obtained a satisfactory recommendation through several interactions with the system, the final modified ***CR***s will be integrated into the ***Color Range Database***. The second one is that, referring to the latest color trend, new ***CIW***s and their related ***CR***s will be integrated into the ***Color Range Database*** through a knowledge-based human evaluation process. New ***CIW***s will be characterized in the proposed ***CIS*** regarding ***BCSA***s. When a new ***CIW*** is applied by the system, its related ***CR***s will be retained in the proposed ***Color Range Database***.

(3) *Case*, *success case* and *SCD*

A case is defined as a representative consumer together with his/her personal profile (social-cultural background data such as *gender, education background, religion…*), color image perception data and related color recommendations. It incorporates three major functions: social-cultural description, preference description, and solution. In a case-based learning method, a case is described by a set of attributes or aims that identify the instance of related color recommendation for a user. Social-cultural and preference descriptions are documented using natural language descriptors or a linguistic scale.

If the proposed recommendation system has been successfully applied to a case, it will be considered as a successful case. All the successful cases are retained in an ***SCD*** as case-based learning rules. These successful cases provide a knowledge support to the proposed color recommendation system. A new user of this system will be assigned as a new case. The data of the new case will be matched with the existing cases of the ***SCD*** using the similarity degree measurement.

A case is a two-tuple, i.e. $C_j = <\{<f_i:v_{ij}>|\ i=1,\ ...,\ n,\ f_i \in F,\ v_{ij} \in V_i\},\ CR_j>$, where n is the number of all the user's descriptive features, f_i is the i-th descriptive feature, F is the set of all features, v_{ij} is the current value of f_i in Case C_j, and V_i is the set of all values corresponding to f_i, and CR_j is the user's satisfied CR in the case C_j. For example, a specific case C_1 can be expressed by C_1= *<{<Nationality: French>, <Education background: Medical master>, <Religion: Catholic>, <Age: 34>, <Gender: male>, <Color temperature perception: very cold>, <Color distance perception: a little closed>, <Successful recommendation frequency: 1>}, {Color 1: P26, Color 2: P23, Color 3: P44}>*. In this example, we have 8 user's descriptive features (n=8).

F includes three types of features: users' social-cultural attributes, color image perception attributes and successful recommendation frequency. Related to personalized color preference, the social-cultural attributes include gender, education, religion, and nationality, etc. These social-cultural attributes have been chosen from a wide range used in the related literature. For a specific application, the feature selection process has been conducted through interactions with a number of experts. Natural linguistic descriptors are used to describe the social-cultural attributes. Color image perception attributes are defined using the predefined ***BCSA***s. The successful recommendation frequency describes the frequency of the concerned case, which will be recommended to a new user and can be accepted by him/her directly.

2.2.2 *Fabric Selection System (FSS)*

Fabric selection is an important session in clothing design. Fabrics chosen for a garment will directly affect the hand, appearance (folds, wrinkles and stretches) and mechanical comfort of the final product. In this section, we wish to select the most relevant fabric based on the color already selected in the previous subsystem.

2.2.2.1 Fabric Selection: Basic Principle and Classic Procedure

In industries, there are two categories of methods for fabric selection. One is based on physical measurements using professional devices while the other utilizes human sensory evaluations. Using a method of physical measurements, we obtain values of a set of mechanical and optical parameters on the alternative fabrics such as shearing, tensile and texture. Next, a number of statistical models are applied in order to recommend appropriate fabrics. However, these methods are expensive and far from human perception on fabric products, which is the most important criterion for business transactions.

Since 1950s, sensory evaluation has been widely recognized as an efficient tool for fabric performance prediction. Fabric sensations describing the overall performance of fabric products, such as comfort, style, and appearance can be decomposed into a set of sensory descriptors. Using sensory evaluation, professional designers' knowledge, usually expressed as design rules, can be integrated into the fabric performance prediction without instrumental tests. Sensory evaluation permits to realize a fast and efficient fabric recommendation, satisfying the requirements of automatic design and production.

Using sensory evaluation-based method, fabrics will be selected by the designers referring to the current fashion trend, the customer's requirements and designers' design concept to be expressed. Alternative fabrics will be assessed by designers with regard to these conflicting criteria. In this context, the sensory evaluation-based fabric selection can be regarded as a multi-criteria decision-making problem including subjective and ambiguous data given by both designers and customers. However, such fabric selection process is not only time-consuming, but also far from consumer's evolutionary requirements.

In order to solve the restrictions in the traditional fabric selection process, we propose a knowledge-based dynamic ***Fabric Selection System (FSS)***. The ***FSS*** recommendation system adopts an interactive hierarchical structure, permitting to decompose the decision problem into five levels: goal, evaluation criteria identification (requirements of the target consumers), sub evaluation criteria identification (fabric properties), rating scale selection, and determination of alternatives. New requirements and new fabrics can be integrated into the proposed system and generate new recommendation. Designers and consumers are invited to participate in different decision-making levels of a hierarchical structure and determine the relative importance levels (weight) of evaluation criteria (both evaluation criteria and sub evaluation criteria) respectively. These interactions are critical for reducing the PD&P (product design and production) cost and increasing the decision-making quality. Information exchange can then be strengthened between designers and consumers in the decision-making process.

2.2.2.2 Working Process of the Proposed Fabric Selection System

In my PhD research, a perception-based fabric recommendation system is proposed on the basis of a collaborative design process. Perceptual data of consumers on the desired product is extracted and analyzed by the knowledge and experience of designers using an interactive procedure.

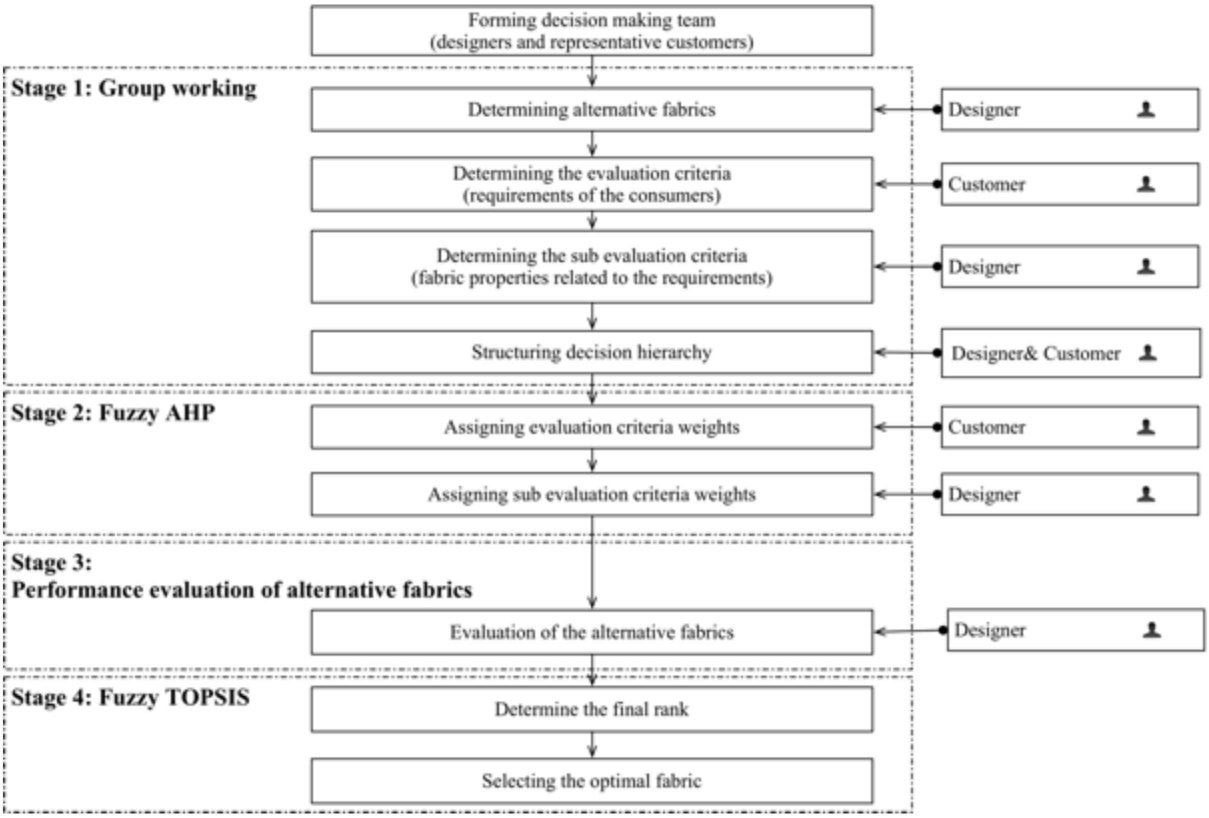


Figure 2-7: Schematic working process of the proposed fabric recommendation system.

The proposed system decomposes the decision-making problem of fabric selection into four levels. Relationships among the four levels follow a hierarchy structure, in which the general objectives can be found on the root, the evaluation criteria (along with the sub evaluation criteria) on the branches, and the alternative fabrics on the leaves. In this context, we propose the ***Fuzzy AHP*** to structure the fabric selection problem. Relevant importance levels of the concerned multiple criteria and corresponding components is defined using the ***Fuzzy AHP*** model. It can effectively reduce the complexity of the decision problem, make the definition of roles clearer for different involved decision-makers and guarantee communication between them. Due to there is both negative and positive evaluation criteria involved in the proposed system, which is difficult to make a global judgment about the performance, the ***Fuzzy TOPSIS*** method is introduced to solve this problem. Using the ***Fuzzy TOPSIS*** method, evaluation data of alternative fabrics regarding different evaluation criteria generated from the ***Fuzzy AHP*** model will be processed and give final total ranking to the involved fabric alternatives. Besides, a novel integration algorithm is adapted into the ***Fuzzy AHP*** and ***Fuzzy TOPSIS*** integrated algorithms. New requirements can be integrated into the proposed system through a set of sensory evaluation by designers. Associations of the new requirements will be accessed with the existing requirements of the proposed system and then integrated into the system using the proposed integration algorithm.

First, the ***AHP*** model is applied for modeling the interactive structure between different levels of decision making for designers and consumers. Different evaluation criteria of the desired product and their relevant weights are then obtained using the interactive ***AHP*** model. Sensory evaluation is the main evaluation tool to evaluate the alternatives. After that, the ***TOPSIS*** method is used to rank all the alternatives in the database in order to recommend the most appropriate product based on the perception of consumers. In order to formalize the vagueness and uncertainty of the sensory evaluation, fuzzy set theory is introduced to the ***AHP*** modeling procedure and ***TOPSIS*** analysis procedure. The combination of the ***Fuzzy AHP*** and ***Fuzzy TOPSIS*** using a sensory evaluation procedure and a collaborative design process constitutes the main methodology of the proposed recommendation system.

The proposed fabric recommendation system using composed ***FAHP*** and ***Fuzzy TOPSIS*** methods, consists of four stages: (1) identification of different level of evaluation criteria (requirements of consumer and related fabric properties), (2) ***AHP*** computations of the relative weights of the evaluation criteria, (3) assessment of alternative fabrics using regarding fabric properties generated from the previous step, and (4) ***Fuzzy TOPSIS*** process of the evaluation data and determination of the final rank of all alternative fabrics. Figure 2-7 presents the working process of the proposed recommendation system.

In the first stage, alternative fabrics and the evaluation criteria employed in the recommendation system as well as the corresponding decision hierarchical structure are all determined. In the ***FAHP*** decision hierarchical model, the objective is at the first level, criteria (requirements of the consumers) are placed at the second level, sub evaluation criteria (fabric properties related to consumers' requirements) are placed at the third level and alternative fabrics are placed at the fourth level. A number of representative consumers are carefully selected in order to identify the evaluation criteria and a number of designers determine the fabric properties related to the requirements. At the end of this stage, all the decision-makers (selected consumers and designers) are invited to approve the decision hierarchical structure obtained in the previous operations. This hierarchical structure of related ***FAHP*** components: Goal (fabric recommendation), Criteria (requirements of the target consumers), Sub evaluation criteria (fabric properties), Rating scale and Alternatives (alternative fabrics pre-selected by the designers) can be depicted as Figure 2-8. Different actors in the collaborative process are also summarized in Figure 2-8.

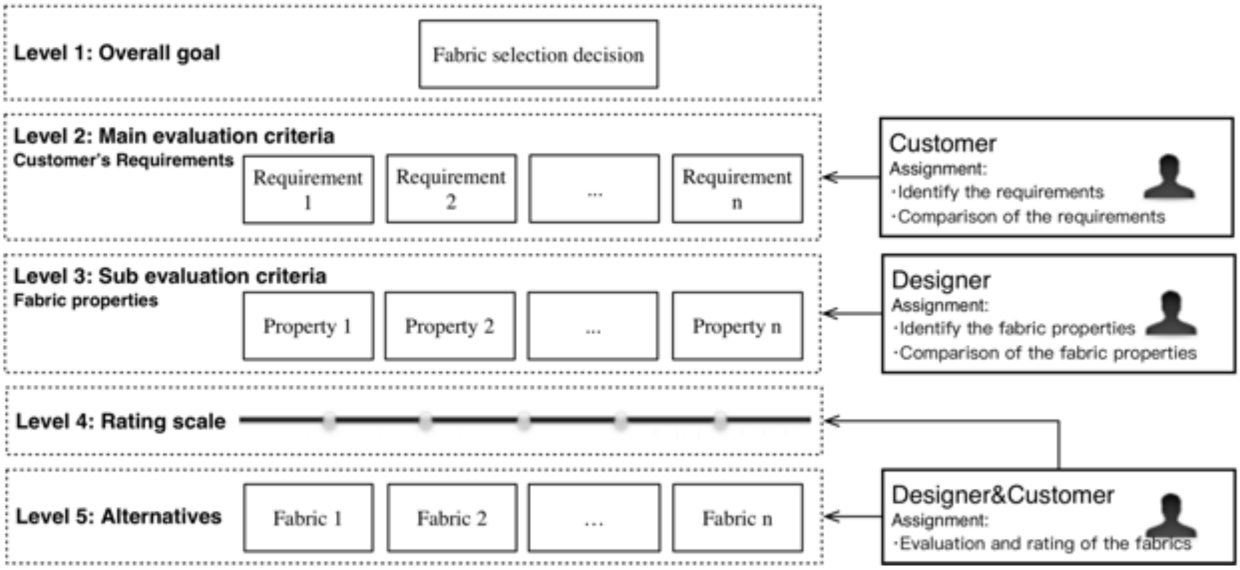


Figure 2-8: The collaborative hierarchical structure of fabric recommendation.

In the second stage, the weights of different levels of evaluation criteria (requirements of consumer and related fabric properties) involved in the fabric selection from the approved decision hierarchical structure are determined using ***FAHP***. Actors involved in different levels of the ***FAHP*** model will determine their relative weight of evaluation criteria. These weights show the importance level of different evaluation criteria in fabric selection. The pairwise comparison matrices of the relative importance values are formed to determine these criteria weights. The entire decision-makers make individual evaluations using a linguistic rating scale.

The linguistic rating scale using in this stage is *{extremely less important, less important, a little less important, equal, a little more important, more important, and extremely more important}*, as presented in Table 2-1.

Then the pairwise comparison matrices about the relative importance inside the two levels of evaluation criteria (the main evaluation criteria and sub evaluation criteria) will be transferred into ***Triangular Fuzzy Numbers (TFN)*** and then further processed by using fuzzy set tools. Relevant importance of two levels of evaluation criteria will be obtained and normalized. The final importance level of the sub evaluation criteria (fabric properties) will be weighted by that of their upper evaluation criteria (consumers' requirement). After another normalization process, the normalized importance level of the sub evaluation criteria can be obtained. These fabric properties will be further applied to evaluate the performance of the alternative fabrics.

Table 2-1: Linguistic rating scale and corresponding fuzzy numbers.

Linguistic values	TFNs
Extremely more important (EMI)	(3.5,4,4.5)
More important (MI)	(3,3.5,4)
A little more important (AMI)	(2.5,3,3.5)
Equal (E)	(2,2.5,3)
A little less important (ALI)	(1.5,2,2.5)
Less important (LI)	(1,1.5,2)
Extremely less important (ELI)	(0.5,1,1.5)

Table 2-2: Linguistic rating scale and corresponding fuzzy numbers for the sub evaluation criterion of *"softness"*.

Linguistic values	TFNs
Very soft	(2.5,3,3.5)
A little soft	(2,2.5,3)
Equal	(1.5,2,2.5)
A little stiff	(1,1.5,2)
Very stiff	(0.5,1,1.5)

In next stage, all the decision-makers (selected representative consumers and designers) are invited to evaluate all the alternative fabrics. The evaluation will be performed regarding the fabric properties, which is realized by sensory evaluation of designers. Using this method, instrumental measures on features and technical parameters of the fabrics are avoided. Professional experience and knowledge of the designers are extracted in the sensory evaluation process to support the fabric performance evaluation. Using this method, the proposed recommendation system is capable of receiving new alternative fabrics and generates new design solutions. First, the designers evaluate the performance of the alternative fabrics regarding the sub evaluation criteria respectively using a fuzzy linguistic rating scale. The membership functions of these linguistic ratings are presented in Table 2. For example, if there is an evaluation criterion regarding fabric properties *"Softness"*, then the linguistic rating scale can be *{very stiff, a little stiff, equal, a little soft, and very soft}*, as presented in Table 2-2.

Then the obtained data will be quantified into ***TFN*** for further data analysis using ***Fuzzy TOPSIS***.

The last stage is the process of performance evaluation data of alternative fabrics obtained is the previous stage. The performance ranking of the alternative fabrics is determined in this stage. As there are both positive evaluation criteria and negative evaluation criteria regarding the fabric performance, ***Fuzzy TOPSIS*** method is employed to process these data. Regarding the calculations by ***Fuzzy TOPSIS***, the alternative fabric owning the maximum value is considered as the optimal solution.

This system also acquires the designers' and the consumer's perceptual data in a different but more systematic way. Compared with the simple appreciations and ratings used in the existing recommendation systems, the proposed system permits the acquisition of more complete perceptual data on normalized keywords (sensory descriptors and fashion themes) from consumers and designers and is more appropriate for fashion products. More detailed introduction about the general working process of the ***AHP*** model and ***TOPSIS*** model will be presented in Section 3.4.

2.2.2.3 Integration of new requirements of a consumer

The proposed recommendation system is a dynamic and open resource-based system, which is capable of integrating new requirements of consumers. There are two phases for integrating a new requirement (See Figure 2-9). First, a new requirement is extracted by consumers. Next, the extracted requirement is integrated into the existing recommendation system through a group analytics process performed by designers. Finally, the new requirement will be applied together with the existing requirements of the recommendation in order to perform the performance evaluation of the alternative fabrics, trend analysis of the requirements and generation of new design solutions. In order to realize the proposed system, a dynamic integration algorithm is proposed.

As the background of the proposed system is aimed at mass production fashion brands, a new requirement should be the one that is widely concerned by the consumers. Only the requirement approved by most of the consumers can be authorized to be integrated into the proposed recommendation system. The integration of the approved requirement into the proposed recommendation is realized through an interactive analytic process. This process is performed by designers. Let $E = \{e_1, e_2, e_3, \ldots, e_m\}$ be the set of a group of designers in the decision-making team. Let $W= (w_1, w_2, w_3, \ldots, w_n)$ be a set of linguistic terms describing the association between the new requirement and existing requirements.

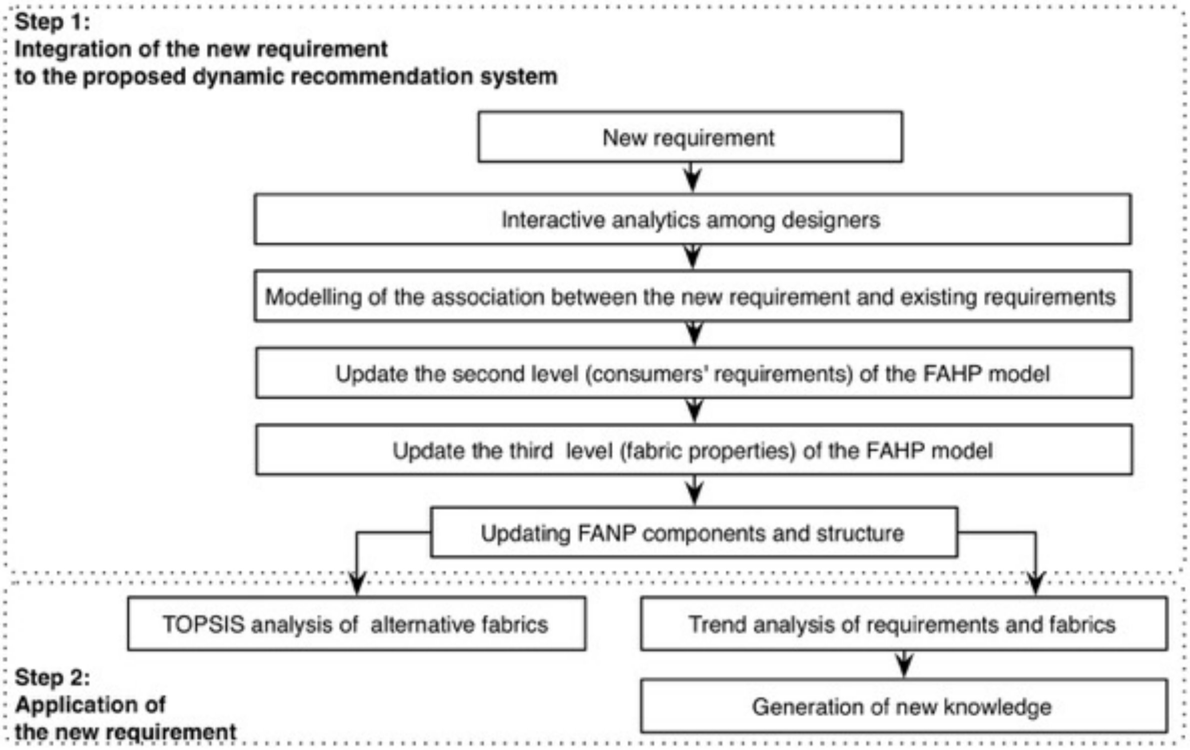


Figure 2-9: Schematic working process of the integration of a new requirement.

Table 2-3: Linguistic rating scale of the association degree and the corresponding fuzzy numbers.

Linguistic values	Numerical equivalence values
Extremely related (ER)	1
Rather related (RR)	0.75
Related (R)	0.5
A little related (AR)	0.25
Not related (NR)	0

Each of the decision-makers e_m is invited to evaluate this association between the new requirement and other existing requirements in the system, by using the linguistic terms in W. The evaluation process is performed based on the professional knowledge and experience of the involved decision-makers. In this study, W is defined as *(Not related, A little related, Related, Rather related, Extremely related),* corresponding to $(w_1, w_2, w_3, \ldots, w_n)$, where $n=5$. These linguistic terms will be further quantified into numerical equivalence values, as presented in Table 2-3.

Let $C= (C_1, C_2, \ldots, C_m)$ be a set of selected requirements existing in the recommendation system, and $L= (l_1, l_2, l_3, \ldots, l_m)$ be the vector of the normalized importance level of C, where n is the number of the existing requirements in the proposed recommendation system.

Let R be a fuzzy evaluation matrix for the associations between the new requirement C_{m+1} with other existing requirements of C, and where r_{ij} $(i=1, 2, \ldots, m; j=1, 2, \ldots, n)$ is the membership function of the ith requirement C_i regarding the jth linguistic term w_j.

For the ith requirement k_i, if there are w_{in} decision-makers choose w_n, then *for* $i=1, 2, \ldots, m, j=1, 2, \ldots, n$, we have

$$r_{ij}=\frac{w_{ij}}{\sum_{i=1}^{n} w_{ij}} \tag{2-1}$$

Using Equation (2-1), all the evaluation results of the involved decision-makers can be aggregated.

After that, the importance level of the new requirement C_{m+1} can be obtained through a fuzzy relations composition method. Let l'_{n+1} be the vector of importance level of the new requirement C_{m+1}, we have

$$l'_{n+1}=L \circ R= (p_1, p_2, \ldots, p_n) \tag{2-2}$$

$$p_n=max\,\{min\,(a_i, r_{ij})\}, \tag{2-3}$$

where $i=1, 2, \ldots, m, j=1, 2, \ldots, n$.

Let $L''=(l''_1, l''_2, \ldots l''_n, l''_{n+1})$ be the vector of the normalized importance level of the new requirement set, we have

$$l''_i=\frac{l'_i}{\sum_{1}^{n+1} l'_i},\ i=1,2,3,\ldots, n,n+1 \tag{2-4}$$

The new requirement and newly calculated normalized importance levels of all the requirements will be stored in the proposed recommendation system. After that, the importance level of fabric properties will be updated correspondingly. The updated recommendation system with integration of the new requirement will be further applied to evaluate the performances of the alternative fabrics regarding the updated fabric properties. Then, these evaluation data will be analyzed using the ***Fuzzy TOPSIS*** method. The requirement trend can also be obtained by visually analyzing the new normalized importance levels of the requirements. A report about the evaluation results and trend analysis will be generated to support decision-making of the company. New knowledge related to the requirement trend will also be generated to provide reference when generating a new requirement and enhance the success of the recommendation system.

Using the proposed dynamic integration algorithm, only designers will be involved in this process, without repeat the ***FAHP*** process. Designers only need to access the association between the new requirement and other existing requirements. Subsequently, related fabric properties and performance score of alternative fabrics will be automatically updated at the same time.

Consumers are not required to participate in this process, which will greatly simplify the working process of the system.

2.2.3 *Garment Style Recommendation Subsystem (GSRS)*

2.2.3.1 Input, output and different modules of the proposed *GSRS*

The proposed ***Garment Style Recommendation Subsystem (GSRS)*** aims at recommending each given consumer the most relevant garment components describing the garment style based on the already selected colored fabric, which meets the specific his/her fashion requirements and body morphology. The input, output and different modules of the proposed ***GSRS*** are illustrated in Figure 2-10.

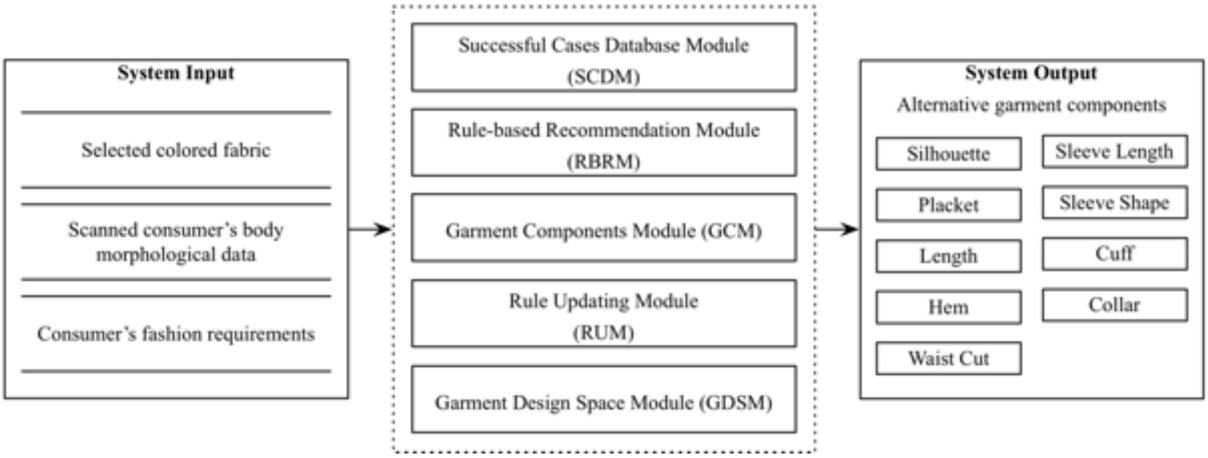


Figure 2-10: The input, output and five Modules of the *GSRS*.

The inputs of the system are the colored fabric selected from the ***Fabric Section System (FSS)***, body scan data of the consumer and consumer's fashion requirements. First, the linguistic input data on fashion requirements will be described using triangular fuzzy numbers by using the ***Garment Design Space Module (GDSM)***. Theses fuzzy numbers constitute the inputs of the two recommendation modules, namely (1) the ***Successful Cases Database Module (SCDM)***, (2) the ***Rule-based Recommendation Module (RBRM).***

SCDM permits to first recommend garments from the past successful cases. If there is no similar past cases, ***RBRM*** will be used for proposing new recommendations from the base of rules, extracted from designer's professional knowledge and experience. These two recommendation modules enable to process different scenarios of recommendation. For a general fashion requirement, a ***SCDM*** can easily deliver a relevant recommendation from the past cases with simplified computation. However, for a more special requirement, the rules of ***RBRM*** will be more efficient for delivering satisfied results.

There are also three modules supporting the previous two recommendation modules (***SCDM*** and ***RBRM***): (1) the ***Rule Updating Module (RUM)***, used for integrating new design rules generated from open resource into the system, and progressively improving the quality of the design rules according to the unsatisfied recommendation results; (2) the ***Garment Components Module (GCM)***, including all the components of any specific garment type; and (3) the ***Garment Design Space Module (GDSM)***, as mentioned before, including a set of sensory descriptors related to consumer's fashion style requirement, consumer's body shape image, and fabric sensory properties.

The output of this style recommendation system consists of a set of selected garment components describing the desired garment type. These garment components are selected from the ***GCM*** by using the ***SCDM*** or the ***RBRM***.

2.2.3.2 ***Garment Design Space Module (GDSM)***

The working process of the proposed ***Garment Style Recommendation System (GSRS)*** follows that of the classical personalized fashion design processes. As we described in Section 2.2.3.1, the ***Garment Design Space Module (GDSM)*** is defined to process all the input data of the system into sensory data using fuzzy numbers. These sensory data can be easily understood by designers and permit to generate related design rules.

The proposed ***GDSM*** includes three individual ***Garment Design Spaces***: ***Fashion Style Space (FASS)***, ***Body Shape Image Space (BSIS)*** and ***Fabric Sensory Property Space (FSPS)***, describing consumer's required fashion style sensory properties, consumer's body shape image sensory properties, and fabric sensory properties respectively. Figure 2-11 presents the structure of the proposed ***GDSM***.

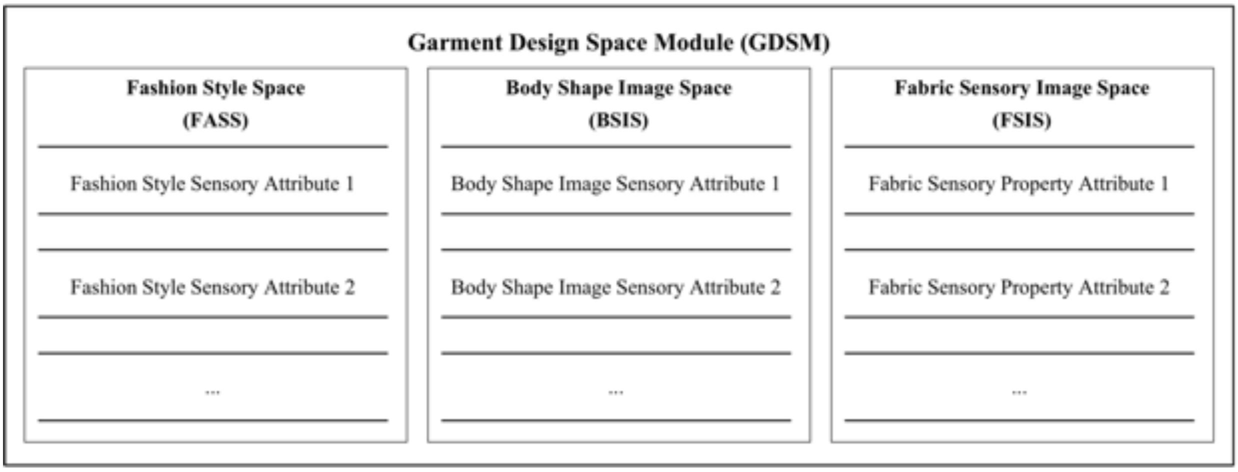


Figure 2-11: Conceptual framework of the *GDSM*: *FASS*, *BSIS*, *FSPS*.

Each of the ***Garment Design Spaces*** is composed of several dimensions, defined as ***Sensory Attributes***. Specifically, the ***Sensory Attributes*** for ***FASS*** are defined as ***Fashion Style Sensory Attributes***, the ***Sensory Attributes*** for ***BSIS*** as ***Body Shape Image Attributes***, and the descriptive features for ***FSPS*** as ***Fabric Sensory Attributes***. These ***Sensory Attributes*** compose the ***Garment Design Sensory Attributes*** of the proposed **GSRS.**

Each of the ***Sensory Attributes*** is described by a word-pair. These word-pairs have been selected by designers from a wide range used in the related literature, such as fashion design theory, fashion trend reports, and fashion magazines. For example, a ***Fashion Style Sensory Attribute*** can be defined as *"Formal-Casual"*. A ***Garment Design Sensory Attributes*** is defined by a scale of 7 intensity levels or evaluation scores. For example, for the ***Fashion Style Sensory Attribute*** of *"Formal-Casual"*, it has 7 intensity levels represented by $\{C_1, C_2, C_3, C_4, C_5, C_6, C_7\}$, corresponding to the linguistic values *{Extremely Formal, Very Formal, A little Formal, Medium, A little Casual, Very Casual, and Extremely Casual}*.

These ***Sensory Attributes*** have two functions: (1) identify consumer's garment perception, and (2) identify design rules of designers (knowledge acquisition). For example, for the ***Fashion Style Sensory Attribute*** of *"Formal-Casual"*, a ***PWAM*** may use it to define his/her required fashion style sensory property as "*A little Formal*". Also, a designer may use the ***FASS*** to generate a design rule that "The ***Fashion Style Image*** of *"Stand Collar"* is "*A little Formal*". In this case, *"Stand Collar"* of the ***Garment Component Category*** of ***Collar*** as *"Very Formal"* will be recommended to this ***PWAM***. Figure 2-12 presents the working process for processing these sensory input data.

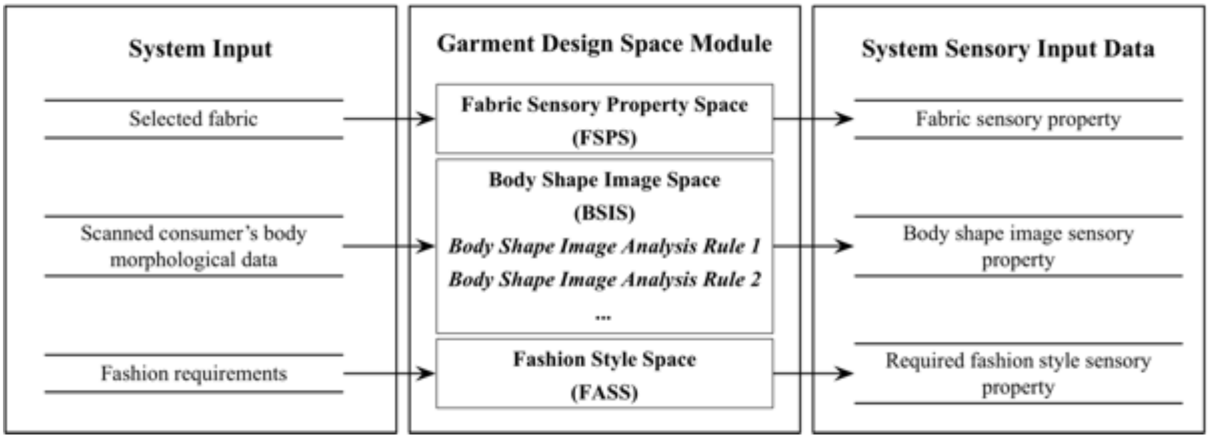


Figure 2-12: Working process of processing the system input data into system sensory input.

The sensory inputs of the proposed ***Garment Style Recommendation System (GSRS)*** include three components: fabric sensory property generated using the ***FSPS***, consumer's body shape image sensory property, and consumer's fashion style sensory property.

Fabric sensory properties refer to a set of fabric sensory performance perceived by designers, which is vertical in the fashion design process. These sensory properties include fabric hand sensory property (such as softness, flexibility, weight, draping etc.) and fabric visual sensory property (color). The fabric visual sensory property is defined by the recommended color range using the ***Color Recommendation System (CRS)***.

Body shape image sensory properties are obtained from the body scan data by using the body shape analysis rules predefined in the system. Body shape image refers to different sensory aspects considered in the fashion design process. For example, for the sensory image of a man with height=190cm, the body shape image of a consumer may be *"Very tall"*.

Fashion style sensory properties refer to the fashion style preference of a ***PWAM***. It refers to different sensory aspects of fashion preference when a ***PWAM*** selects a garment. For example, it may refer to the occasion of wearing (formal or causal), structure of garment character (simple or gorgeous).

2.2.3.3 *Consumer Profile*

A ***Consumer Profile*** is defined as a user together with a set of ***Consumer Descriptive Features***. These ***Consumer Descriptive Features*** are identified by the descriptive features of the ***GDSM***. These ***Consumer Descriptive Features*** include: the consumer's required fashion style, consumer's body image and fabric sensory property (Figure 2-13). For a specific ***Consumer Profile***, the values of these three ***Consumer Descriptive Features*** are stored in the related ***Garment Design Spaces*** of the ***GDSM***. A number of ***Consumer Profiles*** permit to find the most relevant garment recommendation for a new ***PWAM***.

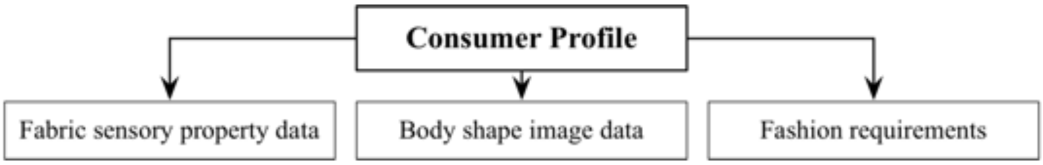


Figure 2-13: *Consumer Descriptive Features* of a *Consumer Profile*.

A ***Consumer Profile*** is a one-tuple in the form of < *Consumer Descriptive Features: Values of Consumer Descriptive Features* >.

Let $D= \{d_1, d_2, ..., d_p\}$ be a set of p ***Consumer Descriptive Features*** describing the features of a consumer. A ***Consumer Profile*** can be defined as $C_j = <\{<d_i:v_{ij}>| \ i=1, ..., n, d_i \in D, v_{ij} \in V_i\}>$, where d_i is the i-th ***Consumer Descriptive Features***, D is the set of all the ***Consumer Descriptive Features***, v_{ij} is the current ***Consumer Descriptive Features*** value of d_i in ***Consumer Profile*** C_j, and V_i is the set of all values corresponding to d_i.

For example, a specific ***Consumer Profile*** S_1 can be expressed by S_1= *{<Construction (Simply-Gorgeous): Very Simple>, <Times (Modern-Classical): Very Classical>, <Occasion (Formal-Casual): A little Formal>, <Acceptance (Occasional-Universal): Extremely Universal>, <Age (Young-Mature): Medium>, <Gender (Feminine-Masculine): Very Masculine>, <Fatness (Slim-Fat): A little Fat>, <Height (Short-High): Extremely High>, <Fabric Softness (Soft-Hard): Soft>, <Fabric Flexibility (Elastic-Inelastic): Inelastic>, <Fabric Weight: (Thin-Thick): Thin>, <Fabric Drapability: (Drapery-Undraped): Very Undraped>}*. In this example, we have 12 ***Consumer Descriptive Features*** ($p=12$).

2.2.3.4 *Garment Components Module (GCM)*

The ***Garment Components Module (GCM)*** consists of several ***Garment Component Categories***. These ***Garment Component Categories*** includes a set of alternative garment components. The classification of these ***Garment Component Categories*** follows the concept of modularized design. For example, Figure 2-14 presents the ***GCM*** of a shirt. ***Garment component Categories*** of a shirt includes: *Silhouette, Placket, Length, Hem, Waist cut, Sleeve length, Sleeve shape, Cuff* and *Collar*. For the ***Garment Component Category*** of ***Collar***, alternative garment components are: *Collarless, Flat collar, Stand collar,* and *Lapel*. The final output of the ***GSRS*** consists of selected alternative garment components of the ***GCM***. These selected garment components constitute the content of a product profile.

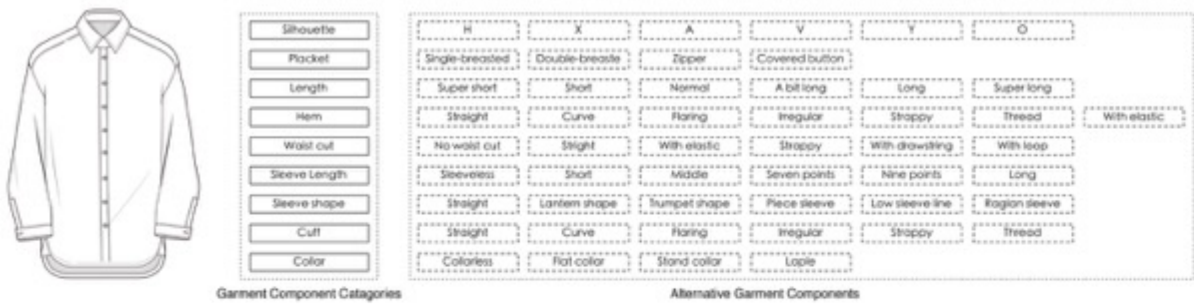


Figure 2-14: *Garment Components Module* (*GCM*) of a shirt: *Garment component Categories* and their alternative garment components.

In this PhD style, the garment type of shirt is chosen for all the case study. Let $G=\{g_1, g_2, \ldots, g_s\}$ be a set of s $(s=9)$ ***Garment Component Categories*** of a shirt, describing the components of a shirt. Specifically, g_1=*Silhouette*, g_2=*Placket*, g_3=*Length*, g_4=*Hem*, g_5=*Waist cut*, g_6=*Sleeve length*, g_7=*Sleeve shape*, g_8=*Cuff*, and g_9=*Collar*.

2.2.3.5 *Product Profile*

Traditionally, a ***Product Profile*** is proposed to provide a summary of the following: (1) the product under development, (2) the product's desired characteristics and features, (3) the studies and activities that must be completed to demonstrate the product's performance, efficacy and safety, and (4) the features of the product that provide a competitive advantage.

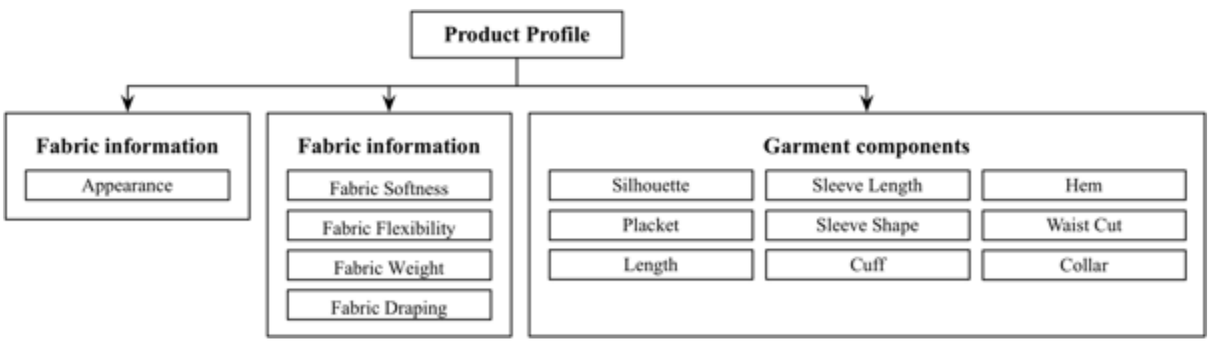


Figure 2-15: An example of a *Product Profile* of the shirt type.

In my PhD research, a ***Product Profile*** is defined to provide all the requirement of the recommended garment and constitute the input of the ***Virtual 3D-to-2D Garment Prototyping Platform (VGPP)***. A ***Product Profile*** is described by several ***Product Descriptive Features***, which includes: (1) fabric information, including fabric appearance and hand properties defined in the ***Fabric Sensory Property Space (FSPS)***, and (2) recommended alternative garment components of each ***Garment Component Categories***. Figure 2-15 presents an example of a product profile of the shirt type.

A ***Product Profile*** is a three-tuple in the form of *{<Fabric Appearance>, < Fabric Hand Sensory Property>, <Garment components>}*.

Let $H=\{h_1, h_2, ..., h_r\}$ is a set of r ***Product Descriptive Features*** describing the components of a product. A ***Product Profile*** can be defined as $P_j = \langle\{\langle h_i{:}y_{ij}\rangle \mid i=1, ..., r, h_i \in H, y_{ij} \in Y_i\}\rangle$, where r is the number of all the ***Product Descriptive Features*** , h_i is the i-th ***Product Descriptive Feature***, H is the set of all the ***Product Descriptive Features***, y_{ij} is the current ***Product Descriptive Feature*** value of h_i in product P_j, and Y_i is the set of all values corresponding to h_i.

For example, a ***Product Profile*** P_1 can be expressed by P_1= *{<{<Appearance: Scanned picture>}>, <{<Fabric Softness (Soft-Hard): Soft>, <Fabric Flexibility (Elastic-Inelastic): Inelastic>, <Fabric Weight: (Thin-Thick): Thin>, <Fabric Draping: (Drapery-Undraped): Very Undraped>}>, <{<Silhouette: X>, <Placket: Zipper>, <Length: Normal>, <Hem: Curve>, <Waist cut: Straight>, <Sleeve length: Short>, <Sleeve shape: Straight>, <Cuff : Curve>, <Collar: Stand Collar>}>}*. In this example, we have 14 ***Product Descriptive Features*** ($m=14$).

2.2.3.6 Successful Cases Database Module (*SCDM*)

If the ***GSRS*** has been successfully applied to a case, this case will be considered as a ***Successful Case***. All the ***Successful Cases*** are retained in the proposed ***SCDM*** as case-based learning rules. Successful recommendation frequency is defined as the extra case feature for a ***Successful Case***. These ***Successful Cases*** provide a knowledge support to the proposed ***GSRS***. A new user of this system will be assigned as a new case. The values of the new case will be matched with those of the existing past ***Successful Cases*** of the ***SCDM*** using a similarity degree measurement algorithm.

A ***Successful Case*** is a three-tuple in the form of *{<Case profile>, <Recommended product profile>, <Successful recommendation frequency>}*.

Let $C=\{c_1, c_2, ..., c_t\}$ is a set of t ***Case Descriptive Features*** describing the components of a ***Successful Case***. A ***Successful Case*** can be defined as $SC_j = \langle\{\langle c_i{:}w_{ij}\rangle \mid i=1, ..., t, c_i \in C, y_{ij} \in Y_i\}\rangle$, where t is the number of all the ***Case Descriptive Features***, c_i is the i-th ***Case Descriptive Features***, C is the set of all the ***Case Descriptive Features***, w_{ij} is the current ***Case***

Descriptive Features value of c_i in a ***Successful Case*** SC_j, and W_i is the set of all values corresponding to C_i.

For example, a specific ***Successful Case*** SC_1 can be expressed by SC_1= *{<{{<Construction (Simply-Gorgeous): Very Simple>, <Times (Modern-Classical): Very Classical>, <Occasion (Formal-Casual): A little Formal>, <Acceptance (Occasional-Universal): Extremely Universal>, <Age (Young-Mature): Medium>, <Gender (Feminine-Masculine): Very Masculine>}, {<Fatness (Slim-Fat): A little Fat>, <Height (Short-High): Extremely High>}, {<Appearance: Scanned picture>, <Fabric Softness (Soft-Hard): A little Soft>, <Fabric Flexibility (Flexible-Inflexible): A little Flexible>, <Fabric Weight: (Light-Heavy): A little Light>, <Fabric Draping: (Overhanging-Anti-overhanging): Very overhanging>}}>, <{<Silhouette: X>, <Placket: Zipper>, <Length: Normal>, <Hem: Curve>, <Waist cut: Straight>, <Sleeve length: Short>, <Sleeve shape: Straight>, <Cuff : Curve>, <Collar: Stand Collar>}>, <{<Successful recommendation frequency: 1>}>}*. In this example, we have 23 ***Case Descriptive Features*** ($t=23$).

Successful Cases are very helpful for increasing the accuracy of the recommendation system. After each successful recommendation satisfied by the consumer, the corresponding two-tuple of *<Case profile, recommended product profile>* will be integrated to the ***SCDM***. When a new consumer arrives, his/her profile will be first compared with the existing ***Successful Cases***. If the similarity of the values of ***Case Descriptive Features*** between a new ***Consumer Profile*** and that of an existing ***Successful Case*** is high, then this module will recommend the corresponding successful product to this consumer. The computation model is the ***Case-Based Reasoning*** technology.

2.2.3.7 *Rule-based Recommendation Module* (*RBRM*)

When a new case comes to the proposed ***GSRS***, if a similar case already exists in the ***Successful Cases Database Module (SCDM),*** the ***Rule-based Recommendation Module (RBRM)*** will be used. Using ***RBRM***, fabric sensory property value generated from the ***FSS***, consumer's body shape image sensory value, and consumer's required fashion style sensory property value will be processed using extracted fashion design rules, in order to generate the desired garment product profile.

There are three different rule bases dealing with different input values. They are the ***Fashion Style Related Garment Design Rule Base (RB1-FS)***, the ***Body Shape Image Related Garment Design Rule Base (RB2-BS)***, and the ***Fabric Sensory Property Related Garment Design Rule Base (RB3-F)***. Fashion design rules of these rule bases are generated based on the experience and knowledge of designers. Related design knowledge and rules of each rule base will be introduced in Section 3.2.3.

For ***RB2-BS*** and ***RB3-F***, they contain both recommendation rules and against rules. A recommendation rule means that one certain alternative garment component is recommended in one certain situation, while an against rules means that one certain alternative garment component is again in this situation. For example, if the body shape image of one ***PWAM*** is regarded as “A little Short”, one recommendation rule of the ***RB2-BS*** may be “*<Length: Normal; Recommended>*“, while one against rule of the ***RB2-BS*** may be “*<Length: Long; Against>*“.

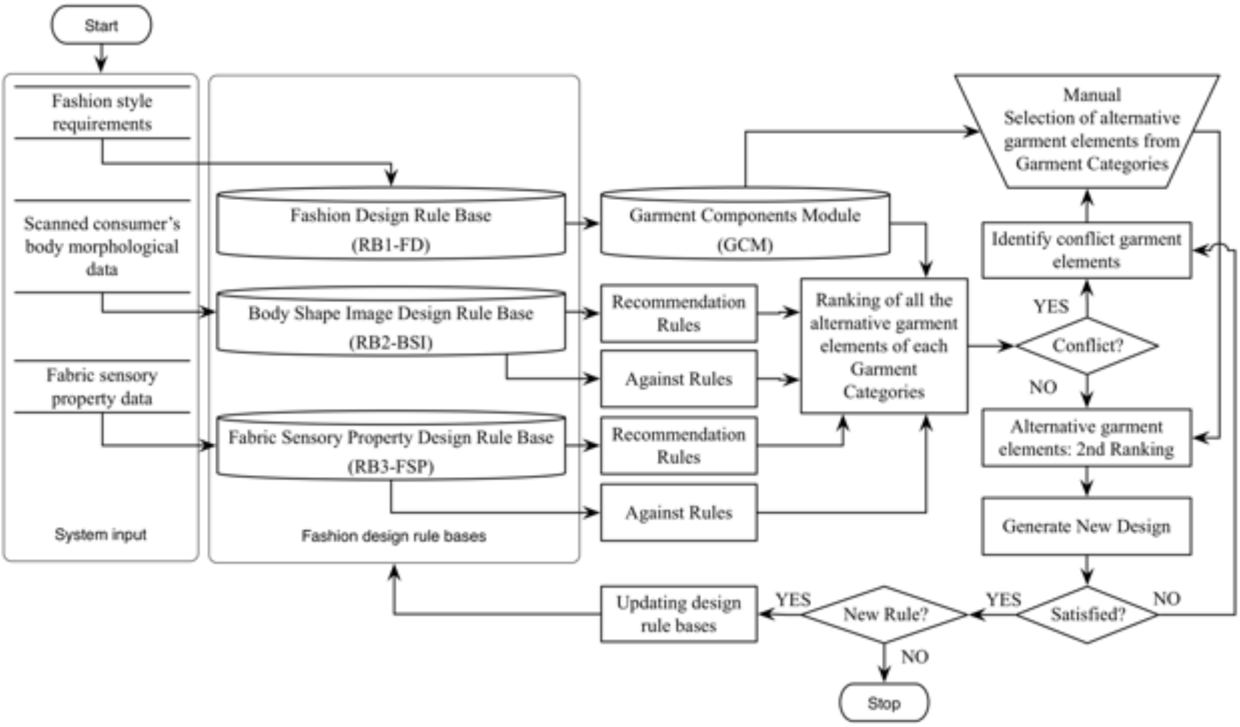


Figure 2-16: Working process of the *Rule-based Recommendation Module (RBRM)*.

Figure 2-16 presents the working process of the ***RBRM***. It starts with processing of the input values, including identified fabric sensory property data (visual and hand sensory property, see Section 3.2.3), consumer’s body shape image sensory data and consumer’s required fashion style sensory property. The general principle of the recommendation is to use design rules of different rule bases to rank all the alternative garment components of each ***Garment Component Category*** of the ***Garment Components Module (GCM)***. First, all the alternative garment components will be ranked based on the consumer’s fashion style requirements. Then this ranking will be filtered based on the design rules of ***RB2-BS*** and ***RB3-F***, including both recommendation rules and against rules. Then a new ranking will be updated based on the filtering process. If there are no conflicts between the rankings of these alternative garment components, the final product profile will be generated by using the best combination of garment components, each corresponding to the highest rank in its ***Garment Component Category***. If there is a conflict between two alternative garment components in different ***Garment Component Categories***, they will be presented to the ***PWAM*** for manually selecting the most preferable garment component in each category in order remove this conflict. The generated product profile will be presented to the consumer. If the consumer is satisfied with the result, the recommendation will be finished. If he/she is not satisfied with the result, he/she can manually select the unsatisfied ***Garment Component Category***. The process will be repeated until the final satisfied product profile is generated. After that, the proposed ***RBRM*** will update the rule base if a new design rule is generated. The main functions of the ***RBRM*** are described in Figure 2-16.

2.2.3.8 *Rule Updating Module (RUM)*

The ***Rule Updating Module (RUM)*** is proposed for enhancing the recommendation accuracy of the proposed ***GSRS***. There are two approaches for the updating of design rules: (1) integrating new design rules from the open resource (fashion trend, new design solutions for ***PWAM*** based on the theory of fashion design for improvement, new functional fabrics for ***PWAM***…), and (2) generating new design rules based on the dissatisfaction of the consumer.

For the first approach, a new design rule will be first identified based on the experience of designer, then, the new design rule will be integrated into the system, based on a collaborative design work among designers. The experimental tool of sensory evaluation will be used to realize this process. For example, "Stand Collar of the Tap Type" (Figure 2-17) is now a new trend for the collar design of shirt. The ***Garment Component Category*** of this rule is "Collar" of the GCM. Then, a new alternative garment component "stand collar of the tap type" will be added to the ***Garment Component Category*** of "***Collar***". After that, a group of designers will be invited to evaluate the "Stand Collar of the Tap Type" using the ***Garment Design Sensory Attribute*** of the ***GDSM***. When the similarity between the fashion style image of the "Stand Collar of the Tap Type" and the fashion style requirement of a ***PWAM*** is higher than that of the other alternative garment components of the ***Garment Component Category*** of "***Collar***", the "Stand Collar of the Tap Type" will be recommended to this ***PWAM***.

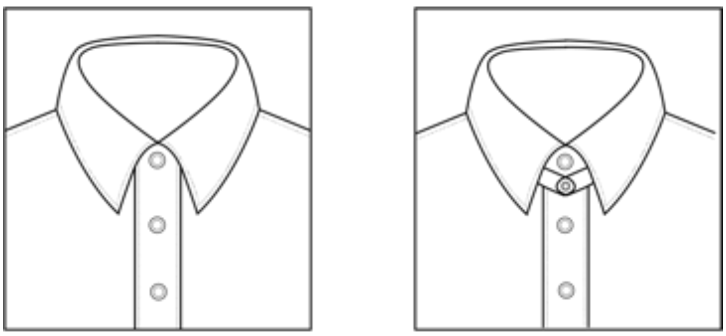


Figure 2-17: Stand collar of the classic type and the tap type.

For the second approach, if a consumer is not satisfied by the recommended result, he/she will quantitatively identify the unsatisfied part of the recommended garment using the sensory evaluation. Then, the system will adjust the related rule base (***RB1-FS, RB2-BS*** or ***RB3-F***) and recommend another product to this consumer. This procedure is repeated until the satisfaction of the recommended result by the consumer. The related rule bases can be progressively improved by integrating the evaluation results of a series of recommended garment components. The proposed ***RUM*** has self-learning ability and the accuracy of the ***GSRS*** will be progressively increased with the number of consumers using the system.

2.2.3.9 Working process of the proposed *GSRS*

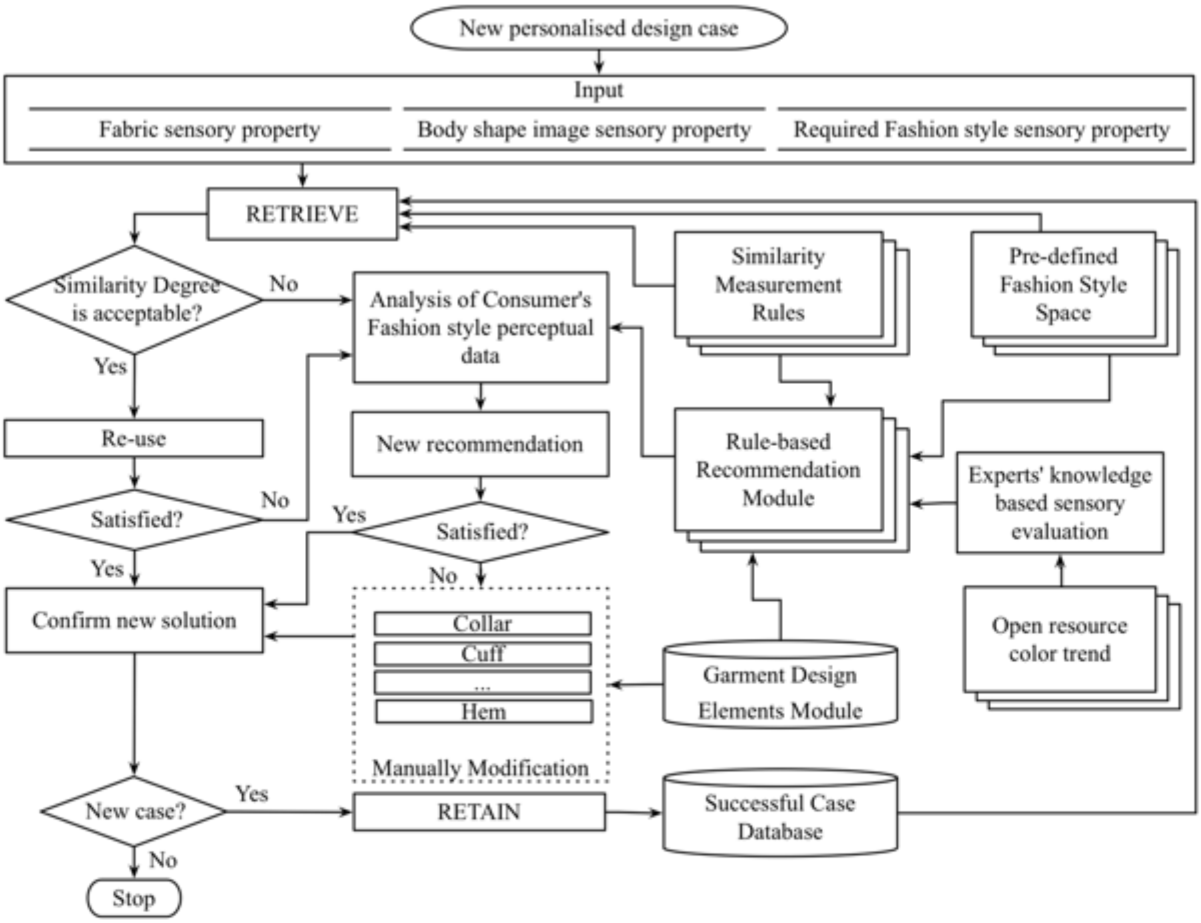


Figure 2-18: Working flowchart of the proposed *Garment Style Recommendation System (GSRS)*.

The proposed ***GSRS*** is a knowledge-based recommendation system. Design knowledge on designer's fashion design perception is extracted to support the recommendation process. The alternative garment components of the target recommended garment are identified in a novel ***GCM*** based on their ***Garment Component Categories***. Fashion style image of these alternative garment components are identified using the ***Garment Design Sensory Descriptive Features*** of the proposed ***GDSM***. The identification of fashion style image of these alternative garment components is performed by designers through a group sensory evaluation process. The consumer's fashion style requirement will be compared with the fashion style images of these alternative garment components in the ***GDSM***, in order to select the most similar fashion style image of these alternative garment components for each ***Garment Component Category***. The selected garment components will generate a product profile, which is oriented based on ***Garment***

Component Categories. The consumer's evaluation on satisfaction of the recommended product profile will be performed regarding each of the ***Garment Component Categories***. According to the evaluation results, these garment components can be further modified or defined. When a recommended product profile is satisfied by the consumer, the pair of the Case profile, recommended product profile will be retained in the ***SCD*** for being recommended to those having similar consumer profiles.

Figure 2-18 presents the working process of the proposed ***GSRS***. When a new user uses the proposed color recommendation system, his/her fabric sensory property value, body shape image value obtained from the body shape analysis rules of the system, consumer's fashion style requirement will be input to the system. These three sets of input data constitute the retrieved new case for being compared with the existing ***Successful Cases*** in the ***SCDM*** in order to find the most relevant case according to a predefined similarity degree.

If the biggest similarity degree between the retrieved new case and the existing Successful Case in the ***SCDM*** is higher than a predefined threshold, the concerned ***Successful Case*** in the ***SCDM*** is then considered as the target case and it will be re-used for recommendation. The corresponding satisfactory product profile of the target case will be presented as recommendation result to the new case. If the user is satisfied with this result, the recommendation process will stop. If there is no target case in the ***SCD*** meeting the required threshold or the new user is not satisfied with the recommended garment component of the target case, a rule-based recommendation using the ***RBRM*** will be performed until a satisfied product profile is obtained. In this situation, the ***RUM*** will be used to update related rule bases.

2.3 Conclusion

In this chapter, the general framework and working process of the proposed ***Personalized Garment Design System (PGDS)*** is introduced. There are several originalities in the proposed system:

- Integration of designers and consumers' knowledge. This thesis enables to design four experiments for data acquisition, then utilize the fuzzy technologies for formalizing the designer's and consumer's knowledge base and integrate this knowledge base into the garment recommendation system.
- Integration of fashion trends. Fashion Trends can be integrated into the recommendation system.
- Establishment of the consumer feedback mechanism and updating of the successful cases database. When one garment is recommended, the consumer will evaluate it. If it is unsatisfied, the consumer will identify the unsatisfactory part, and the system will recommend a new product until the consumer's full satisfaction. If the consumer is satisfied, then the corresponding product

and consumer profile will be added to the database of successful cases, from which new consumers having similar profiles can easily obtain relevant recommendations.

Chapter 3 Fashion Knowledge and Data Acquisition, Modeling, Analysis and Visualization: Basic Concepts and Tools

This chapter gives a comprehensive introduction about the acquisition, modelling, analysis and visualization issues of all the related knowledge and data mentioned in Chapter 2. The features and structure of specific fashion knowledge in personalized fashion design are analyzed in Section 3.2 based on the understanding about the main features of general knowledge in Section 3.1. Subsequently, sensory evaluation tools are employed in this research for acquisition of related fashion knowledge and data, based on the previously identified features and structure. Next, in Section 3.3, we give a systematic introduction about the notions of sensory evaluation. In Section 3.4, we introduce all the computational tools used for modelling of the acquired fashion knowledge and data, including fuzzy techniques (Section 3.4.1), AHP (Section 3.4.2), and CBR model (Section 3.4.4). The related data analysis tools, such as TOPSIS, are also introduced (Section 3.4.3). In Section 3.5, we present a number of virtual-reality based CAD software used for the fashion knowledge visualization and product design. Figure 3-1 presents the organization of this chapter.

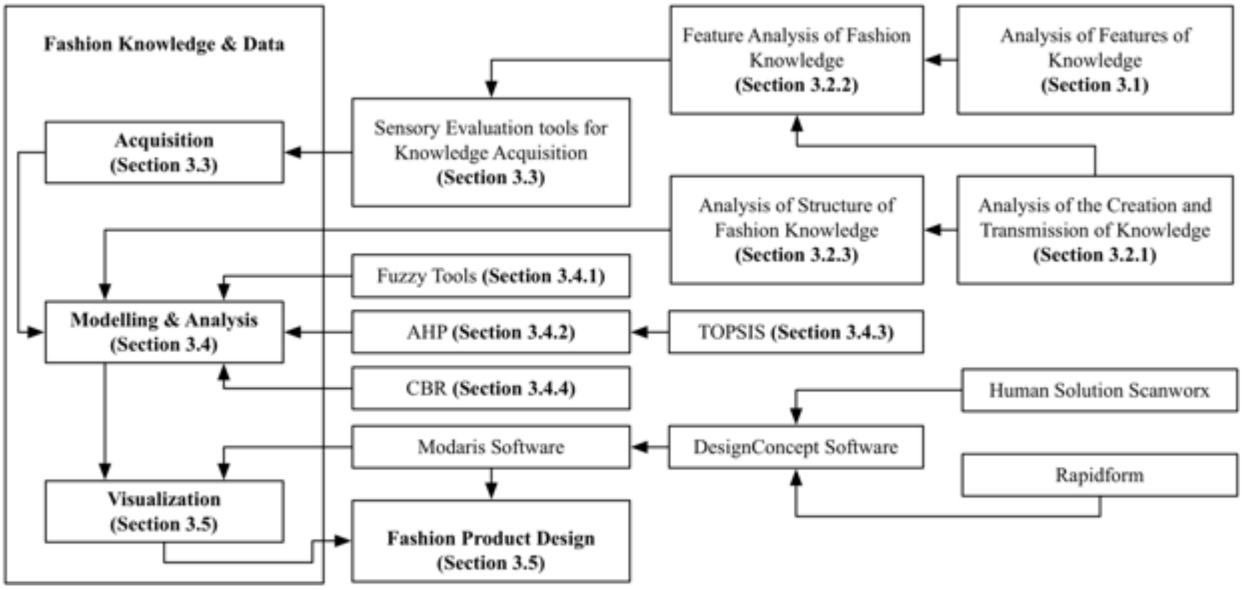


Figure 3-1: Organization of Chapter 3.

3.1 Knowledge and its features

In my thesis, fashion knowledge acquisition is the foundation of all research work. In order to analyze fashion knowledge, general notions of knowledge are presented in this section. Knowledge is a familiarity, awareness or understanding of someone or something, such as facts, information, descriptions, or skills, which is acquired through experience or education by perceiving, discovering, or learning [69].

3.1.1 Classification of Knowledge

Knowledge can be divided into explicit knowledge and implicit knowledge based on the way of its acquisition [70]. The explicit knowledge, referring to knowledge that can be explicitly expressed, can be acquired from oral instructions, textbooks, references, periodicals, patents, software and database and so on [70]. This knowledge is the theoretical understanding of a subject. The explicit knowledge can be propagated through languages, books, text, database, and can be easily learned by human [71]. Implicit knowledge is practical skill or expertise, which refers to the knowledge mastered by people in terms of skills and recognition, including not only skills and experiences that are informal and hard to express, but also insights, intuitions, inspirations, etc. Implicit knowledge exists in expert's brains, which dominate its various applications by human [72].

3.1.2 Knowledge Acquisition

Knowledge acquisition involves complex cognitive processes: perception, communication, and reasoning; while knowledge is also said to be related to the capacity of acknowledgment in fashion designers [73].

The knowledge engineers can acquire knowledge from three sources [74]:

(1) Indirect knowledge: experts provide their empirical and non-structured knowledge related to their past experiences by responding a well-organized questionnaire in some real scenarios.

(2) Direct knowledge: experts (fashion designers and pattern designers) directly express their well-structured and formalized knowledge under the forms of generalized rules and relations.

(3) Knowledge from data: knowledge can be automatically and progressively learned from data.

3.2 Fashion Knowledge and its Formalization

Fashion knowledge is part of aesthetic knowledge, which is regarded as unstable and constantly changing. Fashion concepts are regarded as multiple cultural-oriented. It is complex, socially constructed and widely tacit [75]. In this section, the creation, transmission of fashion knowledge and its features are analyzed.

3.2.1 Creation and Transmission of Fashion Knowledge

Similar to other forms of expert knowledge, fashion knowledge gravitates to international fashion centers, especially Paris, Milan, New York and London. These cities are widely recognized in the fashion world as the headstream of fashion knowledge. They create and transmit fashion knowledge. Fashion designers work across time and space to create fashion knowledge (new ideas and fashion innovations) in these cities. This innovation process of fashion knowledge relies on the percolation of ideas: recycling ideas from earlier eras, collecting ideas from avant-garde urban groups or borrowing them from ethnic communities.

The original fashion knowledge can be perceived by other actors in the fashion world and then forms the tacit knowledge through a codified formalization. The codified fashion knowledge is formulated in books, magazines, electronic data, expertise, and so on [74]. Generally, there are two groups of people performing this fashion knowledge transmission. They are (1) institutional researchers, such as fashion institute and fashion trend analysis agency, or (2) fashion designers from fashion brands which belong to a lower innovation level. Correspondingly, there are two forms of codified fashion knowledge, namely the institutional and industrial formalization. In fact, a fashion knowledge transmission enables to generate an "imported creation" instead of an "original creation".

When the original fashion knowledge is received and applied by designers in other places, a learning process is performed. The original fashion knowledge is promoted by proximity or by "being there". This learning process makes the original fashion knowledge to be territorially specific by creating a localized innovative thinking.

However, in the market cycle, consumers perceive fashion knowledge through fashion products designed by local fashion designers using the "learned" fashion knowledge. Even though a consumer is not able to tell the "original" or "learned" fashion knowledge, this interaction process still contributes a lot to promotion of the innovation thinking.

3.2.2 Features of Fashion Knowledge

As described in Section 2, this thesis mainly deals with indirect knowledge. For an accurate and objective expression of knowledge on garments, it is important to analyze the features of knowledge on garments. As the main features of general knowledge are fuzziness, complexity, and integrity [76], in this section, we analyze fashion knowledge in terms of these three aspects.

(1) Fuzziness

Human perception on garments is fuzzy, and cannot be easily expressed [77]. Thus, it is difficult to obtain quantitative results with traditional theories and methods when evaluating the human perception on a garment. Also, the evaluation rules cannot be explicitly understood and stated with Boolean logic. The sensory data expressed by any specific evaluation subject is not only uncertain but also multiple [78]. Consequently, in practice, the sensory data on garments can be expressed by utilizing fuzzy sets [79].

(2) Complexity

Garments are the most commonly used consumer goods [80]. However, its information is very complicated and rich [81]. The complexity of a garment is not only embodied in its own structure and aesthetic perception, but also concerns the relationship between garments and body shapes [82]. For example, the same garment fitting with different consumer sizes, usually leads to a big difference in vision. This is so-called sensory attraction of garments, which is complex but characterize the quality of garment styles and values of brands.

(3) Integrity

For garment products, design elements include a number of sensory descriptive features on patterns, details, fabrics and so on [83]. These elements are independent but interconnected between them, in order to show one specific identity. The perception on garments is related to the overall sensory effects on the combination of these elements. Therefore, the evaluation on garments is performed with respect to overall perception.

The main computational tools used in this thesis are selected for modeling and analysis of professional knowledge and human perceptions at different levels by taking into account the previous features. Fuzzy techniques have been selected as the main tool for processing the uncertainty and imprecision of these data [84].

3.2.3 Structure of Fashion Knowledge in Personalized Fashion Design

Fashion knowledge includes: 1) designer's perception on the performance of garment design elements, such as color, fabric, and garment style (garment style is composed of garment components, such as silhouette, blanket, length…); 2) associations between garment design elements, body morphologies, consumer fashion requirements, and normalized sensory properties charactering products to be designed. For example, the Color Design Knowledge can be described by a series of associations between color ranges and designer's perception on color sensory properties (such as brightness, distance and volume …), as well as preference of consumers on colors. These associations have been extracted from designer's experience in the past.

Apart from the previous two categories, the past successful personalized design cases with related consumer profiles are also considered as important fashion knowledge. This kind of knowledge can be processed by ***Case-Based Reasoning***, which will be discussed in Section 3.4.4.

Figure 3-2 describes the structure of all fashion knowledge in a personalized fashion design process. As described in Section 2.1.1, the personalized fashion design knowledge is composed of three categories of knowledge: ***color design knowledge***, ***fabric selection knowledge***, and ***garment style design knowledge***.

The fabric selection knowledge is composed of the ***Visual Sensory Properties*** and ***Fabric Hand Sensory Properties***. The ***Visual Sensory Properties*** include human perception on brightness, distance, volume and other visual aspects describing fabrics. The ***Fabric Hand Sensory Properties*** include human perception on hand feeling of fabrics, such as softness and drapability.

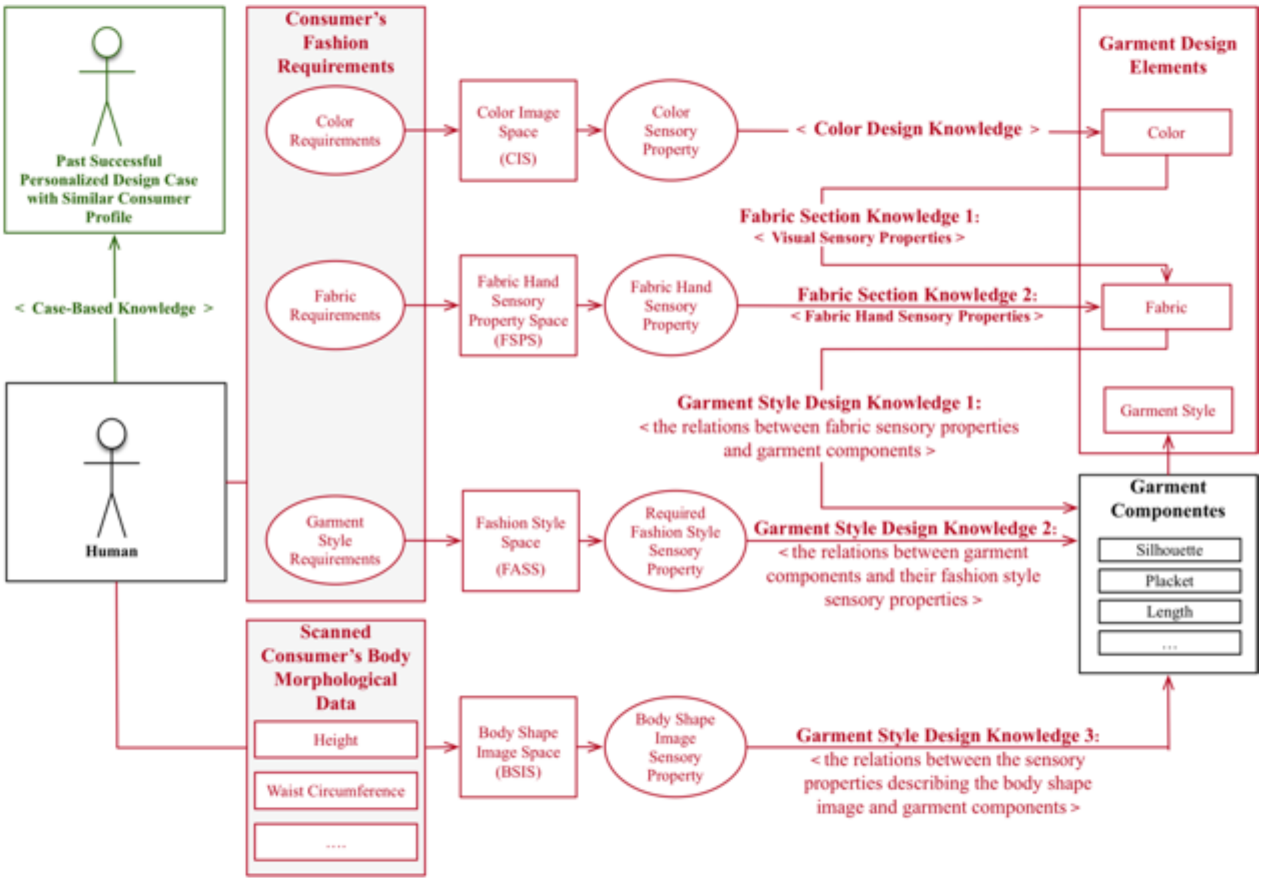


Figure 3-2: Structure of Fashion Knowledge in Personalized Fashion Design.

The garment style design knowledge is composed of (1) the relations between fabric sensory properties (visual and fabric hand properties) and garment components (collar, sleeve, cuff …), (2) the relations between garment components (collar, sleeve, cuff …) and their fashion style sensory properties (such as *Construction (Complex-Simple)*, *Times (Modern-Classical)*, *Gender (Female-Male)*, *Acceptance (Occasional-Universal)* …), (3) the relations between the sensory properties describing the body shape image (such as height, fatness …) and garment components (collar, sleeve, cuff …). These three categories of garment style design knowledge are stored in the ***Fashion Style Related Garment Design Rule Base (RB1-FS)***, the ***Body Shape Image Related Garment Design Rule Base (RB2-BS)***, and the ***Fabric Sensory Property Related Garment Design Rule Base (RB3-F)*** respectively, as described in Section 2.2.3.7.

3.3 Fashion Data Acquisition by Using Sensory Evaluation

In order to obtain consumer's fashion perceptual data and integrate fashion knowledge into the proposed system, sensory evaluation is used as a standardized and systematic research method to extract reliable knowledge from designers.

3.3.1 Fashion Knowledge Acquisition Using Sensory Evaluation

In my thesis, the proposed system has to deal with a lot of fashion data: designer's fashion design knowledge data and consumer's fashion perceptual data. In this context, fashion knowledge and data acquisition is the foundation of all research work. As described in Section 3.2.3, fashion knowledge is designer's perception describing the performance of garment design elements and associations between design elements, consumer requirements and technical properties on products. In a general context, sensory evaluation is an appropriate method for obtaining human perception on products by using evaluators' five senses. Compared with objective data measured by devices, these sensory data are relatively vague and imprecise. Sensory evaluation permits to extract and formalize reliable fashion knowledge in a standardized and systematic study way. Using sensory evaluation, a fast and efficient fashion style recommendation, satisfying the requirements of automatic design and production, can be realized.

In this section, sensory evaluation experiments for acquisition of the related fashion knowledge as described in Section 3.2.3 are introduced.

In this research, there are four sensory experiments designed to establish sensory evaluation spaces of the ***Garment Design Space Module (GDSM)***, namely the ***Color Image Space (CIS)***, ***Fabric Sensory Property Space (FSPS)***, ***Fashion Style Space (FASS)***, and ***Body Shape Image Space (BSIS)***. As introduced in Section 2.2.3.2, these spaces enable the acquisition of the perceptual data of both designers and consumers.

In my study, we designed five sensory experiments for acquiring related fashion knowledge. These experiments include:

Sensory Evaluation Experiment I is designed to obtain the ***Color Design Knowledge***, namely the relationship between color image words and their associated color image sensory descriptive features. More details will be given in Section 4.1.3.

Sensory Evaluation Experiment II is designed to obtain the ***Color Sensory Property Related Fabric Selection Knowledge***, namely the relationship between color image words and their associated color image sensory descriptive features. More details will be given in Section 4.2.2.

Sensory Evaluation Experiment III is designed to obtain the ***Fabric Sensory Property Related Garment Style Design Knowledge***, namely the relationship between fabric sensory property and garment components. More details will be given in Section 4.3.2.

Sensory Evaluation Experiment IV is designed to obtain the ***Body Shape Image Related Garment Style Design Knowledge***, namely the relationship between body shape image sensory properties and garment components. More details will be given in Section 4.3.2.

Sensory Evaluation Experiment V is designed to obtain the ***Fashion Style Related Garment Style Design Knowledge***, namely the relationship between fashion style sensory properties and garment components. More details will be given in Section 4.3.2.

For ***Fabric Selection Knowledge***, it can be obtained from a normalized sensory evaluation procedure directly. The general procedure of these sensory experiments will be presented in Section 3.3.2.

3.3.2 Basic Concept of Sensory Evaluation

Sensory evaluation is a scientific discipline that applies the principles of experimental design and statistical analysis with the human senses (sight, smell, taste, touch and hearing) for evaluating consumer products [85]. The discipline requires panels of human assessors, on whom the products are tested for recording perceptive responses to evaluated objects [86]. By applying statistical techniques to the perception data, it is possible to make inferences and insights about the properties of products [87]. Many large companies of consumer goods have internal departments dedicated to sensory analysis.

Sensory evaluation is developed to improve consumer's sense on a garment. The investigator is guided to represent the sense by using descriptors and associated scores, and processes the data by using factorial analysis and other statistical tools, thereby evaluates whether the consumer accepts the garment or not, and predicts his/her future purchase preferences.

Besides the garment industry, the most developed application sectors of sensory evaluation are food industry, automobile industry and cosmetic industry. In these industrial sectors, sensory evaluation can effectively provide means for development and promotion of new products and exploitation of new markets.

3.3.2.1 Sensory Participants

Sensory evaluation is carried out by several sensory participants. Sensory participants are a group of individuals organized to evaluate a set of representative samples. During a sensory evaluation, each sensory participant is asked to, according to their personal or professional experience; give a score to a set of linguistic descriptors selected for the samples to be evaluated.

The sensory participant can be generally classified into the following five categories:

(1) Experts: the professional experts specialized in a specific technology (fabric hand, color, material surface, ...), invited to evaluate typical products and define evaluation criteria.

(2) Sensory participant specialized in analysis of quantitative description: the sensory participant trained to evaluate the products using standard linguistic terms.

(3) Sensory participant of free choice: the sensory participant trained to evaluate the products using their own words.

(4) Consumers in laboratory: the non-trained consumers invited to evaluate products whose experimental conditions (light, temperature, humidity, ...) are well controlled.

(5) Consumers in real purchasing scenarios: the non-trained consumers randomly selected to evaluate products in real scenarios (shopping centers, brand shops, Internet, ...).

3.3.2.2 Design of Experiments

A good experimental design of experiments is the premise of obtaining reliable data. As the data structures for different types of experiments are different, each experimental design, including the detailed experimental procedure and the recruitment of experimenter, should be different from the others.

If the sensory experimenter consists of non-trained consumers, a good questionnaire should be designed to trigger the responders' true and exact perceptions about the specific samples to be evaluated.

On the other hand, if the sensory experimenter is composed of specialized experts, the evaluation procedure should be designed to help us acquire the maximum amount of information from the samples to be evaluated.

In fact, the key issue during the collection of sensory data is to design an optimal experimental project according to which the products of interest can be evaluated in the same optimized way, i.e. the number of experiments is minimized, the number of products is big enough and the time for evaluation is limited.

During the process of a design of experiments for sensory analysis, we should keep in mind the research strategy, involving the objectives of the experiments, the method of giving problems and the way of getting results. They will influence all the sectors involved in a sensory experiment, including the preparation of samples, the way of displaying the samples, the definition of evaluating techniques, and the arrangement of experimental procedures, etc.

3.3.2.3 Modelling of relations in sensory analysis

(1) Multisensory analysis

It is known that the most significant part of a sensory study is the communication between human elements and product elements. For a garment item, the human elements refer to both the experts' professional knowledge and consumers' personal preference which are expressed through sensory experiments. In industry, it is necessary for manufacturers to identify the real relations between the product elements and human factors (perception, emotions, body shapes, ergonomics, ...). This will enable them to detect the changes of markets, and integrate consumers' demands into new product designs.

There are two principal studies in sensory analysis. One type is to study the relations between product elements and human elements about a specific product. The other type concerns the multisensory analysis dealing with perceptions in different channels (hand feeling, vision, hearing, ...). The multisensory analysis includes two categories. One is aimed to formalize consumers' complex emotional and social demands on the products which give rise to the concepts such as the comfort, well-being, and sustainable development and so on. The other category is dedicated to study the interactive relations between different human perceptions. It is often used to enrich to the biggest extent our consumers' purchasing experience and increase their satisfaction towards the specific product.

(2) Modeling of relations between different sensory data

It is important to find a good mathematical approach to model the relations between different sensory data. Many methods have been developed for exploiting complex relations among multiple data. Nowadays, the most used methods are based on statistics, including linear regression analysis, Principal component analysis (PCA), Multiple factor analysis and correlation coefficient analysis. These methods are effective in solving many problems in sensory evaluation, because it is a good way of studying linear patterns of different information and then discovering correlations relations.

However, since modeling of relations between different sensory data usually deals with uncertainty and vague, the classical methods are gradually showing their drawbacks in practice. More detailed analysis is given below.

First, when a problem is dealing with knowledge, the concerned relations are often nonlinear. The application of the statistical techniques might cause important information loss.

Second, in many situation, there exists high uncertainty and vague in sensory analysis. But most of the classical analysis methods can only process precise numerical data.

Third, the classical methods cannot always lead to precise interpretation of data, and the correlation results cannot be used to analyze all types of relations between data such as inclusion, causal and association relations.

In this thesis, intelligent computational techniques, such as fuzzy set, AHP and many hybrid applications of these tools, have largely been applied to modeling and analysis with sensory data.

They have advantages in: (1) Solving nonlinear problems, (2) Dealing with both numerical and linguistic data, and (3) Modeling expert reasoning so as to produce precise and straightforward interpretation of results. Compared with the classical methods, the intelligent techniques have been practiced in many fields of sensory analysis such as food, automobile, cosmetic and garment, and get more successful and significant results.

3.4 Mathematic Modeling Tools for Fashion Knowledge Representation

For formalizing and modelling human perception data, we choose several intelligent techniques, including fuzzy techniques, ***Fuzzy AHP (Fuzzy Analytical Hierarchy Process)***, ***TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)*** and ***Case-based reasoning***.

We first introduce the concepts of fuzzy sets, fuzzy relations and the related operations, which is able to deal with the vague and uncertain human perception data obtained in the sensory evaluation process.

Based on these basic concepts, two classical computing methods for ranking and clustering, i.e. ***Fuzzy AHP*** and ***Fuzzy TOPSIS*** are presented. ***Fuzzy AHP*** is applied to modeling the hierarchical knowledge structure in fashion recommendation, and ***Fuzzy TOPSIS*** is a data analysis tool, which is utilized to make global decision-making based on different mathematic models.

Finally, the ***Case-Based Reasoning*** technology is presented to show how to recommend relevant garments to each consumer by comparing his/her profile with the database of successful cases, gathering all the successful recommended product profiles in the past shopping experience.

3.4.1 Fuzzy Theory and Related Technique

The entire real world is complex and the complexity arises from vagueness [88]. If the complexity of a problem exceeds a certain threshold, the system must become vague in nature [89]. And with the increase of complexity, our ability of making precise judgments about the behavior of the system diminishes. There is a rapid decline in the information afforded by traditional mathematical models due to their insistence on precision. In our study, sensory evaluation has been used in this research for knowledge acquisition, which is based on human perception and judgement. Due to the fact that there are vagueness and uncertainty in human perception, fuzzy set theory is used for processing the uncertain data in sensory evaluation.

3.4.1.1 Fuzzy sets theory

Words like “young”, “tall”, “good”, and “high” are fuzzy. There is no single quantitative value for characterizing the term “young”. For some people, the age of 20 is young, and for others, the age of 30 is young. The concept of “young” has no clear boundary.

The age of 10 is definitely young and the age of 80 is definitely not young. Age 28 has some possibility of being young. This concept usually depends on the context in which it is being considered.

In the real world, there exists a lot of human knowledge. By nature, knowledge is vague, imprecise, uncertain, ambiguous, or probabilistic. Human thinking and reasoning frequently involve fuzzy information, originating from vague human concepts. Humans can give satisfactory answers, which are probably true.

However, most of automatic systems are designed based upon classical set theory and two-valued logic, which is unable to cope with unreliable and incomplete information and give expert opinions. In this situation, fuzzy sets have shown their special advantages of dealing with both human knowledge and uncertain information.

Fuzzy sets were introduced by Lotfi A. Zadeh and Dieter Klaua in 1965 as an extension of the classical notion of set [90]. In the same time, Salii defined a more general kind of structure called an L-relation, which he studied in an abstract algebraic context [91]. Fuzzy relations, currently used in different areas, such as linguistics, decision-making and clustering, are special cases of L-relations when L is the unit interval [92].

In classical set theory, the membership of elements in a set is assessed in binary terms according to a bivalent condition: an element either belongs or does not belong to the set. By contrast, fuzzy set theory permits the gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the unit interval [92]. Fuzzy sets generalize classical sets, since the indicator functions of classical sets are special cases of the fuzzy membership functions of fuzzy sets, if the latter only take values 0 or 1.

In fuzzy set theory, classical bivalent sets are usually called crisp sets. The fuzzy set theory can be used in a wide range of domains in which information is incomplete or vague, such as bioinformatics and so on.

Classical Set Theory

A Set is any well-defined collection of objects. An object in a set is called an element or member of that set [93].

Sets are defined by a simple statement describing whether a particular element having a certain property belongs to that particular set. Classical set theory enumerates all its elements using $A = \{a_1, a_2, a_3, \ldots, a_n\}$. If the elements a_i (i□$\{1,2,3, \cdots n\}$) of a set A are subset of the universal set X, then the set A can be represented for all elements x □ X by its characteristic function.

$$\mu_A = \begin{cases} 1 & if \ \ x \in X \\ 0 & otherwise \end{cases} \tag{3-1}$$

Definition of a Fuzzy Set

The membership function in a crisp set A maps its whole members in the universal set X to the set {0,1} as

$$\mu_A: X \rightarrow \{0,1\}.$$

In a fuzzy set A, each element is mapped to [92] by its membership function as

$$\mu_A: X \rightarrow [92, 94]$$

which means that the membership function takes real values between 0 and 1 (including 0 and 1).

Consequently, a fuzzy set is a 'vague boundary set' of a crisp set. The difference between a crisp set and a fuzzy set is identified by their fuzzy membership functions.

For example, considering that a fuzzy set *A= 'two or so'* is defined on the universe *X* of positive real numbers, i.e. *X={1,2,3,4,5,6,⋯},* its membership function can be defined by a series of discrete real numbers:

$$\mu_A(1) = 0, \mu_A(2) = 1, \mu_A(3) = 0.5, \mu_A(4) = 0\cdots$$

Another example is a statement *"Tom is young"*. At this time, the term *"young"* is vague. To represent the meaning of *"vague"* exactly, it would be necessary to define its membership function as in Figure 3-3. When we refer *"young"*, there might be age which lies in the range [95] and we can account *"young age"* in this range as a continuous set.

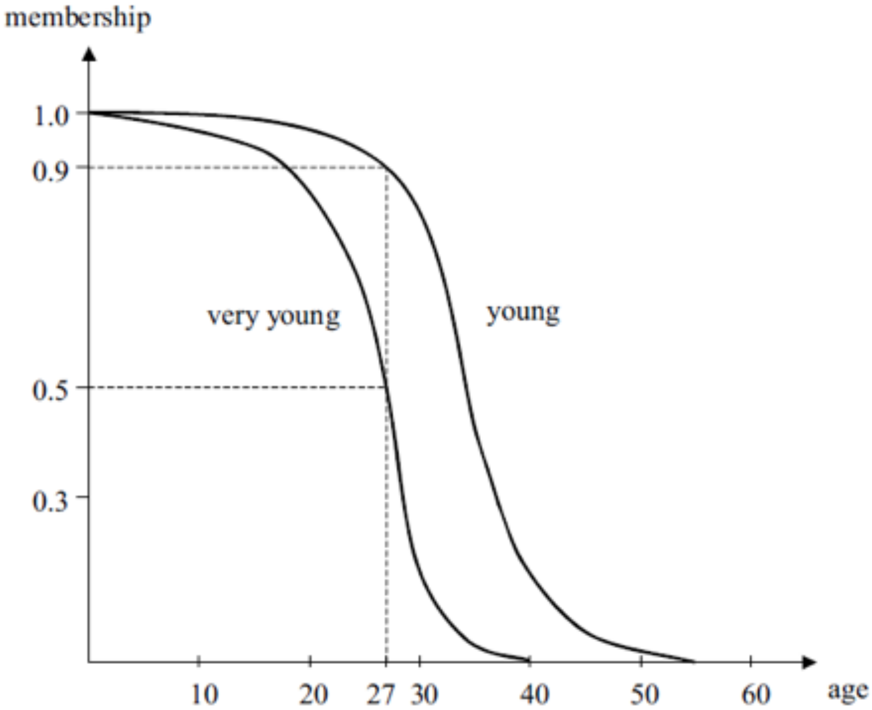


Figure 3-3: Fuzzy sets representing "young" and "very young".

The horizontal axis shows age and the vertical one means numerical values of the membership function. The curve in this figure shows the possibility (value of membership function) of belonging to the fuzzy set *"young"*.

Also, we can manipulate another close statement "*Tom is very young"*. In order to be included in the set of *"very young",* the age should be lowered and let us think that the curve is moved leftward as in the Figure 3-3. If we define a fuzzy set as such, only the person who is under forty years old can be included in the set of "very young". Now the possibility of a man of twenty-seven years old is being included in this set is 0.5. That is, if we denote $A=$ *"young"* and B = *"very young",*

We have $\mu_A(27)$=0.9, $\mu_B(27)$=0.5.

3.4.1.2 Standard Operations of Fuzzy Sets

Complement

For the complement set $\bar{A}$ of a fuzzy set *A*, its membership function is defined as follows.

$$U_{\bar{A}}(x)=1-U_A(x),\ \forall x \in X \tag{3-2}$$

Union

The membership value of an element *x* in the union takes the greater value of the corresponding membership degrees of *A* and *B*

$$U_{A\cup B}(x)=Max[U_A(x),\ U_B(x)],\ \forall x \in X \tag{3-3}$$

Intersection

The membership function of the intersection of two fuzzy sets *A* and *B* takes smaller value of the membership functions of *A* and *B* $A\cup B = B\cup A$

$$U(A \cap B)(x)=Min\ [U_A(x),\ U_B(x)],\ \forall x \in X \tag{3-4}$$

3.4.1.3 Properties of fuzzy sets

Considering three fuzzy sets *A*, *B* and *C* defined on the universe *X*, the properties of classical sets are also suitable to fuzzy sets. They include:

Commutativity:

$$A\cup B = B\cup A \tag{3-5}$$

$$A\cap B = B\cap A \tag{3-6}$$

Associativity:

$$A\cup(B\cup C) = (A\cup B)\cup C \tag{3-7}$$

$$A\cap(B\cap C) = (A\cap B)\cap C \tag{3-8}$$

Distributivity:

$$A\cup(B\cap C) = (A\cup B)\cap(A\cup C) \tag{3-9}$$

$$A\cap(B\cup C) = (A\cap B)\cup(A\cap C) \tag{3-10}$$

Identity:

$$A\cup\emptyset = A \text{ and } A\cap X = A \tag{3-11}$$

$$A\cap\emptyset = \emptyset \text{ and } A\cup X = X \tag{3-12}$$

Transitivity:

If $A\subset B\subset C$ then $A\subset C$.

3.4.1.4 Triangular Fuzzy Number

A ***Triangular Fuzzy Number (TFN)*** is one of the most commonly used fuzzy [96]. A ***TFN***, *M*, is usually denoted using n-tuples formalism as $M=(l,\ m,\ u)$ or $M=(l \mid m,\ m \mid u)$, where *l, m* and *u* denote the smallest possible value, the most possible value, and the largest possible value of a fuzzy event respectively as presented in Figure 3-4 [97]. Each set of ***TFN*** has linear representations on its left and right side [98]. The membership function of a set of ***TFN*** can be defined as [99]:

$$\mu_m(x) = \begin{cases} 0, \ x \in [-\infty, l] \\ \frac{x-l}{m-l}, \ x \in [l, m] \\ \frac{x-u}{m-u}, \ x \in [m, u] \\ 0, \ x \in [u, +\infty] \end{cases} \tag{3-13}$$

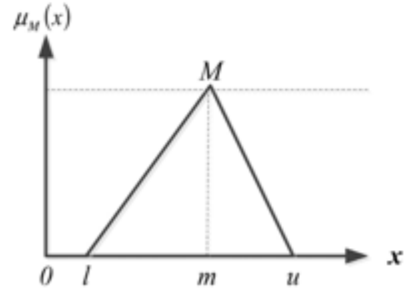


Figure 3-4: The Triangular Fuzzy Number.

If $M_1=(l_1, m_1, u_1)$ and $M_2=(l_2, m_2, u_2)$ are two ***TFN***s, the basic operations between them can be defined as [96]:

$$M_1+M_2 = (l_1+l_2, m_1+m_2, u_1+u_2) \tag{3-14}$$

$$M_1-M_2 = (l_1-l_2, m_1-m_2, u_1-u_2) \tag{3-15}$$

$$\lambda * M_1 = (\lambda * l_1, \lambda * m_1, \lambda * u_1) \tag{3-16}$$

$$1/M_1 = (1/u_1, 1/m_1, 1/l_1) \tag{3-17}$$

where denotes extended summation of two ***TFN***s, and denotes the extended multiplication.

Similarity Measurement

Euclidean distance can be used to describe the distance between two ***TFN***s [100]. The distance between $M_1= (l_1, m_1, u_1)$ and $M_2= (l_2, m_2, u_2)$ can be denoted as [101]:

$$d\ (M_1, M_2)= \sqrt{\frac{1}{3}[(l_1-l_2)^2+(m_1-m_2)^2+(u_1-u_2)^2]}. \tag{3-18}$$

Based on Equation (3-18), the similarity of two different ***TFN***s $M_1= (l_1, m_1, u_1)$ and $M_2= (l_2, m_2, u_2)$ can be denoted as [101]:

$$S\ (M_1, M_2)=1- d\ (M_1, M_2)\ = 1- \frac{\sqrt{\frac{1}{3}[(n_1-m_1)^2+(n_2-m_2)^2+(n_3-m_3)^2]}}{10}. \tag{3-19}$$

In order to realize the similarity measurement of Equation (5-1), the aggregation process of evaluation data is also concerned in this chapter.

Aggregation

Let $TFN\ (F_{b1})$ be the evaluation scores of an evaluation rating scale (for example, Table 4-1). Let $TFN\ (F_{b1})$, $TFN\ (F_{b2})$, and $TFN\ (F_{b3})$ represent the smallest possible value, the most possible value, and the largest possible value of $TFN\ (F_b)$ respectively. Let $N\ (F_b)\ (b=1,2,3\ldots,7)$ be the number of evaluators selecting the score F_b during the evaluation experiment, the aggregated value of a_m can be defined as:

$$a_m = \left(\frac{\sum_{b=1}^{7} TFN\ (F_{b1}) \times N\ (F_b)}{\sum_{b=1}^{7} N\ (F_b)}, \frac{\sum_{b=1}^{7} TFN\ (F_{b2}) \times N\ (F_b)}{\sum_{b=1}^{7} N\ (F_b)}, \frac{\sum_{b=1}^{7} TFN\ (F_{b3}) \times N\ (F_b)}{\sum_{b=1}^{7} N\ (F_b)}\right) \tag{3-20}$$

Examples of the utilization of Equation (3-20) will be presented in Chapter 4.1.

Extent Analysis

The values using extent analysis are denoted as:

$$M_{E_i}^1, M_{E_i}^2, \dots M_{E_i}^m, \quad i=1, 2, \dots, n$$

where $M_{E_i}^1$ ($i=1, 2, \dots, n$) are all ***TFN***s. Then, the value of fuzzy synthetic extent with respect to the *i-th* object is defined as [102]:

$$S_i = \sum_{j=1}^{m} M_{E_i}^j \odot \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{E_i}^j\right]^{-1} \tag{3-21}$$

Let consider that $A = (a_{ij})_{n \times m}$ is the fuzzy analytical matrix, where $a_{ij} = (l_{ij}, m_{ij}, u_{ij})$ are defined by the calculated values:

$$l_{ij} = \frac{1}{l_{ij}};\ m_{ij} = \frac{1}{m_{ij}};\ u_{ij} = \frac{1}{u_{ij}}. \tag{3-22}$$

If we denote $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ as two ***TFN***s, the degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined by [103]:

$$V(M_2 \geq M_1) = SUP_{y \geq x}\left[min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right] \tag{3-23}$$

and can be expressed as follows [104], as presented in Figure 3-5, where the intersection point *D* is the ordinate of the highest intersection point between M_1 and M_2.

$$V(M_2 \geq M_1) = hgt\ (M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & if\ M_2 \geq M_1 \\ 0, & if\ l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases} \tag{3-24}$$

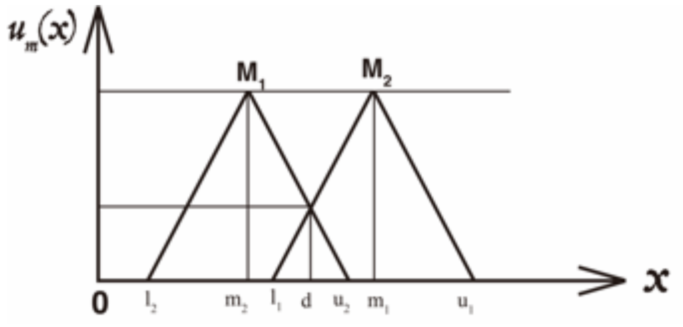


Figure 3-5: The intersection between M_1 and M_2.

In order to compare M_1 and M_2, both the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are required. The possibility degree, for a convex fuzzy number to be greater than *k* convex fuzzy M_i $(i = 1, 2, \dots, k)$ numbers, can be determined as:

$$V(M \geq M_1, M_2, \dots, M_k) = V[(M \geq M_1 and\ M \geq M_2 and \dots M \geq M_k)$$
$$= min\ V(M \geq M_i), \tag{3-25}$$

Assuming that $d(A_i) = min\ V(S_i \geq S_k)$ for $k=1, 2, \ldots, n;\ k \neq i$, the weight vector will be defined as:

$$W' = \left(d'(A_1), d'(A_2), \ldots d'(A_n)\right)^T \quad (3\text{-}26)$$

where $i=1,2,\ldots,n,$ which is denoted as i-th element among n number of elements.

A fuzzy number is a convex, normalized fuzzy set $\widetilde{A \subseteq \mathcal{R}}$ whose membership function is at least segmentally continuous and has the functional value $\mu_{\widetilde{A}}(x) = 1$ at precisely on an element [97].

Using classic normalization operations, the normalized weight vectors are denoted as:

$$W = \left(d(A_1), d(A_2), \ldots d(A_n)\right)^T \quad (3\text{-}27)$$

where W is a non-fuzzy number.

3.4.1.5 Advantages of fuzzy sets

Compared with traditional system modeling and analysis techniques, fuzzy sets have the following strengths: (1) It is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are simple. (2) It is tolerant with vague data. Most of things are imprecise even on careful inspection. Fuzzy reasoning permits to build this understanding into the process rather than tacking it onto the end. (3) It is based on natural language. The basis for fuzzy logic is the basis for human communication. Natural language is the carrier of efficient communication. Since fuzzy logic is built atop the structures of qualitative description used in everyday language, it is easy to use.

Some major areas of fuzzy applications in textile/garment industry include classifications, recommendations, decision-making and so on, related to materials, finished products, consumers, markets and manufacturing processes. An example is body size classification using the fuzzy c-means clustering algorithm [105]. Also, a method of fuzzy comprehensive evaluation has been investigated for fabric stiffness handle [106]. And an intelligent system based on fuzzy logic has been developed for optimization of the textile and garment supply chain [101]. Moreover, an intelligent system based on the fuzzy techniques has been developed to evaluate fabric shape style based on motion capture [89].

In this thesis, fuzzy sets theory has been used as the major computational technique for modeling and analysis. Especially, fuzzy sets and fuzzy operations have been applied to the processing of sensory data. The main ideas of these techniques are described below.

3.4.2 AHP

The ***Analytic Hierarchy Process (AHP)*** is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology [107]. It was developed by Thomas L. Saaty in the 1970s and has been extensively studied and refined since then [108].

It has particular application in group decision making, and is used around the world in a wide variety of decision situations, in fields such as government, business, industry, healthcare, shipbuilding and education [109]. Due to the fact that there are always a lot of decision-makers involved in the sensory evaluation process, the ***AHP*** model is used to modeling this kind of group decision making process.

Rather than prescribing a "correct" decision, the AHP helps decision makers find one that best suits their goal and their understanding of the problem [110]. It provides a comprehensive and rational framework for structuring a decision problem, for representing and quantifying its elements, for relating those elements to overall goals, and for evaluating alternative solutions [111].

Users of the ***AHP*** first decompose their decision problem into a hierarchy of more easily comprehended sub-problems, each of which can be analyzed independently [112]. The elements of the hierarchy can relate to any aspect of the decision problem—tangible or intangible, carefully measured or roughly estimated, well or poorly understood—anything at all that applies to the decision at hand [113].

Once the hierarchy is built, the decision makers systematically evaluate its various elements by comparing them to each other two at a time, with respect to their impact on an element above them in the hierarchy [114]. In making the comparisons, the decision makers can use concrete data about the elements, but they typically use their judgments about the elements' relative meaning and importance [110]. It is the essence of the AHP that human judgments, and not just the underlying information, can be used in performing the evaluations.

The ***AHP*** converts these evaluations to numerical values that can be processed and compared over the entire range of the problem [115]. A numerical weight or priority is derived for each element of the hierarchy, allowing diverse and often incommensurable elements to be compared to one another in a rational and consistent way [111]. This capability distinguishes the ***AHP*** from other decision-making techniques [116].

In the final step of the process, numerical priorities are calculated for each of the decision alternatives [109]. These numbers represent the alternatives' relative ability to achieve the decision goal, so they allow a straightforward consideration of the various courses of action. The AHP decomposes complex problems into multiple criteria and makes up hierarchical structures according to the dominance relation between these criteria. The relative importance of various criteria is identified by using pairwise comparison judgment and sorted by synthesizing judgment of deciders.

3.4.3 TOPSIS

The ***Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)*** was originally developed by Hwang and Yoon in 1981 with further developments by Yoon in 1987, and Hwang, Lai and Liu in 1993 [117]. ***TOPSIS*** is based on the concept that the chosen alternative should have the shortest geometric distance from the ***Positive Ideal Solution (PIS)*** and the longest geometric distance from the ***Negative Ideal Solution (NIS)*** [118]. It is a method of compensatory aggregation that compares a set of alternatives by identifying weights for each criterion, normalizing scores for each criterion and calculating the geometric distance between each alternative and the ideal alternative, which is the best score in each criterion [119]. An assumption of ***TOPSIS*** is that the criteria are monotonically increasing or decreasing [120]. Normalization is usually required as the parameters or criteria are often of incongruous dimensions in multi-criteria problems.

The ***TOPSIS*** is developed by Hwang & Yoon (1981)[121]. As a multiple criteria decision-making technique, ***TOPSIS*** helps to select the most ideal alternative among a finite set of options. The principle of ***TOPSIS*** is that the best solution is defined as the one farthest from the negative ideal solution and nearest to the positive ideal solution [122]. The positive ideal solution is the one that minimizes the cost criteria and maximizes the benefit criteria, whereas the negative ideal solution minimizes the benefit criteria and maximizes the cost criteria [123] [117]. In short, the negative ideal solution consists of all worst values attainable from the criteria, whereas the positive-ideal solution is composed of all best values attainable from the criteria [124]. Since there are both positive and negative evaluation criteria when evaluate the alternative fabrics, ***TOPSIS*** is introduced to my PhD research.

The ***Fuzzy TOPSIS*** was introduced to ***MCDM*** in the fuzzy environment by Chen (2000) to deal with the problem of uncertainty in the evaluation, judgment and assessment [98]. Using ***Fuzzy TOPSIS***, ***decision-makers (DMs)*** are able to incorporate incomplete information, unquantifiable information, partially ignorant facts and non-obtainable information into a decision model [101]. As a result, ***Fuzzy TOPSIS*** and its extensions are able to solve ranking and justification problems [120]. In this study, ***TFN*** is applied together to ***Fuzzy TOPSIS*** to express the linguistic opinions of the experts using a rating scale.

The application of ***Fuzzy TOPSIS*** method consists of the following steps:

Step 1: Fuzzy Rating of the alternatives and aggregating the results

An assessment session of the alternatives is firstly performed by the invited ***DM***s. Each of the alternative options will be evaluated regarding the evaluation criteria given in the ***FAHP*** analysis, using a pre-defined fuzzy linguistic scale. Then, fuzzy linguistic ratings of an option given by ***DM***s will be expressed into ***TFN***s. By performing an aggregation operation for all the rating scores of all the ***DM***s, the decision matrix of the assessment of alternative options for the performance ranking can be set up.

By using this methodology, we denote *N* ***DM***s in the evaluation; A_i as the alternative *i, i=1,2,…,I;* F_j as the j^{th} criterion related to i^{th} alternative. The rating of the i^{th} alternative for j^{th} criterion as can be secured as $\widetilde{f_{ij}} = (f_{ija}, f_{ijb}, f_{ijc})$. Subsequently, the aggregated rating is expressed as [125]:

$$f_{ija} = \frac{1}{N}[f_{ija}^{1} + f_{ija}^{2} + \cdots + f_{ija}^{N}] \tag{3-28}$$

$$f_{ijb} = \frac{1}{N}[f_{ijb}^{1} + f_{ijb}^{2} + \cdots + f_{ijb}^{N}] \tag{3-29}$$

$$f_{ijc} = \frac{1}{N}[f_{ijc}^{1} + f_{ijc}^{2} + \cdots + f_{ijc}^{N}] \tag{3-30}$$

Step 2: Establishment of a fuzzy decision matrix for the performance ranking

Using the aggregated ratings of the alternative options, a fuzzy decision matrix can be expressed in the following form:

$$\widetilde{DM} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_J \end{array} \begin{array}{c} \begin{array}{cccccc} F_1 & F_2 & \cdots & F_j & \cdots & F_n \end{array} \\ \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1j} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2j} & \cdots & f_{2n} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{i1} & f_{i2} & \cdots & f_{ij} & \cdots & f_{in} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{J1} & f_{J2} & \cdots & f_{Jj} & \cdots & f_{Jn} \end{bmatrix} \end{array} \tag{3-31}$$

where f_{ij} is the aggregated value indicating the fuzzy performance rating of each alternative A_i with respect to each criterion F_j.

Step 3: Calculation of the normalized decision matrix

The linear scale transformation is applied to carry out the normalization of a decision matrix $\widetilde{DM}$. The linear scale transformation is performed as follows [126]:

$$R = [r_{ij}]_{m \times n} \tag{3-32}$$

$$r_{ij} = \left(\frac{f_{ija}}{d_j^*}, \frac{f_{ijb}}{d_j^*}, \frac{f_{ijc}}{d_j^*}\right),\ d_j^* = max(f_{ijc}),\ j=1,\ 2,\ \ldots,\ j;\ i=1,\ 2,\ \ldots,\ n, \tag{3-33}$$

where r_{ij} is the normalized rating of the option.

Step 4: Calculation of the weighted normalized decision matrix

By multiplying the normalized decision matrix with its associated weights, the weighted normalized value v_{ij} is then calculated as:

$$\tilde{V} = [\widetilde{v_{ij}}]_{m \times n} \tag{3-34}$$

$$\widetilde{v_{ij}} = w_i \times r_{ij},\ j=1,\ 2,\ \ldots,\ j;\ i=1,\ 2,\ \ldots,\ n. \tag{3-35}$$

where w_i represents the weight of the i^{th} criterion and V_{ij} is a normalized fuzzy number, the elements of which are in the range of [0,1].

Step 5: Determination of the positive ideal and negative ideal solutions

A ***PIS*** allows minimizing the cost attributes and maximizing the benefit attributes. On the contrary, a ***NIS*** performs to maximize the cost attributes and minimize the benefit attributes. The option farther from the ***NIS*** and closer to the ***PIS*** is the leading solution [127]. ***FNIS***, A^{-} (the ***Fuzzy Negative-Ideal Solution***) and ***FPIS***, A^{+} (the ***Fuzzy Positive-Ideal Solution***) are shown in the following equations:

$$A^{-} = \{\tilde{v}_1^{-}, \tilde{v}_2^{-}, \cdots \tilde{v}_j^{-}\} \tag{3-36}$$

$$A^{+} = \{\tilde{v}_1^{+}, \tilde{v}_2^{+}, \cdots \tilde{v}_j^{+}\} \tag{3-37}$$

where $\tilde{v}_j^{-} = (0,0,0)$ and $\tilde{v}_j^{+} = (1,1,1)$ [128].

Step 6: Calculation of the separation distance of each alternative option from *FNIS* and *FPIS*

By computing the separation distance of each alternative option from ***FNIS*** and ***FPIS***, a measurement of the closeness of the alternatives from the ***FNIS*** and the ***FPIS*** is obtained. Euclidean distance is applied to determine the of ***TFN***s [100]. According to Equation 2-6, the separation distance can be defined as the following equations:

$$d(\widetilde{v_{ij}}, \tilde{v}_j^{+}) = \sqrt{\frac{1}{3}[(\widetilde{v_{ija}} - \tilde{v}_{ja}^{+})^2 + (\widetilde{v_{ijb}} - \tilde{v}_{jb}^{+})^2 + (\widetilde{v_{ijc}} - \tilde{v}_{jc}^{+})^2]} \tag{3-38}$$

$$d(\widetilde{v_{ij}}, \tilde{v}_j^{-}) = \sqrt{\frac{1}{3}[(\widetilde{v_{ija}} - \tilde{v}_{ja}^{-})^2 + (\widetilde{v_{ijb}} - \tilde{v}_{jb}^{-})^2 + (\widetilde{v_{ijc}} - \tilde{v}_{jc}^{-})^2]} \tag{3-39}$$

$$d_j^{+} = \sum_{j=1}^{n} d(\widetilde{v_{ij}}, \tilde{v}_j^{+}), i = 1,2,3,\cdots,m \tag{3-40}$$

$$d_j^{-} = \sum_{j=1}^{n} d(\widetilde{v_{ij}}, \tilde{v}_j^{-}), i = 1,2,3,\cdots,m \tag{3-41}$$

Step 7: Calculation of the relative closeness coefficient *(CC_i)*

CC_i (The relative closeness coefficient) of each alternative option regarding (***FNIS***, A^{-}) and the (***FPIS***, A^{+}) is determined by the following equation [122]:

$$CC_i = \frac{(d_i^{-})}{(d_i^{+} + d_i^{-})}, \ i=1,\ 2,\ 3,\ \ldots,\ m \tag{3-42}$$

Step 8: Rank the performance of the alternatives

The ranking of the alternative options can be generated according to the values of closeness coefficients. The best alternative for the decision-making will be the farthest to the ***FNI***s and the closest to the ***FPI***s.

3.4.4 Case-Based Reasoning

Case-Based Reasoning is the process of solving new problems based on the solutions of similar past problems [129]. For example, a doctor who cures a patient by recalling another patient that exhibited similar symptoms is using ***Case-Based Reasoning***. A lawyer who advocates a particular result in a trial based on legal precedents and a judge who creates case law is using ***Case-Based Reasoning***. ***Case-Based Reasoning*** is a prominent kind of analogy making [130].

Case-Based Reasoning is not only a powerful way for computer reasoning, but also a pervasive behavior in everyday human problem solving. More radically, that all reasoning is based on past cases personally experienced. This view is related to prototype theory, which is most deeply explored in cognitive science [96].

As shown in Figure 3-6, ***Case-Based Reasoning*** is described using a cyclic process as follows.

(1) Retrieve the most similar case or cases.

(2) Re-use the knowledge in that case in order to solve the problem.

(3) Revise the proposed solution.

(4) Retain the experience for next problem solving.

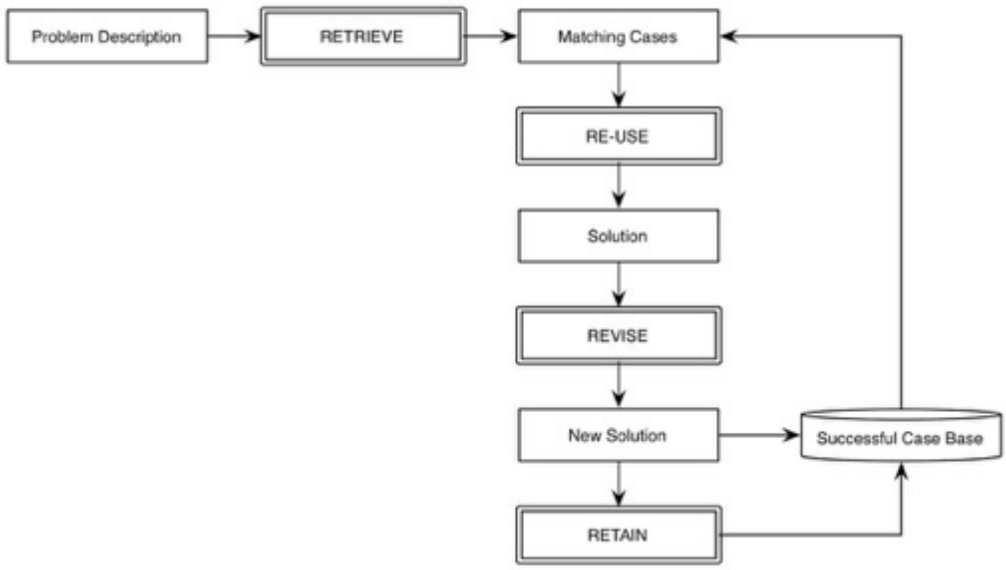


Figure 3-6: Cyclic process of Case-based reasoning.

3.5 Fashion CAD Tools for Fashion Knowledge Visualization and Product Design

In this study, several computer-aided design (CAD) software are applied to construct a virtual design platform for the proposed design method, permitting 3D scanning, 3D human body modeling, 3D garment construction, 2D pattern design and 3D virtual try-on (see Figure 3-7).

(1) Human Solution Scanworx

ScanWorX, developed by Human Solution Company, is used to control the body scanning process and record body scan result. Body scan data obtained from the 3D scanning is a set of points (point cloud) simulated as the shape of the scanned object.

(2) RAPIDFORM

Rapidform software was developed by INUS Technology to edit 3D objects. Point clouds of the scanning result will be simulated by the meshing tool of Rapidform and a smooth body surface can be obtained. Also, Rapidform ensures the 3D form to be re-triangulated and those error holes, which are invariably made as a result of scanning, to be filled. After that, a unique surface modeled by many small facets is obtained.

(3) DESIGNCONCEPT

DesignConcept developed by Lectra is able to create points, lines, curves and surfaces in a 3D environment, which permits 3D garment prototyping and flattening corresponding 2D patterns.

(4) MODARIS

Modaris software developed by Lectra can be used to create and edit 2D garment patterns and perform a virtual try-on process. Fabric parameters of the proposed design can be modeled in the try-on process at the same time.

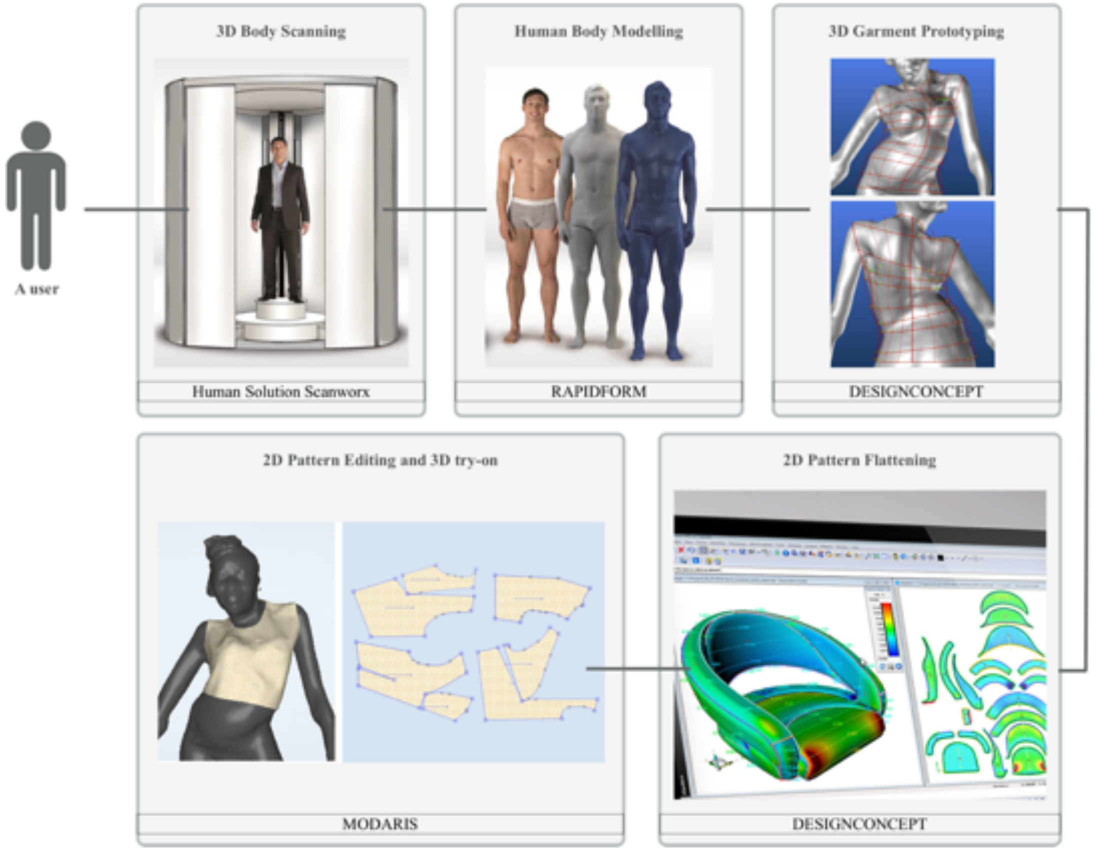


Figure 3-7: Different fashion CAD software used in this research, their functions and relations.

3.6 Conclusion

In this chapter, the acquisition, modelling, analysis and visualization issues of all the related knowledge and data have been introduced. The features and structure of fashion knowledge in personalized fashion design are analyzed. Related tools for knowledge acquisition, data computation and data modelling, such as sensory evaluation, fuzzy logic, ***Fuzzy AHP*** and ***Fuzzy***

TOPSIS are also presented. Besides, the involved virtual-reality based CAD software used for the fashion knowledge visualization and product design are also described.

(1) Sensory evaluation has been used to extract designer's design knowledge and experience, and formalize design rules related to different garment design elements (fabric, color and style).

(2) Due to the fact that vagueness and uncertainty exist in the sensory evaluation process, Fuzzy Techniques constitute the main tool of modeling and formalization.

(3) Several other intelligent tools, such as the ***FAHP***, ***Fuzzy TOPSIS***, and ***Case-Based Reasoning*** have been used for modeling the design elements and concerned relations in a design process and providing decision support for all proposed design solutions.

(4) Several garment CAD software have been used in my PhD research to create a Virtual 3D-to-2D Garment Prototyping Platform, which ensures the virtual 3D-to-2D garment prototyping.

Chapter 4 Personalized Fashion Recommendation System (*PFRS*)

In this section, the realization of the proposed ***PFRS*** will be introduced. For each subsystem ***(CRS: Color Recommendation System, FSS: Fabric Selection System, and GSRS: Garment Style Recommendation System)*** of the proposed ***PFRS,*** the concerned experiments, data processing and modelling approaches are presented.

As described in Section 2.2.1.2, there are two working processes of the proposed ***CRS***: knowledge-based recommendation, and ***Case-based Reasoning***. In this PhD study, similarity measurement (Equation (3-19) in Section 3.4.1.4) will be used in these two recommendation processes as the main computational tool. The similarity measurement tool is applied in two aspects: (1) comparison of designers' perception and user's perception in the knowledge-based recommendation process, and (2) searching for the most relevant case (target case) from an ***SCD*** predefined in the system when introducing a new user.

As described in Section 2.2.1.2, fabric selection can be regarded as a multi-criteria decision-making problem. In this context, we proposed in this PhD research to use the ***Fuzzy AHP*** model, which is a classical multi-criteria decision-making model to realize the proposed ***FSS***. Related computational tools in Section 3.4.2 will be used.

The working process of the proposed ***GSRS*** is the same with ***CRS***. The knowledge-based recommendation, and ***Case-based Reasoning*** will be utilized together to realize this subsystem.

As described in Section 2.1, the proposed ***PFRS*** is realized based on the definition of ***Consumer Profile*** and ***Product Profile***. The experiments designed to define the ***Consumer Descriptive Features*** and ***Product Descriptive Features*** of the concerned ***Consumer Profile*** will be also presented in this study (Section 4.1.2.1, 4.2.2, and 4.3.1.1).

4.1 PFRS-Color Recommendation Subsystem (*CRS*)

4.1.1 Data acquisition, quantification and processing

The data in the proposed ***Color Recommendation Subsystem (CRS)*** are acquired from the evaluations of both designers and consumers. These data are presented as linguistic descriptors or terms that contain uncertainty and imprecision. In this situation, fuzzy sets are used for analysis and modeling these data. Using fuzzy sets, all of the concerned linguistic data can be quantified for further data processing. For example, when measuring a user's color image perception on the ***BCSA*** *"Cold - Warm"*, his/her preference is initially defined using a fuzzy linguistic rating scale of *{extremely cold, very cold, rather cold, average, rather warm, very warm, extremely warm},* as presented in Figure 4-1. Using this scale, different fuzzy numbers can be assigned to describe these rating results. Numerical equivalence values of fuzzy linguistic terms are applied to quantify the related color image perceptual data, as presented in Table 4-1.

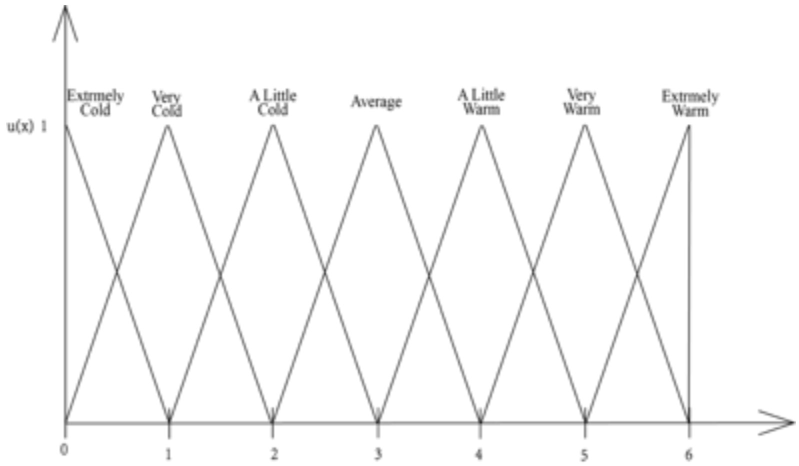


Figure 4-1: Fuzzy linguistic rating scale of "cold–warm" degree.

Using fuzzy set theory, group decision-making of designers about color image perception can be realized. The perceptual data of designers of a specific ***CIW*** regarding the proposed ***BCSA***s can be aggregated in order to obtain a normalized color image perception of this ***CIW*** in the ***CIS***.

Let X be the evaluation vector of the associations between one specific ***CIW***s and w ***BCSA***s. Let a_m $(m=1,2,\ldots w)$ be the dimensions of this evaluation vector X. Let F_b be a set of a set of seven linguistic scores $\{F_1, F_2, F_3, F_4, F_5, F_6, F_7\}$ (as described in Figure 4-1).

Table 4-1: Fuzzy linguistic rating scale and corresponding numerical equivalence values.

Linguistic rating terms	**TFNs** (F_b)
Extremely warm	(5,6,6)
Very warm	(4,5,6)
A little warm	(3,4,5)
Average	(2,3,4)
A little cold	(1,2,3)
Very cold	(0,1,2)
Extremely cold	(0,0,1)

Let X be the evaluation vector of the relations between one specific CIWs (emotional words) and w BCSAs (non-emotional basic attributes). Let F_b be a set of seven linguistic scores $\{F_1, F_2, F_3, F_4, F_5, F_6, F_7\}$ (as described in Table 1). In order to quantify the linguistic evaluation data, we transform them into their TFNs, denoted as $TFN\ (F_b)$ $(b=1,2,3\ldots,7)$, which are uniformly distributed on the interval of [0,6], where $TFN\ (F_1)= (0,0,1)$, $TFN\ (F_2)= (0,1,2)$, $TFN\ (F_3)= (1,2,3)$, $TFN\ (F_4)= (2,3,4)$, $TFN\ (F_5)= (3,4,5)$, $TFN\ (F_6)= (4,5,6)$, and $TFN\ (F_7)= (5,6,6)$.

The extraction of designer's knowledge is a group decision-making process. Using fuzzy set theory, a group decision-making with multiple designers on relations between the ***CIW***s and

BCSAs can be realized. The perceptual data provided by designers on a specific ***CIW*** can be aggregated to obtain a normalized color image perception in the newly generated ***CIS***. In order to process this data, an aggregation method is used in this study to obtain the normalized and unique color image of a ***CIW*** regarding ***BCSA***s *(Ma, et al., 2010)*.

For exploring the relation between the ***CIW*** k_1*=Romantic* and one ***BCSA*** a_1*= Cold/Warm (Temperature)*, we have mobilized 31 experts for the evaluation. If one expert considers that k_1*=Romantic* is *"A little cold"*, three experts determine that k_1*=Romantic* is *"Average between cold and warm"*, eight experts think that k_1*=Romantic* is *"A little warm"*, nine experts believe that k_1*=Romantic is* "*Very Warm"*, and ten experts conclude that k_1*=Romantic is "Extremely Warm"*, based on Equation (3-20), the relation of the ***CIW*** (k_1*=Romantic)* and the ***BCSA*** (a_1*=Cold/Warm (Temperature))* can be expressed as follows:

$$(0*TFN\ (F_1)+0*TFN\ (F_2)+1*TFN\ (F_3)+3*TFN\ (F_4)+7*TFN\ (F_5)+9*TFN\ (F_6)+10*TFN\ (F_7))/31=(3.677,4.645,5.29)$$

It means that the aggregated result is also a TFN fuzzy number, whose most possible value is 4.645 (between F_5 and F_6), with 3.677 and 5.29 as the smallest possible and largest possible values respectively. Similarly, the associations between the ***CIW*** k_1*=Romantic* and other ***BCSA***s can also be quantified. A vector of color image perception for the ***CIW*** k_1*=Romantic can be obtained.* The dimension of this vector is decided by the number of the BCSAs.

The proposed recommendation starts with case retrieval, which is also the most important process in the case-based learning recommendation system. When a new user *C* is introduced to the proposed system, a case retrieval process will be performed. First, the socio-cultural attributes of *C* are matched with the cases of the ***SCD*** in order to find those who have the same values of the socio-cultural attributes. The extracted cases constitute a subset of the ***SCD***, denoted as $SCD\_SC=\{C_1, C_2, \ldots, C_m\}$.

Next, we calculate the similarity degrees of the color image perception attributes of the user *C* with those of the cases in *SCD_SC* in order to find the target query case, corresponding to the maximal similarity degree. As values of the color image perception attributes are numerical and distributed on the interval [0, 1], this similarity degree is calculated from the corresponding Euclidean distance, i.e. $Similarity\ (C, C_i)=1-Distance\ (C, C_i)$ for $i=1, \ldots, m$.

However, in the real recommendation procedure, it usually occurs that there are several cases in the ***SCD*** having the same balanced similarity degrees related to the target query case. In this situation, the case in the ***SCD*** having the highest successful recommendation frequency will be recommended.

4.1.2 Experiments

To realize the proposed system, three experiments are performed. The first one is designed to establish the proposed ***CIS*** and determine the related ***BCSA***s. The second is designed to define the social-cultural attributes that associated with a specific user's color image perception. In the third experiment, a number of designers are invited to evaluate the 180 ***CIW***s in the proposed system adapted from the Color Image Scale developed by Kobayashi [37]. The color design knowledge is extracted in the second experiment.

4.1.2.1 *Experiment I*: Establishment of the proposed *CIS* and determination of the related *BCSA*s

In *Experiment I*, a set of ***BCSA***s concerning color image perception is carefully defined. These ***BCSA***s constitute the unique ***CIS*** that can be used to measure color-image perceptions for both designers and consumers.

Table 4-2: Definition of *BCSAs* involved in the proposed *CIS*.

Color sensory category	*BCSAs*
Temperature	Cold–Warm
Distance	Forward–Backward
Weight	Light–Heavy
Volume	Closed–Open
Brightness	Dark–Bright
Excitement	Calm–Exciting
Freshness	Gloomy–Chipper
Construction	Plain–Abundant
Hardness	Soft–Hard
Gender	Masculine–Feminine

For this purpose, we perform a knowledge-based sensory evaluation process procedure. The selection of ***BCSA***s is performed according to the following two principles: (1) the selected ***BCSA***s should be easily understood by both designers and consumers with respect to the image of color, (2) ***BCSA***s with ambiguity and uncertainty should be removed. Based on the stated selection principles, *Experiment I* is described as follows. It is a procedure of descriptive and quantitative sensory evaluation. 31 experienced designers are invited to participate in the ***BCSA*** selection. A training session is organized in order to help these designers to understand the purpose of this experiment. Each trained panelist generates an exhaustive list of color sensory categories and their descriptive ***BCSA***s describing color image perceptions according to his/her professional knowledge. Then, a screening is performed by a "round table" discussion among all of the invited designers to select the most appropriate ***BCSA*** criteria and corresponding ***BCSA***s.

This step leads to the generation of normalized descriptors describing the basic feeling of the color image. Finally, we obtain 10 normalized color sensory categories and their descriptive ***BCSA***s, which are considered normalized basic criteria for the proposed ***CIS*** as presented in Table 4-2.

Thereafter, each ***BCSA*** is expressed with a fuzzy linguistic rating scale of seven scores (See Figure 4-1). Additionally, the corresponding Numerical Equivalence Value of each linguistic score is also given in Table 4-1.

4.1.2.2 *Experiment II*: Selection of social-cultural attributes related to the user's personal profile

Table 4-3: Different Social-cultural attributes involved in the user's personal profile.

Social-cultural attributes	Description	Data type
Gender	F/M	Choice
Nationality	A list of country names	Choice
Religion	A list of religion types	Choice
Education Degree	A list of education levels	Choice

Experiment II is designed to select the most appropriate social-cultural attributes of the user's personal profile. The process of selection follows the procedure in ***Experiment I***. Finally, 4 attributes are selected. These attributes are represented by the choice of data type in the database, as presented in Table 4-3.

4.1.2.3 *Experiment III*: Knowledge acquisition and color image perception definition of related *CIW*s in *CIS*

In product design and development, the descriptive sensory evaluation is usually performed by a trained panel composed of experienced experts for judging products on a number of analytical and neutral linguistic descriptors. A descriptive sensory evaluation permits the extraction of neutral and normalized sensory descriptors and normalized sensory data describing a collection of products (Zhu, et al., 2010). Independent of involved evaluators and social contexts, the evaluation is only related to the basic nature of the products and is thus considered an objectified evaluation characterizing human perceptions. Product designers can master the association of these sensory attributes with the ***CIW***s from their professional experience.

In this section, designer's color image perceptions of CIWs are characterized using classical descriptive sensory evaluation. Professional knowledge is extracted and exploited in order to characterize the ***CIW***s in the defined ***CIS***. In ***Experiment III****,* 31 designers are selected and invited to perform the color-image perception identification process for the related ***CIW***s in the proposed ***CIS***. Each of the designers is invited to give a linguistic score using the terms of Table 1 for each ***CIW*** regarding each ***BCSA***. The corresponding formalization is given below.

Let K be a collection of m ***CIW***s defined by Kobayashi, denoted as $K=\{k_1 \ldots k_m\}$ (initially $m=180$ in our case).

Let E be a set of l selected experts performing the sensory experiment, denoted as $E= \{e_1 \ldots e_l\}$ ($l=31$ in our case).

Let A be a set of p ***BCSA***s describing ***CIW***s (Table 2), denoted as $A=\{a_1, \ldots, a_p\}$,, ($p=10$ in our case).

Let D be a set of s normalized linguistic terms generated by a group of m $(m=180)$ trained designers for describing the human perceptions (31 designers and 81 consumers) on the color image themes, denoted as $D= \{d_1, \ldots, d_s\}$, ($s=7$ in our case).

Based on the previous formalization, by using the Numerical Equivalence Values defined in Table 4-1, all of the linguistic scores expressed by linguistic terms can be quantified. Then, the evaluation data of all of the invited designers is aggregated as a 10-dimensional vector. Using the same method as the example in Section 4.1.1, the associations of the other ***CIW***s with the ***BCSA***s can also be expressed. We consider that the disconformity between these trained experts is very small because they have similar professional training background on the evaluated ***CIW***s. Through this process, designers' knowledge about all the associations between ***CIW***s and ***BCSA***s can be extracted. The identified associations between ***CIW***s and ***BCSA***s can be considered as design rules or design knowledge for being used in the future recommendations.

4.1.3 Validation of the proposed recommendation system

To verify the usefulness of the proposed color recommendation system, 81 people in France (37 males and 44 females) are invited to use the proposed system. Selected users have no professional knowledge about color, art or design. At religion level, they include Muslims, Catholics, and Buddhists. They have different education levels, including engineer degrees, master degrees, and license degrees. Their ages are distributed randomly.

Each of the invited users is requested to evaluate his/her color image perceptions on the ***BCSA*** d_s of the defined ***CIS***. The color image perceptions of these users are recorded in the database (Medina-Oliva, Weber, & Iung, 2015). Let U be a collection of n users, i.e. $U= \{u_1, \ldots, u_n\}$. In our specific scenario, we have $n=81$.

In order to validate the effectiveness of the proposed recommendation system, three different cases for different users are discussed.

4.1.3.1 *Case study I*: An example of a knowledge-based recommendation process (case study of the first user)

In this case, the proposed system enables to understand the unsatisfied attributes of the current recommendation result and then recommend a new color range using the feedback procedure described previously.

The first user u_1 is female. At the beginning of the recommendation, u_1 is asked to input her color image preference into the system by using the linguistic scores in Table 1 for all the ***BCSA***s in Table 4-2. These linguistic evaluation scores are quantified using the Numerical equivalence values in Table 4-1. The related data are presented in Table 4-4.

As the first user of this system, there is no learning rule in the ***SCD***. Thus, only the professional knowledge is available for the recommendation. The similarity degrees between the consumer's color image perceptual data and that of ***CIW***s predefined in the system are computed. The computation is performed regarding each of the ***BCSA***s. For example, as explained in Section 4.1.1, the associations of ***CIW*** k_1*=Romantic* and all the ***BCSA***s, recognized by experts is *(0.798, 0.5, 0.404, 0.46, 0.69, 0.6, 0.62, 0.59, 0.26, 0.34*) (Table 4-4). Also, the color image perception of c_1 related to all the ***BCSA*** is *(0.5, 0.17, 0.5, 0.17, 0.5, 0.33, 0.33, 0.5, 0.17, 0.17)* (Table 4-4).

Then, using Equation (3-18) we calculate the similarity degree of the color image perception between c_1 and k_1*=Romantic* as 94%, meaning that this similarity is very high.

Table 4-4: Color image preference of the first user u_1.

Color sensory category	Linguistic color image perception	Color image perception in TFNs	Association of CIW k_1=*Romantic* and all BCSAS
Temperature	Averaged temperature	0.5	0.798
Distance	Very forward distance	0.17	0.5
Weight	Averaged weight	0.5	0.404
Volume	A little closed volume	0.17	0.46
Brightness	Averaged brightness	0.5	0.69
Excitement	A little calm	0.33	0.6
Freshness	Very chipper	0.33	0.62
Construction	Averaged construction	0.5	0.59
Hardness	Very soft	0.17	0.26
Gender	A little masculine	0.17	0.34

Similarly, the color image perception of u_1 is compared with all ***CIW***s. Thereafter, the ***CIW*** which has the highest similarity degree (95.7%), i.e. k_9*=Casual*, is selected. Then, using the principle of Kobayashi (Figure 2-4 and 2-5), the ***CR*** described by k_9=*Casual* is recommended (See Figure 4-2-a). It is a range of three colors: P130 (dark red), P143 (white) and P106 (dark blue).

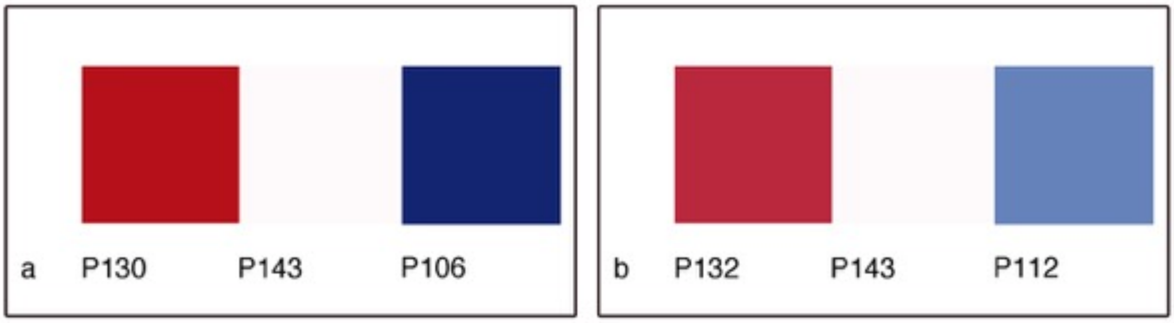


Figure 4-2: Color recommendation result of the first user: (a) initial recommendation and (b) adjusted recommendation after the consumer evaluation.

Next, the evaluation of the recommended ***CR*** is performed by u_1 in terms of the basic color physical properties (*hue, lightness and purity*). The evaluation results of u_1 include: (1) the color hue of the first recommended color (P130) should be slightly enhanced; (2) the brightness of the third recommended color (P106) should also be slightly enhanced. In this situation, by visualizing the neighboring colors on the same columns (PB series and RP series) around P130 and P106 in Figure 2-5, the user manually selects P132 to replace P130 and P112 to replace P106. By performing the same evaluation procedure on this new ***CR***, we can find that it is fully satisfied by c_1. The final satisfied result is presented in Figure 4-2-b.

The personal profile data and color image perceptual data of u_1 along with the satisfactory ***CR*** in Figure 4-2-b will then be retained as the first learning rule and stored in the proposed ***SCD*** as well as the ***CR*** database. Similarly, the recommendation processes of the other 80 users are also performed and stored as learning rules in the proposed ***SCD***.

4.1.3.2 *Case study II*: An example of the case-based learning process using human-machine interaction (for the 77th user)

The recommendation process of the 77th user u_{77} is presented to explain the case-based recommendation process, in which the learning rules from the proposed ***SCD*** effectively an efficient support and a new learning rule is generated from this case. u_{77} is a male user. Like *Case study I*, the recommendation process of u_{77} starts by inputting his personal profile and color image perception using the predefined descriptive features. First, the retrieval process is performed to check whether the historic learning data exist or not in the system by using the similarity degree. Finally, the case of the target user u_{32} in the ***SCD*** is selected because its similarity degree with u_{77} is the biggest (98.35%) and higher than the threshold (85%). Then, the recommended ***CR*** associated with u_{32} will be proposed to u_{77}. Next, an evaluation procedure is used to check for the satisfaction of u_{77}. As u_{77} is not satisfied with the recommended ***CR*** in the aspect of lightness, we start a feedback process for modifying or adjusting the recommendation result. After several interactions with the system, a final satisfied result is obtained. Then, the recommendation case of u_{77} is retained in the ***SCD*** as a new learning rule.

In this case, it has been found that the proposed system is an open system, capable of integrating new design rules along with related ***CR***s based on the color image perceptual data of new cases. ***SCD*** can be dynamically updated through the knowledge-based recommendation and consumer feedback integrated process.

4.1.3.3 *Case study III*: An example of the case-based recommendation process using the concept of machine learning (case study of the 80th user)

A female consumer u_{80} is introduced to the recommendation system. First, c_{80} is invited to provide her color image perception in the 10-dimensional ***CIS*** regarding all the ***BCSA***s. Then, the personal profile and color image perception of u_{80} are compared with all of the existing cases in the ***SCD***. According to the computation of the similarity degrees of u_{80} related to the cases in ***SCD****,* we find that there are two similar cases (u_{47} and u_{66}) existing in the ***SCD***, with a similarity degree of 0.868 (> the threshold 85%). In this situation, the successful recommendation frequencies of u_{47} and u_{66} will be compared. From the computation, we find that the successful recommendation frequency of u_{47} is 2 and that of u_{66} is 0. Therefore, this module will recommend the retained ***CR*** of u_{47} to the consumer u_{80}. Based on the evaluation of u_{80}, she is satisfied with the recommendation result reused of u_{47}. In this situation, the recommendation process for u_{80} is finished but the case of u_{80} will not be retained in the system as a new case-based learning rule because the corresponding rule already exists in ***SCD***. Also, successful recommendation frequency of u_{47} will be changed into 3.

4.2 PFRS-Fabric Selection System (*FSS*)

The objective is to select a suitable fabric for designing a summer dress for the ***PWAM*** whose ages vary from 28 to 30 with medium salaries. As their related professions include engineers, teachers, and nurses etc., they belong to a social group of good taste. Based on the steps mentioned in Section 3.4.2, there are three experiments in the application.

First, a pre-selection procedure has been carried out. In *Experiment I*, the representative consumers are invited to determine the evaluation criteria for their requirements; a group of experienced designers are invited to determine the sub evaluation criteria of the fabric properties related to the requirements provided by the representative consumers. In *Experiment II*, representative consumers are invited to assign evaluation criteria weights; a group of experienced designers are invited to assign sub evaluation criteria weights. In *Experiment III*, a set of pre-selected alternative fabrics are assessed by designers and consumers respectively about the performance of their properties listed in the sub evaluation criteria.

4.2.1 Subjects

Figure 4-3: Dresses in the same style produced with the alternative fabrics.

To carry out the procedure, a number of designers (fashion designers and textile designers) and representative female ***PWAM*** are selected respectively. The selected designers should meet the following three requirements: (1) he / she has been working in fashion and textile industry for more than 5 years; (2) he / she has clear understanding of the process of fabric of a design collection; (3) he / she is very experienced at material properties. Finally, 40 ***PWAM*** and 24 designers are selected. These ***PWAM*** and designers form a decision-making team.

Based on the design purpose (a female summer dress for ***PWAM***), a pre-selection is performed by the designers in the decision-making team. Finally, a collection of 5 different types of alternative fabrics (F_1, F_2, F_3, F_4, F_5) is selected and approved by all the designers, as shown in Figure 4-3.

4.2.2 *Experiment I*: Determination of evaluation criteria and their characters

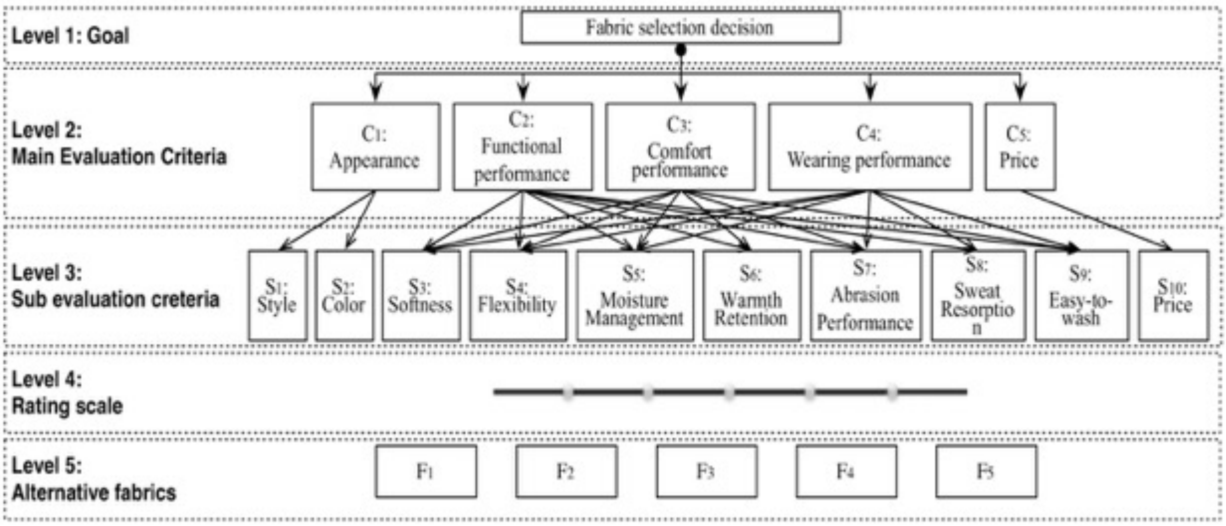


Figure 4-4: The decision hierarchy of fabric selection.

Each of the invited representative ***PWAM*** is asked to give in-depth interviews on an exhaustive list of the relevant requirements of the fabric, based on the design purpose of a summer dress. Secondly, a screening is performed by a "round table" discussion among all the invited representative ***PWAM***, to select the most appropriate requirements. Similar procedure has been carried out with designers to determine the sub evaluation criteria. Finally, the main evaluation criterion of 5 dimensions (requirements of ***PWAM***) and the sub evaluation criterion of 10 dimensions (fabric properties) are selected. After the approval of the entire decision-making team, the decision hierarchy is structured with the determined alternative fabrics and evaluation criteria (Figure 4-4).

In the decision hierarchy, the first level is the main evaluation criteria. The main evaluation criteria have 5 dimensions: *Appearance (C1), Functional Performance (C2), Comfort Performance (C3), Wearing Performance (C4),* and *Price (C5)*.

A set of 10 dimensions of sub evaluation criteria is defined based on the main evaluation criteria. *Appearance (C1)* can be regarded as an evaluation criterion in terms of the textile art design. Satisfaction of the consumer with regard to the fabric aesthetic properties: *Style (S1)* and *Color (S2)* are noted with concern in this category. *Functional Performance (C2), Comfort Performance (C3)* and *Wearing Performance (C4)* are linked to the requirements of the daily life of the consumers.

This category includes fabric physical properties, such as *Softness (S3), Flexibility (S4), Moisture Management (S5), Warmth Retention (S6), Abrasion Performance (S7), Sweat Resorption (S8),* and *Easy-to-wash (S9)*. *Price (S10)* is taken as fabric value property.

The fourth level of the decision hierarchy is a rating scale. The rating scales use a pair of sensory descriptors, which appear in the form of word-pair. The word-pair has 7 intensity levels or evaluation scores represented by $\{A_1, A_2, A_3, A_4, A_5, A_6, A_7\}$.

For *Style (S1)*, *Color (S2), and Price (S10)*, the rating scale is formed by a set of linguistic values as *{Extremely Satisfying, Very Satisfying, A little Satisfying, Normal, A little Unsatisfying, Very unsatisfying, and Extremely Unsatisfying}*. These linguistic values correspond to $\{A_1, A_2, A_3, A_4, A_5, A_6, A_7\}$.

For $S_{3\text{-}9}$, different word-pairs are defined for each dimension of the sub evaluation criteria. Figure 4-5 presents the rating scale of $S_{3\text{-}9}$.

Using this process, requirements of ***PWAM*** related to fabric are transferred into concerning fabric properties (aesthetic, physical and value properties) using a collaborative design process. Designers' knowledge is extracted to modeling the relationship between consumer's requirement (main evaluation criteria) and desired fabric properties (sub evaluation criterion).

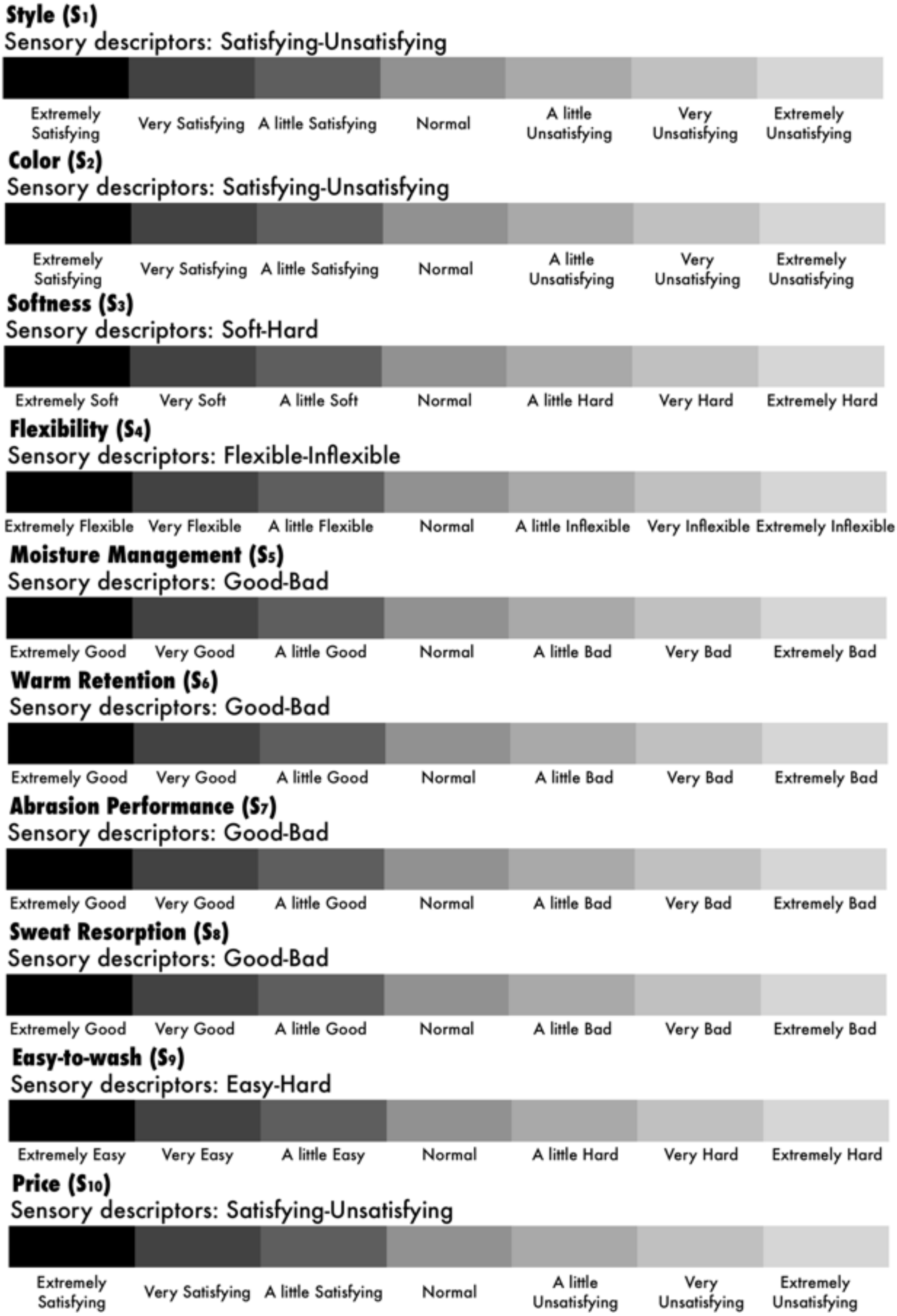


Figure 4-5: Rating scale of fabric properties *$S_{1\text{-}10}$*.

4.2.3 *Experiment II*: Weight determination and *Fuzzy AHP* computing

The weights of the evaluation criteria to be used in the alternative fabric performance evaluation process are calculated by using the ***FAHP*** method in *Experiment II*. Designers and representative ***PWAM*** of the decision-making team are assigned to form individual pairwise comparison matrix using the relative importance rating scale presented in Table 4-5, instead of using strict and precise values.

Table 4-5: Relative importance rating scale.

Linguistic values	TFNs
Extremely more important (EMI)	(3.5,4,4.5)
More important (MI)	(3,3.5,4)
A little more important (AMI)	(2.5,3,3.5)
Equal (E)	(2,2.5,3)
A little less important (ALI)	(1.5,2,2.5)
Less important (LI)	(1,1.5,2)
Extremely less important (ELI)	(0.5,1,1.5)

Table 4-6: Normalized relative weight of inner dimensions of Level 2.

Dimensions of Level 2	Normalized relative weight of inner dimensions of Level 2
Appearance (C1)	0.2153
Functional Performance (C2)	0.2744
Comfort Performance (C3)	0.1953
Wearing Performance (C4)	0.1232
Price (C5)	0.1919

For the main evaluation criteria (*Level 2*), the comparisons among the elements are performed regarding the overall goal (*Level 1*), by the 40 representative consumers using the linguistic scale (Table 4-5).

For the sub evaluation criteria (*Level 3*), the comparisons among the elements are performed with respect to their higher-level criteria in *Level 2*, by the 24 designers using the linguistic scale. There is no comparison under "*Price*" because there is only one sub criterion belong to it.

Table 4-7: Normalized relative weight of Level 3 regarding Level 2.

Level 2	Relative weight of Level 2	Level 3	Relative weight of Level 3 regarding Level 2	Weighted Relative weight of Level 3 regarding Level 2
C1	0.2153	S1	0.5	0.1077
		S2	0.5	0.1077
C2	0.2744	S3	0.1333	0.0366
		S4	0.1617	0.0444
		S5	0.1526	0.0419
		S6	0.1575	0.0432
		S7	0.1663	0.0456
		S8	0.1236	0.0339
		S9	0.1049	0.0288
C3	0.1953	S3	0.1913	0.0374
		S4	0.1601	0.0313
		S5	0.1738	0.0339
		S6	0.1096	0.0214
		S7	0.1003	0.0196
		S8	0.1418	0.0277
		S9	0.1232	0.0241
C4	0.1232	S3	0.3668	0.0452
		S4	0.2840	0.0350
		S5	0.1266	0.0156
		S6	0.0426	0.0053
		S7	0.0426	0.0053
		S8	0.0426	0.0053
		S9	0.0947	0.0117
C5	0.1919	S10	1	0.1919

As explained in Section 3.2.4, the normalized weight of the aggregated evaluation matrix could be obtained using a series of fuzzy synthetic extent, possibility calculations and weight vectors determination.

Similarly, the normalized weight for all evaluation matrixes can be achieved as Table 4-8. Then the normalized weight of each component of the sub evaluation criteria is aggregated with respect to the weight of its corresponding main evaluation criteria. After that, the aggregated weight of each element of the sub evaluation criteria is summed up to obtain the global weight of all the sub evaluation criteria components, as presented in Table 4-7 and 4-8.

Table 4-8: Normalized relative weight of Level 3 regarding Level 1.

Dimensions of Level 3	Weighted Relative weight of Level 3 regarding upper evaluation criteria of Level 1
Style (S1)	0.1077
Color (S2)	0.1077
Softness (S3)	0.1191
Flexibility (S4)	0.1106
Moisture Management (S5)	0.0914
Warmth Retention (S6)	0.0699
Abrasion Performance (S7)	0.0705
Sweat Resorption (S8)	0.0669
Easy-to-wash (S9)	0.0645
Price (S10)	0.1919

4.2.4 *Experiment III*: Fabric assessment and *TOPSIS* analysis

To assess the fabric alternatives, designers are required to assess different alternative fabrics regarding different fabric properties using the rating scales of *Level 4* of the decision hierarchy as explained in Section 4.2.2.

However, some of the sub evaluation criteria are very positive, others are negative. For example, if the design purpose is summer dress, the higher evaluation score regarding "*Warmth Retention (S6)*" indicate worse fabric performance. "*Warmth Retention (S6)*" is regarded as negative. For "*Moisture Management (S5)*", we expect better evaluation score of the alternative fabric regarding moisture management. "*Moisture Management (S5)*" is regarded as positive.

Conclusively, the desired fabrics properties should have the maximum values with regard to *Style (S1)*, *Color (S2)*, *Softness (S3), Flexibility (S4), Moisture Management (S5), Abrasion Performance (S7), Sweat Resorption (S8),* and *Easy-to-wash (S9),* and minimum values of *Warmth Retention (S6)* and *Price (S10)*. In this situation, it is very difficult to give a global performance order when evaluate alternative fabrics.

As explained in Section 3.2.5, ***Fuzzy TOPSIS*** is able to give the performance of objects regarding both positive and negative evaluation criteria. ***Fuzzy TOPSIS*** is used to solve this problem. After the ***Fuzzy TOPSIS*** process (Equation (3-28)-(3-42)) of the evaluation data, the separation distances and ***Closeness Coefficients (CCs)*** for all the alternative fabrics are summarized in Table 4-9. As explained in Section 3.2.5, the best alternative will be the farthest to the ***FNI***s and the closest to the ***FPI***s. The proposed evaluation methods indicate that the best alternative fabric is F_4 with relative ***CCs*** of 0.3925.

Table 4-9: *Closeness coefficients (CCs)* for all the alternative fabrics.

	F_1	F_2	F_3	F_4	F_5
Closeness coefficients values (CCs)	0.3615	0.3640	0.3652	0.3925	0.3908

4.2.5 *Experiment IV*: Integration of a new requirement and updating the proposed recommendation system

In *Experiment IV*, a new requirement *"Trendy level"* is generated as C_6. *"Trendy level"* indicates that if a piece of fabric is trendy or not, which is a global requirement refers to several fabric properties, such as style, color, softness, flexibility.

In order to integrate this new requirement into the proposed system, associations of C_6 and C_{1-5} are evaluated by a group of 24 designers. These associations are expressed using linguistic terms in Table 4-5. Table 4-10 presents the aggregated evaluation results.

Table 4-10: Aggregated evaluation results of the association between C_6 and C_{1-5}.

F_1	F_2	F_3	F_4	F_5
0.431	0.362	0.118	0.06	0.029

Then, using Equation (2-3), the importance level of C_6 can be defined as *Max (min (0.431, 0.2153), min (0.362, 0.2744), min (0.118, 0.1953), min (0.06, 0.1232), min (0.029, 0.1919)) = Max (0.2153, 0.2744, 0.118, 0.06, 0.029) = 0.2744.* After that, using the normalization process of Equation (2-4), the normalized importance level of the new set of requirements can be defined as *(0.1689, 0.2153, 0.1532, 0.0967, 0.1505, 0.2153)*, where the normalized importance level of C_6 is 0.2153. Using the new set of importance level, the normalized importance level of fabric properties can also be updated. Table 4-11 presents the updated important level of all the requirements and fabric properties.

Table 4-11: **Normalized weight of different decision levels of the updated recommendation system.**

Weight of Level 2		**Weight of Level 3**		**Global weight**
Main Evaluation criteria	Normalized importance of the Main Evaluation criteria	Sub Evaluation criteria	Normalized weight of Main Evaluation criteria	Aggregated weight with respect to main evaluation criteria
	0.1689		0.5	0.08445
			0.5	0.08445
			0.2159	0.04648327
			0.2185	0.04704305
	0.2153		0.1951	0.04200503
			0.203	0.0437059
			0.1675	0.03606275
			0.1672	0.02561504
			0.2137	0.03273884
	0.1532		0.1786	0.02736152
			0.2215	0.0339338
			0.2189	0.03353548
			0.2742	0.02651514
			0.2313	0.02236671
	0.0967		0.1456	0.01407952
			0.1709	0.01652603
			0.1779	0.01720293
	0.1505		1	0.1505
			0.453	0.0975309
C_6	0.2153		0.386	0.0831058
			0.129	0.0277737
			0.032	0.0068896

From Table 4-12, we can obtain the normalized importance level of all fabric properties as *(0.182, 0.168, 0.126, 0.109, 0.083, 0.094, 0.087, 0.15)*, corresponding to $S_{1\text{-}8}$.

Table 4-12: ***Closeness coefficients (CCs)*** **for all the alternative fabrics based on the updated recommendation system.**

Closeness coefficients values (CCs)	F_1	F_2	F_3	F_4	F_5
	0.3615	0.3840	0.3652	0.3925	0.3708

Correspondingly, the separation distances and closeness coefficients (CCs) for all the alternative fabrics are also changed. Table 4-12 presents the new CCs of the five alternative fabrics.

4.2.5 Validation of the proposed recommendation system

In order to validate the proposed fabric selection system, a collection of summer dresses (D_1, D_2, D_3, D_4, D_5) designed in the same style are produced (Figure 4-3). These dresses are only different in the used fabric and each of them uses the involved alternative fabrics $F_{1\text{-}5}$ respectively.

4.2.6.1 Experiment design

In the validation experiment, another group of 40 representative consumers are involved. The selection of the 40 members has been explained in Section 4.2.1. In the validation experiment, each of the consumers is required to give a ranking of all the dress samples. The label of each dress is provided with the price information as well as the fabric content information. After that, all of the consumers are assigned to observe and touch these dresses. Then, a scale of five evaluation degrees, ranging from *A* to *E* (*A, B, C, D, E*) are given by each consumer based on the overall evaluation of these dresses (Table 4-13). "*A"* means that the best among all these dresses, while *"E"* means that the worst among all these dresses. A set of linguistic terms of the level of performance is applied to describe the evaluation degrees. In order to quantify the evaluation degrees, a set of fuzzy numbers is assigned to each of the linguistic term. The involved evaluation degrees, their corresponding linguistic term and fuzzy numbers are described in Table 4-13.

Table 4-13: Evaluation degrees, their corresponding linguistic term and fuzzy numbers.

Evaluation degrees	Linguistic term	Fuzzy numbers
A	*Best (BE)*	(2.5,3,3.5)
B	*Relatively good (RG)*	(2,2.5,3)
C	*Average (AV)*	(1.5,2,2.5)
D	*Relatively poor (RP)*	(1,1.5,2)
E	*Worst (WO)*	(0.5,1,1.5)

4.2.6.3 Result Discussion

Using Equation (3-20), the evaluation result of all the evaluators can be aggregated. Figure 4-6 shows distances of aggregated evaluation result of each dress samples to each evaluation degree. These distances indicate the membership degree of each dress sample to different evaluation degrees. Shorter distance indicates higher membership degree.

In general, all the dress samples can be regarded as *"Best (BE)"* or *"Very good (VG)"*, which indicates that, the pre-selected alternative fabrics meet the market position of the fashion brand in this study. Invited designers in this research were able to understand the design position based on the market position and select appropriate fabric correspondingly.

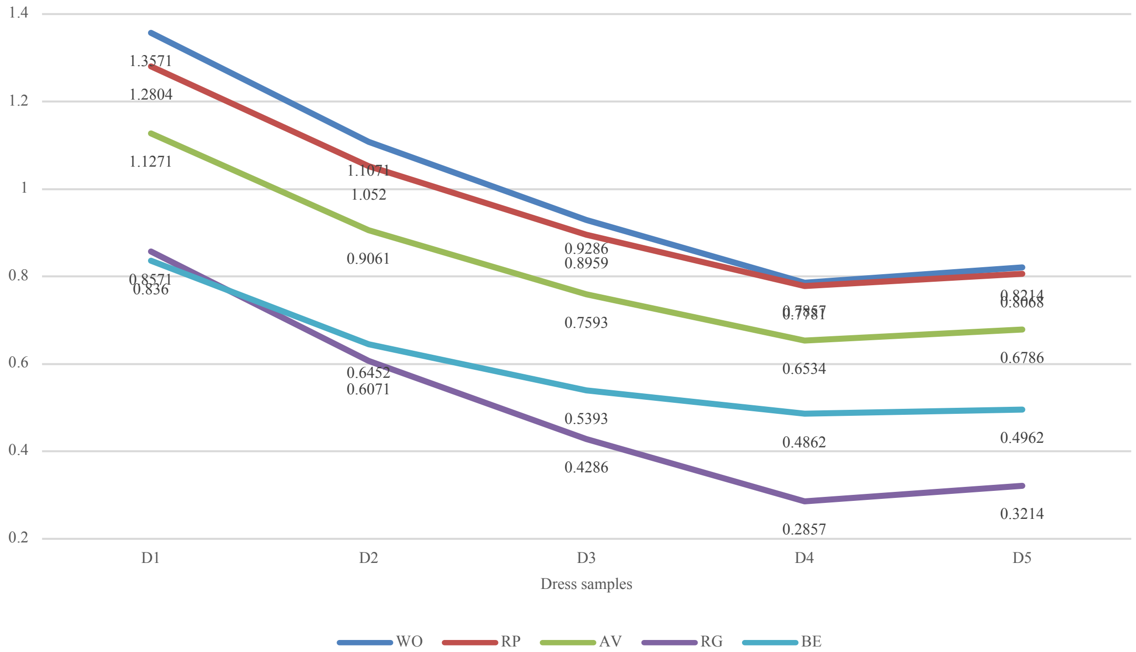


Figure 4-6: Dresses in the same style produced with the alternative fabrics.

In order to give a performance ranking for all dress samples, more attention should be paid to the distance to the evaluation degree of *"Best (BE)"*. In this condition, the distance from the shortest to the longest are D_4 (0.4862), D_5 (0.4962), D_3 (0.5393), D_2 (0.6452), D_1 (0.836), which indicated that the most popular dress sample is D_4, the rest are D_5, D_3, D_2 and D_1. This ranking exactly matches the selection result obtained from the proposed selection system, which shows that the proposed model is able to capture the requirements of the consumers and select appropriate fabrics based on the market position of mass production fashion brands. Also, design knowledge of the designers can be extracted and applied in the interactive process to the construction of the ***AHP*** model.

From the result of the validation experiment, it can be proved that the proposed system is able to significantly increase the efficiency and satisfaction of decision–making process of fabric selection. The results of the proposed system are realistic and precise and evaluation criteria determined by the collaborative ***Fuzzy AHP*** analysis can significantly ensure the results of ***TOPSIS*** analysis to be more reliable.

4.3 PFRS-Garment Style Recommendation System (GSRS)

As introduced in Section 3.3.1, we have defined five sensory experiments for collecting human perception data. These experiments aim at finding out the relations between body shape images, fashion style, visual images and garment components.

4.3.1 Establishment of the Garment Design Space Module (*GDSM*)

4.3.1.1 *Fashion Style Space (FASS)* and *Fashion Style Sensory Attributes (FSSA)*

In order to establish the proposed ***Fashion Style Space (FASS)***, a set of ***Fashion Style Sensory Attributes (FSSA)*** is extracted. As discussed in Section 2.2.3.2, these ***Fashion Style Sensory Attributes (FSSA)*** describe the fashion style perception of human being, which constitute the common communication language between fashion designers, pattern makers and garment consumers. A sensory experiment is carried out to generate the desired sensory attributes.

(1) Participants

100 experienced fashion designers are involved in the selection of ***Fashion Style Sensory Attributes***. These designers are experienced designer from fashion industry. All of them have been working in fashion design for more than 10 years. These designers are from different countries, including France, Sweden, Italy, UK, Romania, USA, China and Japan.

Before this sensory experiment, its purpose is presented to all the participants (invited designers). A training session about the procedure of the experiment is organized to train these subjects. This study is approved by the ethics committee of ENSAIT and strictly performed in agreement with the legal requirements and international norms [131]. Each participant signs a written consent form prior to participation.

(2) Sensory experiment

Step 1: Selection of categories of *Fashion Style Sensory Attributes*

First, each of the trained designers generates an exhaustive list of categories describing fashion styles according to his/her professional knowledge through a brainstorming process. Then, the generated words representing the desired categories are collected and screened to all the participants. A deep discussion among all the participants is then carried out to vote for all the words. There are two principles for the vote: (1) Words with repeated meaning should be avoided, and (2) the selected words should try to cover all the ***FEA Considerations*** of fashion. After that, six categories are selected: *A1: Construction, A2: Times, A3: Occasion, A4: Acceptance, A5: Age* and *A6: Gender*. The collected categories are approved by all the invited designers.

Step 2: Selection of *Fashion Style Sensory Attributes*

Each of the designers is invited to collect word-pairs for each of the categories describing fashion styles generated from Step 1. These word-pairs are collected from the literature based on the knowledge and experience of the invited designers.

Table 4-14: *Fashion Style Sensory Attributes* and their categories of the *FASS*.

Definition	Category	Fashion Style Sensory Attributes	Belonging Descriptor
Structure Character	Construction	Simple Gorgeous	*Compact Earthy* *Luxury Plush Luxury …*
Duration of Prevailing	Times	Modern Classical	*Fashionable Novel Distinctive* *Retro Classic Conservative …*
Occasion of Wearing	Occasion	Formal Casual	*Dignified Professionalism* *Serious Leisure Airy Casual* *Motion Active Easy …*
Acceptant Degree	Acceptance	Occasional Universal	*Individuality Special Distinctive* *Common General Daily …*
Age Orientation	Age	Young Mature	*Mature Intellectual Generous* *Princess Sweet Dream …*
Sex Orientation	Gender	Feminine Masculine	*Ladies Feminine Subtle* *Handsome Cool Neutralized …*

After that, all the listed word-pairs collected by the invited designers are screened for all the designers. A selection procedure is carried out for the word-pairs of each category, through a discussion among the participants. In the selection process, derogatory terms, words easily leading to confusions, and nouns far away from the context of this study are removed. After this step, there is only few word-pairs remained in the list.

Then, a vote procedure is carried out to select the most appropriate word-pair for each category. The principle of the vote is that, the selected word-pairs should be easily understood by both designers and consumers.

Finally, six word-pairs are selected and converted into adjective form. Each category has one word-pair. Table 4-14 describes the selected ***Fashion Style Sensory Attributes*** and their categories. For each pair of descriptors, their belonging descriptors are also given. If there exist several explanations on one word, the final word will be selected by the fashion experts according to the level of comprehension by the participants.

Using the set of six pairs of ***Fashion Style Sensory Attributes***, the proposed ***FASS*** can be established (Figure 4-7). The selected 6 word-pairs describing the ***Fashion Style Sensory Attributes*** are normalized sensory evaluation criteria, which are different from other neutral and non-hedonic sensory descriptors describing products. Instead of describing products, these normalized sensory criteria are more basic, natural and abstract. They are very strong in dealing with social-cultural context of products. In fact, it is easier for consumers to express their expectations and preferences than classical sensory descriptors describing products only. We consider that a relationship between fashion style with ***FEA Considerations*** and products can be set up on the basis of these 6 pairs of ***Fashion Style Sensory Attributes***.

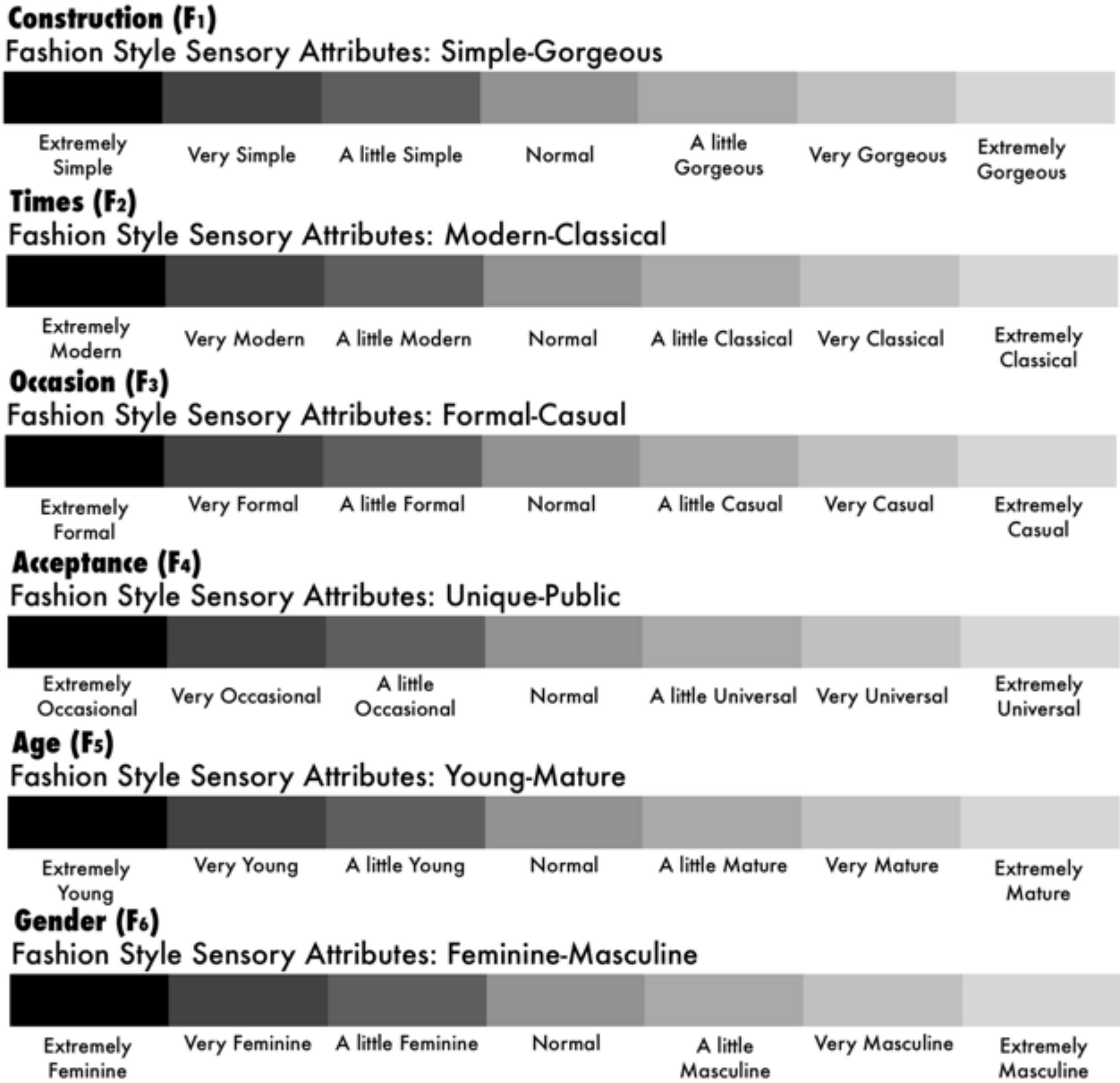


Figure 4-7: Rating Scale for the identification of fashion style.

(3) Definition of the rating scale

Six ***Fashion Style Sensory Attributes*** will be used to identify six rating scales. Each of the word-pairs of the six ***Fashion Style Sensory Attributes*** is defined to be 7 intensity levels or evaluation scores represented by $\{B_1, B_2, B_3, B_4, B_5, B_6, B_7\}$. These rating scales will be further applied to the identification of Fashion style image and fashion style perception.

For example, for the ***Fashion Style Sensory Attributes*** of "Simple and Gorgeous", the rating scale is defined as *{Extremely Simple, Very Simple, A little Simple, Normal, A little Gorgeous, Very Gorgeous, and Extremely Gorgeous}*. Figure 4-6 presents all the rating scale defined using the proposed ***FASS***.

4.3.1.2 Body Shape Image Space (BSIS) and Body Shape Image Attributes

The establishment of the ***Body Shape Image Space (BSIS)*** refers to ***Romanian Standard SR-13545:2010*** "Clothing. Women's Body Measurement and Garment Sizes" is available in our study [132]. This standard covers the body types of the whole Romanian female population in 2010. The statures of these samples are arranged from 148cm to 180 cm with a drop of 8 cm. According to this database, four standard body types (A, B, C, D, E, F) are defined from the difference of chest Circumference and hip Circumference.

A: means that Chest Circumference minus Hip Circumference is between -4cm-0cm.

B: means that Chest Circumference minus Hip Circumference is between 0cm-4cm.

C: means that Chest Circumference minus Hip Circumference is between 4cm-8cm.

D: means that Chest Circumference minus Hip Circumference is between 8cm-12cm.

E: means that Chest Circumference minus Hip Circumference is between 12cm-16cm.

In practice, these five body types cover more than 99% of the whole population of Romanian women. According to ***Romanian Standard SR-13545:2010***, 164C is generally taken as the standard body shape for the Romanian female population. The height of 148 cm and 180 cm can be considered as the lower and upper bounds of the height of the whole population. -4cm and 16cm can be considered as the lower and upper bounds of Chest Circumference minus Hip Circumference. There are 6 classes of height with a drop of 8cm and 5 classes of Chest Circumference minus Hip Circumference with a drop of 4cm.

Based on ***Romanian Standard SR-13545:2010***, we use two word-pairs of ***Body Shape Image Attributes*** to describe a body shape image, namely *Height (Short-Tall)* and *Fatness (Slim-Fat)*, which enables the establishment of the ***BSIS*** of the ***GDSM***.

Two rules can be generated to analyze the body shape image regarding two ***Body Shape Image Attributes*** of *Height (Short-Tall)* and *Fatness (Slim-Fat)*.

***Body Shape Image Analysis Rule 1*- Height (Short-Tall):**

We can describe the *Height (Short-Tall)* as 6 levels: *X1: very short (-148cm), X2: short (148.1-155.9cm), X3: a little short (160-163.9cm), X4: a little tall (164cm-171.9cm), X5: tall (172-179.9cm), X6: very tall (180cm +)*.

***Body Shape Image Analysis Rule 2*- Fatness (Slim-Fat):**

We can define *Fatness (Slim-Fat)* as 5 levels: *Y1: very slim (A: -4-0cm), Y2: slim (B: 0-4cm), Y3: middle (C: 4-8cm), Y4: fat (D: 8-12cm), Y5: very fat (E: 12-16cm)*. Therefore, the whole body-shapes can be described by 30 kinds of combination.

For example, if the height of a consumer is 168cm, her body shape image data of Height (Short-Tall) is *X4: a little tall (164cm-171.9cm)*. If her Chest Circumference is 90cm and Hip

Circumference is 84cm, her body shape image data of Fatness (Slim-Fat) is *Y3: middle (C: 4-8cm).*

Figure 4-8: Body Shape Image Attributes of the BSIS and Rating Scale for the body shape image.

Using the defined two rules, body shape image data can be generated from height measurement, chest Circumference and hip Circumference automatically. In this study, 3D body scanning is used to obtain these measurements.

4.3.1.3 Fabric Sensory Property Space (*FSPS*)

Fabric Sensory Property Space (FSPS) is established to identify the fabric sensory property, using a set of ***Fabric Sensory Attributes***. As the desired fabric for the ***PWAM*** is selected from the ***Fabric Selection System*** (***FSS)***, ***FSPS*** serves for the identification of the fabric sensory property.

In a real design process, there are some garment components, which is not possible to be realized by the determined fabric, while there are also same garment components can be well designed from the determined fabric. Using the identified fabric sensory property, the most suitable garment components, which can be realized by the determined fabric, can be determined. In this section, experiments designed to establish the proposed ***FSPS*** is introduced. These experiments follow that of the ***Fashion Style Space (FASS)***.

Table 4-15 presents the final selected ***Fabric Sensory Attributes*** and their definition. We use four pairs of ***Fabric Sensory Attributes*** to describe the fabric sensory property of a piece of fabric, namely *Softness (Soft-Stiff), Flexibility (Elastic-Inelastic), Weight (Thin-Thick), and Drapability (Drapery-Undraped)* which enables the establishment of the ***FSPS*** of the ***GDSM***.

Table 4-15: Fabric Sensory Attributes and their categories of the *FSPS*.

Category	Fabric Sensory Property Attributes	Definition
Softness	Soft-Stiff	The smooth and agreeable to the touch of the fabric.
Flexibility	Elastic-Inelastic	The property of the capability of being bent.
Weight	Thin–Thick	The force that the gravitation of a piece of

		fabric exerts upon a body.
Drapability	Drapery-Undraped	The capability of creating folds when a piece of fabric being hanged on an objective.

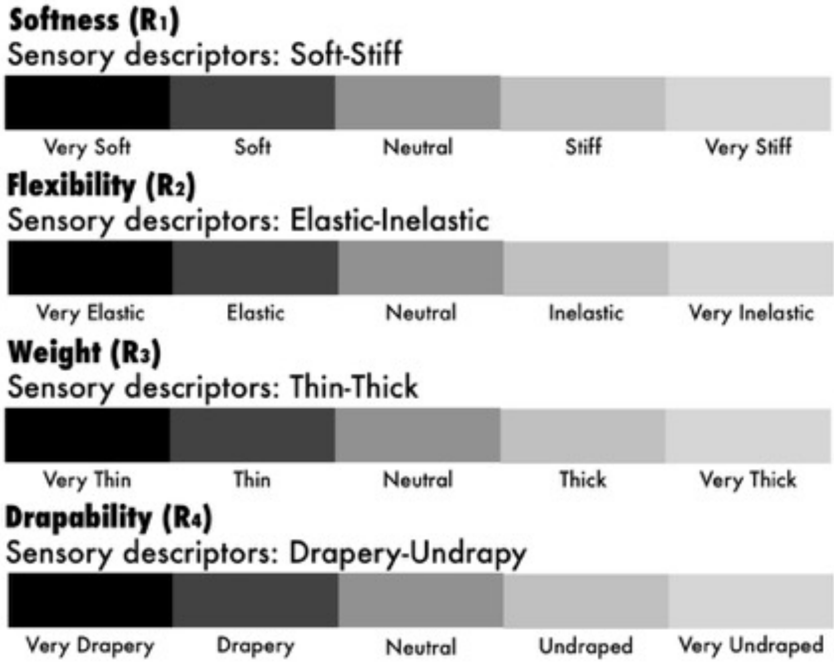


Figure 4-9: Fabric Sensory Attributes of the proposed FSPS and their inside levels.

The proposed four ***Fabric Sensory Attributes*** will be classified into 5 levels. Correspondingly, each of the word-pairs of the four ***Fabric Sensory Attributes*** is defined to be 5 intensity levels or evaluation scores.

Specifically, for the ***Fabric Sensory Attributes*** of *"Softness (Soft-Stiff)" (R_1)*, the rating scale is defined as

{Very Soft (R_{11}), Soft (R_{12}), Neutral(R_{13}), Stiff (R_{14}), Very Stiff (R_{15})},

for the Fabric Sensory Attributes of *"Flexibility (Elastic-Inelastic)" (R_2)*, the rating scale is defined as

{Very Elastic (R_{21}), Elastic (R_{22}), Neutral(R_{23}), Inelastic (R_{24}), Very Inelastic (R_{25})},

for the Fabric Sensory Attributes of *"Weight (Thin-Thick)" (R_3)*, the rating scale is defined as

{Very Thin (R_{31}), Thin (R_{32}), Neutral(R_{33}), Thick (R_{34}), Very Thick (R_{35})},

for the Fabric Sensory Attributes of *"Drapability (Drapery-Undraped)" (R_4)*, the rating scale is defined as

{Very Drapery (R_{41}), Drapery (R_{42}), Neutral(R_{43}), Undraped (R_{44}), Very Undraped (R_{45})}.

Figure 4-9 presents all the ***Fabric Sensory Attributes*** and their inside levels. Using the proposed classification, there are 625 kinds of combination, representing different Fabric sensory property types. These ***Fabric Sensory Attributes*** with defined levels will be further applied to the identification of fabric sensory property of determined fabric and fabric related fashion design rules.

4.3.1.4 The proposed *Garment Design Space Module (GDSM)*

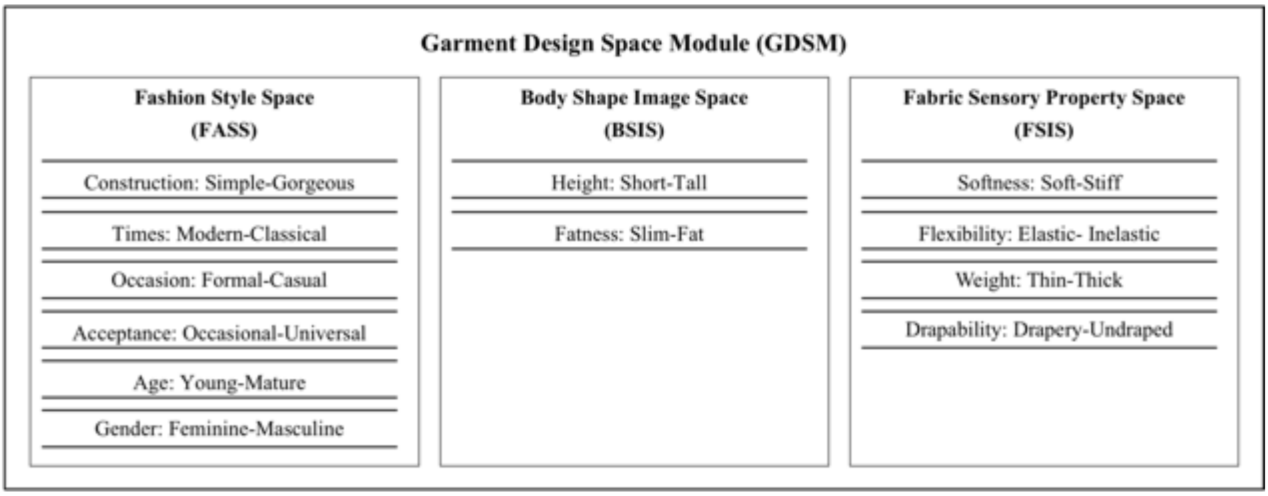


Figure 4-10: Framework of the *GDSM: FASS, BSIS, FSPS.*

Based on the experiment result of Section 4.3.1.1-4.3.1.3, the proposed ***GDSM*** can be realized, as presented in Figure 4-10. The proposed ***GDSM*** has 12 attributes, where ***FASS*** has 6 attributes, ***BSIS*** has 2 attributes and ***FSIS*** has 4 attributes. Figure 4-10 presents the proposed ***GDSM***.

4.3.2 Extraction of recommendation rules

Due to the fact that there are two approaches of recommendation of the proposed ***GSRS***, there are two kinds of recommendation rules: (1) case-based recommendation rules (for the ***SCDM***), and (2) design rules extracted from the knowledge and experience of designers (for the ***RBRM***). Case based recommendation rules utilize the ***Case-Based Reasoning***, as discussed in Section 3.4.4. In this section, the extraction of design knowledge/rules will be presented along with several experiments.

Design rules support the garment design process. Design rules of fashion design are situation-oriented knowledge, which can be applied to a particular situation for a specific consumer. For example, as discussed in Section 1.2.1.1, the design rule can be concluded as *"When design the collar for a consumer, if he/she is too fatty and his/her neck is relative short (Figure 1-15 A), open collar should be chosen to reduce the visual extension in the horizontal direction (Figure 1-15 B)."*. The situation of this design rule is "*a consumer is very fatty or his/her neck is relative short*", and the related situated knowledge/design rule is *"the collar designed for him/her is open collar"*.

Figure 4-11 presents the working process and function of the design rules of the ***RBRM***. As described in Section 3.2.3, system sensory input will be processed by different garment design rules. More specifically, fashion style sensory property value of a certain consumer will be processed by ***RB1-FS (Fashion Style Related Garment Design Rule Base)***, body shape image value will be processed by ***RB2-BS (Body Shape Related Garment Design Rule Base)***, and fabric sensory property value will be processed by ***RB3-F (Fabric Related Garment Design Rule Base)***.

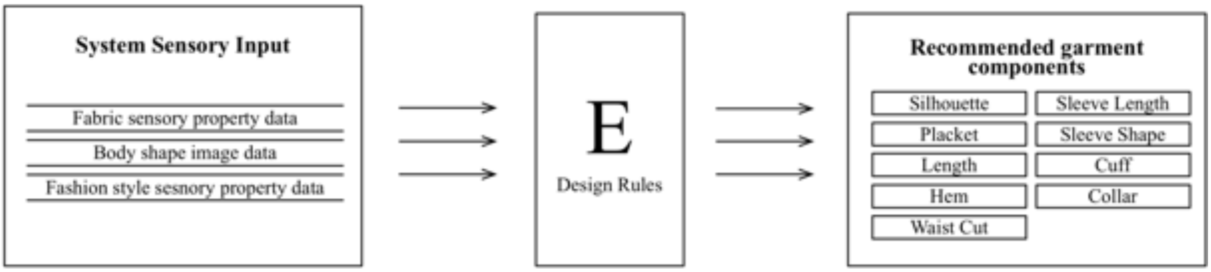


Figure 4-11: Function of design rules: from system sensory input into specific recommended garment components.

4.3.2.1 *Experiment I*: Extraction of fashion style related garment design rules for *RB1-FS*

In the real recommendation process using the ***RBRM***, the similarity between the required fashion style of a consumer and the fashion style image of all alternative garment components of each ***Garment Component Categories***, will be computed. In one ***Garment Component Categories***, the alternative garment component, which has the highest similarity, will be the first recommendation result for this ***Garment Component Categories***. Both the required fashion style of a consumer and the fashion style image of all alternative garment components in each ***Garment Component Categories*** are measured using the proposed ***Fashion Style Sensory Attributes*** of the ***FASS*** in Section 4.3.1.1. ***Experiment I*** enables to identify the relations between garment components of the ***GCM*** and ***Fashion Style Sensory Attributes*** of the ***FASS***. These relations should be identified by the experience and knowledge of designers. Sensory evaluation is utilized to realize this identification process. The components, procedure and mathematical formulation of this experiment will be given below.

(1) Components

Alternative garment components:

Alternative garment components of the ***GCM***, as discussed in Section 2.2.3.4 will be evaluated in these experiments.

Fashion style image rating scales:

Six fashion style image rating scales obtained in Section 4.3.1.1 will be used to identify the fashion style image of all the alternative garment components.

Designers:

A group of 100 experienced fashion designers are involved in ***Experiment I***. These designers are experienced designer from fashion industry. All of them have been working in fashion design for more than 10 years. These designers are from different countries, including France, Sweden, Italy, UK, Romania, USA, China and Japan.

(2) Procedure

Before the selection experiments, the purpose of ***Experiment I*** is presented to all the invited designers. A training session is organized for these subjects. This study is approved by the ethics committee of ENSAIT and strictly performed in agreement with the legal requirements and international norms [131]. Each participant signed a written consent form prior to participation.

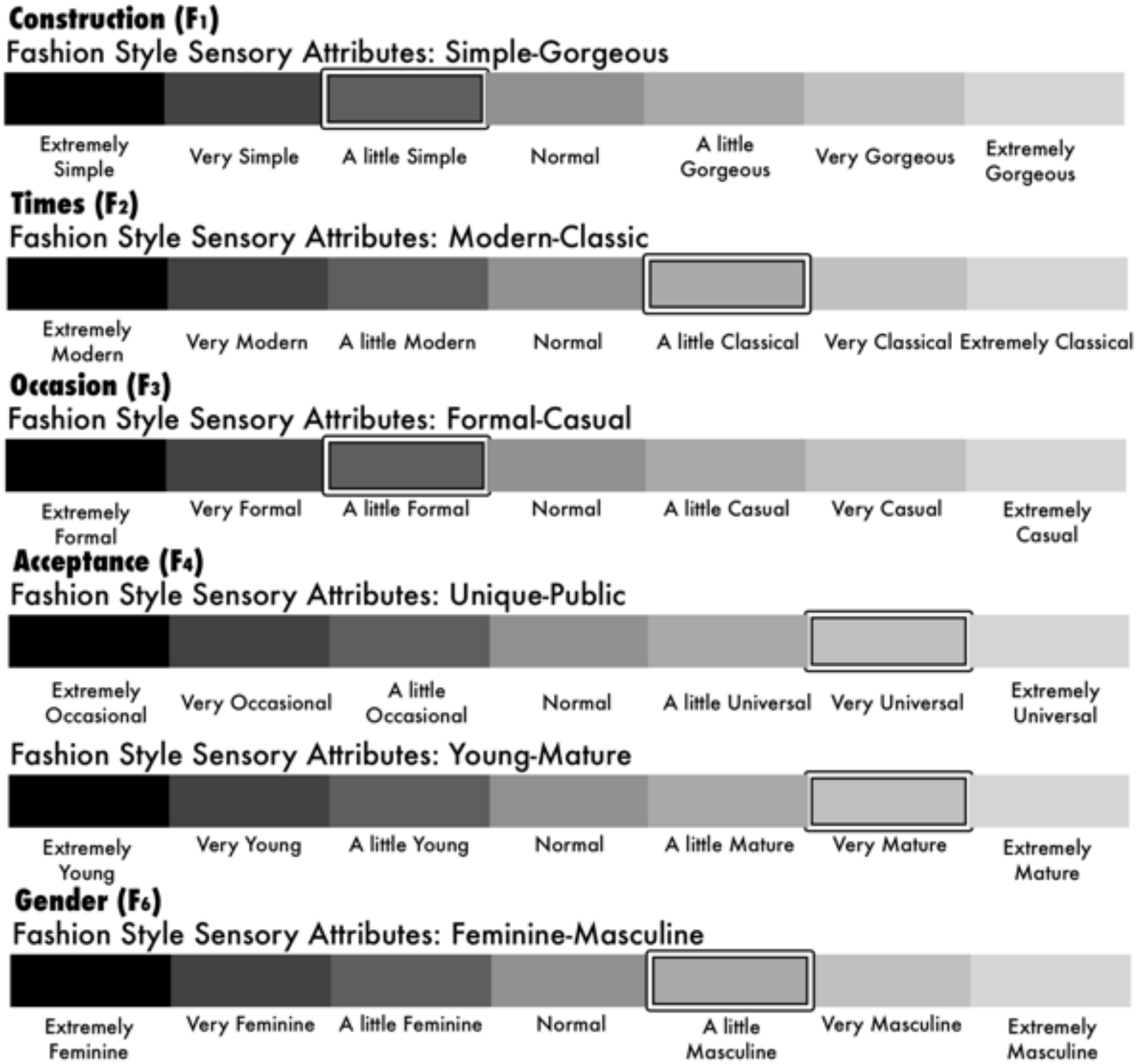


Figure 4-12: Fashion style image of the garment component of "Stand collar" by one of the evaluator.

During the evaluation procedure, the trained designers are asked to indicate which linguistic value of the rating scales is the best for describing their perception on the alternative garment components. Fashion style image of each alternative garment component will be identified in the six rating scales.

For example, Figure 4-12 presents the fashion style image of the garment component of "Stand collar" by one of the evaluator. Based on the perception of this designer, the fashion style image of "Stand collar" regarding *Construction (Simply-Gorgeous)* is *"A little Simple"*, *Times*

(Modern-Classical) is *"A little Classical"*, *Occasion (Formal-Casual)* is *"A little Formal"*, *Acceptance (Occasional-Universal)* is *"Very Universal"*, *Age (Young-Mature)* is *"Very Mature"*, and *Gender (Feminine-Masculine)* is *"A little Masculine"*.

(3) Mathematical formalization and data processing

We will collect the evaluation results on each of the garment components carried out by all the 100 designers regarding 6 garment rating scales. These evaluation results are presented in linguistic values taken from Figure 4-7. Using fuzzy set theory, a group decision-making about the evaluation results will be processed by Numerical Equivalence Values. Table 4-16 presents the linguistic values and related Numerical Equivalence Values.

Let X be the evaluation vector of the fashion style image for one specific alternative garment component regarding six Fashion Style Image Attributes.

Let FR_m $(m=1,2,\dots w)$ be the dimensions of the FASS, where $w=6$.

Let $L=\{L_1, L_2, L_3, \dots L_b\}$, where b=7 be a set of a set of linguistic scores (as described in Figure 4-7).

Table 4-16: Numerical equivalence values of linguistic values of rating scales of the FASS.

Rating scales of the FASS						Numerical equivalence values Num (Fb)
Construction	**Times**	**Occasion**	**Acceptance**	**Age**	**Gender**	
Extremely Simple	Extremely Modern	Extremely Formal	Extremely Occasional	Extremely Young	Extremely Feminine	1
Very Simple	Very Modern	Very Formal	Very Occasional	Very Young	Very Feminine	0.84
A little Simple	A little Modern	A little Formal	A little Occasional	A little Young	A little Feminine	0.67
Normal	Normal	Normal	Normal	Normal	Normal	0.5
A little Gorgeous	A little Classical	A little Casual	A little Universal	A little Mature	A little Masculine	0.33
Very Gorgeous	Very Classical	Very Casual	Very Universal	Very Mature	Very Masculine	0.17
Extremely Gorgeous	Extremely Classical	Extremely Casual	Extremely Universal	Extremely Mature	Extremely Masculine	0

In order to quantify these linguistic evaluation data, we transform these linguistic values into their numerical equivalence values $Num(L_b)$ $(b=1,2,3\dots,7)$, which is uniformly distributed on [0,1], where $Num(L_1)=0$, $Num(L_2)=0.17$, $Num(L_3)=0.33$, $Num(L_4)=0.5$, $Num(L_5)=0.67$, $Num(L_6)=0.84$, and $Num(L_7)=1$. Let $N(L_b)$ $(b=1,2,3\dots,7)$ be the number of evaluators selecting the score L_b during the evaluation experiment, the aggregated value of a_m can be obtained using Equation (3-20).

For example, for evaluating the fashion style image of the garment component of "Stand collar" regarding *"Construction (Simply-Gorgeous)" (FR1)*, we have 100 experts. If 10 experts considers that "Stand collar" is *"Extremely Simple"*, 20 experts consider that "Stand collar" is *"Very Simple"*, 30 experts consider that "Stand collar" is *"A little Simple"*, 20 experts consider that "Stand collar" is *"Normal"*, and 20 experts believe that "Stand collar" is *"A little Gorgeous"*, based on the previous equation, the fashion style image of the garment component of "Stand collar" can be defined as follows:

$$(1*10+0.84*20+0.67*30+0.5*20+1*0.33*20)/100 = 0.635$$

Similarly, the fashion style image of each of the alternative garment component can be quantified as a vector. There are six components of this vector corresponding to the number of dimensions of the ***FASS***.

Based on ***Experiment I***, each of the alternative garment components will be given a vector of the fashion style image values. The proposed ***RB1-FS*** is established based on the experiment result of ***Experiment I***.

4.3.2.2 *Experiment II*: Extraction of body shape related garment design rules for RB2-BS

Experiment II is designed to extract the garment design rules related to body shapes. These rules should be identified by the experience and knowledge of designers. Sensory evaluation is utilized to realize this identification process. The components, procedure and mathematical formulation of this experiment will be given below.

Alternative garment components and designers participated in this experiment are the same as Section 4.3.2.1. Especially, the body shape and recommendation attributes rating scale is defined in this experiment.

Body shape classification

30 categories of body shapes with scoliosis defined in Section 4.3.1.2 will be used for the analysis.

Recommendation attributes rating scale

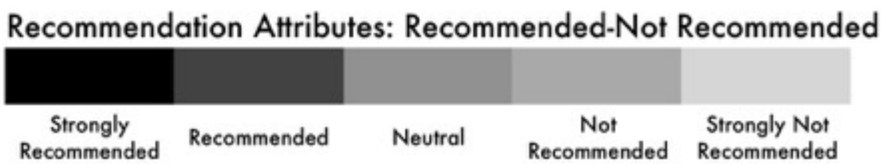


Figure 4-13: Recommendation attributes rating scale.

In ***Experiment II***, a rating scale is used to describe the recommendation level of one alternative garment component to one body shape of ***PWAM***. The rating scale occurs in the form of word-pair. The word-pair has 5 intensity levels represented by *{E_1, E_2, E_3, E_4, E_5}* (evaluation scores), corresponding to the set *{"Strongly Recommended (SR)", "Recommended (R)", "Neutral (N)", "Not Recommended (NR)", and "Strongly not Recommended (SNR)"}* respectively (Figure 4-13).

Body shape related recommendation attributes (BSRA)

BSRA is defined to describe the recommendation attributes of one garment component in one specific situation of the consumer's body shape. These recommendation attributes will be expressed by evaluation scores of the set in the proposed rating scale. For example, if the body shape of a ***PWAM*** is "*X5: tall+Y5: very fat"*, and one designer considers that, for this body shape, the garment component of "Collarless" should be "*Strongly Recommended*". In this condition, based on the perception of this designer, the recommendation attributes of *"Collarless"* for consumer with "*X5: tall+Y5: very fat"* is *"Strongly Recommended (SR)"*.

The procedure and data analysis of ***Experiment II*** follows that of ***Experiment I***.

Table 4-17: Numerical Equivalence Values of linguistic values of rating scales of the *BSRA*.

C	SNR	NR	N	R	SR
Corresponding Numerical equivalence values	0	0.25	0.5	0.75	1

Table 4-17 presents the Corresponding Numerical Equivalence values of each evaluation scores. Using these Numerical equivalence values, evaluation results of the 100 designers can be aggregated as the numerical values of the ***BSRA***.

In my PhD research, we define the aggregated ***BSRA*** value of one certain alternative garment as a linguistic score, which takes value from *{"Strongly Recommended (SR)", "Recommended (R)", "Neutral (N)", "Not Recommended (NR)", and "Strongly not Recommended (SNR)"}*. Numerical values of the BSRA will be transferred into linguistic values. Using linguistic values of the ***BSRA***, the proposed system is easier to process all the body shape related design rules.

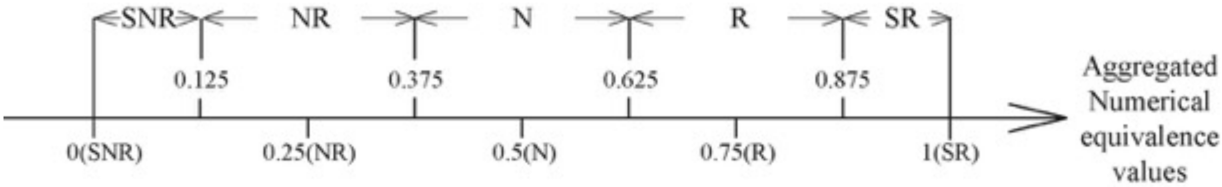


Figure 4-14: From aggregated Numerical equivalence values to linguistic scores of BSRA.

Figure 4-14 presents the rule transferring the aggregated Numerical equivalence values into linguistic scores. Let m be the aggregated Numerical equivalence value of one alternative garment component for one body shape. For this alternative garment component,

if $m \leq 0.125$, its ***BSRA*** = SNR,

if $0.125 < m \leq 0.375$, its ***BSRA*** = NR, if $0.375 < m \leq 0.625$, its ***BSRA*** = N,

if $0.625 < m \leq 0.875$, its ***BSRA*** = R, and

if $0.875 < m \leq 1$, its ***BSRA*** = SR.

For example, for evaluating the ***BSRA*** of the garment component of "Stand collar" regarding the body shape type of "*X5: tall + Y5: very fat"*, we have 100 experts. If 50 experts consider that "Stand collar" is "*Strongly Recommended*", 30 experts consider that "Stand collar" is "*Recommended*", 20 experts consider that "Stand collar" is "*Neutral*", based on Equation (1), the fashion style image of the garment component of "Stand collar" can be defined as follows:

$$m= (1*50+0.75*30+0.5*20)/100 = 0.825.$$

As 0.625 < m (=0.825) ≤ 0.875, the ***BSRA*** of the garment component of "Stand collar" regarding the body shape type of "*X5: tall+Y5: very fat"* is *"R"*.

Based on ***Experiment II***, for each of the alternative garment components, a linguistic ***BSRA*** value will be given to each of the body shape image type. The proposed ***RB2-BS*** is established based on the experiment result of ***Experiment II***.

4.3.2.3 *Experiment III*: Extraction of fabric related garment design rules for RB3-F

Experiment III is designed to extract garment design rules related to fabrics. The relationship between a fabric (hand) sensory property and alternative garment components will be modeled. This relationship constitutes fashion design rules related to fabrics. These design rules can be identified by designers, based on their experience and knowledge. Sensory evaluation is utilized to realize this identification process. The components, procedure and mathematical formulation of this experiment will be given below.

Alternative garment components and designers participated in this experiment are the same as Section 4.3.2.1. Specifically, types of fabric sensory property and recommendation attributes rating scale are defined in this experiment.

Type of fabric sensory properties

625 fabric samples with all different sensory properties, defined in Section 4.3.1.3, will be used in the experiment. One fabric is characterized by four sensory properties: *Softness (Soft-Stiff), Flexibility (Elastic-Inelastic), Weight (Thin-Thick), and Drapability (Drapery-Undraped).* Values of each sensory property can be divided into five levels.

For example, Figure 4-15 presents the fabric sensory properties of one of the fabric samples. In this case, the fabric sensory properties of this sample correspond to *"R14+R22+R33+R44"*, namely *"Softness level: Stiff" (R14), "Flexibility level: Elastic" (R22), "Weight level: Neutral" (R33), "Drapability level: Undraped" (R44).*

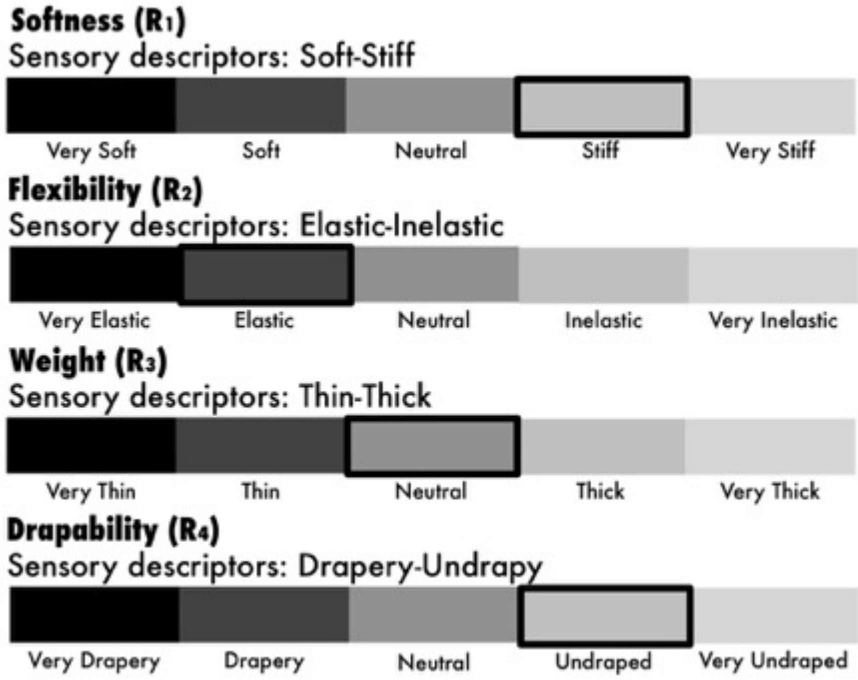


Figure 4-15: An example of sensory properties for one fabric sample.

Recommendation attributes rating scale

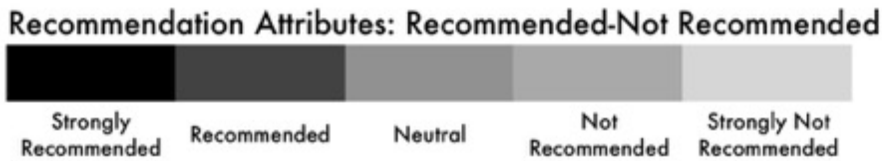


Figure 4-16: Recommendation attributes rating scale

In ***Experiment III***, a rating scale is used to describe the recommendation level of one specific alternative garment component to one fabric sensory property. The rating scale appears in the form of word-pair. The word-pair has 5 intensity levels represented by *{G_1, G_2, G_3, G_4, G_5}*, taking evaluation scores from the set *{"Strongly Recommended (SR)", "Recommended (R)", "Neutral (N)", "Not Recommended (NR)", and "Strongly not Recommended (SNR)"}* respectively (Figure 4-16).

Fabric related Recommendation Attributes (*FRA*)

FRA is defined to describe the recommendation attributes of one garment component in one specific scenario of a selected fabric. These recommendation attributes will be expressed by evaluation scores taken from the set of the proposed rating scale. For example, if the fabric sensory property of a ***PWAM*** is *"R_{14}: Stiff + R_{22}: Elastic + R_{33}: Neutral + R_{44}: Undraped"*, and one designer thinks for this fabric, the garment component of *"Stand Collar"* should be "*Strongly Recommended*". In this condition, based on the perception of this designer, the recommendation attributes of *"Stand Collar"* for the fabric of *"R_{14}: Stiff + R_{22}: Elastic + R_{33}: Neutral + R_{44}: Undraped"* is *"Strongly Recommended (SR)"*.

The procedure and data analysis of ***Experiment III*** follows that of ***Experiment I***.

Table 4-18: Numerical equivalence values of linguistic values of rating scales of the *FRA*.

C	SNR	NR	N	R	SR
Corresponding Numerical equivalence values	0	0.25	0.5	0.75	1

Table 4-18 presents the Corresponding Numerical Equivalence Values of each evaluation scores. Using these Numerical Equivalence Values, evaluation results of the 100 designers can be aggregated as the numerical values of the ***FRA***.

In my PhD research, we define the aggregated ***FRA*** value of one alternative garment as a linguistic score, which takes value from *{"Strongly Recommended (SR)", "Recommended (R)", "Neutral (N)", "Not Recommended (NR)", and "Strongly not Recommended (SNR)"}*.

Numerical values of the ***FRA*** will be transferred into linguistic values. Using linguistic values of the ***FRA***, the proposed system can easily process all the fabric related garment design rules.

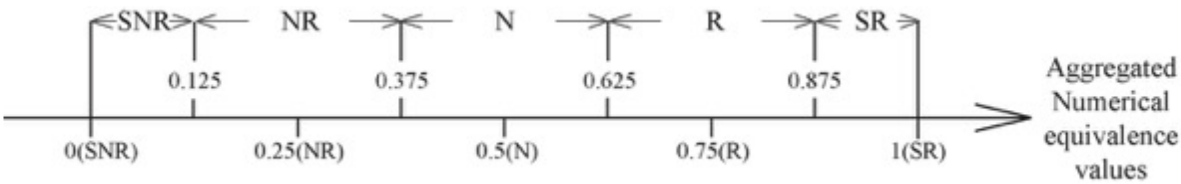


Figure 4-17: From aggregated Numerical equivalence value to linguistic scores of FRA.

Figure 4-17 presents the rule transferring the aggregated Numerical Equivalence Value into linguistic scores. Let n be the aggregated Numerical Equivalence Value of one alternative garment component for one fabric with certain sensory property type. For this alternative garment component,

if $n \leq 0.125$, its ***FRA*** = SNR,

if $0.125 < n \leq 0.375$, its ***FRA*** = NR,

if $0.375 < n \leq 0.625$, its ***FRA*** = N,

if $0.625 < n \leq 0.875$, its ***FRA*** = R, and

if $0.875 < n \leq 1$, its ***FRA*** = SR.

For example, for evaluating the ***FRA*** of the garment component of *"Stand collar"* regarding a specific fabric sample with the following sensory properties: "*R14: Stiff + R22: Elastic + R33: Neutral + R44: Undraped"*, we have selected 100 experts. If 50 experts consider that "Stand collar" is "*Strongly Recommended*", 30 experts consider that "Stand collar" is "*Recommended*", 20 experts consider that "Stand collar" is "*Neutral*", based on Equation (4-2), the fashion style image of the garment component of "Stand collar" can be defined as follows:

$$m= (1*50+0.75*30+0.5*20)/100 = 0.825.$$

As $0.625 < n$ $(=0.825) \leq 0.875$, the ***FRA*** of the garment component of "Stand collar" regarding the fabric with "R_{14}: *Stiff* + R_{22}: *Elastic* + R_{33}: *Neutral* + R_{44}: *Undraped*" is "*R*".

Based on *Experiment III*, for each of the alternative garment components, a linguistic ***FRA*** value will be given to each kind of fabric sensory property. The proposed ***RB3-F*** is established based on the experimental result of ***Experiment III***.

4.3.3 Establishment of the proposed recommendation modules

Based on the experimental result of Section 4.3.1 and 4.3.2, two recommendation modules of the proposed ***GSRS***, namely ***SCDM*** and ***RBRM*** have been established.

4.3.3.1 SCDM

(1) General principle of the proposed *SCDM*

As defined in Section 2.2.3.6, a ***Successful Case*** is a three-tuple in the form of *{<Case profile>, <Recommended Product Profile>, <Successful recommendation frequency>}*. $C= \{c_1, c_2, \ldots, c_t\}$ is defined as a set of t ***Case Features*** describing the components of a product. In this study, $c_{1\text{-}6}$ corresponds to $f_{1\text{-}6}$, $c_{7\text{-}8}$ corresponds to $b_{1\text{-}2}$, $c_{9\text{-}12}$ corresponds to $r_{1\text{-}4}$, $c_{13\text{-}21}$ corresponds to $g_{1\text{-}9}$, c_{22} corresponds to h_{14}, and c_{23}= Successful recommendation frequency. We have $t=23$.

In the proposed ***SCDM***, we use the ***Case-Based Reasoning*** technology to recommend relevant product profiles to each new consumer by comparing his/her ***Consumer Profile*** with the past ***Successful Cases***. The general principle of the proposed ***SCDM*** is to identify the relevant past ***Successful Cases***, in which satisfied ***Product Profiles*** have been successfully recommended to consumers having similar profiles. If the similarity value between the new ***Consumer Profile*** and the existing ***Successful Cases*** is higher than a predefined threshold □, the ***SCDM*** will be applied as the recommendation module of the system before the ***RBRM***. In practice, this module will enable to propose more satisfactory products to a consumer with a new ***Consumer Profile*** because it is closer to the successful real recommendation experience. In this context, the comparison between the ***Consumer Profile*** and the past ***Successful Cases*** is particularly important. In this study, □ is set to be 85%.

(2) Similarity measurements and *Case-Based Reasoning* rules

The similarity degree between a new ***Consumer Profile (CP)*** and the past ***Successful Cases*** of the ***SCD***, denoted as ***Similarity (CP, SCD)***, is measure using classic similarity measurement tools. This similarity degree varies between 0 and 1. The closer the new ***CP*** is to the existing w ***Successful Cases*** CP_i $(i=1,2,3, \ldots, w)$, the closer their similarity degree is to 1.

According to these similarity degrees, ***Product Profiles*** of the most relevant ***Successful Cases*** will be recommended to the new consumer ***CP*** by using the ***Case-Based Reasoning*** method. There are several rules for the ***Case-Based Reasoning*** process:

SCDM-Rule 1:

If for all $i=1, ..., w$, ***Similarity (CP, SCD)*** ≤ □, then there is no similar consumer profile in the database ***SCD*** and the system will start the ***RBRM*** for ***CP***.

SCDM-Rule 2:

If there exists only one CP_i, which makes ***Similarity (CP, SCD)*** ≤ □, ***Product Profile*** of the CP_i will be recommended to this ***CP***. If the product profile of the CP_i is not accepted by the consumer of the new case, the system will start the ***RBRM*** for ***CP***.

SCDM-Rule 3:

If there exists more than one CP_i, which makes ***Similarity (CP, SCD)*** ≤ □, the one with highest c_{23} value will be recommended to ***CP***.

product profile of the CP_i will be recommended to ***CP***. If the product profile of the *CPi* is not accepted by the consumer of the new case, the system will start the ***RBRM*** for ***CP***. If the product profile of the CP_i is not accepted by the consumer of the new case, the system will start the ***RBRM*** for ***CP***.

4.3.3.2 *RBRM*

For a given ***Case Profile***, values of this case regarding all the case descriptive features will be identified as the input of the ***RB1-FS***, ***RB2-BS***, and ***RB3-F***. After applying the garment design rules of these rule bases, we obtain for each alternative garment component three values: similarity of ***Fashion Style Image***, ***BSRA*** value and ***FRA*** value. ***BSRA*** and ***FRA*** are linguistic values. After that, for each ***Garment Component Category***, the most suitable alternative garment component will be recommended.

In order to realize the selection of the most suitable garment component, several rules are defined for the ***RBRM***. We assume that for all the alternative garment components are arranged in a hierarchical structure. The position of each alternative garment component in an ordering hierarchy can be defined using the garment design rules in ***RB1-FS***, ***RB2-BS***, and ***RB3-F***. These design rules can be regarded as the ordering rules for each branchy of the hierarchical structure. The element at the top of this structure will be first recommended.

As there are three categories of different rules that will influence the position of each garment component in an ordering hierarchy, we define in my PhD research several ordering rules to organize the hierarchical structure. More specifically, these rules are defined to identify the priorities of three categories of different design rules of the ***RB1-FS***, ***RB2-BS***, and ***RB3-F***.

There are two ordering rules to be defined:

Ordering Rule 1:

When any value of ***Fabric related Recommendation Attributes (FRA)*** or ***Body shape related recommendation attributes (BSRA)*** of an alternative garment component is assigned as either "***NR***" or "***SNR***", this alternative garment component will not be recommended.

This rule is defined because: (1) The working flow of the proposed system is from ***Fabric Selection System (FSS)*** to ***Garment Style Recommendation System (GSRS)***, which means that Fabric has already been defined before the working process of the ***GSRS***, and for any given fabric, not all the desired garment components can be realized, so any garment component which is not recommended based on the fabric property required by a consumer should not be recommended. (2) The target consumers are the ***PWAM***, any garment component which is not recommended based on the body shape image of a consumer should not be recommended.

Ordering Rule 2:

When both value of ***Fabric related Recommendation Attributes (FRA)*** or ***Body shape related recommendation attributes (BSRA)*** of an alternative garment component is assigned as either "R" or "SR", this alternative garment component will be recommended based on the recommendation attribute of ***Body shape related recommendation attributes (BSRA)***.

This is because, target consumers are the ***PWAM***, garment design rules of the ***RB2-BS*** should have higher priorities than that of the ***RB1-FS***. Based on the two rules, related ordering algorithms are developed and presented in ***Appendix 2***.

After the ranking list of the hierarchical structure is determined, the system will recommend the top two recommended alternative garment components. A ***PWAM*** can choose one from them. If this ***PWAM*** is not satisfied with both of them, the system will recommend two next top alternative garment components in the hierarchical structure. If the results recommended by ***RBRM*** has cannot be accepted by the ***PWAM*** for three times, the system will give all the alternative garment components to the ***PWAM*** so that he/she can select any alternative garment components from the concerned ***Garment Component Category***.

4.3.4 Validation of the proposed recommendation system

To verify the usefulness of the proposed ***Garment Style Recommendation System (GSRS)***, 100 ***PWAM*** are invited to use the proposed system. Each of the invited ***PWAM*** is required to evaluate their ***Fashion Style Image*** on the ***Fashion Style Sensory Attributes*** of the defined ***Fashion Style Space***. Her desired fabric has been selected by the proposed ***Fabric Selection System (FSS)***. Hand property of the concerned fabric has been evaluated in the ***Fabric Sensory Property Space (FSPS)***. Her body morphological data has been input to the system using body scanner in order to analyse the body shape image.

Let TC be a collection of n users, i.e. $TC= \{TC_1, \ldots, TC_n\}$. In our specific scenario, we have n=100.

In order to validate the effectiveness of the proposed recommendation system, three different cases for different users are discussed.

4.3.4.1 *Case study I: An example of the recommendation process using RBRM (case study of the first user)*

In this case, the proposed ***Garment Style Recommendation System (GSRS)*** enables to understand the unsatisfied attributes of the current recommendation result and then recommend a new product profile using the feedback procedure described previously.

As the first user of the system, there is no past ***Successful Cases*** in the system. In this situation, the ***RBRM*** will be utilized to realize the recommendation for this user.

The first user TC_1 is female. The required fashion style image of TC_1 is presented in Table 4-19 using linguistic evaluation scores. These linguistic evaluation scores are quantified using the Numerical equivalence values in Table 4-16.

Table 4-19: Consumer Profile of the first user TC1 and related data process

Color sensory category	Related input data	Sensory data
Construction	*A little Simple*	0.67
Times	*A little Classical*	0.33
Occasion	*A little Formal*	0.67
Acceptance	*Very Universal*	0.17
Age	*A little Mature*	0.17
Gender	*A little Feminine*	0.33
Softness	*Very Soft*	-
Flexibility	*Neutral*	-
Weight	*Thin*	-
Drapability	*Drapery*	-
Height	*150 cm*	Short
Fatness	*Y5*	Very Fat

Based on the required fashion style of TC_1, ***RB1-FS*** will be firstly used to offer a primary ordering hierarchy of all the alternative garment components of the ***Garment Components Module (GCM)***. Table 4-19 presented the ordering hierarchy, which is obtained using the garment design rules of ***RB1-FS***.

Based on the required fabric and scanned body morphological data, ***Fabric related Recommendation Attributes (FRA)*** and ***Body shape related recommendation attributes (BSRA)*** are assigned to all the alternative garment components. Due to the context limit, only part of the results is presented here. Table 4-20 presented the ***FRA*** and ***BSRA*** values of all the alternative garment components of the ***Garment Component Category*** of the "***Silhouette***" type.

From Table 4-20 we can find out that, the alternative garment components of the "*X*", "*A*", "*V*", "*O*" types will not be recommended based on ***Ordering Rule 1*** in Section 4.3.4.2.

Table 4-20: Ordering hierarchy of all the alternative garment components ranked using garment design rules of the *RB1-FS*

Garment Component Category	Ordering hierarchy of all the alternative garment components					
Silhouette	*X*	*H*	*A*	*V*	*Y*	*O*	
Placket	*Single-Breasted*	*Covered Button*	*Double Breasted*	*Zipper*			
Length	*Normal*	*A bit Long*	*Short*	*Long*	*Super Short*	*Super Long*	
Hem	*Curve*	*With Elastic*	*Straight*	*Irregular*	*Strappy*	*Thread*	*Flaring*
Waist Cut	*No waist cut*	*Straight*	*With Elastic*	*Strappy*	*With drawstring*	*With Loop*	
Sleeve Length	*Long*	*Nine points*	*Seven points*	*Middle*	*Short*	*Sleeveless*	
Sleeve Shape	*Straight*	*Lantern shape*	*Trumpet shape*	*Piece sleeve*	*Low sleeve line*	*Raglan Sleeve*	
Cuff	*Curve*	*Straight*	*Flaring*	*Irregular*	*Strappy*	*Thread*	
Collar	*Stand collar*	*Lapel*	*Flat collar*	*Collarless*			

Table 4-21: *FRA* and *BSRA* values of all the alternative garment components of the *Garment Component Category* of the "*Silhouette*" type

Garment Component	***FRA***	***BSRA***
X	*NR*	*NR*
H	*R*	*SR*
A	*NR*	*NR*
V	*R*	*NR*
Y	*R*	*R*
O	*NR*	*SR*

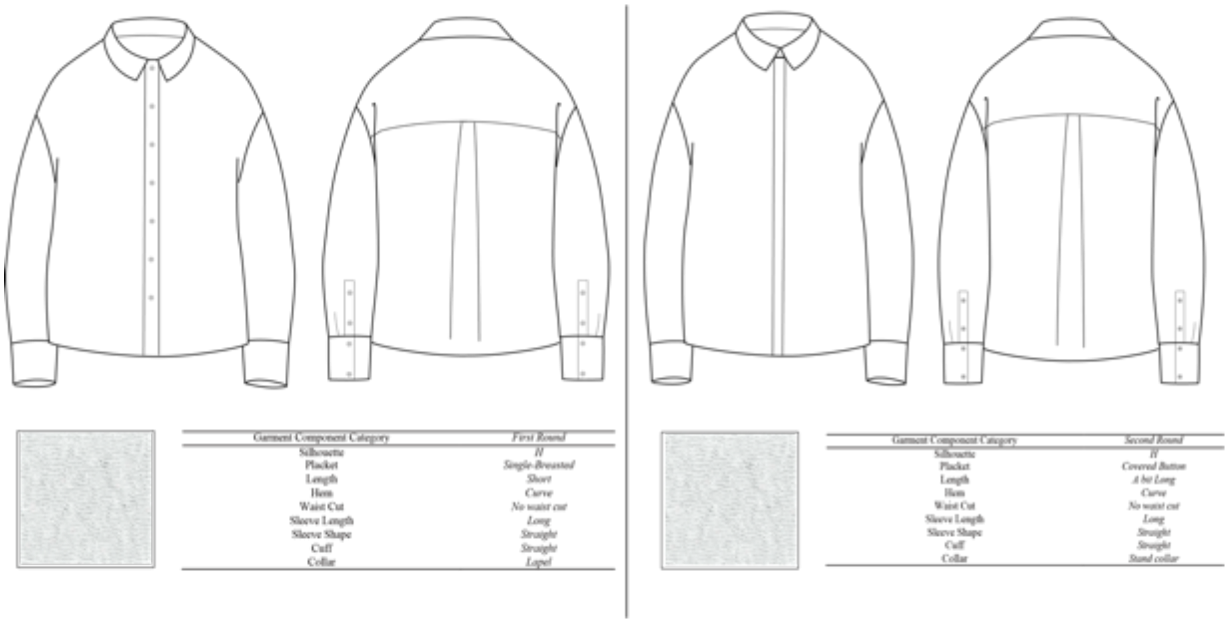
For the alternative garment components of the "*H*" type, its ***FRA*** value is "*R*" and its ***BSRA*** value is "*SR*". Based on ***Ordering Rule 1*** in Section 4.3.4.2, its recommendation attribute should be assigned as "*SR*".

For the alternative garment components of the "*Y*" type, its ***FRA*** value is "*R*" and its ***BSRA*** value is "*R*". In this context, its recommendation attribute should be assigned as "*R*".

In conclusion, for the ***Garment Component Category*** of the "*Silhouette*" type, the most recommended garment component is "*H*", and the second recommended garment component is "*Y*". Using the same procedure, recommendation result of all the ***Garment Component Category*** can be realized.

Then, a product profile made from this recommendation result is presented to this user. She is not satisfied with the recommendation result of the ***Garment Component Category*** of the

"*Length*" type and "*Collar*" type. Correspondingly, the second alternative garment component of these two categories is recommended respectively. Finally, she is satisfied with this result and the recommendation result is finished. Figure 4-18 presents the recommendation results of the first and second rounds. In this situation, the recommendation process for TC_1 is finished. Her ***Consumer Profile*** and related ***Product Profile*** will be retained in the system as a new ***Successful Case*** in the ***SCD***.



Garment Component Category	*First Round*
Silhouette	*H*
Placket	*Single-Breasted*
Length	*Short*
Hem	*Curve*
Waist Cut	*No waist cut*
Sleeve Length	*Long*
Sleeve Shape	*Straight*
Cuff	*Straight*
Collar	*Lapel*

Garment Component Category	*Second Round*
Silhouette	*H*
Placket	*Covered Button*
Length	*A bit Long*
Hem	*Curve*
Waist Cut	*No waist cut*
Sleeve Length	*Long*
Sleeve Shape	*Straight*
Cuff	*Straight*
Collar	*Stand collar*

Figure 4-18: Recommendation results to the user TC_1.

This case study presents the application of the ***RBRM*** to realize the recommendation process. Also, how is the dissatisfaction of a user is adapted by the system is also presented.

4.3.4.2 *Case study II*: An example of the recommendation process using *SCDM* (case study of the 86th user)

Another consumer TC_{86} is introduced to the recommendation system. First, TC_{86} is invited to provide her ***Consumer Profile***. Then, the ***Consumer Profile*** of TC_{86} are compared with all of the existing cases in the ***SCD***. According to the computation of the similarity degrees of c_{80} related to the cases in ***SCD,*** we find that there are two similar cases (TC_{38} and TC_{55}) existing in the ***SCD***, with a similarity degree of 88% which is bigger than the threshold of 85%. In this situation, the successful recommendation frequencies of TC_{38} and TC_{55} will be compared. From the computation, we find that the successful recommendation frequency of TC_{38} is 1 and that of TC_{55} is 0. Therefore, this module will recommend the retained ***Product Profile*** of TC_{38} to the consumer TC_{86}. Based on the evaluation of TC_{86}, she is satisfied with the recommendation result reused of TC_{38}. In this situation, the recommendation process for TC_{86} is finished, but the case of TC_{86} will not be retained in the system as a new case-based learning rule because the similar rule already exists in ***SCD***. Also, successful recommendation frequency of TC_{38} will be changed into 2.

4.4 System evaluation

In this section, the evaluation of the proposed ***Personalized Fashion Recommendation System (PFRS)***. Due to the fact that three subsystems ***(Color Recommendation Subsystem (CRS)***, ***Fabric Selection System (FSS)*** and ***Garment Style Recommendation System (GSRS))*** the ***PFRS*** are independent, the evaluation of the proposed PFRS are preformed separately on these three subsystems.

The proposed ***CRS*** and ***GSRS*** utilize similar algorithms for predicting recommendations based on consumer's requirements found in the ***Consumer Profile***. To evaluate the performance of these two prediction algorithms, we compare between them and two other frequently used recommendation approaches: ***Artificial Neural Network (ANN)*** and ***Adaptive Neuro-Fuzzy Inference System (ANFIS)*** [133], already used in fashion recommendations in different studies [133]. The evaluation of the proposed ***CRS*** and ***GSRS*** algorithms focuses on their accuracy, efficiency and complexity.

The proposed ***FSS*** is a collaborative design process, which largely depends on the involved designers. The evaluation of the proposed ***FSS*** focuses on its accuracy.

4.4.1 Evaluation methods

4.4.1 Accuracy evaluation

MAE is a statistical accuracy metric frequently used for measuring the prediction quality of an algorithm [134]. The lower value of ***MAE*** is, the more the prediction is accurate. In order to collect raw data for the MAE analysis, we invite *t* users to apply the recommendation systems using different algorithms respectively. Each invited user is asked to give a satisfaction degree of each system in terms of prediction accuracy.

Let p_t denote the prediction satisfaction degree of each user given for one of the system, where $p_t \in [0,1]$. Let *p* denote the ideal satisfaction degree *(p=1)*, ***MAE*** can be given by

$$MAE = \frac{1}{N} \sum_{t=1}^{N} |p_t - p| \tag{4-1}$$

In our experiments, the proposed ***MAE*** evaluation is based on the leave-one-out cross-validation method. According to this method, the *t* users' evaluation data are split into two sets, i.e. *t-1* data for training and the remaining one for testing. This procedure repeats for *t* times until each of the *t* data has been selected for testing. We use their averaged ***MAE*** value to represent the performance of the corresponding recommendation system.

4.4.2 Efficiency evaluation

For the evaluation of efficiency, interactions between the system and a user for obtaining a satisfied recommendation result (***SRT***s) are defined in this study. For example, if the ***SRT*** value of a user is 1, it means that this user obtains a satisfied result through one-time interaction with the system. Lower ***SRT*** value of a case indicates that a user can obtain a satisfied recommendation result through lower interaction times with the system, which means it is more efficient.

We divide the *t* users into 4 groups according to their arrival time. Each group contains *t/4* users. For each group, the ***SRT*** frequency and the average ***SRT*** are calculated.

4.4.3 Complexity comparison

In the specific scenarios of fashion recommendation, the comparison of complexity between the concerned algorithms can be performed by measuring the number of parameters of each model, number of training iterations and number of updating. The number of training iterations corresponds roughly to stopping the training when the minimum of model prediction error is achieved.

4.4.2 Evaluation results

4.4.2.1 Evaluation results of the proposed *CRS*

In order to collect raw data for the MAE analysis, we invite *81* users to apply the recommendation systems using different algorithms respectively.

(1) Accuracy evaluation

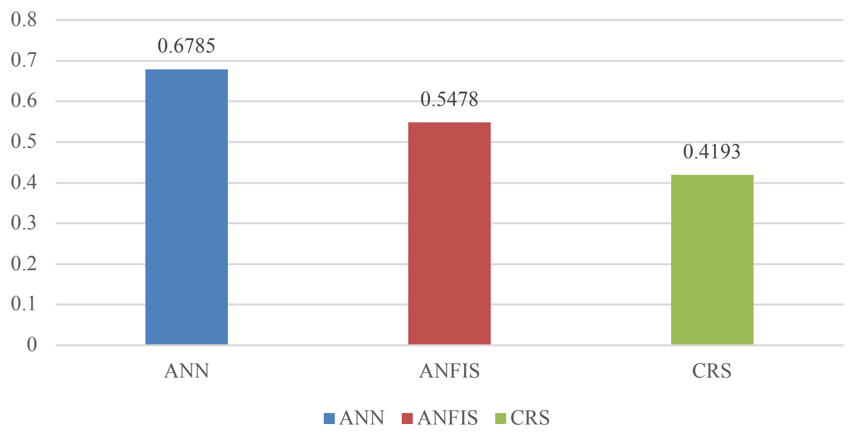


Figure 4-19: Comparison of *ANN*s, *ANFIS*, and *CRS* using MAE.

Figure 4-19 shows the averaged MAE values of ***ANNs***, ***ANFIS*** and ***CRS*** when recommending colors. It could be found that the MAE value of ***CRS*** (0.4193) is much lower than those of ***ANN*** (0.6785) and ***ANFIS*** (0.5478). Thus, the proposed ***CRS*** can provide more accurate predictions than the classical methods ***ANN*** and ***ANFIS***.

(2) Efficiency evaluation

Figure 4-20 presents the ***SRT*** values of the 81 users in the experiment. We divide the 81 users into 3 groups according to their arrival time. Each group contains 27 users. For each group, the ***SRT*** frequency and the average ***SRT*** are calculated. Table 5 presents the related statistical data for each group.

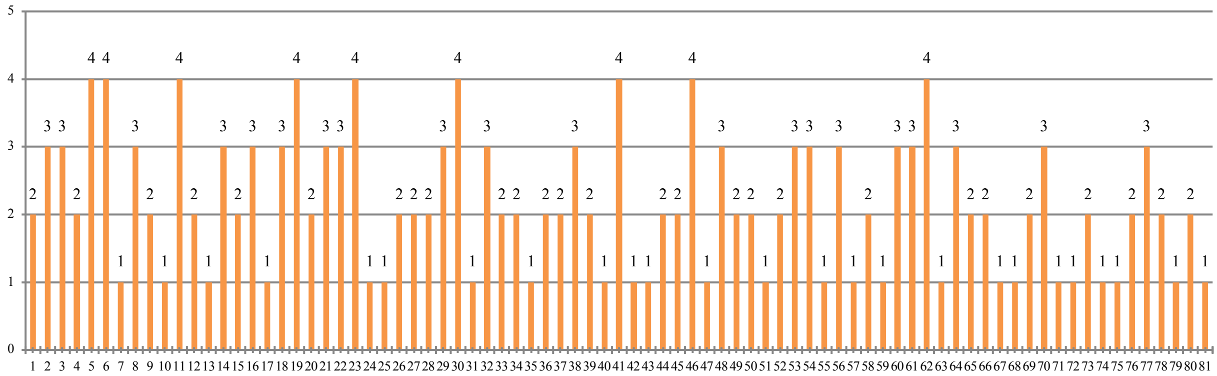


Figure 4-20: Color recommendation times until obtaining satisfied results for all the users.

Table 4-22: SRT Frequency and average SRT for different groups.

Number of times needed for a successful recommendation		Group I 1st-27th users	Group II 28th-54th users	Group III 55th-81th users	Total
SRT Frequency	1	6 (22.2%)	7 (25.9%)	12 (44.4%)	25 (30.86%)
	2	8 (29.6%)	11 (40.7%)	8 (29.6%)	27 (33.33%)
	3	8 (29.6%)	6 (22.2%)	6 (22.2%)	20 (24.69%)
	4	5 (18.5%)	3 (11.1%)	1 (3.7%)	9 (11.11%)
Average SRT		2.44	2.185	1.85	2.16

For all of the 81 cases, the highest ***SRT*** is 4, and the lowest is 1. The average SRT for all of the cases is 2.16. In 25 cases, users can obtain satisfactory recommendations after a one-time interaction with the system (30.86%). In 27 cases, the consumers can obtain satisfactory recommendations after two interactions with the system (one time of feedback) (33.33%). In 20 cases, the consumers can obtain satisfactory recommendations after three interactions with the system (two time of feedback) (24.69%). In 9 cases, the consumers can obtain satisfactory recommendations after four interactions with the system (three time of feedback) (11.11%). In total, in 64.19% of the cases, users can obtain satisfactory recommendations within two interactions with the system.

The global recommendation efficiency is rather high. Users can obtain satisfactory recommendations very quickly. Compared with the traditional color recommendation methods, the proposed knowledge-based color recommendation system, supported by case-based learning and design knowledge, can recommend faster and more satisfying results. As the system is able to understand the unsatisfied attributes of the user when evaluating the recommended color range, and can dynamically modify the recommendation result, the proposed system can be more adapted to the changes of the outside environment.

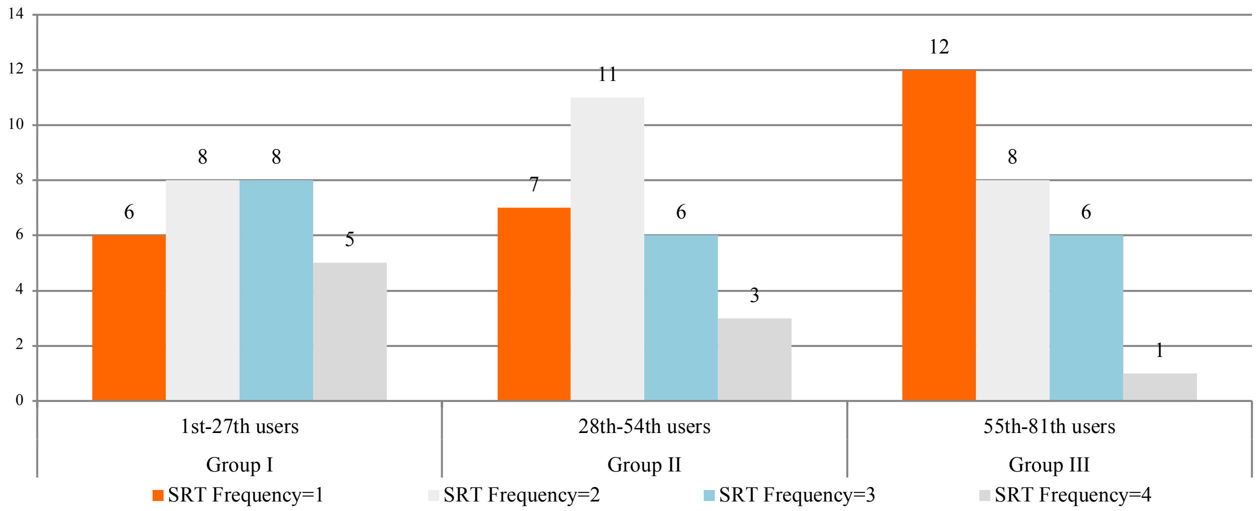


Figure 4-21: Distribution of SRT frequencies for different groups.

Figure 4-21 presents the SRT frequency of three different groups divided according to time order. In the first 27 cases, 6 users obtain satisfactory recommendations after one interaction with the system (22.2%). In the second group of 27 cases, 7 users obtain satisfactory recommendations after one interaction with the system (25.9%). In the third group of 27 cases, 12 users obtain satisfactory recommendations after one interaction with the system (44.4%). In other words, the rate of success for recommendation is increasing when the system is used by more and more users and the corresponding *SCD* is enhanced.

Figure 4-22 presents the average SRTs for different groups divided by time order. Figure 4-22 shows that the average SRT decreases when the proposed recommendation system is applied by more and more users.

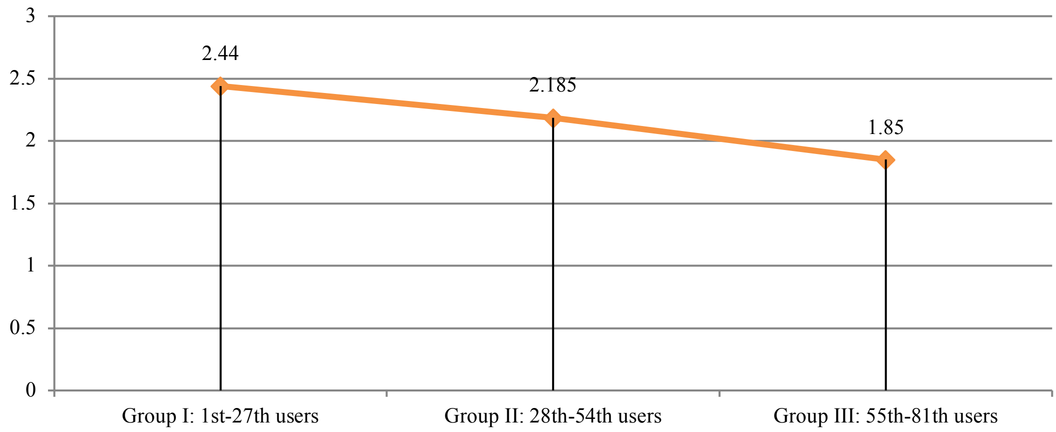


Figure 4-22: Average SRTs for different groups divided by time order.

Figure 4-21 and Figure 4-22 show that, by using the case-based learning mechanism, users' color image perception can be easily captured and progressively understood by the proposed system. The system is able to find a similar case for recommendation to a new user when the number of cases stored in the ***SCD*** is important. When the number of users of the proposed color recommendation system is increasing, more learning rules can be generated in order to further improve the recommendation quality. In this way, the working efficiency of color recommendations can be largely increased with reduced costs.

(3) Complexity evaluation

The complexity comparison results between ***ANN*, *ANFIS* and *CRS*** are shown in Table 4-23. From these results, we can find that the proposed ***CRS*** method is more performant than ***ANN*** and ***ANFIS*** in terms of training time, number of training iterations and number of parameters. In fact, ***CRS*** is based on computation of similarity degrees and the number of its parameters is much less than the other methods.

Table 4-23: Complexity comparison: *ANN*, *ANFIS* and *CRS*.

Complexity comparison	ANN (MLP)	ANFIS	CRS
Number of parameters	20	28	13
Number of training iterations	3	20	3
Training time (sec)	0.504	0.008	0.002

4.4.2.2 Evaluation results of the proposed *FSS*

In order to evaluate the effectiveness of the proposed system, 23 application cases beyond the study of involved brand in Section 4.2 are also tested. Some of these application cases deals with the fabric selection of the design of different garment categories, such as men's wear (Yannic Hong), women's jeans-wear (NotNow), children's wear (PETICHOCHO), men's homewear (MinorMax)… These application cases follow the standard procedure of the proposed system. And we have conducted a survey about the developed functions of the proposed fabric selection system.

The survey response indicates that above 85 percent of users believe that the proposed system is user-friendly with capacities of flexible settings for modelling, and processing various information of fabric selection, and delivering reasonable results.

4.4.2.3 Evaluation results of the proposed *GSRS*

In order to collect raw data for the MAE analysis, we invite *100* users to apply the recommendation systems using different algorithms respectively.

(1) Accuracy evaluation

Figure 4-23 shows the averaged ***MAE*** values of ***ANN***s, ***ANFIS*** and ***GSRS*** when recommending garment products. It could be found that the ***MAE*** value of ***GSRS*** (0.3993) is much lower than those of ***ANN*** (0.6795) and ***ANFIS*** (0.5578). Thus, the proposed ***GSRS*** can provide more accurate predictions than the classical methods ***ANN*** and ***ANFIS***.

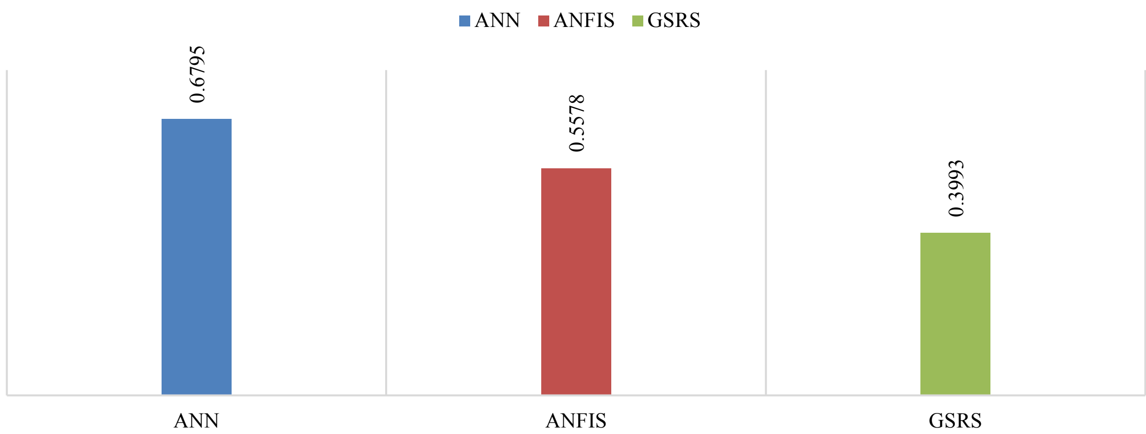


Figure 4-23:Comparison of *ANN*s, *ANFIS*, and *PFRS* using *MAE*.

(2) Efficiency evaluation

Table 4-22 presents the related statistical data for each group.

For all of the 100 cases, the highest ***SRT*** is 4, and the lowest is 1. The average ***SRT*** for all of the cases is 2.08. In 40 cases, users can obtain satisfactory recommendations after a one-time interaction with the system (40%). In 33 cases, the consumers can obtain satisfactory recommendations after two interactions with the system (one time of feedback) (33%). In 23 cases, the consumers can obtain satisfactory recommendations after three interactions with the system (two time of feedback) (23%). In 10 cases, the consumers can obtain satisfactory recommendations after four interactions with the system (three time of feedback) (10%). In total, in 73% of the cases, users can obtain satisfactory recommendations within two interactions with the system.

Table 4-24: *SRT* Frequency and average *SRT* of different groups

Number of times needed for a successful recommendation		Group I 1^{st}-25^{th} users	Group II 26^{th}-50^{th} users	Group III 51^{th}-75^{th} users	Group IV 76^{th}-100^{th} users	Total
SRT Frequency	1	6 (24%)	7 (28%)	12 (48%)	15 (60%)	40 (40%)
	2	8 (32%)	11 (44%)	8 (32%	6 (24%)	33 (33%)
	3	8 (32%)	6 (24%)	6 (24%)	3 (12%)	23 (23%)
	4	5 (20%)	3 (12%)	1 (4%)	1 (4%)	10 (10%)
Average SRT		2.44	2.185	1.85	1.6	2.08

The global recommendation efficiency is rather high. Users can obtain satisfactory recommendations very quickly. Compared with the traditional fashion recommendation methods, the proposed knowledge-based fashion recommendation system, supported by case-based learning and design knowledge, can recommend faster and more satisfying results. As the system is able to understand the unsatisfied attributes of the user when evaluating the recommended product profile, and can dynamically modify the recommendation result, the proposed system can be more adapted to the changes of the outside environment.

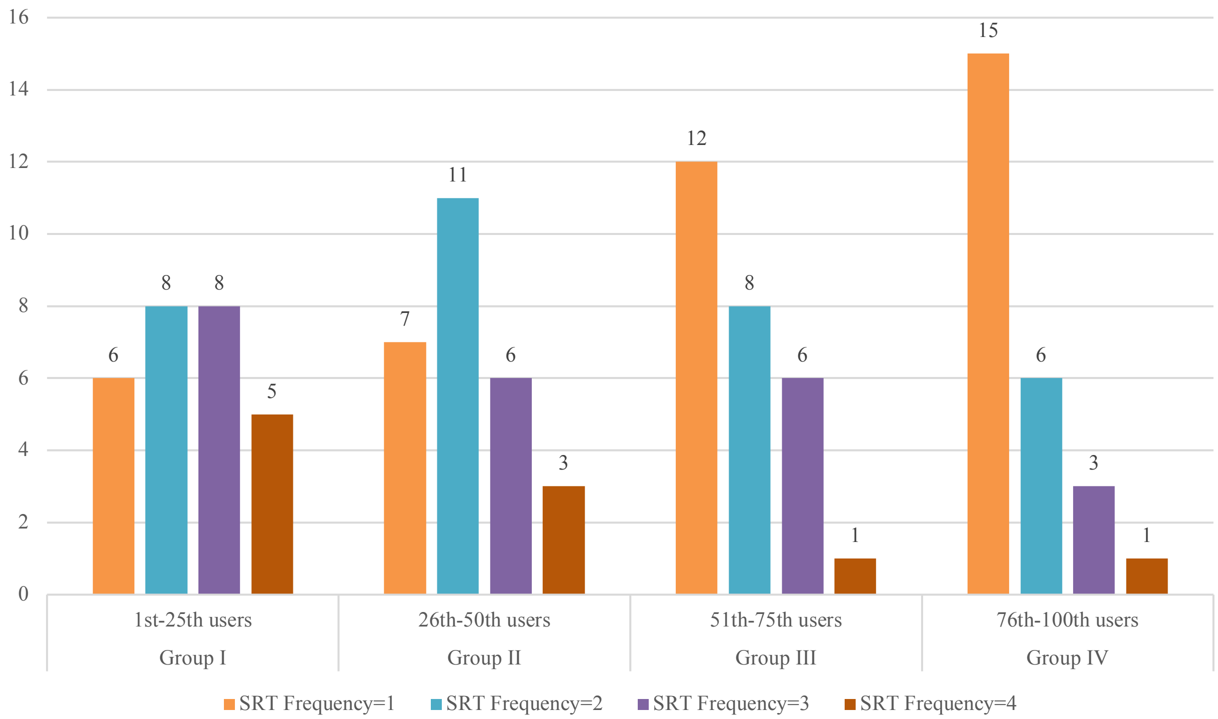


Figure 4-24: Distribution of *SRT* frequencies of different groups.

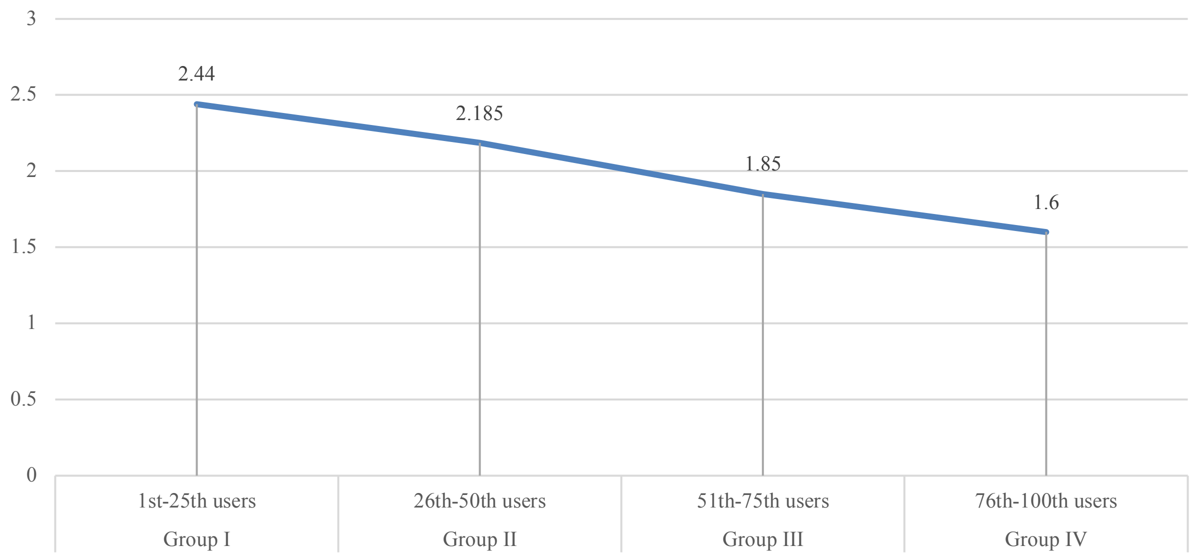


Figure 4-25:Average *SRT*s of different groups divided by time order.

Figure 4-24 presents the ***SRT*** frequency of three different groups divided according to time order. In the first 25 cases, 6 users obtain satisfactory recommendations after one interaction with the system (24%). In the second group of 25 cases, 7 users obtain satisfactory recommendations after one interaction with the system (28%). In the third group of 25 cases, 12 users obtain satisfactory recommendations after one interaction with the system (48%). In the last group of 25 cases, 15 users obtain satisfactory recommendations after one interaction with the system (60%). In other words, the rate of success for recommendation is increasing when the system is used by more and more users and the corresponding ***SCD*** is enhanced. Figure 4-25 presents the average ***SRT***s for different groups divided by time order. Figure 8 shows that the average ***SRT*** decreases when the proposed recommendation system is applied by more and more users.

Figure 4-24 and Figure 4-25 show that, by using the case-based learning mechanism, users' requirements can be easily captured and progressively understood by the proposed system. The system is able to find a similar case for recommendation to a new user when the number of cases stored in the ***SCD*** is important. When the number of users of the proposed fashion recommendation system is increasing, more learning rules can be generated in order to further improve the recommendation quality. In this way, the working efficiency of fashion recommendations can be largely increased with reduced costs.

(3) Complexity evaluation

The comparison results regarding complexity between ***ANN***, ***ANFIS*** and ***GSRS*** are shown in Table 4-23. From these results, we can find that the proposed ***PFRS*** method is more performant than ***ANN*** and ***ANFIS*** in terms of training time, number of training iterations and number of parameters. In fact, ***PFRS*** is based on computation of similarity degrees and the number of its parameters is much less than the other methods.

Table 4-25: Complexity comparison: *ANN*, *ANFIS* and *GSRS*.

Complexity comparison	ANN (MLP)	ANFIS	GSRS
Number of parameters	20	28	12
Number of training iterations	3	20	3
Training time (sec)	0.504	0.008	0.002

4.5 Conclusion

In this section, we introduce all the sensory experiments designed for acquisition of data necessary for building the fashion recommendation system, as well as related procedures for data processing and modelling. The proposed recommendation system is able to propose the most relevant color, fabric and style for garments in response to the morphology and fashion needs of each specific consumer. A personalized garment product profile will be generated based on the consumer profile, including the requirements on garment style (collar type, shirt type, length type, etc.,), fabrics (selection of fabrics from the database) and color information. The efficiency of the system has been validated by a series of evaluations.

Chapter 5 Virtual 3D-to-2D Garment Prototyping Platform (*VGPP*)

In this study, a ***Virtual 3D-to-2D Garment Prototyping Platform (VGPP)*** is developed in order to make interactions between the designer and consumer around the designed virtual product with the proposed recommendation system and transmit designed technical parameters to the manufacturing system. This platform is able to generate virtual garment patterns based on the personalized garment product profile obtained from the proposed garment recommendation system.

Using the proposed ***VGPP***, the development of a personalized garment patterns starts with a personalized pattern garment block. This process is inspired by the general principle of the classical garment block design method (Figure 1-18), developed by Appel and Stein. In fact, a garment surface framework can be obtained by connecting different points of the human body surface with a given allowance. It can be realized by different lines or curves following the general shape of a garment.

5.1 Digitalized human body modeling

5.1.1 3D Human Body Scanning for Human Body Modeling

The proposed design method starts with 3D scanning. The involved consumer is required to wear bra and underwear during the scanning procedure, making sure the quality of the scanned result is in good condition, especially in the breast area. The scanning result will be further modeled as a digitalized human body model. The general process of the human body modeling using 3D scan result has been explained in detail.

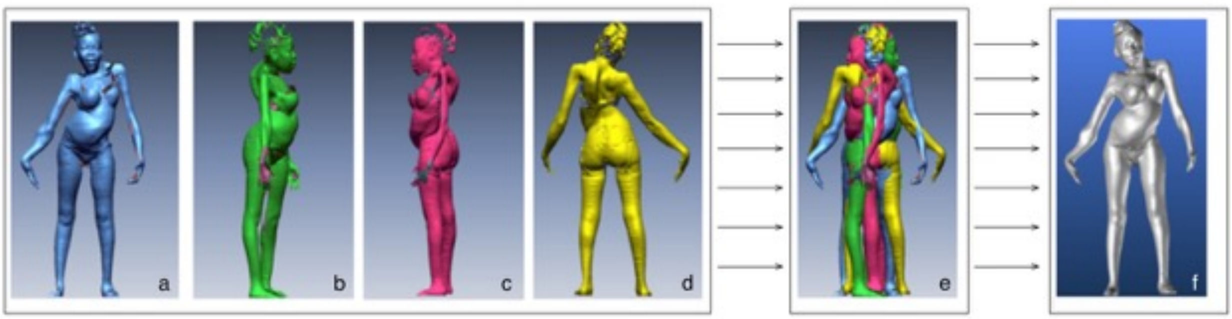


Figure 5-1: From the scanning results to the digitalized human body model.

At this step, data on a body shape are acquired using a 3D scanner and the software *ScanWorX* of the Human Solutions Company. Then, the data from the scanned body shape are imported to the *RapidForm* software for editing and correcting the defects of the 3D meshed object. After that, using the *DesignConcept* software, the 3D surface of the body shape can be modeled and simulated. The operation of 3D scanning permits to directly obtain a 3D body surface, on which 3D draping of a virtual garment can be realized. The detailed body measurements will not be necessary.

For the people with normal body shapes, a standard body measurement procedure can be performed by locating the key feature points, such as neck points, on the virtual body model with a standard posture. Based on these symmetric and easily identified key features points, the procedure of body measurements will become very simple. However, for disabled people of scoliosis type, it is not easy to locate these key feature points because of their atypical body shapes. Many key positions (neck points, scapular points etc.,) are hidden inside the body surface because their standard postures cannot be obtained. The anthropometric landmarks of atypical body shapes cannot be detected automatically and a lot of manual adjustments are needed for obtaining a complete 3D body shape. In this situation, a traditional pattern making method, strongly related to the accurate measurements of body shape, is not available and 2D garment patterns cannot be easily obtained from designer's experience in a classical way.

5.1.2 Digitalized Human Body Modelling from 3D Human Body Scanning

In this study, a new method for characterizing the human body shape without concrete body measurements is developed. This method first takes various scanning pictures in different views for the same consumer with the same posture (Figure 5-1-a, b, c, d) during the 3D scanning procedure.

Each of these pictures, taken with the same reference axis of the 3D scanner from different views, can be regarded as 1/4 of the full scan result. Next, using the *RapidForm* software, these four pictures (Figure 5-1-e) are combined, rotated and merged in order to generate one complete 3D virtual human body model (Figure 5-1-f).

By using this reference axis, the corresponding positions of different images or different views can be easily found in order to generate the unique virtual human body model. The proposed method will permit to generate the digitalized 3D human body model.

The mesh of the 3D shape is then re-triangulated using *RapidForm* software. The holes that are invariably made as a result of scanning are filled. Irregular forms generated as a result of filling holes, like near the hands and feet, are removed. A plane is used to cut the bottom of the feet to make it parallel to the X-axis. The body form is smoothened using a smoothing tool. It is ensured that all holes (near hair and armpit area) are filled. Normally the holes will be in the hair and armpit and in small size. Plain planes are created to repair the holes. As the sizes of these holes are small and the wearing allowance will be designed in future operation, plain planes will be created to fill the holes. A special function of *RapidForm* is applied to mesh the surface of the body model with 600-700 facets. With this procedure, the body made of point clouds will be transferred into small facets. These facets can be regarded as the subsurface of the body, which can be modified. The number of the facets will determine the quality of the virtual body surface. If the precision of the virtual body is not high enough, more facets can be added to meet the desired precision. The 3D body model modified by *RapidForm* is then imported into *DesignConcept*. The result obtained in *DesignConcept* is the final digitalized human body model (Figure 5-1-f), from which a 3D garment can be created.

5.2 Virtual Garment Prototyping on 3D Human Body Model

5.2.1 Establishing reference planes

At this step, several reference planes will be established for simulating the consumer's morphological shape and locating feature points of a human body. The quantity and orientation of the reference planes are different from the normal people because of the deformation.

The definition of these reference planes follows the following principles: (1) follow the traditional 3D real draping method, (2) satisfy the requirements of the disability, (3) meet the requirement of better observing the human body and (4) fully simulating the consumer's morphological shape with all the required information for the design process. These reference planes will be defined by several coordinate axes.

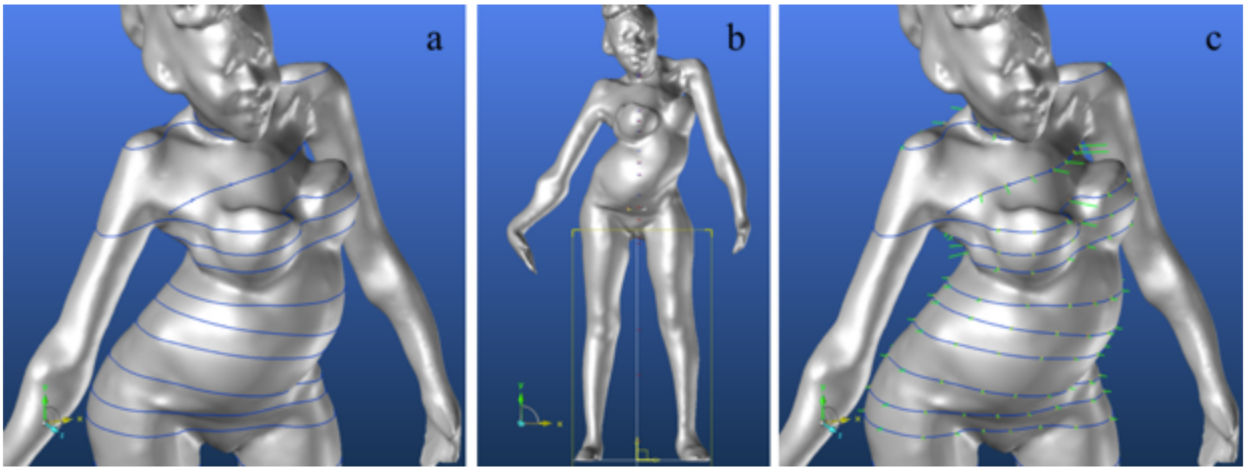


Figure 5-2: The morphological curves of the consumer and the subsequent red axes (a set of short red lines in the middle of the human body in Figure 5-2-b) for establishing the morphological curves.

In this context, the different XY planes are oriented in the 3D space in the design process to help to cut the body and create the morphological curves (the morphological curves are curves in Figure 5-2-a). By adjusting the inclinations of the XY planes, the morphological curves can then be adjusted visually. The yellow axis between the feet is perpendicular to the ground. The red axis between the feet is parallel to the ground. All the subsequent red axes made on the body form are parallel to the ground (Figure 5-2-b). Since the legs of the woman are more or less similar to those of normal people, all the axes between the legs are parallel to the floor.

A set of special planes is defined following the shape of spine in the position of waist, hip and breast, which are important positions for garment design. Considering the irregular shape of the body and 3D hyperbolic-curvature of the spine, more planes close to those defined initially are defined in order to ensure proper drape and fit of the garment. As shown in Figure 5-2, three such planes are made in the waist region, one being on the waist, one above and another below it; three planes are made in the chest area, one running through the bust points, one below and another above it; other three planes are made on the hip region. These planes are defined in the *DesignConcept* software taking the reference on the ground floor. The distance between the plane and the ground floor can be adjusted and tested until the numbers of the planes and distances are qualified enough to model the shape of the human body.

5.2.2 Feature alignment and ease distribution

The next procedure follows the conical principle developed by Efrat [135], which is intended to establish 2D co-ordinates for the crucial pattern shaping points. A bodice is specified with several crucial ***Shaping Controlling Points (SCPs)***.

Then, the bodice is defined by several triangular planes for both front and back. The bust and shoulder blades are the two prominent points, which are used to generate these triangular planes. Each triangle is formed by connecting two adjacent perimeter points and the appropriate apex. Orthogonal projections of the triangles are assembled to produce front and back bodice patterns; proportional corrections are made in the back-shoulder area for the difference between the Euclidean distance calculated from coordinates and the actual curvature of the back.

First, a set of ***Anatomical Landmarks for Garment Design (ALGD)*** (green points in Figure 5-3-b) is selected as part of the ***SCPs*** from the scanned body surface. Eight ***ALGDs*** are selected in close connection with the classic garment block design method, including the waist, side, neck, armhole and shoulder, as presented in Figure 5-3-b. Afterwards, the selected ***ALGDs*** will be connected with lines or curves, to create the general framework of the virtual garment block. Lines are marked with yellow and curves are marked with blue, as presented in Figure 5-3-c. In the procedure of developing the previous lines and curves, other ***SCPs*** are developed from the human body surface with given ease allowance (yellow points in Figure 5-3-b and Figure 5-3-c). The quantity and position of these ***SCPs*** also follow the classic garment block generation method, including one point on either side of the shoulder line and three points on either side of the pattern perimeters. After that, two prominent points, namely the apex of the bust and the apex of the shoulder blade, are used to generate the desired triangular planes, presented with purple color in Figure 5-3-b. Twenty-four ***SCPs*** are defined to determine the general framework of the proposed garment block.

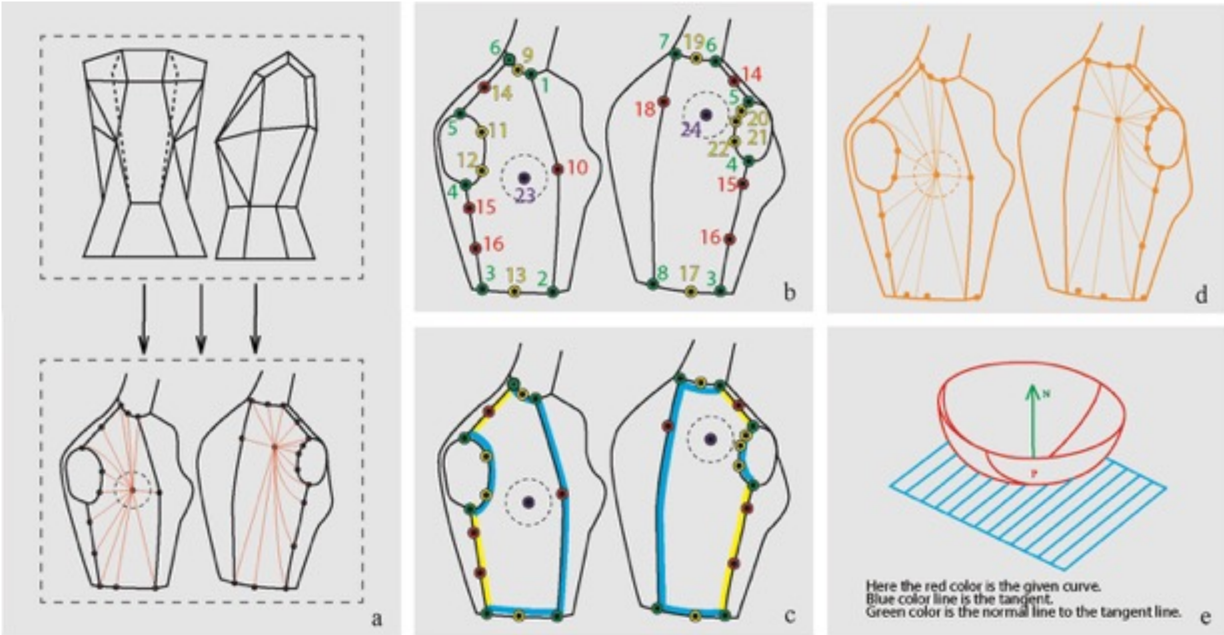


Figure 5-3: The process of the proposed design method: (a) general principle of the classic garment block design method; (b) selected anatomical landmarks for garment design; (c) Definition of different shape controlling points, lines and curves; (d) developing the proposed garment block framework from shape controlling points of the breasts and scapular points; (e) general principle of defining the Normal Line of a curve.

Using the predefined ***SCPs***, a general framework of a virtual garment block can be defined. A set of curves is developed from the shape controlling points of the apex of the bust and end with other ***SCPs*** to define the 3D garment block surface using several triangular planes. The shapes of these curves begin with curves near the breast area, following the shape of the breast, and end with straight lines when they turn to be far away from the breast area (Figure 5-3-e). Finally, 28 triangular planes are obtained, including 13 for the front and 15 for the back panels. By adjusting the position of the shape controlling points of the two breasts, an ideal framework of the proposed virtual garment block can be defined.

Actually, the distances between ***SCPs*** of the breasts and the real apex of the bust indicate the real ease allowance of the breast area. As the design object is a garment block, which contains very limited ease allowance, the "ideal position" of the shape controlling points of the breast should be that which ensures the shortest distance mentioned before, which consequently ensures smooth surface of the framework without any overlapping between the proposed garment block surface and the human body.

5.3 2D Garment Block Patterns Development

5.3.1 Development of 3D Garment Block Surface

The wireframe of the garment block is then modeled by triangulating and assembling different parts bounded by the deformed wireframe. The technical method is the same as the creation of a digitized human body model using the *RapidForm* software. The number and size of the mesh is determined by the designers using several experimental adjustments until the final result is acceptable for the flattening operation. As the fabric information will be given in the virtual try-on session, there will be no specific requirement for the number and size of the mesh. The meshed garment block surface can then be applied to generate with the flattening operation to obtain the corresponding 2D pattern.

5.3.2 2D Garment Block Pattern Flattening

The generation of flattened 2D pattern also strictly follows the principle of the classical 2D pattern design knowledge. Darts, folds, opening, fabric direction (Warp and Weft direction) and other important 2D pattern design elements should be fully considered. Then the meshed virtual garment surface is divided into 4 parts: right front, left front, right back and left back. Eight different surfaces are generated: 4 in the front and 4 in the back. Then the 2D patterns can be flattened automatically and easily.

To make sure that the final result can be applicable for industry, the flattened 2D pattern is then input into *Modaris* software for adjustment in order to satisfy the desired practical properties used in apparel industry. Then a customized garment block and corresponding 2D patterns with the proposed method can be generated and applied for industrial use.

5.4 Case study: Development of Personalized Garment Blocks for Physically Disabled People with Scoliosis (PDPS)

In this section, a case study of the research subject in this system will be presented. The proposed case study includes four experiments, as shown in Figure 5-4. This case study takes ***Physically Disabled People with Scoliosis (PDPS)*** as the research subject. More information about ***PDPS*** is presented in Section 5.4.

In *Experiment I*, instrumental testing of the fabric property is carried out, using ***Fabric Assurance by Simple Testing Systems (FAST)*** system. Related fabric property information will be further applied to simulate the virtual try-on of the garment block. Also, real garment blocks will be produced using the real fabric to validate the design idea.

Experiment II explains how an application case of the proposed design method is applied to obtain a personalized garment block for ***Physically Disabled People with Scoliosis (PDPS)***. Corresponding 2D patterns will be generated and further applied to a 3D virtual try-on procedure.

Experiment III and *Experiment IV* are the validation for evaluating the proposed design method in terms of garment fitting. Several ***Key Fit Measurements (KFMs)*** are defined. These

KFMs are further applied to a normalized subjective visual evaluation in *Experiment III* and *Experiment IV*.

In *Experiment III*, visual evaluation is used by a group of designers to obtain a normalized opinion of the garment fitting based on the expert's knowledge and experience. Several modifications will be carried out in conformity with the designers' recommendations. The corresponding modified 2D patterns will be generated and utilized to perform another 3D virtual try-on.

In *Experiment IV*, two real garments, using the primary garment patterns and modified garment patterns respectively, will be produced using the proposed fabrics. Comparisons of the pre-defined ***KFMs*** between the 3D simulation results and real try-on results are carried out in order to validate the proposed design method.

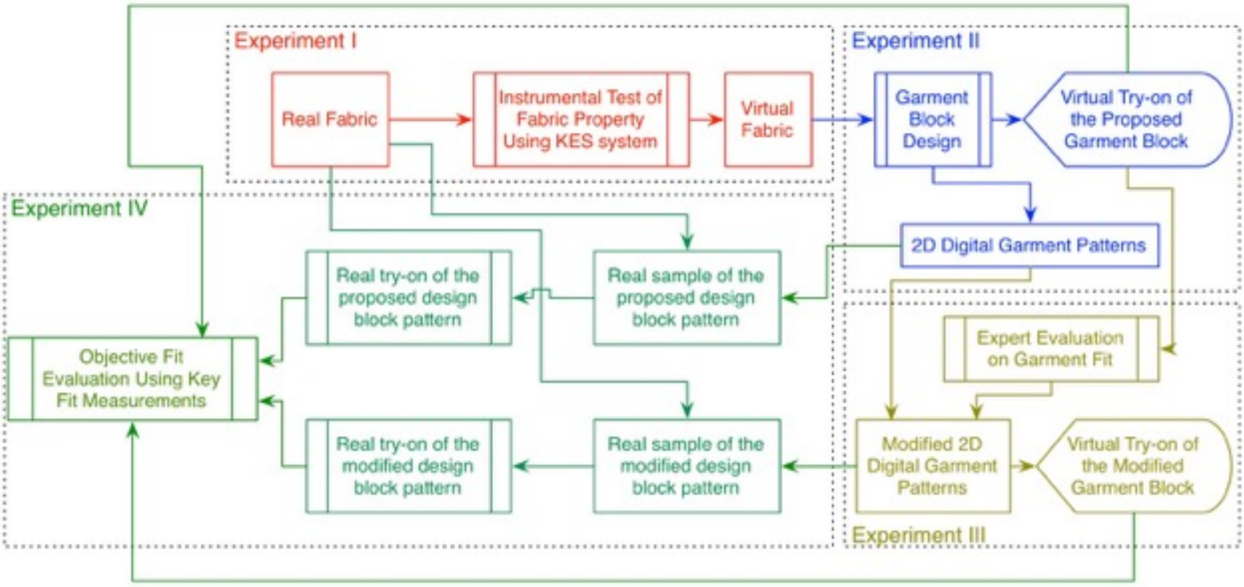


Figure 5-4: Experiment design and working process of this study.

5.4.1 Morphology of PDPS and Their Fashion Issues

PDPS is a special category of the group of ***PWAM*** [131]. Scoliosis is a medical condition in which a person's spine has a sideways curve [136]. Spine of ***PDPS*** twists and curves to the side [137]. The curve is usually "S"- or "C"-shaped (Figure 5-5) [138]. Scoliosis can affect people of any age, from babies to adults, but most often starts in children aged 10-15 [139]. About 3% of people of the population have this problem [3]. It most commonly occurs between the ages of ten and twenty [140]. Girls typically are more severely affected than boys [6]. There are many causes of scoliosis, including congenital spine deformities (those present at birth like cerebral palsy, spina bifida) and neuromuscular problems, inherited diseases or conditions caused by the environment, limb length inequality and tumors [3]. It is estimated that 65% of scoliosis cases are idiopathic, about 15% are congenital and about 10% are secondary to a neuromuscular disease [141].

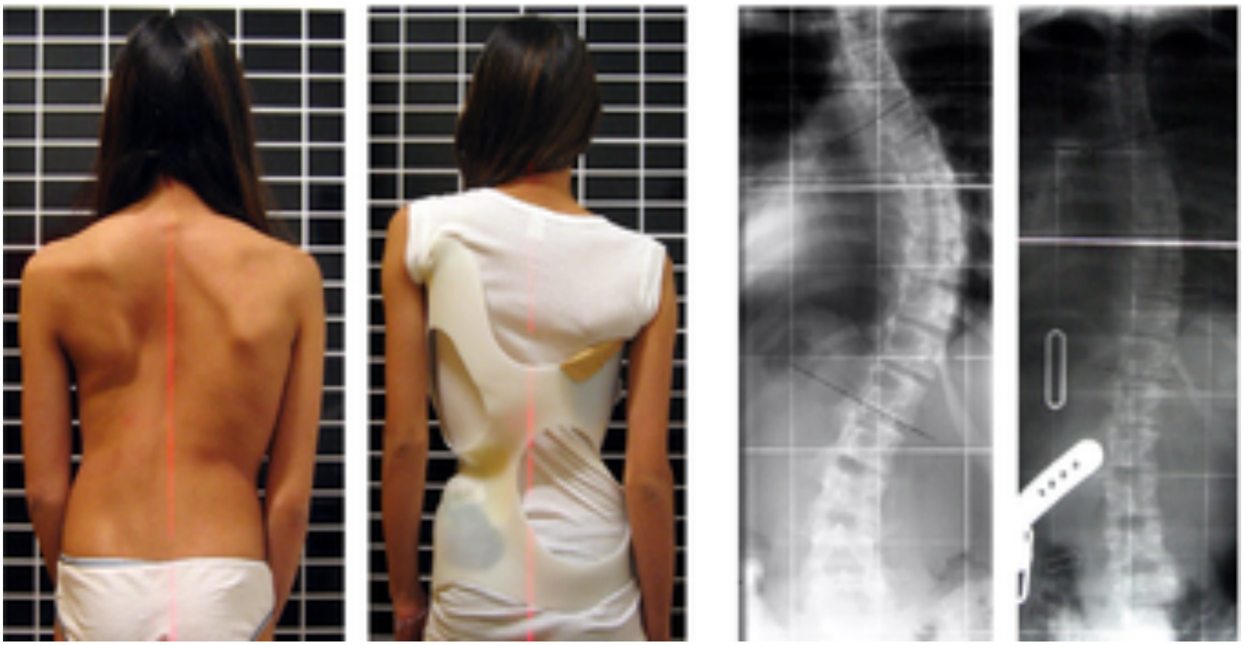


Figure 5-5: Symptoms of scoliosis.

PDPS is rather representative in the group of atypical morphology. There are some symptoms of ***PDPS***: (1) ***PDPS*** has a visibly curved spine, which leans to one side. (2) Shoulders of ***PDPS*** are uneven. (3) One shoulder or hip of ***PDPS*** will always sticks out. (4) The ribs of ***PDPS*** stick out on one side [142]. Due to these symptoms, garment for ***PDPS*** does fit well all the time. Modern garment design and construction theory is based on the fact that spine is straight. Garment structure lines start with a straight line follows that of spine. That is the reason that garment fitting of ***PDPS*** is always to be managed by designers. Figure 1-2 presents the systems of a scoliosis [143].

5.4.2 KES Test and Modelling of Fabric (*Experiment I*)

As the virtual fitting is strongly related to the fabric properties, *Experiment I* is designed to obtain fabric properties related to the virtual draping and try-on. A piece of woven fabric of the Greige cloth type, which is widely used in clothing draping experiment, is being tested. The Greige cloth is selected because it can represent the most popular fabrics used in apparel product development. Normally, an objective measurement of the sample fabric can be performed using ***Fabric Assurance by Simple Testing Systems (FAST)*** or ***Kawabata Evaluation Systems (KES)***. The experimental data of the test results of both FAST system and KES system can be uploaded to the *Modaris* software to define fabrics in the simulation session of *Experiment II* and *Experiment III*. In this study, KES system is applied to the fabric property test. Compared with FAST system, KES systems are more specialized in fabric surface performance test, which is more applicable in my PhD research. By using fabric property presented in Table 5-1, virtual fabric is simulated in *Modaris* software.

Table 5-1: Fabric property of the sample fabric.

Fabric property criteria	Fabric property	
Raw material	100%Cotton (Wrap and Weft)	
Weave structure	3/1/1/1/1/1 Right hand Twill	
Weight (g/m2)	156	
Thickness (mm)	0.596	
Yarn fineness (tex=g/km)	Wrap	50
	Weft	57
Yarn density (yarns/cm)	Wrap	12
	Weft	13
Bending (10^{-6}N·m)	Wrap	3.3735
	Weft	1.4024
Shearing (N·m^{-1}/°)	Wrap	1.471
	Weft	1.5985
Tensile (N/m)	Wrap	4.364
	Weft	13.0919

5.4.3 Virtual Prototyping for Personalized Garment Block (*Experiment II*)

In *Experiment II*, personalized garment block design cases are performed using the proposed garment design method. Figure 5-6 presents the design process using the proposed design method and related software. The proposed 3D method consists of several design phases, namely 1) 3D scanning (Section A in Figure 5-6), 2) digitalized 3D human body modeling (Section B and C in Figure 5-6), 3) mechanical 3D garment block generation (Section D, E, F and G in Figure 5-6), 4) interactive 3D garment surface (without fabric property) modeling and 5) 2D garment pattern design (Section H in Figure 5-6).

Using this process, a set of personalized garment block patterns are generated. Openings and darts are given in this interactive process. The pattern generation is an interactive process between 3D virtual garment surface and 2D garment block pattern. Several modifications of the generated 2D pattern in a 2D environment using classical 2D pattern design knowledge to ensure the flattened 2D could be further applied to the real simulation. These modifications included: 1) smoothening the serrated curves, 2) correcting length of corresponding curves of pair patterns and 3) rectifying position and volume of darts.

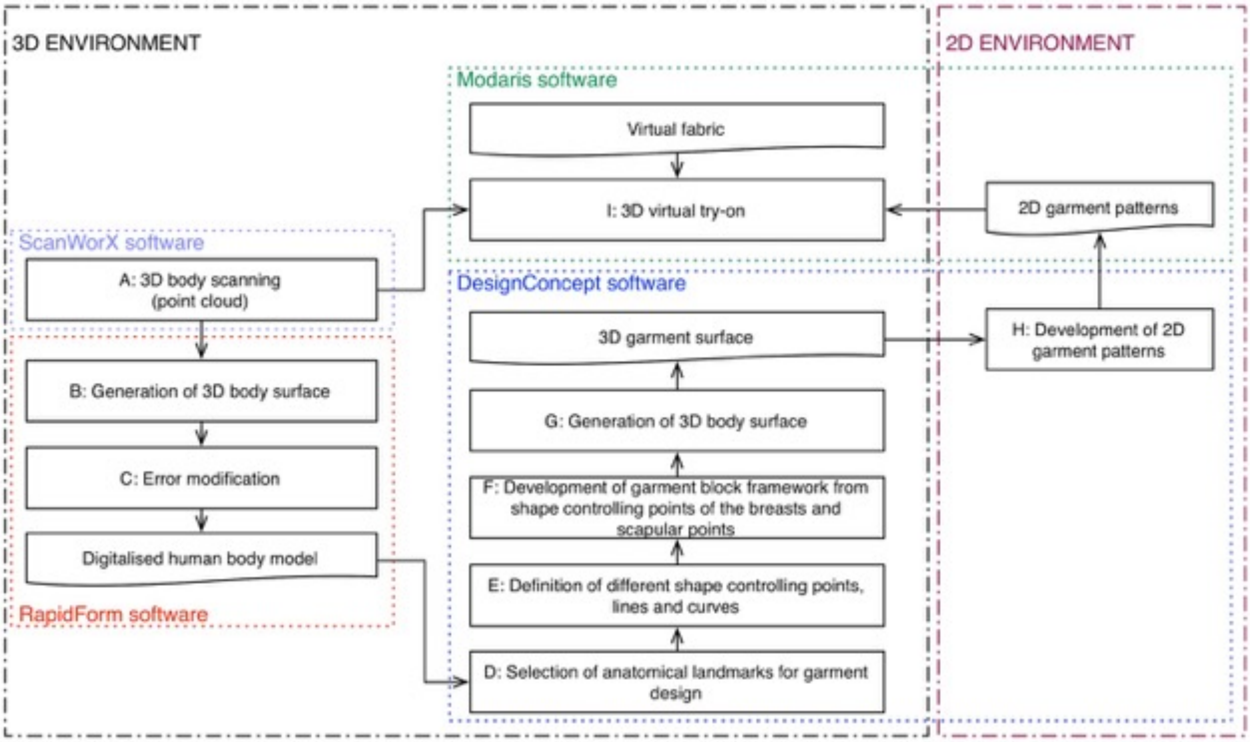


Figure 5-6: Garment block generation process using the proposed design method, related software and different working environment.

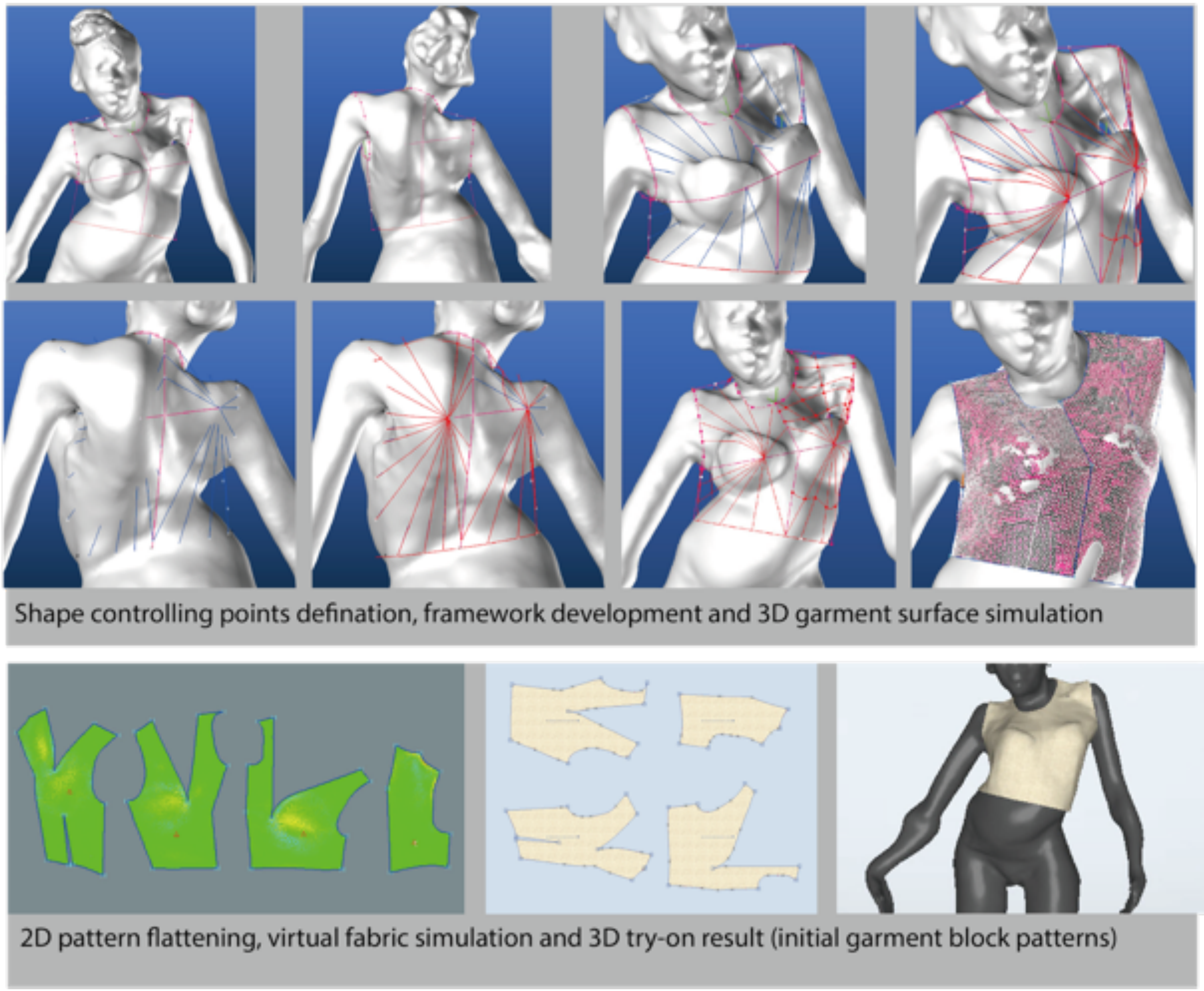


Figure 5-7: Details of the design process for designing a personalized garment block.

Based on the flattened 2D garment block pattern obtained from the 3D garment surface, digitalized human body model of the consumer, and virtual fabric obtained from *Experiment I*, a 3D virtual try-on is carried out in *Modaris* software. Through this operation, 2D technical environment is lined with 3D virtual display environment. Based on the 3D virtual try-on display, designers and consumers are able to give feedback to the design result. The design case of C_1 is presented in Figure 5-7 to show the details of the design procedure and the final result. Other design cases are not presented due to the context limit.

5.4.4 Design Evaluation of the Personzlied Garment Block (*Experiment III*)

Experiments III is proposed to evaluate 3D virtual try-on of the garment blocks of each ***PDPS***. A group of designers are invited to this session to make a group decision and give feedback to the design solution in each case.

In order to identify the fit effect of the proposed garment block, a set of normalized ***KFMs*** are extracted, which constituted the common communication language between fashion designers, pattern makers and garment consumers. Five experienced fashion designers are involved in the selection of ***KFMs***. Training sessions with the invited designers are organized in order to make them understand the purpose of their evaluation and take measurements meeting both width and length requirements. Each trained designer generates an exhaustive list of categories describing the garment fit performance according to his/her professional knowledge. The most relevant three categories describing the ***KFMs*** of the garment block are selected: "F_A *Fit in length*", "F_B *Fit in width*" and "F_C *Fit in details*". Then, a list of ***KFMs*** characterizing garment fit in different categories, is generated by the designers using their garment and pattern design knowledge. After that, a "round table" discussion among the panelists is performed to reduce redundant ***KFMs*** and those irrelevant to fit. This step leads to the generation of 6 normalized KFMs assessing the apparel fit performance (see Table 5-2).

Subsequently, a scale of five evaluation scores, ranging from -2 to 2 (-2, -1, 0, 1, 2), is defined to describe ***KFMs***. "-" means that the garment is tight or small related to the body shape, while "+" goes in the opposite direction (big or loose) and 0 a perfect fit on the wearer.

Using these ***KFMs***, a group decision-making is performed in order to assess the fit effect of the 3D virtual try-on result obtained in *Experiment II*. First, five experienced designers (D_1, D_2, D_3, D_4 and D_5) are invited to evaluate the 3D virtual try-on result using the proposed ***KFMs***. The proposed 3D virtual try-on result is displayed on a screen in front of the invited designers. Each of the designers is assigned to evaluate the 3D virtual try-on result independently without previously discussing with other designers. Designers are free to operate the computer to observe the 3D model under all aspects.

Table 5-2: KFMs describing the apparel fit performance.

***KFMs* Categories**	**Apparel *KFMs***
F_A: *Fit in length*	F_{A1} *Length*
F_B: *Fit in width*	F_{B1} *Waist width*
	F_{B2} *Breast width*
F_C: *Fit in details*	F_{C1} *Shoulder fit*
	F_{C2} *Neck fit*
	F_{C3} *Arm hole fit*

Each of the designers is requested to record the fit effect in terms of ***KFMs*** presented in Table 5-2, using the predefined evaluation score. Table 5-3 presents the evaluation result of all invited designers about the fit effect of the 3D virtual try-on result.

Table 5-3: Evaluation results of all invited designers regarding the garment block.

	F_{A1}	F_{B1}	F_{B2}	F_{C1}	F_{C2}	F_{C3}
D_1	0	-1	-1	0	0	-1
D_2	1	-1	-2	0	0	-2
D_3	1	0	-1	0	-1	-1
D_4	0	0	-1	0	0	-1
D_5	1	-1	-2	0	-1	-1

Experiments designed for the fit effect assessment are based on human visual evaluation. In this procedure, uncertain and imprecise linguistic expressions are often used by both designers and consumers for evaluating the garment block. Fuzzy set, as an intelligent technique, is developed to handle the vagueness of human thought, which is full of uncertainty and imprecision. In this situation, fuzzy set theory is applied as a relevant method for processing uncertain data obtained from this evaluation.

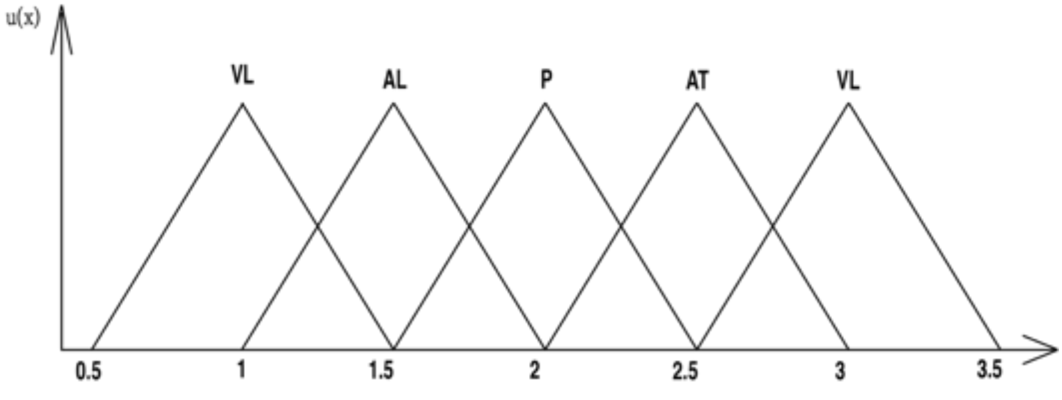


Figure 5-8: The fuzzy linguistic rating scale and related TFNs.

Using fuzzy set tools, a set of linguistic terms, describing the evaluation criteria, can be quantified in the universe of respective and discourse membership function (Figure 5-8). ***Triangular fuzzy numbers (TFN)***, as a classic fuzzy set tool, are used to quantify the utilized linguistic terms in my PhD research. Each score of the scale is defined by a corresponding linguistic term. In order to quantify these linguistic terms, corresponding ***Triangular Fuzzy Numbers (TFNs)*** are also given, as presented in Table 5-4.

Table 5-4: Evaluation scores, corresponding Linguistic terms and TFNs.

Evaluation scores	Linguistic terms	TFNs
2	*Very loose/big (VL)*	(2.5,3,3.5)
1	*A little loose/big (AL)*	(2,2.5,3)
0	*Perfect (P)*	(1.5,2,2.5)
-1	*A little tight/small (AT)*	(1,1.5,2)
-2	*Very tight/small (VT)*	(0.5,1,1.5)

Then, the aggregation operation of the quantized evaluation results is performed using Equation (3-20). Using this method, evaluation results of the designer can be quantified and aggregated into a group decision related to the fit effect of the proposed garment block displayed in the 3D virtual try-on.

For example, for the group perception of the invited designers (D_1, D_2, D_3, D_4 and D_5) in terms of F_{A1} of the garment block design for C_1, can be formulated as a new triangular fuzzy number using Equation (3-20):

$$\left(\frac{1.5 \times 2 + 2 \times 3}{5}, \frac{2 \times 2 + 2.5 \times 3}{5}, \frac{2.5 \times 2 + 3 \times 3}{5}\right)$$
$$= (1.8,2.3,2.8).$$

Using the same calculation process, the perception of all the designers can be aggregated in terms of different ***KFMs***, as presented in Table 5-5.

After that, in order to investigate the fit effect of different garment block positions regarding various ***KFMs***, the distance of all the aggregated ***TFNs*** are measured to the "*Perfect*" condition, whose corresponding ***TFN*** is (1.5,2,2.5). When the distance is shorter, the satisfaction is higher. For example, using Equation (3-18), the fit effect of F_{A1} can be calculated as:

$$\sqrt{\frac{1}{3}[(1.8-1.5)^2+(2.3-2)^2+(2.8-2.5)^2]} = 0.17$$

Similarly, all the aggregated TFNs and corresponding distance to the "*Perfect*" condition can be formulated as presented in Table 5-5.

Table 5-5: Aggregated evaluation result and corresponding distance to the "Perfect" condition of the design case of C_1.

	F_{A1}	F_{B1}	F_{B2}	F_{C1}	F_{C2}	F_{C3}
Aggregated evaluation result	(1.8,2.3,2.8)	(1,1.5,2)	(0.7,1.2,1.7)	(1.5,2,2.5)	(1.4,1.9,2.4)	(0.8,1.3,1.8)
Distance to the "Perfect" condition	0,17	0,17	0,40	0,00	0,12	0,35

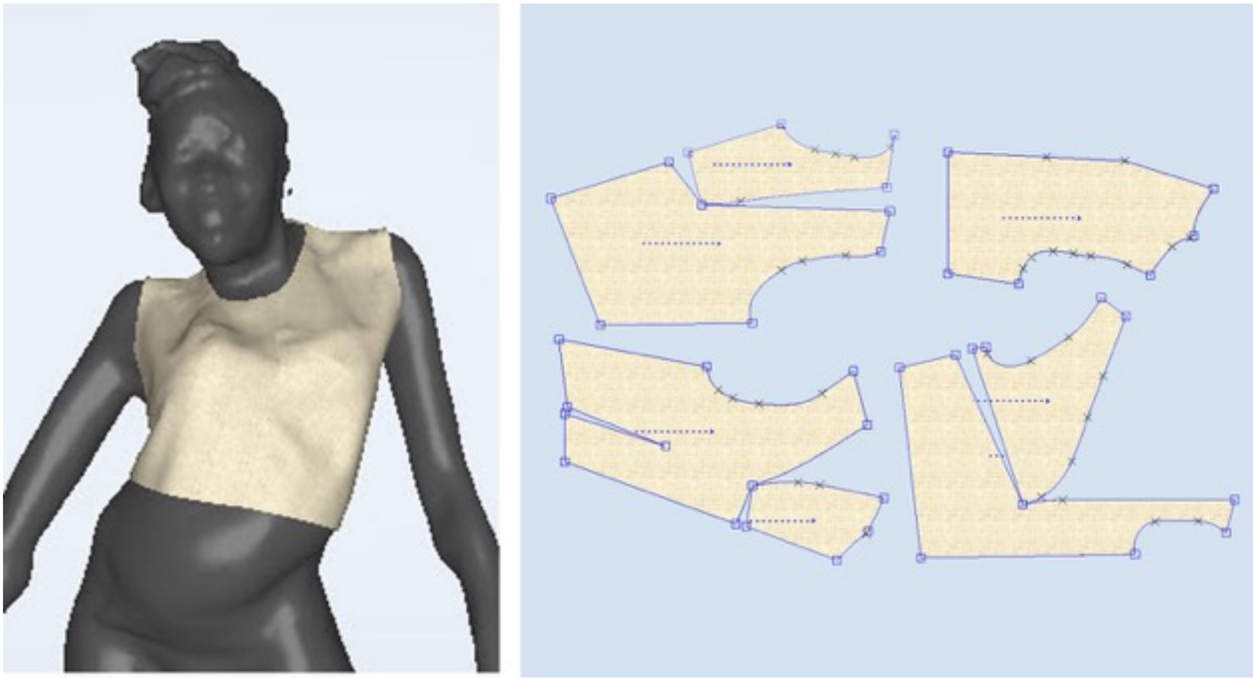


Figure 5-9: The modified garment block patterns and corresponding virtual try-on result.

Based on the result obtained, a group discussion is organized again to decide a pattern medication plan. Then, the garment patterns are modified in a 2D environment according to the professional knowledge of pattern designers. The modified patterns are simulated in a 3D virtual environment again to be analyzed by the designers. The same evaluation procedure that is applied at the previous stage is carried out again. The sequence of *Design – Display – Evaluation – Adjustment* can be performed repeatedly until a satisfying design solution is obtained. Figure 5-9 presents the modified garment block patterns and corresponding virtual try-on result.

5.4.5 Real Personalized Garment Block Development for Virtual Design Validation (*Experiment IV*)

Experiment IV is designed to validate the proposed design process. Real samples for both initial and modified design results are simulated using the proposed fabric in *Experiment I* and different garment block patterns in *Experiment II* and *Experiment III*.

Figure 5-10 presents two real samples of the design case of C_1. Another group of 5 experienced designers are also invited to evaluate the two real samples tried on by C_1, according to ***KFMs*** presented in Table 5-2, using the evaluation scores presented in Table 5-4. Each of the designers is assigned to evaluate the 3D virtual try-on result one by one, avoiding any discussions with other designers. During the evaluation session, designers are free to observe the consumer with the two different pieces of garment block from various angles. Each of the designers is requested to record the fit effect in terms of the ***KFMs*** in Table 5-2, using the predefined evaluation score. After the evaluation of each designer, there is a rest period for the ***PDPS***.

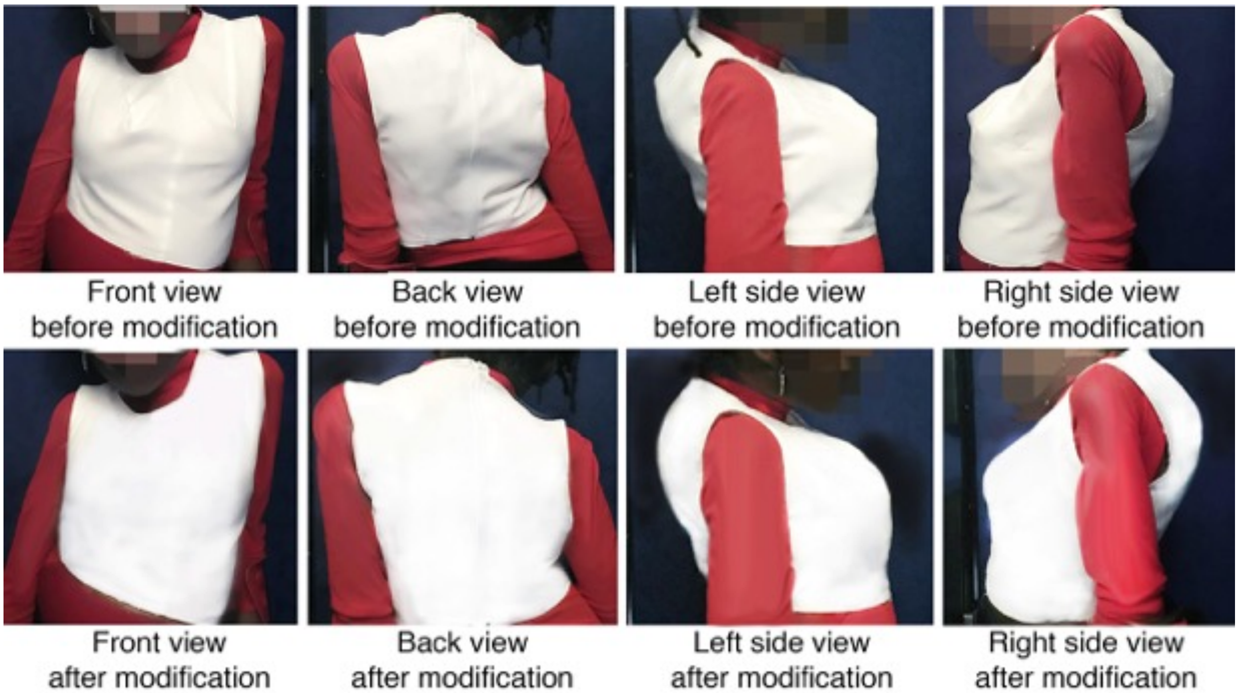


Figure 5-10: Different views of two sets of real samples of C_1, produced by initial and modified garment block patterns, and the proposed woven fabric of the Greige cloth type.

The evaluation results for real samples of *Experiment IV* are collected and aggregated using Equation (5-1), as presented in Table 5-6. According to the result presented in Table 5, the difference of designers' perception on fit effect, between various garment positions on the real garment block sample regarding different ***KFMs***, and the "Perfection" condition, are all very small. Thus, it can be concluded that the satisfaction of the real garment block sample, produced using the modified garment block patterns, is very high in general.

We can find that, through a human visual evaluation performed by the invited designers regarding the proposed ***KFMs***, the design effect can effectively be identified in order to generate a knowledge-oriented pattern modification session, which can fully ensure the satisfaction of the final product. As a knowledge-based process, knowledge and experience of the designers can be largely extracted and applied to support the design process and enhance a desired garment design effect.

Table 5-6: Aggregated evaluation result for garment samples of C_1, produced by initial and modified garment block patterns and corresponding distances to the "Perfect" condition.

Aggregated evaluation result	F_{A1}	F_{B1}	F_{B2}	F_{C1}	F_{C2}	F_{C3}
Real sample of initial garment block patterns	(1.8,2.3,2.8)	(1.2,1.7,2.2)	(0.8,1.3,1.8)	(1.5,2,2.5)	(1.3,1.8,2.3)	(0.9,1.4,1.9)
Real sample of modified garment block patterns	(1.33,1.83,2.33)	(1.5,2,2.5)	(1.67,2.17,2.67)	(1.5,2,2.5)	(1.33,1.83,2.33)	(1.17,1.67,2.17)

Distance to the "Perfect" condition	F_{A1}	F_{B1}	F_{B2}	F_{C1}	F_{C2}	F_{C3}
Real sample of initial garment block patterns	0,17	0,29	0,46	0,00	0,06	0,40
Real sample of modified garment block patterns	0.10	0.00	0.10	0.00	0.10	0.19

Also, in order to validate if the proposed design method is a normalized method which can be generally applied to provide design solution for consumers with atypical morphology, comparisons of the similarity degrees between evaluation results of virtual samples and real samples using the initial garment block patterns are performed. The similarity degree of the aggregated evaluation results between virtual and real garment try-on results using the initial garment block pattern, regarding different KFMs, can be obtained using Equation (3-19). For example, concerning F_{B1} *Waist width*, the similarity degree of aggregated evaluation results between virtual result (1,1.5,2) and real garment try-on result (1.2,1.7,2.2) can be calculated as:

$$\left(1-\frac{\sqrt{\frac{1}{3}[(1-1.2)^2+(1.5-1.7)^2+(2-2.2)^2]}}{10}\right)\times 100\%\text{=88.45\%.}$$

All the similarity degrees are calculated in the same way and the results are presented in Figure 5-11.

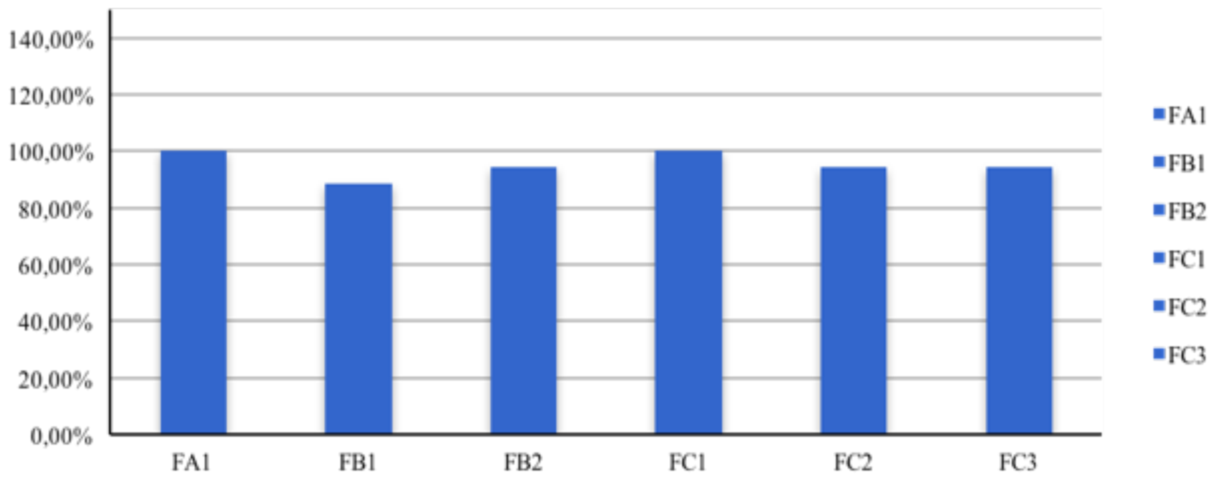


Figure 5-11: Similarity degree of the designer's perception between virtual and real samples using the initial garment block pattern in the design case of C_1.

From Figure 5-11 it can be seen that the highest similarity degree is 100% (F_{A1} *Length* and F_{C1} *Shoulder fit*), most of the similarity degrees are higher than 94% (F_{A1} *Length,* F_{B2} *Breast width,* F_{C1} *Shoulder fit,* F_{C2} *Neck fit* and F_{C3} *Arm hole fit*), and the lowest is 88% (F_{B1} *Waist width*). It can be concluded that the general similarity degrees of aggregated evaluation results between virtual and real garment try-on results, using the initial garment block pattern, are in a high level, which indicates that different groups of designers can have the common perception with the real and virtual perception, and current virtual software can simulate virtual products with a high fidelity.

5.5 From Personalized Garment Block to Manufacturing System

In this section, the extension of the personalized garment block to ready-to-wear garment patterns will be introduced. The obtained ready-to-wear garment patterns will be based by the manufacturing system for further production. This process ensures the connection of the proposed ***PGDSS*** to the manufacturing system. Using this process, the whole ***PGDSS*** can be fully performed online, which can be easily integrated with e-commerce services.

5.5.1 Production pattern design and 3D virtual try-on (*Experiment I*)

In order to explain the application of the personalized garment block patterns, a design case of a personalized blouse is presented in this section. The specifications design sheet in Figure 5-12 describes the requirements for the design elements of the shirt designed by designers in this study. Then, several extensions and sizing procedure are performed in order to obtain the desired garment style in Figure 5-12. Professional knowledge of pattern designers is utilized to support this process. These operations are:

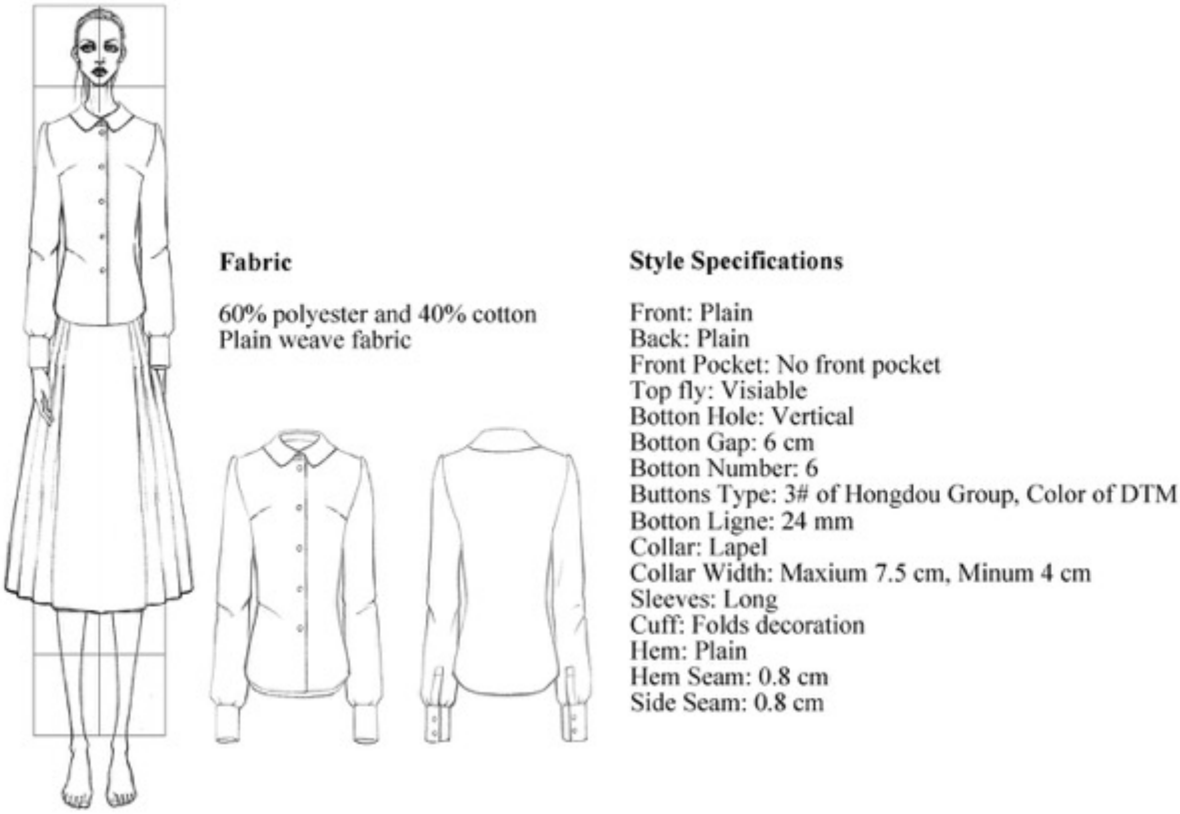


Figure 5-12: The design specifications sheet of the blouse.

Step 1: Adding 1cm to the side seam, center front and back lines for all patterns, creating the buttonholes.

Step 2: Drawing vertical lines from the lowest armhole points to create the new side seam lines, increasing the length of the new side seam lines by 24.5cm from the waistlines and drawing new lines vertical to the side seam lines to be the new bottom lines.

Step 3: Symmetrizing the back waist dart with the same value in the opposite direction of the original dart, while the symmetrical line is the end of dart legs (The two lines that converge at a predetermined point on the pattern.).

Step 4: Drawing a straight line to be the grainline (the center of the sleeve from top of curved top of the sleeve top to wrist level) of the sleeve, measuring the front and back armholes of the previous patterns, recording the measurements on the patterns for future reference, adding the front and back armhole measurements together and divide the value into four to be the cap height of the sleeve (the distance from widest line of the sleeve to the top at the grainline).

Step 5: Determining the length of the cuff as 20cm (add 4cm to the girth of artifice as 16cm), the width of cuff as 5cm.

Step 6: Determining the height of the stand collar as 3cm and the height of the top collar as 4cm

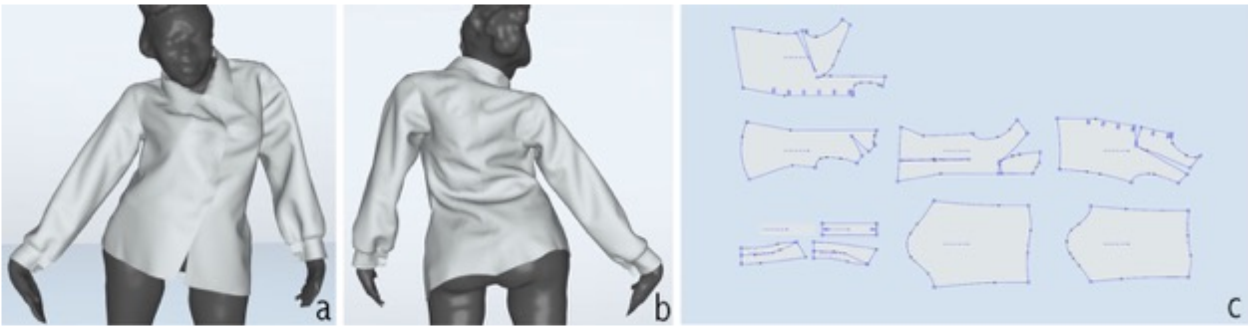


Figure 5-13: Design result in both front and back views, and the corresponding garment patterns.

By adding seam allowances and using *Modaris* software also with the virtual fabric, the production patterns of the designed shirt are finished, shown in Figure 5-13.

5.5.2 Evaluation and adjustment of the 3D try-on perception (*Experiment II*)

In this study, a session of sensory evaluation is realized by a group of fashion designers and pattern makers in order to quantitatively characterize the 3D virtual try-on perception of the shirt designed using the customized block patterns.

Figure 5-14: Model characterizing the relation between technical parameters and perception on 3D virtual garment try-on.

Then, the adjustment of the shirt patterns can be realized in the 2D technical space according to the sensory evaluation results on the performance of the finished shirt in the 3D virtual try-on space. Evidently, the key issue of this adjustment is to set up a model characterizing the relationship between the technical space and 3D virtual product perceptual space. This model will permit to generate the appropriate technical parameters of the garment according to the desired values of sensory evaluation on the effects of 3D virtual garment try-on (See Figure 5-14).

In this study, the aim of identifying the blouse fit in 3D virtual try-on evaluation is to generate normalized sensory descriptors, which constitute the common communication language between fashion designers, pattern makers and garment consumers [92] [130] [15]. Five experienced fashion designers are involved in the evaluation. The parameters of the fabric chosen by the designers as described in the design specifications sheet as well as the finished production patterns constitute the inputs to the *Modaris* software for realizing 3D virtual try-on. The style and design elements in the design specifications sheet can generate a common idea of the designers for the evaluation. In this context, the sensory evaluation results on the fit of the designed shirt, given by different designers, can be very close to each other. The sensory evaluation procedure used in our study is described as follows.

Each trained designer generates an exhaustive list of categories describing the blouse fit performance according to his/her professional knowledge. The three most relevant categories describing the key positions of the shirt have been selected: "*Overall image*", "*fit in width*" and "*fit in details*". Then, a list of descriptors describing the shirt fit in different categories is generated by the designers using their garment design knowledge and pattern design knowledge.

Table 5-7: Sensory descriptors describing the apparel fit performance.

Categories	Apparel fit performance descriptor
D_A: *Overall image*	D_{A1} *Overall fit*
	D_{A2} *Length*
D_B: *Fit in width*	D_{B1} *Waist fit*
	D_{B2} *Breast fit*
	D_{B3} *Hem fit*
D_C: *Fit in details*	D_{C1} *Shoulder fit*
	D_{C2} *Neck fit*
	D_{C3} *Arm hole fit*

After that, there is a session for reducing redundant descriptors and those irrelevant to the fit of a shirt, by performing a "round table" discussion inside the panelists. This step leads to the generation of 8 normalized descriptors describing the apparel fit performance (see Table 5-7). For each descriptor, a scale of five evaluation scores, ranging from -2 to 2, is also obtained. "-" means that the garment is tight or small related to the body shape while "+" means in the opposite direction (big or loose). 0 is a perfect fit on the wearer. Each score of the scale is defined semantically in Table 5-8.

Table 5-8: Evaluation scores and the corresponding semantics.

Scores	-2	-1	0	1	2
Semantics	Very tight/small	A little tight/small	Perfect	A little loose/big	Very loose/big

By repeating the evaluation two times and taking the average of the evaluation scores for each sensory descriptor, we finally obtain a matrix composed of all evaluation scores.

The adjustment of the current patterns will be realized using a rule-based model characterizing the relation between evaluations values on the blouse fit (perceptual space) and modifications of garment patterns (technical space). It has been established by exploiting the common professional knowledge of pattern makers through a round table discussion between these panelists. Five experienced pattern makers are involved in the production process. There are two steps for modeling the relationship:

<u>Step 1</u>: Identification of the blouse modification rules

These rules will enable to determine the key points or key lengths of the shirt production patterns corresponding to each sensory descriptor in order to make the final shirt very close to the target wearing effect wished by the designers. The final modification rules provided by the pattern makers are given in Table 5-9. Normally, for each sensory descriptor, there are several alternative modification rules. However, in practice, only one rule is applied during the adjustment. One example is given below.

If we wish to modify "overall fit" (D_{A1}), then we can change the length of either waistline (D_{A1a}), or breast line (D_{A1b}) or shoulder line (D_{A1c}).

Table 5-9: Modification rules based on evaluation result.

Sensory descriptors on garment fit	Rule code	Modification rules
D_{A1} *Overall fit*	D_{A1a}	*Change the length of waistline*
	D_{A1b}	*Change the length of breast line*
	D_{A1c}	*Change the length of shoulder line*
D_{A2} *Length*	D_{A2a}	*Change the length of the garment*
D_{B1} *Waist fit*	D_{B1a}	*Change the cut of side seam*
	D_{B1b}	*Change the value of waist dart*
D_{B2} *Breast fit*	D_{B2a}	*Change the cut of side seam*
	D_{B2b}	*Change the value of breast dart*
D_{B3} *Hem fit*	D_{B3a}	*Change the cut of side seam*
D_{C1} *Shoulder*	D_{C1a}	*Change the slope of shoulder line*
	D_{C1b}	*Change the length of shoulder line*
	D_{C1c}	*Change the width of neckline*
D_{C2} *Neck*	D_{C2a}	*Change the width of neckline*
	D_{C2b}	*Change the depth of neckline*
D_{C3} *Armhole*	D_{C3a}	*Change the position of sleeve top*
	D_{C3b}	*Change the curvature of the armhole*

<u>Step 2</u>: Identification of the new values of change for garment patterns

For each modification rule, the change of the identified key point or key length is determined according to the evaluation score of the corresponding sensory descriptor. The whole values of change of patterns related to all the modification rules, provided by the designers, are shown in Table 5-10. For example, when applying the modification rule D_{A1a} related to the "overall fit", if the evaluation score is -1 (a little tight), then 4cm will be added to the width of waistline in horizontal direction.

In practice, one modification rule and its corresponding pattern changing value can be arbitrarily selected and its try-on result can be quantitatively characterized using the sensory evaluation. If the adjustment result is not satisfying, another rule of the same sensory descriptor will be selected in order to generate a new try-on result. This procedure can be carried out repeatedly until finding the most relevant adjustment plan.

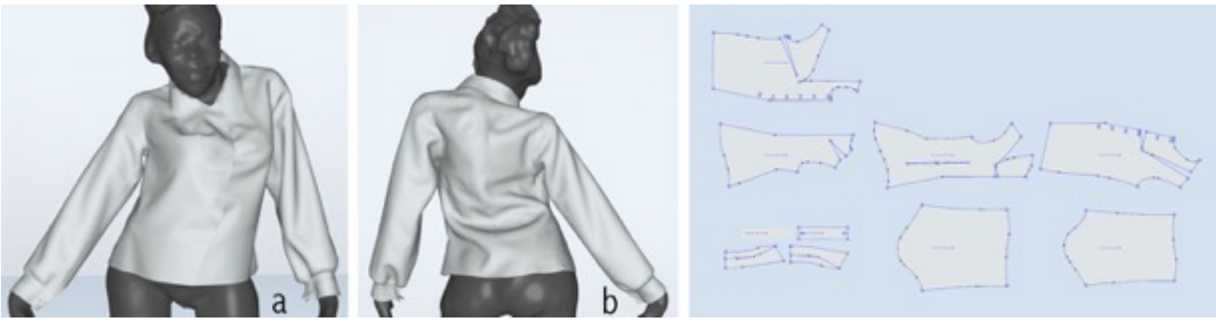


Figure 5-15: Design result after modification in both front and back views, and the corresponding garment patterns.

By using the previous two steps, we set up the relationship between 3D virtual shirt try-on results and 2D pattern parameters (key points and key lengths). This rule-based model permits to reach a desired perception of shirt fit by adjusting the 2D pattern parameters. In this study, the procedure of *Design – Display – Evaluation – Adjustment* with the model can be performed repeatedly until a satisfying design solution is obtained. D_{A2} *Length,* D_{B1} *Waist fit,* D_{B2} *Breast fit,* D_{B3} *Hem fit,* D_{C1} *Shoulder fit* and D_{C2} *Neck fit* of the initial pattern is modified using the rule-based model based on the perception of the involved designers.

To validate the design result, following the design specifications sheet, the garment is produced following the garment patterns after modification. To evaluate the real shirt produced using the pattern modified as the evaluation results before, a fitting procedure is proposed. The fitting result is shown in Figure 5-15. As for the consumer, the look and comfort of the shirt are perceived as fine during the fitting.

In order to validate the proposed design process, another group of designers are invited to compare the initial garment virtual try-on result and the final modified garment virtual try-on result using the evaluation criteria presented in Table 5-7.

First, there is a training session about the purposed of the evaluation. Then both the initial garment virtual try-on result and the final modified garment virtual try-on are presented to the invited designer group. The invited designers are free to operate the computer to observe the virtual try-on results. Each of the invited designers is assigned to finish the evaluation independently without any discussion with other designers.

Table 5-10: Values of change for shirt production patterns.

Evaluation. Scores	-2	-1	1	2
D_{A1a}	+8cm	+4 cm	-4 cm	-8 cm
D_{A1b}	+8 cm	+4 cm	-4 cm	-8 cm
D_{A1c}	+4 cm	+2 cm	-2 cm	-4 cm
D_{A2a}	+4 cm	+2 cm	-2 cm	-4 cm
D_{B1a}	+3 cm	+1 cm	-1 cm	-3 cm
D_{B1b}	+2 cm	+1 cm	-1 cm	-2 cm
D_{B2a}	+3 cm	+1 cm	-1 cm	-3 cm
D_{B2b}	+2 cm	+1 cm	-1 cm	-2 cm
D_{B3a}	+3 cm	+1 cm	-1 cm	-3 cm
D_{C1a}	+4°	+2°	-2°	-4°
D_{C1b}	+3 cm	+1 cm	-1 cm	-3 cm
D_{C1c}	+3 cm	+1 cm	-1 cm	-3 cm
D_{C2a}	+3 cm	+1 cm	-1 cm	-3 cm
D_{C2b}	+3 cm	+1 cm	-1 cm	-3 cm
D_{C3a}	+2 cm	+1 cm	-1 cm	-2 cm
D_{C3b}	+2 cm	+1 cm	-1 cm	-2 cm

5.5.3 Design Validation

In order to quantify the evaluation degrees, a set of fuzzy numbers is assigned to each of the linguistic term. The involved evaluation linguistic term and their corresponding fuzzy numbers are described in Table 5-11.

Table 5-11: Linguistic rating scale and corresponding fuzzy numbers.

Linguistic values	TFNs
Very loose/big	(2.5,3,3.5)
A little loose/big	(2,2.5,3)
Perfect	(1.5,2,2.5)
A little tight/small	(1,1.5,2)
Very tight/small	(0.5,1,1.5)

Then, using Equation (5-1), the evaluation result of all the involved designers can be aggregated. Then, Euclidean distance of between all the aggregated evaluation results to the semantic degree "*Perfect*" (1.5,2,2.5) is calculated in order to measure the satisfaction of invited designers of both initial garment virtual try-on result and finial modified virtual try-on result, as presented in Figure 5-16. These distances indicate the satisfaction degree of each part of the virtual try-on result in terms of different evaluation criteria. Shorter distance indicates higher membership degree.

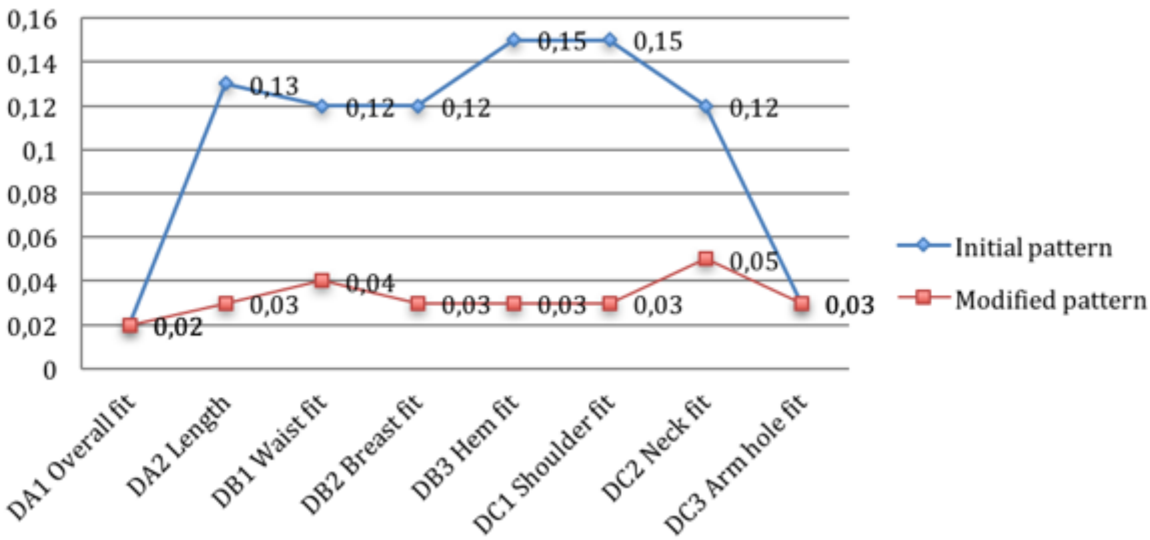


Figure 5-16: Distances of aggregated evaluation results of all evaluation criteria to the degree of "Perfect (1.5,2,2.5)".

D_{A2} Length, D_{B1} Waist fit, D_{B2} Breast fit, D_{B3} Hem fit, D_{C1} Shoulder fit and *D_{C2} Neck fit* are less satisfactory compared to the initial pattern. Some modification should be performed on these parts, matching the designers' idea referring to *Experiment II*.

Generally, the modified pattern is more "perfect" compared with the initial pattern, which indicates that the proposed *Design – Display – Evaluation – Adjustments* procedure is able to help to reach a desired perception of shirt fit by adjusting the 2D pattern parameters using the proposed rule-based model. 2D pattern parameters (key points and key lengths) can be adjusted by the evaluation result of the 3D virtual try-on results.

5.6 Conclusion

In this chapter, the proposed ***Virtual 3D-to-2D Garment Prototyping Platform (VGPP)*** is presented. The proposed platform is able to generate virtual garment patterns based on the personalized garment product profile obtained from the proposed garment recommendation system. The efficiency of the proposed ***VGPP*** has been validated by different case studies.

In the proposed platform, a parameterization process is first performed on a set of scanned 3D points to create a digitalized model of the human body surface, permitting simulation of the consumer's morphological shape with atypical physical deformations. Feature points of the human body for designing a garment block are discussed and classified with ease allowance for obtaining a desired fit effect based on the parameterized model. A basic garment block wire-frame aligned with body features is then established based on the defined feature points of the human body. Based on the deformed wireframe, a 3D expandable garment block is modelled.

Compared with the conventional block pattern-making methods, the proposed method is easier to be implemented and can generate garment patterns with satisfactory fit. This method can be used to create fit-ensured mass-customized apparel products (the top body type) for disabled people with scoliosis. Also, comfort issues caused by garments are also solved in the proposed prototyping method.

Chapter 6 General Conclusion and Prospect

In my PhD research, an intelligent Personalized Garment Design Support System for ***PWAM*** is proposed. This system can be used by both designers and consumers when designing personalized garment for ***PWAM***. The proposed system is capable of helping designers to understand dynamically changing requirements of consumers and designing and prototyping PEA-oriented personalized garments for ***PWAM***.

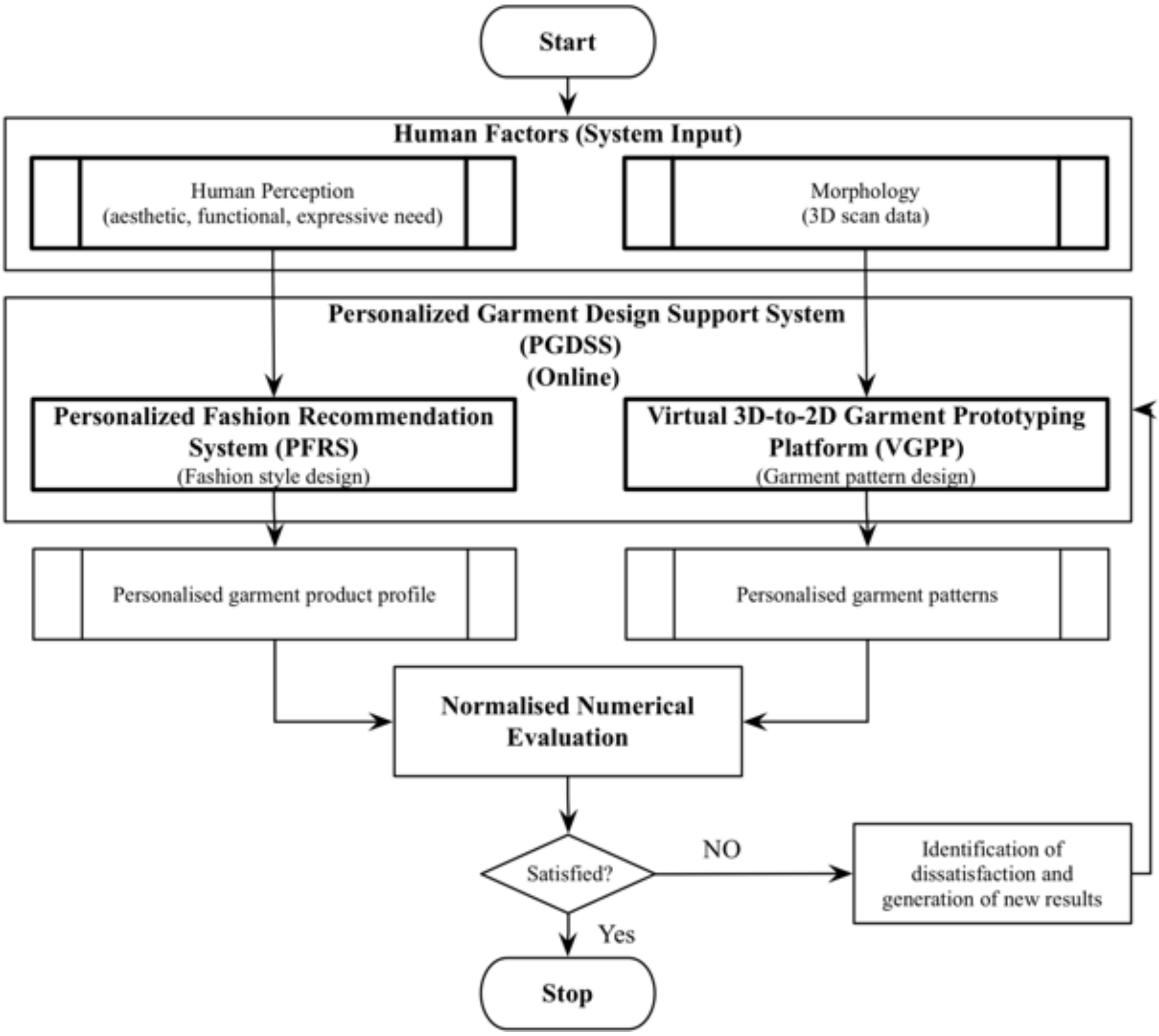


Figure 6-1: Summarized research framework of this PhD thesis.

Figure 6-1 presents the summarized research framework of this PhD thesis. The proposed system has two functions: personalized fashion recommendation system and garment virtual prototyping platform. The use of the proposed recommendation system starts with 3D scanning of the consumer's body shape and input of consumers' perceptual requirements. The output of the system is the final personalized garment product. All the process can be presented to the consumer through an online platform, which ensures interactions between the designer and consumer in order to find the most relevant design solution. The proposed system can be integrated into an e-shopping system or automatic manufacturing system, permitting to provide consumers with more convenient data-based intelligent services on product design.

The main contributions of my PhD research concern the three following areas:

In the Area of Personalized Fashion Recommendation System Development

My contributions include:

(1) Sensory analysis has been used for extracting a set of basic fashion sensory attributes, which can be easily recognized by general public without professional knowledge. These attributes are independent of the concerned social-cultural context.

(2) Rich emotion and perception of consumers on fashion products in a specific social-cultural context have been extracted using sensory evaluation and formalized using fuzzy techniques.

(3) Characters and structure of fashion design knowledge are firstly analyzed. Designer's professional knowledge is originally formalized into linguistic design rules, permitting to link consumer needs and fashion design elements (fabric, garment style, color).

(4) The computation in the proposed recommendation system is realized by using a series of operations on the formalized knowledge and case-based learning.

(5) The proposed system is an open resource-based system, capable of progressively integrating new recommendation rules (new fashion style trends, fabric trends, color trends) from successful applications in order to improve the quality of forthcoming recommendations.

In the Area of Rapid Garment Prototyping (For Atypical Morphology)

Compared with the conventional garment prototyping method,

(1) the proposed garment prototyping solution begins with a personalized garment block, thus avoiding complicated operations during the 3D garment simulation in the virtual environment;

(2) the proposed design process can be fully interactive between the designer and consumer, which ensures the involvement of the consumer throughout the design;

(3) a sequence of *Design – Display – Evaluation – Adjustment* is put forward in the proposed design process. It is technically accomplished through the virtual 3D-to-2D design method and 3D virtual try-on, so that the proposed patterns and principles of elaborating personalized garment products can be validated within a very short time;

(4) as a knowledge-support process, designers' ideas and principles on personalized design can be fully extracted from predefined surveys and mathematically formalized in order to enhance satisfaction of the final product;

(5) garment fit and comfort issues can be quickly solved using the proposed method.

In the Area of Quantified Evaluation of Fashion design

Previously, most of the fashion design issues were solved by human operators using experience-based qualitative methods with a strong subjectivity. In my thesis, we applied or adapted a number of systematic methods to perform quantitative evaluation on fashion creations, including:

(1) a systematic evaluation procedure based on the concept of sensory evaluation for fashion data acquisition and fuzzy techniques for formalization and modeling of evaluated data;

(2) a series of sensory evaluation methods for characterizing different issues in fashion design, such as color, fabric, garment elements, and fit. These standard evaluation methods will help designers' have a deep understanding about how to integrate creative and conceptual fashion design into practical product development.

(3) Professional designers are strongly involved in the proposed evaluation methods. Their knowledge and experience can be integrated in this knowledge-based design process.

Due to time limitation, the current work is still far from being perfect. In the future research, more efforts can be dedicated to the following aspects:

(1) The number of samples involved in the present study is quite limited and the conclusions are drawn upon one specific type of garment products (shirt) only. In practice, reliable recommendation results depend on a big and comprehensive experimental dataset. Therefore, in the future, in order to obtain more generalized and representative knowledge, it is imperative to integrate more types of samples with more diversified garment styles and details into the system.

(2) The current knowledge base has been set up by exploiting evaluation data given by the designers involved in this study. Moreover, the knowledge base can be automatically adjusted or updated by progressively learning from new evaluation data. However, the proposed learning strategy of the knowledge base is still too simplified. In the future, by using more appropriate intelligent techniques, we hope to develop a more relevant strategy, making the knowledge base more accurate and capable of being adapted to various scenarios.

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ACKNOWLEDGEMENT

As my thesis draws to a conclusion, I would like to take this opportunity to thank all of those individuals who in one way or another contributed and extended their valuable assistance in the preparation and completion of this study.

My deepest gratitude goes first and foremost to my research director, Dr. Xianyi ZENG, professor at ENSAIT, for his constant encouragement, understanding, guidance and precious friendship during my PhD study. He has walked me through all the stages of the writing of this thesis. From the very beginning of literature reading to the final draft, he helps me a lot as it always. Dr. ZENG has been my inspiration as I hurdle all the obstacles in the completion of my research work.

I would like to express my heartfelt gratitude to Dr. Pascal BRUNIAUX, professor at ENSAIT, Dr. Antonela CURTEZA, professor at TUIASI, and Dr. Yan CHEN, professor at Soochow University, for their unselfish and unfailing support as my thesis adviser. Thanks to their constant concern and patience, I am able to overcome all the difficulties with great confidence. Their rigorous attitude towards scientific research and dynamic and creative personality have set an excellent example to my endeavor to not only grow as a qualified researcher but also as an independent thinker.

I would also like to thank European Commission and SMDTex project; their fund gave me a chance to do my research between Europe and China. Three years of research in Europe, I find myself deeply in love with this piece of land. I promise I will do my utmost to deepen the friendship between China and Europe.

Then, I would like to thank all staffs of the laboratory GEMTEX (France), ENSAIT (France), TUIASI (Romania) and Soochow University (China) for their warm-hearted help and moral support during my three years of PhD study, the researchers and teachers, Dr. Irina CRISTIAN, Dr. Tomas SEBASTIAN, Dr. Vladan KONCAR, Dr. Peng WANG, Dr. Ludovic KOEHL, Dr. Carmen LOGHIN et al; engineering students, Tao ZHANG, Chen CHEN, Hao SHEN, Qiang FU, Hui CHAN, Kun CHEN et al.

My special thanks go to the individuals who have been willing to spend their precious time in participating in my time-consuming experiments, especially designers from HKPOLYU, Soochow University, Donghua University, University of Edinburgh, ESMOD Paris, and Wuhan Textile University.

My big gratitude goes to my colleagues and close friends for their invaluable support and encouragement which accompanied me all the time during my stay in France. They are Melissa WANGER, Parag BHATIA, Lingshan LIU, Min DONG, Fatma OMRANI, Junjie ZHANG, Xiao CHEN, Ke MA et al. Thank you for being with me.

Finally, my thanks would go to my beloved parents for their loving considerations and great confidence in me all through these years. Without their utmost understanding and mutual support, I could not have achieved a single progress during my study in a foreign country. Thank you for being with me, at every tough and delightful moment.

APPENDIX 1: Consumer behavior and lifestyle analysis on fashion of PWAM

Hello! We are a research team from France, focusing on the developing fashion products for ***PWAM***. This questionnaire is designed to collect data related to fashion consumer behaviour and lifestyle related to ***PWAM***. Thank you for your time.

1. Are ***PWAM*** commonly use auxiliary tools? [Multiple choice]

□ Yes

□ No

2. What kind of auxiliary tools commonly used by ***PWAM***? [Multiple choice]

□ Walking stick

□ Orthosis tool

□ wheelchair

□ Axle stick

3. Is there any special requirement about the garment fabric due to the use of auxiliary tools? [Multiple choice]

□ Moisture management

□ Sweat absorption

□ Abrasion performance

□ Tear resistant

□ Easy to wash

□ Wrinkle-free

4. Is there any special requirement related to garment style related to the auxiliary tool? And state what kind of requirement related to garment style. [Single choice]

○ Yes

○ No

5. Do you think ***PWAM*** like that other people pay more attention to their scoliosis? [Single choice]

○ Yes

○ No

○ I don't care

6. Is there any special requirement about the garment fabric due to the use of auxiliary tools? [Multiple choice]

□ Softness

□ Sweat absorption

□ Thickness

□ Flexibility

7. Is the dressing and undressing activity convenient or not with your current garment? [Single choice]

○ Convenient

○ Inconvenient

○ Very inconvenient

8. What kind of fasteners you think it will help you improve the dressing and undressing? [Multiple choice]

□ Zipper

□ Button

□ Velcro

□ Buckle button

□ Ties

9. What kind of garment category do you think inconvenient for ***PWAM***? [Multiple choice]

□ Shirt

□ Jacket

□ Suits

□ Jeans

□ Dress

□ Sports

10. What is the expectation of ***PWAM*** for garment? [Multiple choice]

□ Comfort

□ Fashionable

□ Easy to match

□ Show your personality

□ Fitting

11. Where will the ***PWAM*** usually go to buy clothes? [Multiple choice]

□ Shopping mall

□ Individual chain store

□ Supermarket

□ Tailors

□ Homemade

12. Can ***PWAM*** easily buy satisfied garment from their fashion shopping places? [Single choice]

○ Not easy

○ It is ok but not satisfied.

○ Easy

13. What is the most dissatisfied factor of ***PWAM*** about e-shopping? [Single choice]

○ Garment fitting

○ Design

○ Quality

○ Price

14. What is the reason for the dissatisfaction of your current garment? [Multiple choice]

□ Fitting

□ Auxiliary tool

□ Style

□ Trouble in visiting shops

APPENDIX 2: Algorithm of the RBRM (Rule-Based Recommendation Module)

Let P be the set of all the alternative garment components for one ***Garment Component Category***, M and N be the two different subsets of P.

Let $BR1=\{br_{11}, br_{12}, \ldots br_{1n}\}$ be the set of garment components whose BSRA value = SR,

Let $BR2=\{br_{21}, br_{22}, \ldots br_{2n}\}$ be the set of garment components whose BSRA value = R,

Let $FR1=\{fr_{11}, fr_{12}, \ldots fr_{1n}\}$ be the set of garment components whose FRA value = SR,

Let $FR2=\{fr_{21}, fr_{22}, \ldots fr_{2n}\}$ be the set of garment components whose FRA value = R,

Let $SR/SR=\{sr/sr_1, sr/sr_2, \ldots sr/sr_n\}$ be the set of garment components whose BSRA and FRA values are both SR

Let $R/R=\{r/r_1, r/r_2, \ldots r/r_n\}$ be the set of garment components whose BSRA and FRA values are both R

Let $SR/R=\{sr/r_1, sr/r_2, \ldots sr/r_n\}$ be the set of garment components whose BSRA = SR and FRA value= R

Let $R/SR=\{r/sr_1, r/sr_2, \ldots r/sr_n\}$ be the set of garment components whose BSRA = R and FRA value= SR

Let $N/SR=\{n/sr_1, n/sr_2, \ldots n/sr_n\}$ be the set of garment components whose BSRA = N and FRA value= SR

Let $N/R=\{n/r_1, n/r_2, \ldots n/r_n\}$ be the set of garment components whose BSRA = N and FRA value= R

Let $SR/N=\{sr/n_1, sr/n_2, \ldots sr/n_n\}$ be the set of garment components whose BSRA = SR and FRA value= N

Let $R/N=\{r/n_1, r/n_2, \ldots r/n_n\}$ be the set of garment components whose BSRA = R and FRA value= N

Let $BN1=\{bn_{11}, bn_{12}, \ldots bn_{1n}\}$ be the set of garment components whose BSRA value = SNR,

Let $BN2=\{bn_{21}, bn_{22}, \ldots bn_{2n}\}$ be the set of garment components whose BSRA value = NR,

Let $FN1=\{fn_{11}, fn_{12}, \ldots fn_{1n}\}$ be the set of garment components whose FRA value = SNR,

Let $FN2=\{fn_{21}, fn_{22}, \ldots fn_{2n}\}$ be the set of garment components whose FRA value = NR,

Let $SNR/SNR=\{snr/snr_1, snr/snr_2, \ldots snr/snr_n\}$ be the set of garment components whose BSRA and FRA values are both SNR

Let $NR/NR=\{nr/nr_1, nr/nr_2, \ldots nr/nr_n\}$ be the set of garment components whose BSRA and FRA values are both NR

Let $SNR/NR=\{snr/nr_1, snr/nr_2, \ldots snr/nr_n\}$ be the set of garment components whose BSRA = SNR and FRA value= NR

Let *NR/SNR= {nr/snr$_1$, nr/snr$_2$, ... nr/snr$_n$}* be the set of garment components whose BSRA = NR and FRA value= SNR

Let *N/SNR= {n/sr$_1$, n/sr$_2$, ... n/sr$_n$}* be the set of garment components whose BSRA = N and FRA value= SNR

Let *N/NR= {n/nr$_1$, n/nr$_2$, ... n/nr$_n$}* be the set of garment components whose BSRA = N and FRA value= NR

Let *SNR/N= {snr/n$_1$, snr/n$_2$, ... snr/n$_n$}* be the set of garment components whose BSRA = SNR and FRA value= N

Let *NR/N = {nr/n$_1$, nr/n$_2$, ... nr/n$_n$}* be the set of garment components whose BSRA = NR and FRA value= N

As explained in Section 4.3.4.2, the general principle of the proposed ***RBRM*** is the ranking of the alternative garment components of each ***Garment Component Category***. Different rules of the ***RB1-FS***, ***RB2-BS***, and ***RB3-F*** are utilized to rank the alternative garment components of each ***Garment Component Category.*** Due to the fact that the priority of different rules of the ***RB1-FS***, ***RB2-BS***, and ***RB3-F*** are different, we define the following actions:

Action 1 (M): sort elements of M in decreasing order according to the value of SFSI of these elements

Action 2-1 (M): move the elements of M to the top of the ranking list

Action 3-1 (M, N): move the group of elements of N after the group of elements of M of the ordering hierarchy

Action 2-2 (M): move the elements of M to the bottom of the ranking list

Action 3-2 (M, N): move the group of elements of N in front of the group of elements of M of the ranking list

We define the following rules:

Rule 1:

If BR$_1$ of P is an empty set and BR$_2$ of P is an empty set,

If FR$_1$ of P is not an empty set, and FR$_2$ of P is an empty set,

Perform Action 1 to FR$_1$ of P

Perform Action 2-1 to FR$_1$ of P

If FR$_1$ of P is an empty set, and FR$_2$ of P is not an empty set,

Perform Action 1 to FR$_2$ of P

Perform Action 2-1 to FR$_2$ of P

If FR$_1$ of P is not an empty set, and FR$_2$ of P is not an empty set,

Perform Action 1 to FR$_1$ of P

Perform Action 1 to FR$_2$ of P

Perform Action 2-1 to FR_1 of P

Perform Action 3-1 (FR_1, FR_2)

If BR_1 of P is not an empty set and BR_2 of P is an empty set,

If FR_1 of P is not an empty set, and FR_2 of P is an empty set,

If FR_1 of BR_1 is not an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to SR/SR of BR_1

If FR_1 of BR_1 is an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 1 to N/SR of P

Perform Action 3-1 to (BR_1, N/SR)

If FR_1 of P is an empty set, FR_2 of P is not an empty set,

If FR_2 of BR_1 is not an empty set

Perform Action 1 to BR1 of P

Perform Action 2-1 to BR1 of P

Perform Action 2-1 to SR/R of BR_1

If FR_2 of BR_1 is an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 1 to N/R of P

Perform Action 3-1 to (BR_1 of P, N/R of P)

If FR_1 of P is not an empty set, and FR_2 of P is not an empty set,

If FR_1 of BR_1 is not an empty set, FR_2 of BR_1 is not an empty set, FR_1 of BR_2 is an empty set, and FR_2 of BR_2 is an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to SR/SR of BR_1 and SR/R of BR_1

Perform Action 3-1 to (SR/SR of BR_1, SR/R of BR_1)

If FR_1 of BR_1 is an empty set, FR_2 of BR_1 is an empty set, FR_1 of BR_2 is not an empty set, and FR_2 of BR_2 is not an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to SR/SR of P and SR/R of P

Perform Action 3-1 to (BR_1 of P, SR/SR of P)

Perform Action 3-1 to (SR/SR of P, SR/R of P)

If FR_1 of BR_1 is not an empty set, FR_2 of BR_1 is an empty set, FR_1 of BR_2 is an empty set, and FR_2 of BR_2 is not an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to SR/SR of BR_1

Perform Action 3-1 to (BR_1 of P, N/R of P)

If FR_1 of BR_1 is an empty set, FR_2 of BR1 is not an empty set, FR_1 of BR_2 is not an empty set, and FR_2 of BR_2 is an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to SR/R of BR_1

Perform Action 3-1 to (BR_1 of P, N/SR of P)

If BR_1 of P is an empty set and BR_2 of P is not an empty set,

If FR_1 of P is not an empty set, and FR_2 of P is an empty set,

If FR_1 of BR1 is not an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to R/SR of BR_1

If FR_1 of BR_1 is an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 1 to N/SR of P

Perform Action 3-1 to (BR_1 of P, N/SR of P)

If FR_1 of P is an empty set, and FR_2 of P is not an empty set,

If FR_2 of BR_1 is not an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to R/R of BR_1

If FR_2 of BR_1 is an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 1 to N/R of P of P

Perform Action 3-1 to (BR_1 of P, N/R of P)

If FR_1 of P is not an empty set, and FR_2 of P is not an empty set,

If FR_1 of BR_1 is not an empty set, FR_2 of BR1 is not an empty set, FR_1 of BR_2 is an empty set, and FR_2 of BR_2 is an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to R/SR of BR_1 and R/R of BR_1

Perform Action 3-1 to (R/SR of BR_1, R/R of BR_1)

If FR_1 of BR_1 is an empty set, FR_2 of BR_1 is an empty set, FR_1 of BR_2 is not an empty set, and FR_2 of BR_2 is not an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to R/SR of P and R/R of P

Perform Action 3-1 to (BR_1 of P, R/SR of P)

Perform Action 3-1 to (R/SR of P, R/R of P)

If FR_1 of BR_1 is not an empty set, FR_2 of BR_1 is an empty set, FR_1 of BR_2 is an empty set, and FR_2 of BR_2 is not an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to R/SR of BR_1

Perform Action 3-1 to (BR_1 of P, N/R of P)

If FR_1 of BR_1 is an empty set, FR_2 of BR_1 is not an empty set, FR_1 of BR_2 is not an empty set, and FR_2 of BR_2 is an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 2-1 to R/R of BR_1

Perform Action 3-1 to (BR_1 of P, N/SR of P)

If BR_1 of P is not an empty set and BR_2 of P is not an empty set,

If FR_1 of P is not an empty set, and FR_2 of P is an empty set,

If FR_1 of BR_1 is not an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 3-1 (BR_1 of P, BR_2 of P)

Perform Action 1 to SR/SR of BR_1

Perform Action 2-1 to SR/SR of BR_1

If FR_1 of BR_1 is an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 1 to R/SR of BR_2

Perform Action 1 to R/R of BR_2

Perform Action 3-1 to (R/SR of BR_2, R/R of BR_2)

If FR_1 of P is an empty set, and FR_2 of P is not an empty set,

If FR_1 of BR_1 is not an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 3-1 (BR_1 of P, BR_2 of P)

Perform Action 1 to SR/R of BR_1

Perform Action 2-1 to SR/R of BR_1

If FR_1 of BR_1 is an empty set

Perform Action 1 to BR_1 of P

Perform Action 2-1 to BR_1 of P

Perform Action 1 to R/R of BR_2

Perform Action 1 to R/R of BR_2

Perform Action 3-1 to (R/R of BR_2, R/N of BR_2)

If FR_1 of P is not an empty set and FR_2 of P is an empty set,

If FR_1 of BR_1 is not an empty set and FR_1 of BR_2 is an empty set

Perform Action 3-1 (BR_1 of P, BR_2 of P)

Perform Action 1 and 2-1 to SR/SR of BR_1

If FR_1 of BR_1 is an empty set and FR_1 of BR_2 is not an empty set

Perform Action 3-1 (BR_1 of P, BR_2 of P)

Perform Action 1 and 2-1 to SR/SR of BR_2

If FR_1 of P is an empty set and FR_2 of P is not an empty set,

If FR_2 of BR_1 is not an empty set and FR_2 of BR_2 is an empty set

Perform Action 3-1 (BR_1 of P, BR_2 of P)

Perform Action 1 and 2-1 to SR/R of BR_1

If FR_2 of BR_1 is an empty set and FR_2 of BR_2 is not an empty set

Perform Action 3-1 (BR_1 of P, BR_2 of P)

Perform Action 1 and 2-1 to SR/R of BR_2

If FR_1 of P is not an empty set and FR_2 of P is not an empty set,

If FR_1 of BR_1 is not an empty set, FR_2 of BR_1 is not an empty set, FR_1 of BR_2 is an empty set, and FR_2 of BR_2 is an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 3-1 to (BR_1 of P, BR_2 of P)

Perform Action 2-1 to SR/SR of BR_1

Perform Action 3-1 to (SR/SR of BR_1, SR/R of BR_1)

If FR_1 of BR_1 is an empty set, FR_2 of BR_1 is an empty set, FR_1 of BR_2 is not an empty set, and FR_2 of BR_2 is not an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 3-1 to (BR_1 of P, BR_2 of P)

Perform Action 2-1 to SR/SR of BR_2

Perform Action 3-1 to (R/SR of BR_2, R/R of BR_2)

If FR_1 of BR_1 is not an empty set, FR_2 of BR_1 is an empty set, FR_1 of BR_2 is an empty set, and FR_2 of BR_2 is not an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 3-1 to (BR_1 of P, BR_2 of P)

Perform Action 2-1 to SR/SR of BR_1

Perform Action 2-1 to R/R of BR_2

If FR_1 of BR_1 is an empty set, FR_2 of BR_1 is not an empty set, FR_1 of BR_2 is not an empty set, and FR_2 of BR_2 is an empty set

Perform Action 2-1 to BR_1 of P

Perform Action 3-1 to (BR_1 of P, BR_2 of P)

Perform Action 2-1 to SR/SR of BR_2

Perform Action 3-1 to (SR/SR of BR_2, SR/R of BR_2)

Rule 2:

If BN_1 of P is an empty set and BN_2 of P is an empty set,

If FN_1 of P is not an empty set, and FN_2 of P is an empty set,

Perform Action 1 to FN_1 of P

Perform Action 2-1 to FN_1 of P

If FN_1 of P is an empty set, and FN_2 of P is not an empty set,

Perform Action 1 to FN_2 of P

Perform Action 2-1 to FN_2 of P

If FN_1 of P is not an empty set, and FN_2 of P is not an empty set,

Perform Action 1 to FN_1 of P

Perform Action 1 to FN_2 of P

Perform Action 2-1 to FN_1 of P

Perform Action 3-1 (FN_1 of P, FN_2 of P)

If BN_1 of P is not an empty set and BN_2 of P is an empty set,

If FN_1 of P is not an empty set, and FN_2 of P is an empty set,

If FN_1 of BN_1 is not an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to SNR/SNR of BN1

If FN_1 of BN_1 is an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 1 to N/SR of P

Perform Action 3-2 (BN_1 of P, N/SR of P)

If FN_1 of P is an empty set, and FN_2 of P is not an empty set,

If FN_2 of BN_1 is not an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to SNR/NR of BN_1

If FN_2 of BN_1 is an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 1 to N/R of P

Perform Action 3-2 (BN_1 of P, N/R of P)

If FN_1 of P is not an empty set, and FN_2 of P is not an empty set,

If FN_1 of BN1 is not an empty set, FN_2 of BN_1 is not an empty set, FN_1 of BN_2 is an empty set, and FN_2 of BN_2 is an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to SNR/SNR of BN_1 and SNR/NR of BN_1

Perform Action 3-2 (SNR/SNR of BN_1, SNR/NR of BN_1)

If FN_1 of BN_1 is an empty set, FN_2 of BN_1 is an empty set, FN_1 of BN_2 is not an empty set, and FN_2 of BN_2 is not an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to SNR/SNR of P and SNR/NR of P

Perform Action 3-2 (BN_1 of P, SNR/SNR of P)

Perform Action 3-2 (SNR/SNR of P, SNR/NR of P)

If FN_1 of BN_1 is not an empty set, FN_2 of BN_1 is an empty set, FN_1 of BN_2 is an empty set, and FN_2 of BN_2 is not an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to SNR/SNR of BN_1

Perform Action 3-2 (BN_1, N/R)

If FN_1 of BN_1 is an empty set, FN_2 of BN_1 is not an empty set, FN_1 of BN_2 is not an empty set, and FN_2 of BN_2 is an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to SNR/NR of BN_1

Perform Action 3-2 (BN_1, N/SR)

If BN_1 of P is an empty set and BN_2 of P is not an empty set,

If FN_1 of P is not an empty set, and FN_2 of P is an empty set,

If FN_1 of BN_1 is not an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to R/SR of BN_1

If FN_1 of BN_1 is an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 1 to N/SR of P of P

Perform Action 3-2 (BN_1, N/SR)

If FN_1 of P is an empty set, and FN_2 of P is not an empty set,

If FN_2 of BN_1 is not an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to NR/NR of BN_1

If FN_2 of BN_1 is an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 1 to N/R of P

Perform Action 3-2 (BN_1 of P, N/R of P)

If FN_1 of P is not an empty set, and FN_2 of P is not an empty set,

If FN_1 of BN1 is not an empty set, FN_2 of BN_1 is not an empty set, FN_1 of BN_2 is an empty set, and FN_2 of BN_2 is an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to R/SR of BN_1 and NR/NR of BN_1

Perform Action 3-2 (R/SR of BN_1, NR/NR of BN_1)

If FN_1 of BN_1 is an empty set, FN_2 of BN_1 is an empty set, FN_1 of BN_2 is not an empty set, and FN_2 of BN_2 is not an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to R/SR of P and NR/NR of P

Perform Action 3-2 (BN_1, R/SR of P)

Perform Action 3-2 (R/SR of P, NR/NR of P)

If FN_1 of BN_1 is not an empty set, FN_2 of BN_1 is an empty set, FN_1 of BN_2 is an empty set, and FN_2 of BN_2 is not an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 2-2 to R/SR of BN_1

Perform Action 3-2 (BN_1 of P, N/R of P)

If FN_1 of BN_1 is an empty set, FN_2 of BN_1 is not an empty set, FN_1 of BN_2 is not an empty set, and FN_2 of BN_2 is an empty set

Perform Action 2-2 to BN_1

Perform Action 2-2 to NR/NR of BN_1

Perform Action 3-2 (BN_1 of P, N/SR of P)

If BN_1 of P is not an empty set and BN_2 of P is not an empty set,

If FN_1 of P is not an empty set, and FN_2 of P is an empty set,

If FN_1 of BN_1 is not an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 1 to SNR/SNR of BN_1

Perform Action 2-2 to SNR/SNR of BN_1

If FN_1 of BN_1 is an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 1 to R/SR of BN_2

Perform Action 1 to NR/NR of BN_2

Perform Action 3-2 (R/SR of BN_2, NR/NR of BN_2)

If FN_1 of P is an empty set, and FN_2 of P is not an empty set,

If FN_1 of BN_1 is not an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 1 to SNR/NR of BN_1

Perform Action 2-2 to SNR/NR of BN_1

If FN_1 of BN_1 is an empty set

Perform Action 1 to BN_1 of P

Perform Action 2-2 to BN_1 of P

Perform Action 1 to NR/NR of BN_2

Perform Action 1 to NR/NR of BN_2

Perform Action 3-2 (NR/NR of BN_2, R/N of BN_2)

If FN_1 of P is not an empty set and FN_2 of P is an empty set,

If FN_1 of BN_1 is not an empty set and FN_1 of BN_2 is an empty set

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 1 and 2-2 to SNR/SNR of BN_1

If FN_1 of BN_1 is an empty set and FN_1 of BN_2 is not an empty set

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 1 and 2-2 to SNR/SNR of BN_2

If FN_1 of P is an empty set and FN_2 of P is not an empty set,

If FN_2 of BN_1 is not an empty set and FN_2 of BN_2 is an empty set

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 1 and 2-2 to SNR/NR of BN_1

If FN_2 of BN_1 is an empty set and FN_2 of BN_2 is not an empty set

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 1 and 2-2 to SNR/NR of BN_2

If FN_1 of P is not an empty set and FN_2 of P is not an empty set,

If FN_1 of BN_1 is not an empty set, FN_2 of BN_1 is not an empty set, FN_1 of BN_2 is an empty set, and FN_2 of BN_2 is an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 2-2 to SNR/SNR of BN_1

Perform Action 3-2 (SNR/SNR of BN_1, SNR/NR of BN_1)

If FN_1 of BN_1 is an empty set, FN_2 of BN_1 is an empty set, FN_1 of BN_2 is not an empty set, and FN_2 of BN_2 is not an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 2-2 to SNR/SNR of BN_2

Perform Action 3-2 (R/SR of BN_2, NR/NR of BN_2)

If FN_1 of BN_1 is not an empty set, FN_2 of BN_1 is an empty set, FN_1 of BN_2 is an empty set, and FN_2 of BN_2 is not an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 2-2 to SNR/SNR of BN_1

Perform Action 2-2 to NR/NR of BN_2

If FN_1 of BN_1 is an empty set, FN_2 of BN_1 is not an empty set, FN_1 of BN_2 is not an empty set, and FN_2 of BN_2 is an empty set

Perform Action 2-2 to BN_1 of P

Perform Action 3-2 (BN_1 of P, BN_2 of P)

Perform Action 2-2 to SNR/SNR of BN_2

Perform Action 3-2 (SNR/SNR of BN_2, SNR/NR of BN_2)

APPENDIX 3: Published Journal Papers

1. **Hong, Y.,** Zeng, X., Wang, Y., Bruniaux, P., & Chen, Y. (2018). CBCRS: An open case-based color recommendation system. **Knowledge-Based Systems**, 141, 113-128. (**IF: 4.53**)

2. **Hong, Y.,** Zeng, X., Bruniaux, P., & Liu, K. (2017). Interactive virtual try-on based three-dimensional garment block design for disabled people of scoliosis type. **Textile Research Journal**, 87(10), 1261-1274. (**IF: 1.443**)

3. **Hong, Y.,** Bruniaux, P., Zeng, X., & Dong, M. (2017). Virtual reality-based collaborative design method for designing customized garment for disabled people with scoliosis. **International Journal of Clothing Science and Technology**, 29(2), 226-237. (**IF: 0.541**)

4. **Hong, Y.,** Bruniaux, P., Zeng, X., Curteza, A., & Liu, K. (2017). Design and evaluation of personalized garment block design method for atypical morphology using the knowledge-supported virtual simulation method. **Textile Research Journal**, 0040517517708537. (Online first) (**IF: 1.443**)

5. **Hong, Y.,** Bruniaux, P., Zeng, X., Liu, K., Curteza, A., & Chen, Y. (2018). Visual-simulation-based personalized garment block design method for physically disabled people with scoliosis (PDPS). **Autex Research Journal**, 18(1), 35-45. (**IF: 0.716**)

6. **Hong, Y.,** Zeng, X., Bruniaux, P., Curteza, A., Stelian, M., & Chen, Y. (2017). Garment opening position evaluation using kinesiological analysis of dressing activities: Case study of physically disabled people with scoliosis (PDPS). **Textile Research Journal**, 0040517517720503. (**IF: 1.443**)

7. **Hong, Y.,** Zeng, X., Bruniaux, P., Chen, Y., & Zhang, X. (2017). Development of a new knowledge-based fabric recommendation system by integrating the collaborative design process and multi-criteria decision support. **Textile Research Journal**, 0040517517729383. (Online first) (**IF: 1.443**)

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13. Kaixuan Liu, Jianping Wang, Chun Zhu, Edwin Kamalha, **Yan Hong**, Junjie Zhang and Min Dong (2017). A mixed human body modeling method based on 3D body scanning for clothing industry. **International Journal of Clothing Science and Technology**, 29(5), 673-685. (**IF: 0.541**)

14. Yuan, H., Zhang, J., Zhang, Y., **Hong, Y**., & Zhao, H. (2017). Effects of agglomeration externalities on total factor productivity: evidence from China's Textile Industry. **Industria Textila**, 68(6), 474-480. (IF: 0.387)

15. Min DONG, **Yan Hong**, Junjie Zhang, Kaixuan Liu, Huiyu Jiang (2018) A fuzzy rough set and sensory evaluation-based classification of lower body shapes for developing customized pants design. **Industria Textila** (Accepted) (**IF: 0.387**)

16. Mulat Alubel Abtew, **Yan Hong**, Linzi Pu (2018) Implementation of Statistical Process Control (SPC) in the Sewing Section of Garment Industry for Quality Improvement. **Autex Research Journal**. (Online first) (**IF: 0.716**)

17. Pu Linzi, **Hong Yan**, Wagner Melissa, Wang Peiguo, Abtew Mulat (2018) Raincoat Design For Children For Age Group 7-8 Years: A Design Development Case Study. **Industria Textila** (Accepted) (**IF: 0.387**)

18. Zhang Junjie, Zeng Xianyi, Liu Kaixuan, **Yan Hong**, Dong Min (2018) Jeans knowledge base development based on sensory evaluation technology for customers' personalized recommendation. **International Journal of Clothing Science and Technology** (Accepted) (**IF: 0.541**)

APPENDIX 4: Published Conference Papers

1. **Hong, Y.**, Zeng, X., Bruniaux, P., Curteza, A., & Chen, Y. (2017, July). Movement Analysis and Ergonomic Garment Opening Design of Garment Block Patterns for Physically Disabled People with Scoliosis Using Fuzzy Logic. In International Conference on Applied Human Factors and Ergonom- ics (pp. 303-314). Springer, Cham.

2. **Hong, Y.**, Curteza, A., Zeng, X., Bruniaux, P., & Chen, Y. (2016, June). Sensory evaluation based fuzzy AHP approach for material selection in customized garment design and development process. In IOP Conference Series: Materials Science and Engineering (Vol. 133, No. 1, p. 012058). IOP Publishing.

3. **Hong, Y.**, Zeng, X., & Bruniaux, P. (2016, August). Selection and application of key performance indicators for design and production process. In Uncertainty modelling in knowledge engineering and decision making: Proceedings of the 12th International FLINS Conference. Roubaix: World Scientific (pp. 1008-14).

4. **HONG, Y**., Zeng, X., & Bruniaux, P. (2016, July). Knowledge Acquisition And Modeling Of Garment Product Development. In Uncertainty Modelling in Knowledge Engineering and Decision Making: Proceedings of the 12th International FLINS Conference (FLINS 2016) (Vol. 10, p. 438). World Scientific.

APPENDIX 5: Academic Awards

1. **Best Paper Award:** 12th International Fuzzy Logic and Intelligent Technologies in Nuclear Science Conference (FLINS 2016): *SELECTION AND APPLIACTION OF KEY PERFORMANCE INDICATORS FOR PERSONALIZED GARMENT DESIGN AND PRODUCTION PROCESS BASED ON FANP*

2. **Gold Award:** 2016 INTERNATIONAL EXHIBITION OF INVENTICS, RESEARCH AND TECHNOLOGICAL TRANSFER: *Customized Garment Design System For Elderly People Or Persons With Physical Disabilities From Body Scan Data*

3. **Gold Award:** 2016 EuroInvent: *Personalized Garment Design System Development*