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A Study on Kansei Data Modeling and Its Application to Personalized Recommendation in Antique Products

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Japan Advanced Institute of Science and Technology

Doctoral Dissertation

A Study on Kansei Data Modeling and Its Application to Personalized Recommendation in Antique Products

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Abstract

The market demand for traditional crafts all over the world is decreasing. Traditional crafts are more expensive but less functional than substitute products. Therefore, the development of traditional crafts is necessary to preserve them. Traditional crafts themselves have aesthetic attributes such as brand image, individual preferences, and cultural backgrounds which do not exist in substitute products. These aesthetic attributes are key factors in attracting the consumers. For traditional products, the decision-making process of the consumer is influenced by their individual feelings. By discovering and transferring these feelings into the product design, we can increase demand for traditional crafts. Our objective in this dissertation is to propose a model for representing these aesthetic aspects of traditional crafts. In Kansei Engineering (KE), these aesthetic attributes are called Kansei attributes and defined using Kansei words.

According to the research by Kansei Engineering (KE) and evaluation, a Kansei experiment is usually conducted in advance to build the Kansei database of products in which products are assessed according to a predefined set of their Kansei attributes from a population of subjects, typically by means of the semantic differential (SD) method. The Kansei database is then used to generate the so-called Kansei profiles of products, which serve as knowledge for the purpose of affective design or consumer-oriented evaluation. Basically, there are two main approaches to modeling Kansei data for generating Kansei profiles. In the first approach, which has been used in many KE studies, Kansei data is usually treated as numerical data in which a Kansei judgment is viewed as a crisp score and the average of scores given by a population of subjects is defined as the Kansei profile of products. Alternatively, the second approach recently proposed is based on voting model semantics for generating Kansei profiles in which Kansei judgment is viewed as categorical data. However, both these approaches of Kansei data modeling do not take into account the fuzziness inherent in Kansei data.

This dissertation addresses the problem of Kansei evaluation and modeling for personalized recommendation and design support. In particular, it first proposes a novel approach to modeling Kansei data that can capture not only the uncertainty of Kansie data due to subjective judgments but also the fuzziness inherent in Kansei data due to their qualitative nature. Then, a new method for generating the Kansei profiles of products making use of the proposed approach of Kansei data modeling is also developed. Eventually, the newly developed method for generating the Kansei profiles is integrated into the target-based decision model in order to develop a consumer-oriented evaluation model for personalized recommendation in traditional products.

Keywords: Kansei data; Linguistic variable; Semantic overlapping; Consumer-oriented evaluation; Decision support system

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Chapter 1

Introduction

1.1 Research context

Currently, the market for traditional crafts all over the world is decreasing. Therefore, promotion and development of traditional crafts are necessary to preserve them. Even in the government sector, The Japanese Ministry of Economic, Trade, and Industry of Japanese (METI) has issued *"Densan Law"* to promote and develop Traditional Craft Industries [1].

In the functional perspective, most of the traditional products have limited functions or features. The prices of the traditional products are relatively high, while the supply is often low because they are usually crafted by an experienced artisan. These factors affect the demand for the traditional product in the current situation. However, traditional products have characteristics that can represent the feeling of the consumer. Each traditional product is unique through regional differences [2]. Therefore, the main reason for purchasing a traditional products is not its functionality, but the aesthetic attributes of the product itself.

1.2 Research Motivation

Apart from functional attributes, the aesthetic attributes of the product are the crucial factor for making a purchase decision, especially when the consumer can quickly make a comparison of products using the internet. Understanding these aesthetic attributes helps to design and evaluate the product. Some studies [3, 4, 5, 6, 7] show that the aesthetic attributes of a product improve the product's attractiveness. This attractiveness affects the satisfaction of consumers regarding the quality of the product. Thus, the aesthetic aspect of a product influences the consumer's purchasing decision. In reality, the purchase decision is usually made according to their aesthetic feeling toward the product. Evaluation of the product's aesthetic feeling is important for designing, marketing and recommending the product [2].

This research is motivated by the effect of the aesthetic attribute of products on consumers' purchasing decisions. Moreover, consumers are willing to pay a premium price for a product that meets their specific preferences. Designing and developing new products or services are the difficult tasks. According to Zaltman [8], 80% of new products and services will fail in the first six months after launching. In product design, consumers' satisfaction is as important as the technical attributes in determining the success [9, 10, 11, 12]. We want to include these preferences into the product design. In this research, we adopt the Kansei engineering method to improve the demand for traditional products.

Kansei Engineering (KE) researches how to translate these attributes into the design elements of a product. The founder of Kansei Engineering, Mitsuo Nagamachi, defines Kansei Engineering as the methodology to convert the feeling and recognition of consumers for a product into the product's design [13]. Kansei Engineering has been used to develop new products and has been applied to many fields [14], including the food industry [15], mobile phones [16, 17, 18], telephones [19], tactile sense on surface roughness [20], chairs [21], machine tool design [22], battery drills [23], cars [13], baby strollers [24], real estate [25] and table glass [26]. *"Kansei"* is a Japanese word that represents a complex expression. This expression can be perceived not only by physical senses such as the sense of sight, hearing, smell, taste, and touch but also recognition [27].

Kansei Engineering is also used to develop the method for product evaluation and recommendation. The product recommendation system has recently become a vital research area [28, 29, 30, 31]. *"Consumer-oriented Kansei evaluation"* [2] which is designed and developed to sizing up consumers' preferences, plays an important role in increasing the attractiveness of a product.

1.3 Statement of problems

In Kansei Engineering, the aesthetic attributes of the product are transferred into knowledge. This knowledge can be used to design new products or evaluate the products. In Kansei Engineering, we refer to these attributes as Kansei attributes. To obtain the knowledge, we need Kansei data acquired by conducting Kansei experiments. Then we interpret Kansei data and find the relationship between design elements and Kansei attributes. Multivariate analysis techniques such as regression analysis or principal component analysis (PCA) are generally used to establish this relationship. However, the consumer's judgment on these attributes is usually vague and ambiguous. To accurately translate these attributes into useful knowledge, data modeling and product evaluation which can help interpret the vagueness and ambiguity of the consumer's judgment are necessary.

The following problems arise in the modeling and evaluating of the feeling of the consumer in product design.

1. Kansei data are usually treated as a crisp value for simplicity. As a result, the qualitative and ambiguous Kansei attributes are not considered.

2. The subject of the Kansei experiment is sometimes not certain about his judgment in the assessments.

3. The evaluation model cannot target the requests specified by the consumer's Kansei preferences.

1.4 Research objectives

To solve the problems mentioned above, we propose a solution which is divided into two parts. In the first part of the solution, we propose a Kansei data model to represent the Kansei data. Kansei data are interpreted and transferred into the Kansei profile. The data model must be able to represent the ambiguity of Kansei data. Furthermore, the uncertainty of the subject's judgment in the Kansei experiment must be considered. For the second part of the solution, we use *Kansei evaluation based on multi-attribute fuzzy target-oriented decision analysis and the prioritized aggregation technique.* This technique can evaluate multiple attributes of the decision-making problem. To target specific preferences of consumers, we implement the concept of prioritized aggregation operators proposed by Yager [32].

To summarize, the objectives of this research are to:

1. Propose an approach to model Kansei data. This approach is based on the linguistic interpretation of Kansei data [33]. The concept of semantic overlapping is extended to this model using the probabilistic semantic of fuzzy sets.

2. Develop a target-based model for consumer-oriented evaluation using the proposed Kansei data modeling approach.

1.5 Research contribution

The main contribution of this research is an alternative method to represent Kansei data. There are original features that set our modeling method apart from the rest.

1. We use linguistic labels which correspond to Kansei attributes to represent the subject's assessment rather than represent the subject's assessment in the Kansei experiment in crisp value.

2. We propose a method to embed the uncertainty of the judgment of the subject.

1.6 Chapter organization

The rest of our thesis is depicted as follows:

- **Chapter 2** describes the background and literature review of related theories. First, we give a brief description of Kansei Engineering and its application. The fundamentals of the fuzzy set is then described in the next section. In the following section we describe a method called *"Computing with Words"* which our Kansei data modeling is based on. The final section discusses "Multi-attribute decision analysis."

- **Chapter 3** proposes a method for Kansei data modeling. We begin with how we acquire Kansei data. Then, we explain the method to modeling Kansei data which incorporates the uncertainty of Kansei data. The proposed modeling method also includes the "semantic overlapping" of the consumer's judgment of a product item. In the last section, we presenet a method to create a Kansei profile of products from the Kansei data.

- **Chapter 4** presents the consumer-oriented evaluation problem. A technique for modeling consumers' specific preferences is explained. Then we discuss how to formulate the consumer's target. In the last section, we propose a method for target-based evaluation.

- **Chapter 5** conducts a case study of the proposed Kansei data modeling. The Kansei data which are collected by a Kansei experiment of traditional products called Kutani cups are used. The Kansei profile is generated and used as the knowledge in the consumer-oriented evaluation.

- **Chapter 6** presents the conclusion of this thesis. We also discuss the academic impact, the social impact, applications, and future works.

Chapter 2

Background of Kansei engineering and related theories

In this chapter, backgrounds, related theories and studies are discussed. We first discuss Kansei engineering and its methodologies to show the fundamental concept and example of applications. In the next section, the fundamentals of the fuzzy set are explained, as a fuzzy set is the primary tool in this research. Then, we summarize the basics of "computing with words" which is used in chapter 3. Finally, we review the multi-attribute decision-making problems and related works that will be implemented in chapter 4.

2.1 Kansei Engineering

The founder of Kansei Engineering, Mitsuo Nagamachi, defines Kansei Engineering as the methodology to convert the feeling and recognition of consumers for a product into the product's design [13]. Kansei engineering has been used to develop new products and applied to many fields [14] such as the food industry [15], mobile phones [16, 17, 18], telephones [19], tactile sense on surface roughness [20], chairs [21], machine tool design [22], battery drills [23], cars [13], baby strollers [24], real estate [25], and table glass [26]. *"Kansei"* is a Japanese word that represents a complex expression. This expression can be perceived not only by physical senses such as the sense of sight, hearing, smell, taste, and touch but also recognition [27].

Many new products have been designed using Kansei engineering such as the Mazda

Miata [14], Wacoal Good-Up Bra [34, 35], Boeing interior design [36], Sharp refrigerator [37], and Sharp camcorder [38]. According to Shimizun[cite], Kansei Engineering is a tool used in product development to find a relation between product properties and the design characteristics.

2.1.1 Kansei methodologies

Nagasawa [39], one of the pioneers of Kansei Engineering, suggests that there are three main focus points in the Kansei Engineering method:

1. Understanding consumers' feelings (Kansei)
2. Translating Kansei understanding into the design of a product
3. Creating a system for Kansei oriented design

Kansei Engineering studies use both qualitative and quantitative methodologies [40, 41, 36, 42, 43, 44, 45]. There are techniques used to collect the information such as focus group [46], self-report system [42, 47, 48], and ethnographic techniques [49]. Currently, there are eight types of KE [34, 10] as follows:

- **KE Type I: Category Classification**

  Methods in this category convert the feelings of the consumer to the design elements of a product. The product is produced according to the designed elements form KE. Mazda Miata [14] is an example of Kansei Engineering in this category.

- **KE Type II: KE System**

  This is a Computer Aided KE System (KES). Examples of this category implementation are flower arrangements [47] and house design support systems [50].

- **KE Type III: KE Modeling**

  In KE Modeling, mathematical modeling is used as logic. The mathematical model represents the knowledge in the system. [51] has implemented the KE Modeling in *"Word sound diagnostic system."*

- **KE Type IV: Hybrid KE**

There are two types of Kansei Engineering Systems (KES) for supporting consumers and designers. Forward Kansei Engineering System (Forward KES) is a consumer decision support system, while Backward Kansei Engineering System (Backward KES) is a designer support system. Hybrid KE combines the systems of both the Forward and Backward KES [52].

- **KE Type V: Virtual KE**

  Virtual KE implements the Virtual Reality (VR) technique in KE. Customers examine a Kansei product and its design elements in the virtual world. For example, Matsushita Electric Works [53] implements Virtual KE to design its kitchen cabinets.

- **KE Type VI: Collaborative KE**

  In this category, designers and consumers cooperate to develop a new design of a product. Designers and consumers are collaborating through a network. Therefore, they are not required to present in the same place. Internet Collaborative Design System is an example of Collaborative KE.

- **KE Type VII: Concurrent KE**

  In this category, we gather the representatives from various departments in a company to conduct a Kansei evaluation and analysis by brainstorming. In [54], the concurrent KE was implemented to design the container for a shampoo.

- **KE Type VIII: Rough Sets KE**

  In general, Kansei has nonlinear characteristics which can be treated independently. The decision rules can be determined by group meaning in If-Then style. In [55], the study of a beer can is demonstrated by using Rough Sets KE.

In this thesis, our framework is based on [56] and shown in figure 2.1.

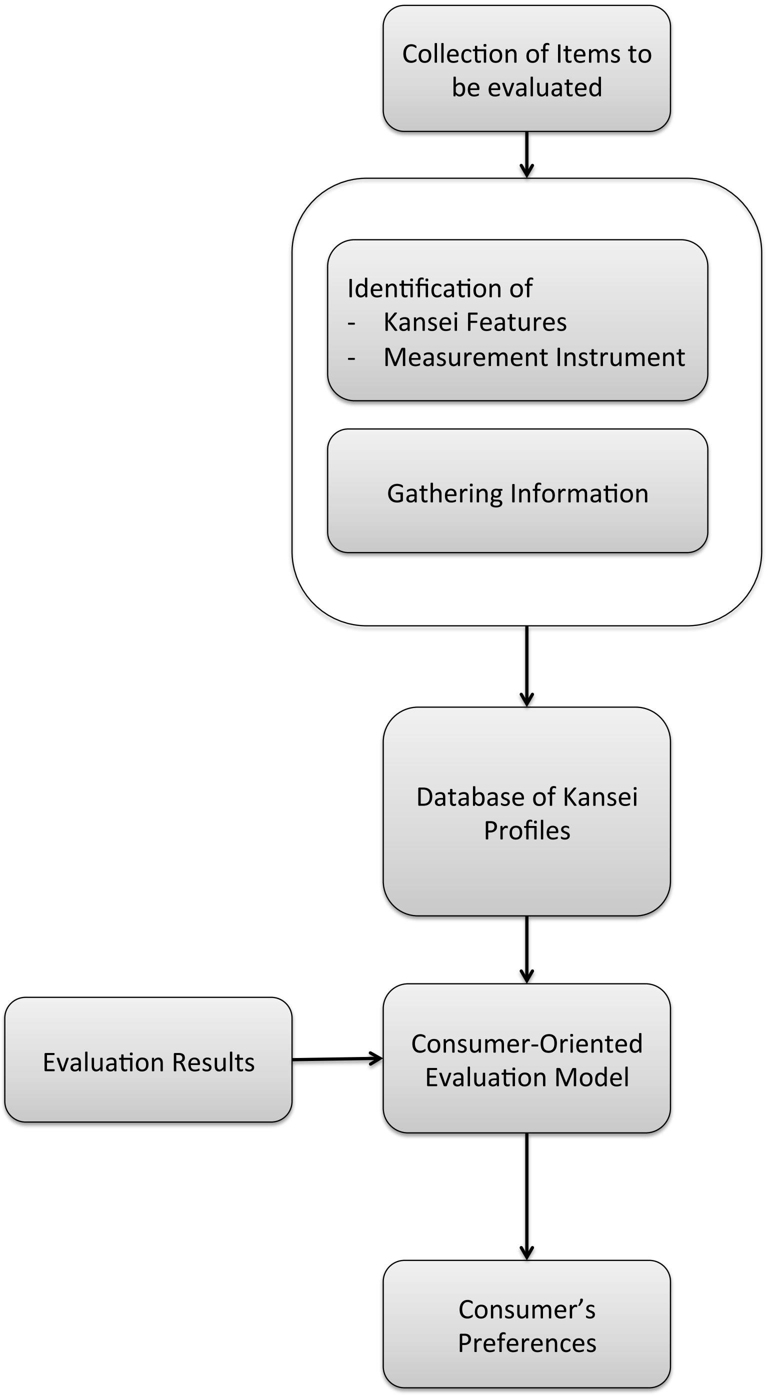


Figure 2.1: Consumer-oriented Evaluation Framework

2.2 Fuzzy set

Fuzzy sets were introduced by Zadeh in 1965 [57]. Fuzzy sets are used in many areas, such as linguistics [58], decision-making [59] and clustering [60]. A fuzzy set is used as a tool in Kansei engineering (Type-III). In the decision-making process, we sometimes cannot precisely define or express our feeling towards products. This section is a summarization from [61] and [62].

A fuzzy set is an extension of the crisp or classic set. In a fuzzy set, every element is a member of the set with membership degree. Contrarily, each element is either a member or not a member of the set.

2.3 Computing with words

Computing with words is a methodology of using words or linguistic terms in place of numbers for computing and reasoning [63, 64]. In [65, 66], the framework and methodology to compute with words are introduced. The knowledge of experts can be embedded into system models using linguistic rules.

2.4 Multi-attribute decision analysis

2.4.1 Introduction

In Multi-attribute decision analysis (MADA) problems, we have to select the best alternative regarding to its fitness [67]. Most of MADA techniques use a concept of a decision matrix, as shown in table 2.1.

In table 2.1, $\mathcal{O} = \{O_1, O_2, ..., O_M\}$ is the set of alternatives (products), and $\mathcal{A} = \{A_1, A_2, ..., A_M\}$) is the set of attributes. The consequence on attribute A_n of alternative O^m is expressed as $A_n(O^m)$ or A_n^m. Based on work by Chen [68, 69], there are three types of preference expressions: value functions (preferences on consequences), weights (preferences on criteria), and aggregation operators (preferences on aggregation modes).

Table 2.1: Multi-attribute decision matrix

Alternatives	Attributes			
	A_1	A_2	...	A_N
O^1	A_1^1	A_2^1	...	A_N^1
O^2	A_1^2	A_2^2	...	A_N^2
....	....	....	....	....
O^M	A_1^M	A_2^M	...	A_M^1

2.4.2 Preferences on consequence data

In multi-attribute decision analysis problems, there are several ways to express preferences based directly on consequences (e.g., definition 16).

Definition 1. *[69] The MADA's preference on consequence for attribute A_n of alternative O^m is a value $c_n(A_n^m) = c_n^m$. The MADA's preference on consequences over all attributes of alternative O^m is the value vector*

$$c^m = (c_1^m, ..., c_N^m). \tag{2.1}$$

The relationship between consequences and values can be expressed as

$$c_n^m = f_n(A_n^m) \tag{2.2}$$

whereas:

$$f_n(A_n^m) : A_n^m \rightarrow [0, 1] \tag{2.3}$$

There are two types of approaches based on [69, 68] to generate values based on consequences: single alternative-based methods and binary alternative-based methods.

1. Single alternative-based methods: Single alternative-based methods focus on the expression of values according to single alternative, such methods are Utility functions [70], Normalization functions [71], Fuzzy set based approach [72], Aspiration-level functions [73].

2. Binary alternative-based methods: Binary alternative-based methods focus on the expression of values comparing two alternatives, such methods are Analytic Hierarchy Process Method [74], ELECTRE [75], the PROMETHEE method [76]

2.4.3 Preferences on attributes

These preferences refer to expressions of the relative importance of attributes which generally called weights [69]. Given the weight for attribute X_n is w_n, we assume that $w_n \geqslant 0$ for all criteria, and $\sum_{n=1}^{N} w_n = 1$. A weight vector is denoted $W = (w_1, ..., w_n, ...w_N)$. The weights approaches are as follows:

1. AHP and geometric ratio weighting
2. Swing weights apply ratio data to represent weights
3. Ordered weighted averaging (OWA) weights
4. Data envelopment analysis (DEA)

2.4.4 Preferences on aggregation modes

These preferences consider that some criteria are more important than others. the multi-attribute decision analysis associates different importance weights with different attributes.

2.4.5 Consumer-oriented evaluation model

Two main problems in consumer-oriented evaluation for multi-attribute decision analysis are aggregation and ranking problems. Among the various studies in Kansei evaluation, statistical analysis is widely accepted [77, 19, 25]. Researchers in [25, 78] used the principal component analysis (PCA) and its extension called fuzzy PCA to reduce the complexity of the Kansei evaluation process. In [26], researchers proposed an approach which evaluates new product prototypes. The evaluation is justified by their relationship to the ideal product. There are also studies on subjective evaluation, decision analysis, and sensory evaluation. These methods have been used in the evaluation problems [79, 80, 81, 82, 83, 84, 85].

To summarize, the main problems of Kansei evaluation process are:

1. The preference of consumer are subjective and vary.
2. It is hard to identify their heuristic functions for Kansei attributes of consumer[86].

3. The priority of Kansei attributes is different according to each consumer.

To solve the problems mentioned above, we use *Kansei evaluation based on multi-attribute fuzzy target-oriented decision analysis and prioritized aggregation* technique. In order to represent vagueness of consumer's preference, we use fuzzy targets. Additionally, there are many Kansei attributes to be considered. To deal with the multiple and prioritized Kansei attributes, Yager[32] propose the prioritized aggregation operators.

2.4.6 Ranking fuzzy numbers

There are many studies comparing and ranking fuzzy numbers, mainly related to applications of fuzzy sets in decision analysis [87, 88, 89, 90, 91]. The collection of cases examined by Bortolan and Degani [92] has been widely used as the benchmark example for comparative studies of ranking methods [93]. Ranking methods can be divided into three types [94].

1. Defining a ranking function or defuzzification function [95, 96, 97, 98].

2. Comparing fuzzy numbers using predefined reference sets [99, 100, 101, 102].

3. Constructing a set of the pairwise relationships between fuzzy numbers to develop a formula to calculate the ranking of these fuzzy numbers using the set of relationships [103, 104, 105, 106].

2.5 Summary

In this chapter, we present the background of Kansei engineering and the related theories to provide the context of our thesis. First, we begin with a basic definition and application of Kansei Engineering. Then, the fundamentals of a fuzzy set are briefly reviewed. A fuzzy set is widely used to solve problems with uncertainty and ambiguity which resemble the fundamental need for Kansei Engineering. We also illustrate a methodology based on the concept of the fuzzy set that uses words or linguistic terms for computing and reasoning. We summarize the methodology proposed by Lawry [66] in this chapter. Finally, a literature review of problems related to muti-attribute decision-making is provided. In the next chapter, a model for representing Kansei data is proposed.

Chapter 3

A Linguistic representation method for Kansei data

In this chapter, we propose a method for modeling Kansei data called "A Linguistic Representation Method for Kansei Data." Naturally, the subjective feeling of a consumer is vague and uncertain. This characteristic of Kansei data is hard to represent. To tackle this issue, we propose a modeling method based on the linguistic interpretation of a Kansei judgment to represent Kansei data. The proposed modeling method incorporates not only the uncertainty in Kansei data but also the phenomenon called "semantic overlapping" of Kansei data.

3.1 Kansei experiment

To acquire Kansei data for modeling, we conduct a Kansei experiment (Figure 3.1). First, we identify the set of product items to be assessed. The number of product items can vary depend on product domain [26, 107, 108, 109, 110, 7].

We denote a set of product items as

$$\mathcal{O} = \{O_1, O_2, \ldots, O_M\}$$

Then, product experts and Kansei engineers, are responsible for identifying a set of Kansei attributes through brainstorming process [27]. These attributes are defined to represent aesthetic attributes regarding selected items. We denote the set of Kansei attributes as

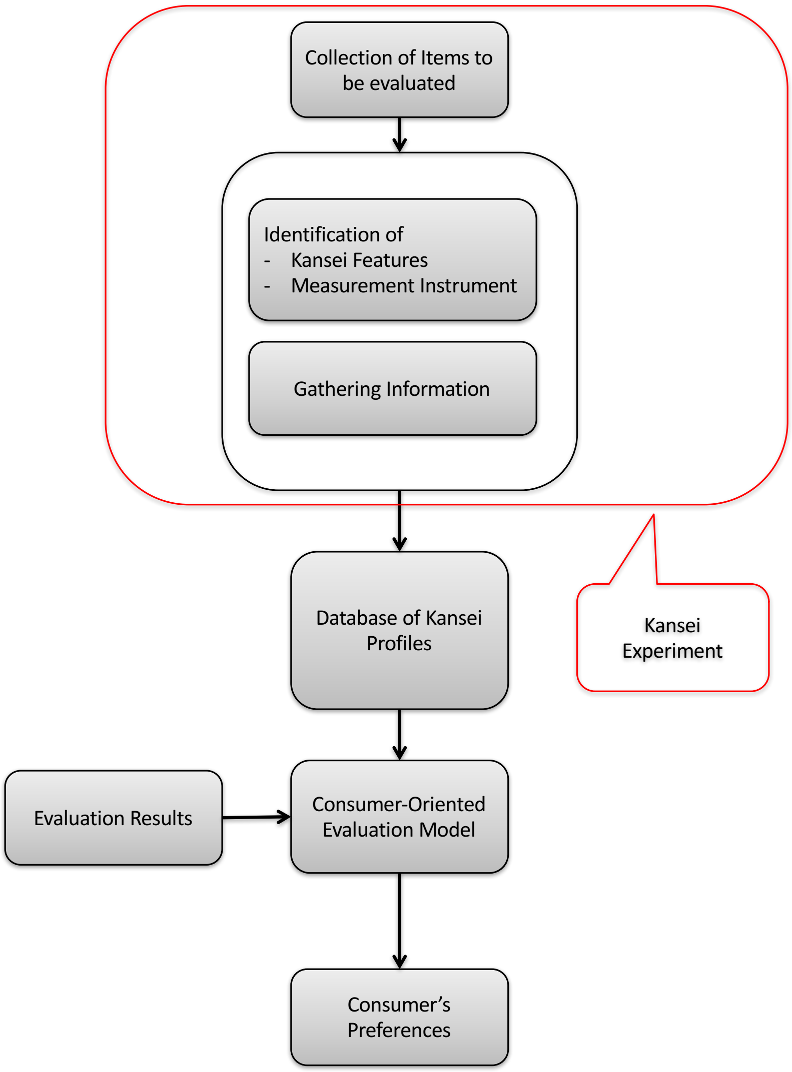


Figure 3.1: Consumer-oriented Evaluation Framework

$$\mathcal{A} = \{A_1, A_2, \ldots, A_N\}$$

We use a bipolar pair of Kansei words $\langle \mathbf{w}_n^-, \mathbf{w}_n^+ \rangle$ to define Kansei attribute A_n [2]. We denote the set of bipolar pair of Kansei words as

$$\mathbf{W} = \left\{ \left\langle \mathbf{w}_n^-, \mathbf{w}_n^+ \right\rangle | n = 1, \ldots, N \right\}.$$

After selecting a set of product items and defining a set of Kansei attributes, we design a questionnaire to assess product items. Typically, we employ the semantic differential (SD) method to design a questionnaire [111].

For each product item in questionnaire, there are N Kansei attributes with a G-points scale denoted as

$$\mathcal{V} = \{v_1, v_2, \ldots, v_G\} \tag{3.1}$$

where $\mathbf{w}_n^-$ and $\mathbf{w}_n^+$ are at the ends between v_1 and v_G as illustrated in Figure 3.2.

A_n

$\mathbf{w}_n^-$	v_1	$\cdots$	v_G	$\mathbf{w}_n^+$

Figure 3.2: Qualitative G-point scale for gathering Kansei data

According to "the rule of seven plus or minus two" [112], we usually use 5-point, 7-point, or 9-point scale in the questionnaire [78, 113, 107, 114, 3].

A population of subjects which is denoted as

$$\mathbf{E} = \{E_1, E_2, \ldots, E_K\}$$

is selected and invited to conduct Kansei experiment. They are requested to assess the product items $\mathcal{O}$ on Kansei attributes $\mathcal{A}$ using the G-point scale.

Let us denote the Kansei database which is assessed by subject subject $e_k \in \mathbf{E}$ for product $O_m \in \mathcal{O}$ on Kansei attribute $A_n \in \mathcal{A}$ as

$$x_m^n(e_k)$$

where:

$$x_m^n(e_k) \quad \in \mathcal{V}$$

for:

$$\begin{aligned} m &= 1, \ldots, M \\ n &= 1, \ldots, N \\ k &= 1, \ldots, K \end{aligned}$$

as shown in Table 3.1.

Table 3.1: Kansei database of product O_m

Subjects $\mathbf{E}$	Kansei attributes $\mathcal{A}$			
	A_1	A_2	$\dots$	A_N
e_1	$x_m^1(e_1)$	$x_m^2(e_1)$	$\dots$	$x_m^N(e_1)$
e_2	$x_m^1(e_2)$	$x_m^2(e_2)$	$\dots$	$x_m^N(e_2)$
$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
e_K	$x_m^1(e_K)$	$x_m^2(e_K)$	$\dots$	$x_m^N(e_K)$

In the rest of this chapter, we describe the proposed method to represent Kansei data acquired from Kansei experiment.

3.2 Linguistic interpretation of Kansei data

For simplicity, most studies in Kansei engineering treat the value of Kansei data in Equation (3.1) as a crisp number. As a result, the qualitative and ambiguous nature of Kansei attributes are not considered. Therefore, we propose an approach which considers $\mathcal{V}$ as a linguistic variable. The linguistic variable is introduced by Zadeh in 1975 [115]. It is developed for reasoning and computing with ambiguity in natural language. Generally, a linguistic variable is defined as

$$\langle \mathcal{L}, \mathrm{T}(\mathcal{L}), \Omega, \mathrm{S}, \mathrm{M} \rangle \tag{3.2}$$

Where:

- $\mathcal{L}$: the name of the variable
- $\mathrm{T}(\mathcal{L})$: the set of labels or words
- Ω : a universe of discourse
- S : a syntactic rule for generating linguistic terms of $\mathrm{T}(\mathcal{L})$
- M : the semantic rule which associates with each linguistic label

Under such an observation, we model Kansei data from Kansei assessment of products as a *Kansei linguistic variable* denoted by

$$\langle \mathcal{L}_n, \mathrm{T}(\mathcal{L}_n), \Omega, \mathrm{M} \rangle \tag{3.3}$$

Where:

$$\begin{aligned} L_g^n &: \ \text{the linguistic value with } v_g \text{ as its modal value} \\ \mathrm{T}(\mathcal{L}_n) &: \ \{L_1^n, L_2^n, \ldots, L_G^n\} \\ \Omega &: \ [1, G] \\ \mathrm{M} &: \ \text{maps linguistic value in } \mathrm{T}(\mathcal{L}_n) \text{ to a } [1, G] \end{aligned}$$

If a subject from population assesses product O_m on Kansei attribute A_n using v_g, it means that the subject has selected Kansei linguistic label L_g^n. This L_g^n is regarding as judgment of a subject. It is expressed by an assertion that "O_m on X_n is L_g^n". However, by the nature of Kansei attributes, a subject sometimes is not certain about his judgment in their assessments. To summarize, if a subject assesses product O_m on attribute A_n using L_g^n, the subject is not 100% certain that L_g^n is perfect representation of his judgement. The other Kansei labels $L_l^n (l \neq g)$ in $\mathcal{L}_n$ can also be used to describe O_m on A_n. We call this phenomenon as *semantic overlapping* of Kansei data. In this context, similar with [116], L_g^n is called the prototype Kansei label of a subject's Kansei judgment. Next, we propose a method for modeling Kansei data.

3.3 Linguistic representation of products' Kansei value

First, we denote the Kansei linguistic variable $\mathcal{L}_n = \{L_1^n, L_2^n, \ldots, L_G^n\}$. It is used for linguistic assessments of products on attribute A_n by subjects. We assume that $\Omega = [1, G]$ is the underlying domain. Kansei linguistic labels in $\mathcal{L}_n$ are semantically represented by fuzzy sets in the underlying domain Ω.

Thus, the Kansei value of products is modeled by a base variable x over Ω. Subjects use the Kansei linguistic labels in $\mathcal{L}_n$ to express their subjective assessment of products.

Let us denote $\mu_{L_g^n} : [1, G] \to [0, 1]$ the membership function of Kansei linguistic label L_g^n. Based on Lawry's notion of the linguistic description of value or (fuzzy) set of values in the underlying domain of a linguistic variable [65], we now introduce in this section the concept of a linguistic representation of products' Kansei (imprecise) value.

For $\omega \in \Omega$, the linguistic description of Kansei value ω relative to the linguistic variable $\mathcal{L}_n$ is a fuzzy set of $\mathcal{L}_n$ whose membership function, denoted by $\text{des}_{\mathcal{L}_n}(\omega)$, is defined by

$$\text{des}_{\mathcal{L}_n}(\omega) = \{(L_g^n, \mu_{L_g^n}(\omega))|g = 1, \ldots, G\} \tag{3.4}$$

Then we can derive the mass assignment of the fuzzy set $\text{des}_{\mathcal{L}_n}(\omega)$ on $\mathcal{L}_n$, that would provide a probabilistic interpretation for the linguistic description of ω [117, 118, 65].

Let $\{\alpha_1, \alpha_2, \ldots, \alpha_J\}$ be the range of the membership function $\text{des}_{\mathcal{L}_n}(\omega)$ such that $\alpha_j > \alpha_{j+1} > 0$. The mass assignment of $\text{des}_{\mathcal{L}_n}(\omega)$, denoted by $\mathbf{m}_\omega$, is a probability distribution on $2^{\mathcal{L}_n}$ satisfying

$$\begin{aligned} \mathbf{m}_\omega(\emptyset) &= 1 - \alpha_1, \\ \mathbf{m}_\omega(F_j) &= \alpha_j - \alpha_{j+1}, \text{ for } j = 1, \ldots, J-1 \text{ and} \\ \mathbf{m}_\omega(F_J) &= \alpha_J, \end{aligned} \tag{3.5}$$

where $F_j = \{L_g^n \in \mathcal{L}_n | \mu_{L_g^n}(\omega) \geqslant \alpha_j\}$ for $j = 1, \ldots, J$, and $\{F_j\}_{j=1}^J$ are the focal elements of the mass assignment $\mathbf{m}_\omega$. The mass $\mathbf{m}_\omega(F_j)$ can be interpreted as the probability that F_j is appropriate to use for description of Kansei value ω. It is easily seen that if $\mathcal{L}_n$ forms a linguistic covering [65] of the domain Ω, i.e.,

$$\forall x \in \Omega, \max_{L_g^n \in \mathcal{L}_n} \{\mu_{L_g^n}(x)\} = 1$$

then $\mathbf{m}_\omega(\emptyset) = 0$.

After some background knowledge is given, we define the linguistic representation of Kansei value using the least prejudiced distribution [118, 65] as follows.

Definition 2. *With the above notations, the linguistic representation of Kansei value ω is defined as a mapping $p_{\mathcal{L}_n}(\cdot|\omega) : \mathcal{L}_n \to [0, 1]$, where*

$$p_{\mathcal{L}_n}(L_g^n|\omega) = \sum_{F_j : L_g^n \in F_j} \frac{\mathbf{m}_\omega(F_j)}{(1 - \boldsymbol{m}_\omega(\emptyset))|F_j|} \tag{3.6}$$

Then we have the following.

Proposition 1. *The linguistic representation of Kansei value ω defined by (3.6) is a probability distribution on $\mathcal{L}_n$.*

Proof. By definition, we have

$$\begin{aligned}
\sum_{L_g^n \in \mathcal{L}_n} p_{\mathcal{L}_n}(L_g^n|\omega) &= \sum_{L_g^n \in \mathcal{L}_n} \sum_{F_j : L_g^n \in F_j} \frac{\mathbf{m}_\omega(F_j)}{(1-\mathbf{m}_\omega(\emptyset))|F_j|} \\
&= \frac{1}{(1-\mathbf{m}_\omega(\emptyset))} \sum_{L_g^n \in \mathcal{L}_n} \sum_{F_j | L_g^n \in F_j} \frac{\mathbf{m}_\omega(F_j)}{|F_j|} \\
&= \frac{1}{(1-\mathbf{m}_\omega(\emptyset))} \sum_{F_j} \sum_{L_g^n \in \mathcal{L}_n | L_g^n \in F_j} \frac{\mathbf{m}_\omega(F_j)}{|F_j|} \\
&= \frac{1}{(1-\mathbf{m}_\omega(\emptyset))} \sum_{F_j} \mathbf{m}_\omega(F_j) \\
&= \frac{\alpha_1}{(1-\mathbf{m}_\omega(\emptyset))} = 1 \qquad \text{(by 3.5)}
\end{aligned}$$

This proves the proposition, and we interpret the value $p_{\mathcal{L}_n}(L_g^n|\omega)$ as the probability that $L_g^n \in \mathcal{L}_n$ is the appropriate prototype Kansei label to describe Kansei value ω.

In Lawry's research [65], we use the concept of the least prejudiced distribution to set the constraint when extending the concept of a linguistic description to the case where the value is imprecisely given as a set or a fuzzy set of the underlying domain. In our case, we use the least prejudiced distribution of a linguistic description as a linguistic representation of the Kansei value ω.

In the following definition, we extend the notion of linguistic representation to the case of interval Kansei value.

Definition 3. *Assume that the Kansei value ω is given imprecisely by an interval $I \subset \Omega$, then the linguistic representation of interval Kansei value I can be defined as a mapping $p_{\mathcal{L}_n}(\cdot|\omega) : \mathcal{L}_n \to [0,1]$ by*

$$p_{\mathcal{L}_n}(L_g^n|I) = \frac{1}{\sigma(I)} \int_I p_{\mathcal{L}_n}(L_g^n|\omega) d\omega \qquad (3.7)$$

where $\sigma(I)$ is the length of interval I.

The rationale behind this definition is the following: the Kansei value ω given imprecisely is regarded as a random variable having a uniform distribution on I, then $p_{\mathcal{L}_n}(L_g^n|I)$ defined by (3.7) can be interpreted as the expected probability that L_g^n is the prototype Kansei label used to describe imprecise Kansei value ω given by I.

By definition and from Proposition 1, the following easily follows.

Proposition 2. *The linguistic representation of interval Kansei value I defined by (3.7) is a probability distribution on $\mathcal{L}_n$.*

Furthermore, the notion of linguistic representation can be extended to the case where the Kansei value ω is given imprecisely by a fuzzy number in Ω.

Definition 4. *Let F be the fuzzy Kansei value represented by a fuzzy set in Ω. Then the linguistic representation of fuzzy Kansei value F is defined by*

$$p_{\mathcal{L}_n}(L_g^n|F) = \int_0^1 \int_{F_\alpha} \frac{p_{\mathcal{L}_n}(L_g^n|\omega)}{\sigma(F_\alpha)} d\omega d\alpha \tag{3.8}$$

where F_α is the alpha-cut of F.

Again it follows by definition and Proposition 1 the following.

Proposition 3. *The linguistic representation of fuzzy Kansei value F defined by (3.8) is a probability distribution on $\mathcal{L}_n$.*

As we already introduce a notation of linguistic representation and its extension. Next, we discuss how to extend a notation of linguistic representation further to capture the semantic overlapping amongst Kansei labels. First, we assume that a subject $e \in \mathbf{E}$ determines a Kansei label $L \in \mathcal{L}_n$ as his judgment for product $o \in \mathbf{O}$ on attribute $a \in \mathbf{A}$. We cannot imply that L is only representation. The other labels could also describe the Kansei value ω. This can be modeled using the linguistic representation of subject e's Kansei judgment L, represented by a membership function μ_L, using Equation (3.8). In other words, taking the semantic overlapping amongst Kansei labels into account the original Kansei judgment of subject e can be now represented as a probability distribution on $\mathcal{L}_n$ as below

$$[p_{\mathcal{L}_n}(L_1^n|L), p_{\mathcal{L}_n}(L_2^n|L), \ldots, p_{\mathcal{L}_n}(L_G^n|L)] \tag{3.9}$$

where $p_{\mathcal{L}_n}(L_g^n|L)$ is interpreted as the probability that Kansei label L_g^n is appropriate to use for the description of the subject's Kansei value of a product, given his/her Kansei judgment L.

3.4 Kansei profiles

To generate Kansei profiles for products, we assume further that there is a probability distribution, denoted by $p_{\mathbf{E}}$, given in the population of subjects $\mathbf{E}$. This probability distribution can be interpreted in a similar way as in the case of multi-expert decision-making with linguistic assessment [119]. In [2], this probability distribution is used as Kansei profile. For illustration, The Kansei profile of product #31 attribute A_7 and A_8 are shown in Figure 3.3 and 3.4 respectively. In Figure 3.5, the profile of all attributes of product #31 are illustrated. After applying proposed method, a new Kansei profile is calculated. Figure 3.6 and 3.7 show the comparison of Kansei profile between two approaches for product #31 attributes A_7 and A_8 respectively. In Figure 3.8, the profile of all attributes of product #31 using proposed method are illustrated. More details are presented and discussed in Chapter 5.

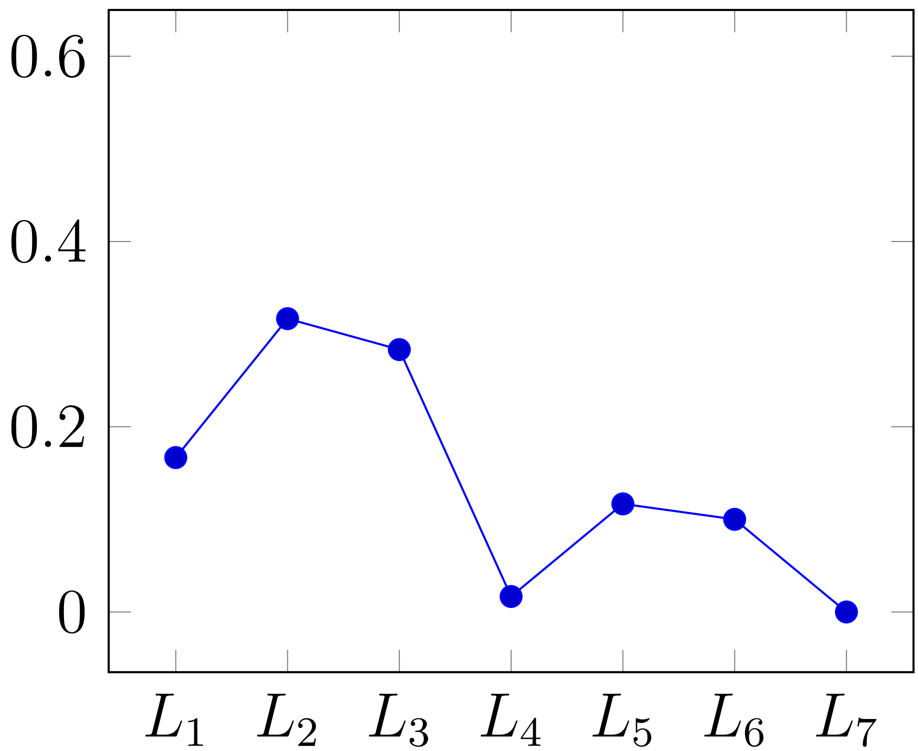


Figure 3.3: Kansei profile of product #31 attribute A_7

Let us return back to Table 3.1. For each Kansei attribute A_n $(n = 1, \ldots, N)$ we have the linguistic variable $\mathcal{L}_n$ used as a means for representing Kansei assessments by subjects. For the Kansei judgment of subject e_k on Kansei attribute A_n of product O_m, $x_m^n(e_k) \in \mathcal{L}_n$, by Equation 3.9 we obtain a linguistic representation of e_k's Kansei judgment $x_m^n(e_k)$ represented as the following distribution on $\mathcal{L}_n$

$$[p_{\mathcal{L}_n}(L_1^n|x_m^n(e_k)), p_{\mathcal{L}_n}(L_2^n|x_m^n(e_k)), \ldots, p_{\mathcal{L}_n}(L_G^n|x_m^n(e_k))]$$

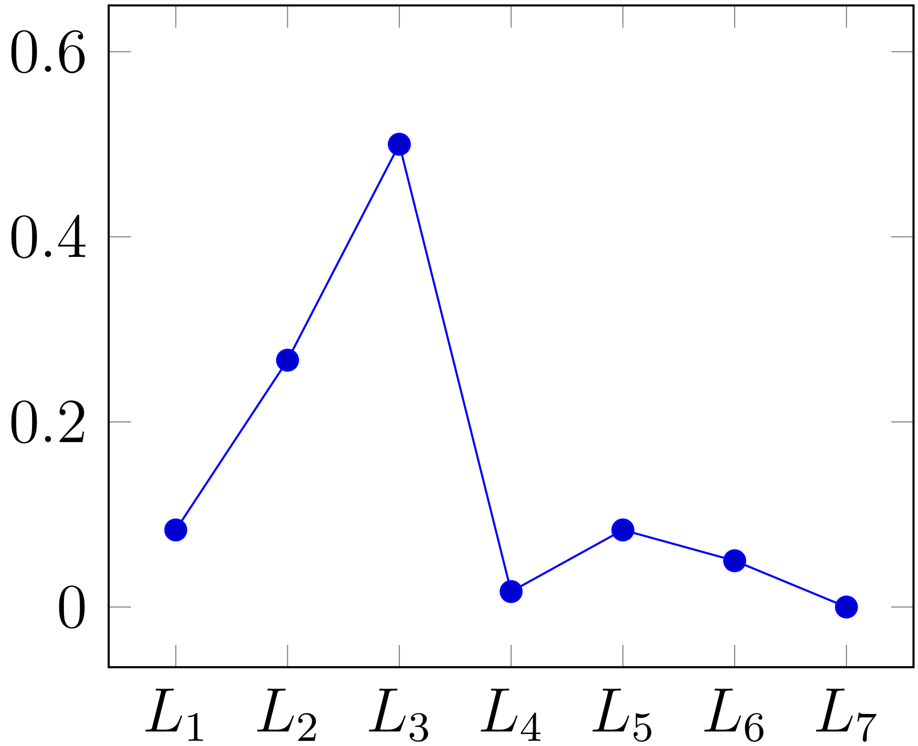


Figure 3.4: Kansei profile of product #31 attribute A_8

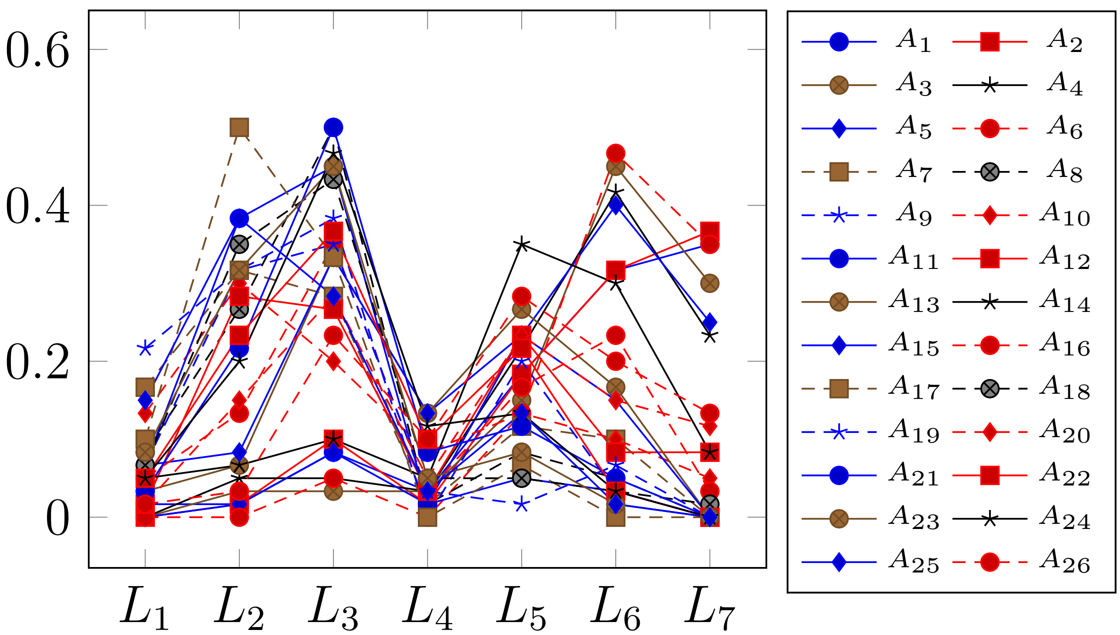


Figure 3.5: Kansei profile of product #31

In addition, taking the distribution $p_{\mathbf{E}}$ into account, we can now define the collective linguistic representation of Kansei judgment on Kansei attribute A_n ($n = 1, \ldots, N$) of product O_m $(m = 1, \ldots, M)$ as follows

$$\begin{aligned}\mathbf{p}_m^n(L_g^n) &= \sum_{e_k \in \mathbf{E}} p_{\mathcal{L}^n}(L_g^n | x_m^n(e_k)) \cdot p_{\mathbf{E}}(e_k) \\ &= \sum_{k=1}^{K} p_{\mathcal{L}^n}(L_g^n | x_m^n(e_k)) \cdot \pi_k,\end{aligned} \tag{3.10}$$

where $\pi_k = p_{\mathbf{E}}(e_k)$ and $g = 1, \ldots, G$.

For each $h = 1, \ldots, G$, let denote

$$\mathbf{E}_h = \{e_k \in \mathbf{E} | x_m^n(e_k) = L_h^n\}$$

and

$$\pi_h = \sum_{e_k \in \mathbf{E}_h} \pi_k$$

Then the collective linguistic representation of Kansei judgment on Kansei attribute A_n of product O_m can be represented by

$$\mathbf{p}_m^n(L_g^n) = \sum_{h=1}^{G} p_{\mathcal{L}^n}(L_g^n | L_h^n) \cdot \pi_h \tag{3.11}$$

for $g = 1, \ldots, G$. We have the following.

Proposition 4. *The collective linguistic representation of Kansei judgment defined by (3.11) is a probability distribution on $\mathcal{L}_n$.*

Proof. Indeed, we have

$$\begin{aligned}\sum_{g=1}^{G} \mathbf{p}_m^n(L_g^n) &= \sum_{g=1}^{G} \sum_{h=1}^{G} p_{\mathcal{L}^n}(L_g^n | L_h^n) \cdot \pi_h \\ &= \sum_{h=1}^{G} \pi_h \sum_{g=1}^{G} p_{\mathcal{L}^n}(L_g^n | L_h^n) \\ &= \sum_{h=1}^{G} \pi_h = 1\end{aligned}$$

which proves the proposition. ∎

Especially, when $p_{\mathbf{E}}$ is a uniform distribution, i.e. all subjects in $\mathbf{E}$ are equally important, we obtain

$$\mathbf{p}_m^n(L_g^n) = \sum_{h=1}^{G} p_{\mathcal{L}^n}(L_g^n | L_h^n) \cdot \frac{|\mathbf{E}_h|}{K} \tag{3.12}$$

In the same way, we can obtain a N-tuple of collective linguistic representations of Kansei judgment on all attributes in $\mathcal{A}$ for product O_m, namely

$$[\mathbf{p}_m^1, \mathbf{p}_m^2, \ldots, \mathbf{p}_m^N] \tag{3.13}$$

which is referred to as Kansei profile of O_m and specifically depicted in Table 3.2.

Table 3.2: Kansei profile of product O_m

$\mathcal{A}$	Kansei linguistic variable $\mathcal{L}_n$			
	L_1^n	L_2^n	$\ldots$	L_G^n
A_1	$\mathbf{p}_m^1(L_1^1)$	$\mathbf{p}_m^1(L_2^1)$	$\ldots$	$\mathbf{p}_m^1(L_G^1)$
A_2	$\mathbf{p}_m^2(L_1^2)$	$\mathbf{p}_m^2(L_2^2)$	$\ldots$	$\mathbf{p}_m^2(L_G^2)$
$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
A_N	$\mathbf{p}_m^N(L_1^N)$	$\mathbf{p}_m^N(L_2^N)$	$\ldots$	$\mathbf{p}_m^N(L_G^N)$

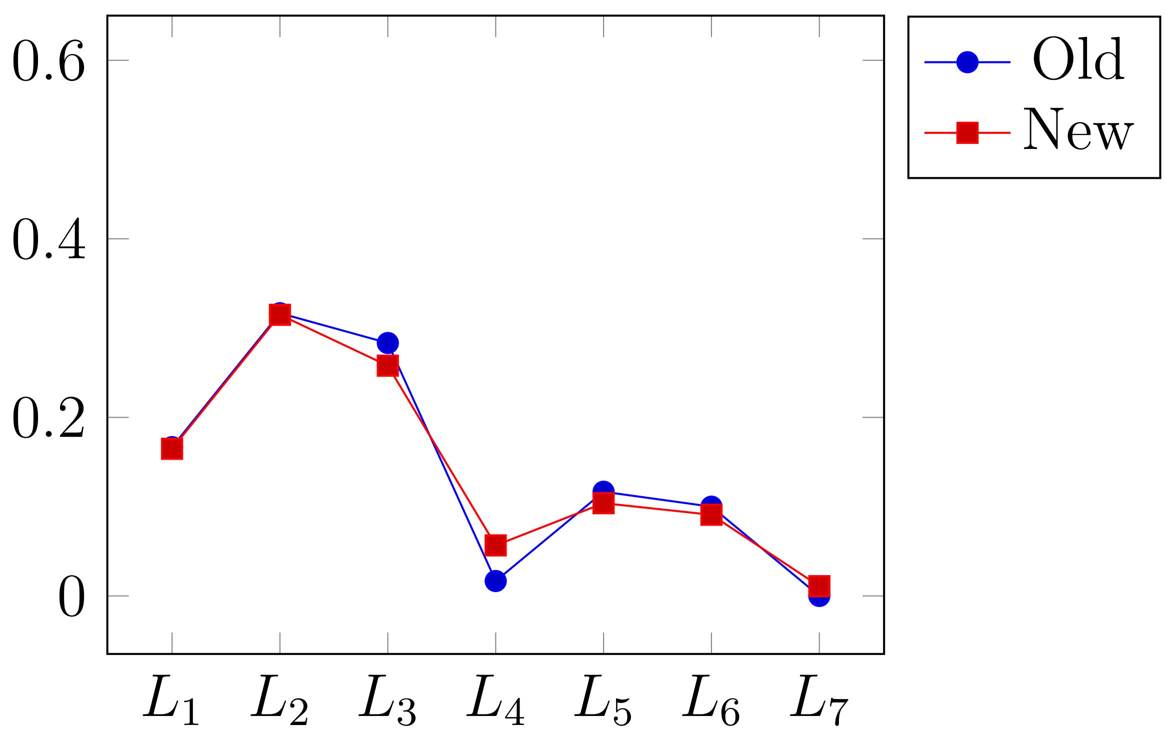


Figure 3.6: Comparison of Kansei profile of product #31 attribute A_7 between two approaches

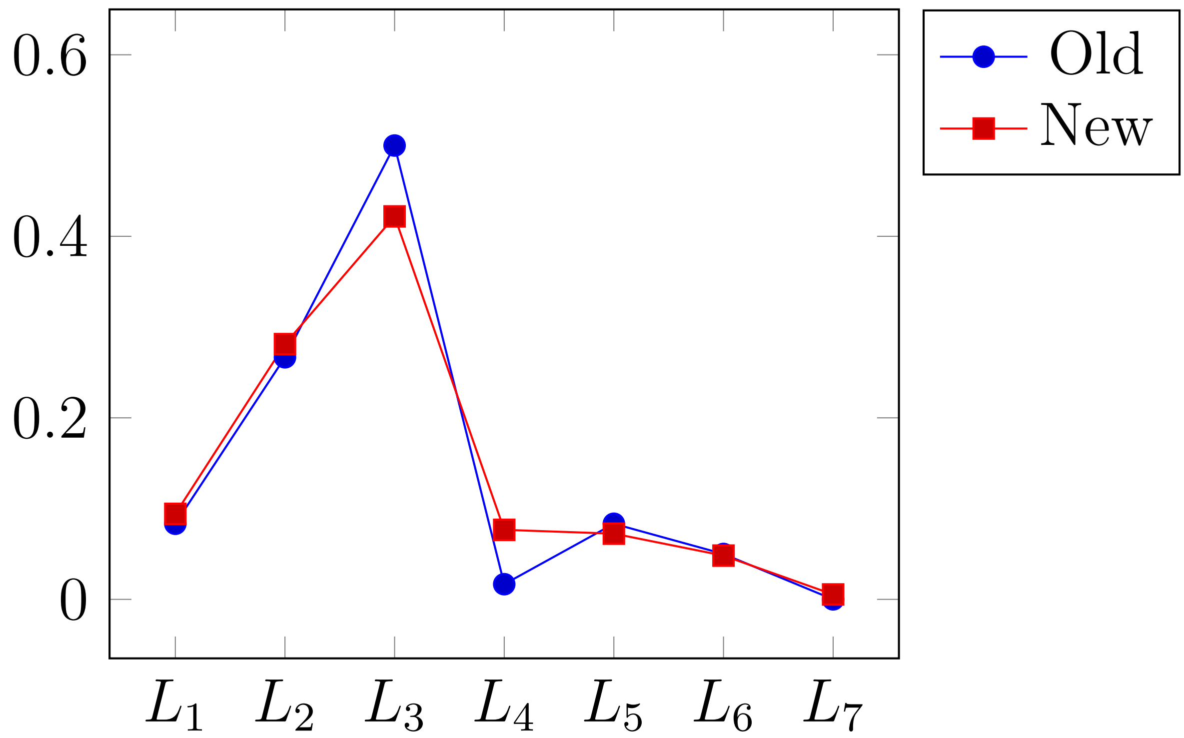


Figure 3.7: Comparison of Kansei profile of product #31 attribute A_8 between two approaches

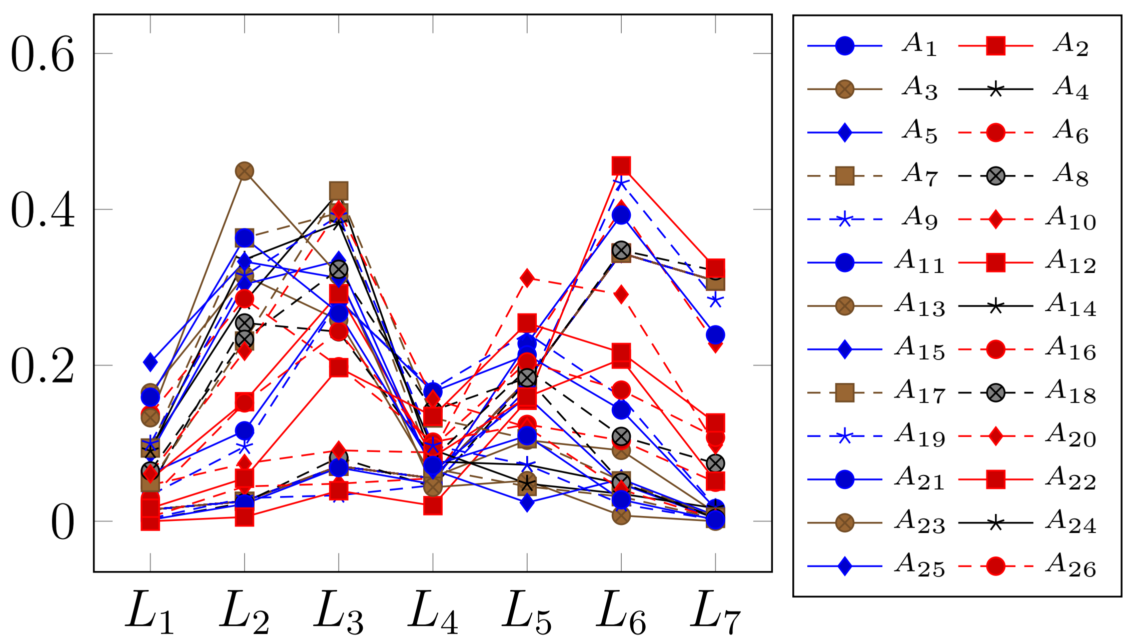


Figure 3.8: New Kansei profile of product #31

3.5 Summary

In this chapter, we propose a modeling method for representing Kansei data. This method is based on the linguistic interpretation of the Kansei judgment and the probabilistic semantics of fuzzy sets.

First, we describe the details of conducting the Kansei experiment. We illustrate the detail of how the Kansei database is acquired from a Kansei experiment. Then we present the concept of linguistic data representation. We demonstrate how to implement linguistic labels in our model to represent Kansei data. We present this interpretation using probability distribution on the set of linguistic variables. These linguistic variables are described using Kansei labels which correspond to a Kansei attribute. Later in this chapter, we implement linguistic interpretation further to represent the Kansei value of the product. This proposed method can handle the semantic overlapping of Kansei judgment between Kansei labels. Finally, we generate a Kansei profile of products. The Kansei profile generated by the proposed method can represent not only the vagueness of Kansei data but also the "semantic overlapping" problem.

Our Kansei profile can be used in many applications such as evaluation of products. In the next chapter, The Kansei profile is used as the knowledge for the personalized evaluation problem [2].

Chapter 4

A Method for Personalized Evaluation

In this chapter, we discuss the method for evaluation of a product. This evaluation problem is the "multi-attribute decision-making problem" discussed in chapter 2. Decision analysis methods are generally used in many kinds of evaluation problems [120, 121, 82, 122, 123, 124, 125, 126]. However, most of the studies on evaluation methods do not take the preference of individual consumers into consideration.

We propose a consumer-oriented evaluation model that targets the requests specified by consumers' Kansei preferences. The most straightforward method is to treat Kansei data as numerical data [127], and then use the multivariate statistical analysis to find linear relations between consumers' preferences and products' design elements. Some scholars argue that there are nonlinear characteristics between consumers' preferences and products' design elements [128, 129]. Some studies apply the Rough Set theory to analyze Kansei data [130, 131, 130]. However, the most commonly used instrument to gather Kansei data is the SD method. The proposed method aims to maximize the probability of a product meeting the feeling targets specified by a particular consumer. This approach itself is intuitively natural. However, some extensions are required to adapt our proposed evaluation method into a really practical application. In a real-world recommendation system, functional and quantitative features of traditional products are also important factors in the decision-making process of the consumer. These factors should be considered in the evaluation framework. Second, the ambiguous and uncertainty of human judgments regarding Kansei features by treating Kansei data are not considered because we represent consumers' judgments as categorical data. This problem can be solved using fuzzy sets and fuzzy-set-based extension of target-oriented decision analysis [132].

4.1 A consumer-oriented Kansei evaluation model for traditional products

Suppose there is a consumer who is interested in selecting the product that matches his preference from the predefined set of the product. Consumer's preference is defined by attributes which is a subset of the set $\mathbf{W}$. More specifically, we can state the specified requests of a consumer in the pattern of the following statement [2]:

> "I am interested in products which would best meet LQ (of) my preference specified in $W \subset \mathbf{W}$" $(\star)$

where LQ is a linguistic quantifier such as *all*, *most*, *at least half*, *as many as possible*, etc.

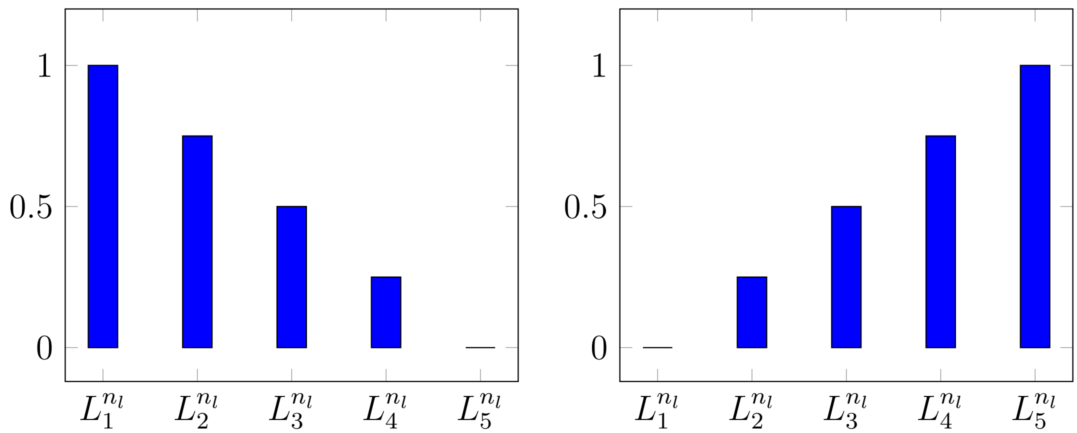
Assume that $W = \{\mathbf{w}^*_{n_1}, \ldots, \mathbf{w}^*_{n_q}\}$ and LQ corresponding to the request specified by consumer as verbally stated in $(\star)$, where $*$ stands for either $-$ or $+$, and $\{n_1, \ldots, n_q\} \subseteq \{1, \ldots, N\}$. Then the problem is now how to evaluate products in $\mathcal{O}$ using products' Kansei profiles taking consumer's request specified as the pair $[W, LQ]$ into account?

Note that by assuming that $*$ stands for either $-$ or $+$ as above, we mean that only one of the two opposite Kansei words, $\mathbf{w}^+_{n_l}$ or $\mathbf{w}^-_{n_l}$ $(l = 1, \ldots, q)$, is present in W. For an instance, the consumer who is interested in products that are *formal*, then he will not be interested in the products that are *casual*.

In the following, we will develop a so-called consumer-oriented evaluation model based on the target-based decision approach for solving this evaluation problem.

4.2 Formulating consumers' Kansei targets

Naturally, if the judgement of consumer on Kansei attribute A_{n_l} $(l = 1, \ldots, q)$ by the *left Kansei word* $\mathbf{w}^-_{n_l}$, then we can implicitly assumes her preference order on the set



(a) $\mathbf{w}_{n_l}^* = \mathbf{w}_{n_l}^-$ (b) $\mathbf{w}_{n_l}^* = \mathbf{w}_{n_l}^+$

Figure 4.1: Possibility distribution where $G = 5$

$\mathcal{L}_{n_l}$ of the Kansei linguistic labels toward $L_1^{n_l}$ where the left Kansei word $\mathbf{w}_{n_l}^-$ is placed. Conversely, if the consumer's preference on that Kansei attribute is the *right Kansei word* $\mathbf{w}_{n_l}^+$, then the preference order on $\mathcal{L}_{n_l}$ should be in the reverse order, i.e. towards the end $L_G^{n_l}$, where the right Kansei word $\mathbf{w}_{n_l}^+$ is placed. Fornally, the preference order relation on Kansei attribute A_{n_l}, denoted by $\succeq_{n_l}$, can be adaptively defined according to consumer's preference as follows:

$$\succeq_{n_l} \Leftrightarrow \begin{cases} L_1^{n_l} \succeq \cdots \succeq L_G^{n_l}, & \text{if } \mathbf{w}_{n_l}^* = \mathbf{w}_{n_l}^-; \\ L_1^{n_l} \preceq \cdots \preceq L_G^{n_l}, & \text{if } \mathbf{w}_{n_l}^* = \mathbf{w}_{n_l}^+. \end{cases} \tag{4.1}$$

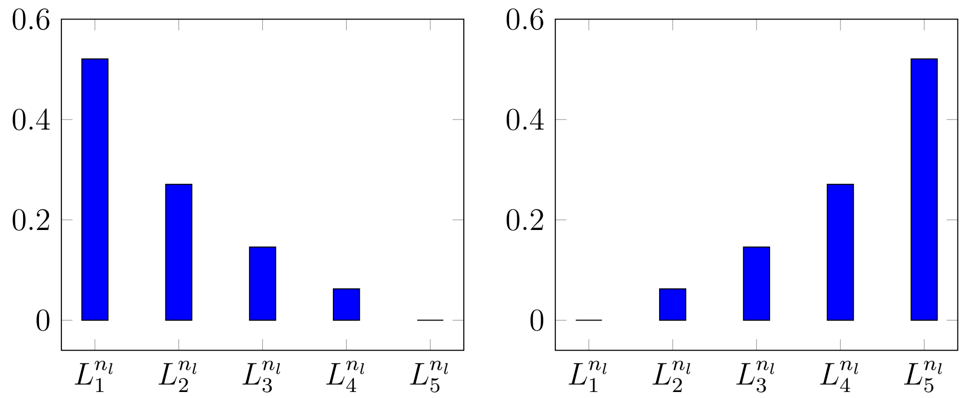
Moreover, due to the vagueness inherent in consumer's expression of preference in terms of Kansei words, similar as in [2] each $\mathbf{w}_{n_l}^*$ is considered as a fuzzy Kansei target, denoted by T_{n_l}, of the consumer with respect to Kansei attribute A_{n_l}, which can be represented as a fuzzy variable on $\mathcal{L}_{n_l}$ whose possibility distribution is defined as

$$\mu_{T_{n_l}}\left(L_g^{n_l}\right) = \begin{cases} \frac{(G-g)}{(G-1)}, & \text{if } \mathbf{w}_{n_l}^* = \mathbf{w}_{n_l}^-; \\ \frac{(g-1)}{(G-1)}, & \text{if } \mathbf{w}_{n_l}^* = \mathbf{w}_{n_l}^+. \end{cases} \tag{4.2}$$

Figure 4.1 illustrates the possibility distribution defined by Equation 4.2 given $G = 5$.

If $\mathbf{w}_{n_l}^* = \mathbf{w}_{n_l}^-$, as discussed in Section 3.3, we easily obtain the mass assignment, denoted by $\mathbf{m}_{n_l} : 2^{\mathcal{L}_{n_l}} \to [0,1]$, corresponding to possibility distribution $\mu_{T_{n_l}}(\cdot)$ such that

$$\begin{aligned} \mathbf{m}_{n_l}(T_{n_l}^g) &= \tfrac{1}{G-1}, \quad \text{for } g = 1, \ldots, G-1, \text{ and } T_{n_l}^g = \{L_1^{n_l}, \ldots, L_g^{n_l}\} \\ \mathbf{m}_{n_l}(F) &= 0, \quad \text{for any } F \in 2^{\mathcal{L}_{n_l}} \backslash \{T_{n_l}^g\}_{g=1}^{G-1} \end{aligned}$$



(a) $\mathbf{w}^*_{n_l} = \mathbf{w}^-_{n_l}$ (b) $\mathbf{w}^*_{n_l} = \mathbf{w}^+_{n_l}$

Figure 4.2: Least prejudice distribution where $G = 5$

Then the mass assignment $\mathbf{m}_{n_l}$ is transformed to the least prejudiced distribution, denoted as $\mathbf{p}_{n_l}$, by

$$\mathbf{p}_{n_l}(L_h^{n_l}) = \sum_{T_{n_l}^g | L_h^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \tag{4.3}$$

for $h = 1, \ldots, G-1$.

In a similar way, but with the reverse order preference on $\mathcal{L}_{n_l}$, we can easily compute the least prejudiced distribution $\mathbf{p}_{n_l}$ for the case $\mathbf{w}^*_{n_l} = \mathbf{w}^+_{n_l}$. Particularly, for $h = 2, \ldots, G$, we have

$$\mathbf{p}_{n_l}(L_h^{n_l}) = \sum_{T_{n_l}^g | L_h^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \tag{4.4}$$

where $T_{n_l}^g = \{L_g^{n_l}, \ldots, L_G^{n_l}\}$ for $g = 2, \ldots, G$.

Figure 4.2 illustrates the least prejudice distribution in case $G = 5$.

4.3 Target-based Kansei evaluation

As defined in Section 3.4, the Kansei profile of product O_m is N-tuple of probability distributions on $\mathcal{L}_n$ (refer to Equation 3.13) so that we obtain Kansei profiles of all products in $\mathcal{O}$ as shown in Table 4.1. This profiles is a knowledge base to evaluate product.

Let us return back to the problem of consumer-oriented evaluation that aims to evaluate products in $\mathcal{O}$ using their Kansei profiles so as to satisfy consumer's request specified as the pair $[W, LQ]$. Now, based on the fuzzy target-based decision model proposed in [93],

Table 4.1: Knowledge base of Kansei profiles of products in $\mathcal{O}$

Products $\mathcal{O}$	Kansei attributes $\mathcal{A}$			
	A_1	A_2	$\dots$	A_N
O_1	$\mathbf{p}_1^1$	$\mathbf{p}_1^2$	$\dots$	$\mathbf{p}_1^N$
O_2	$\mathbf{p}_2^1$	$\mathbf{p}_2^2$	$\dots$	$\mathbf{p}_2^N$
$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
O_M	$\mathbf{p}_M^1$	$\mathbf{p}_M^2$	$\dots$	$\mathbf{p}_M^N$

we develop a so-called target-based method for consumer-oriented evaluation problem as follows.

1. For each $\mathbf{w}_{n_l}^* \in W$, we determine the preference order on $\mathcal{L}_{n_l}$ for Kansei attribute A_{n_l} according to (4.1). Then compute the least prejudiced distribution $\mathbf{p}_{n_l}$ of fuzzy Kansei target T_{n_l} based on (4.3) or (4.4).

2. For each $O_m \in \mathcal{O}$, we get the Kansei profile of O_m: $[\mathbf{p}_m^1, \mathbf{p}_m^2, \dots, \mathbf{p}_m^N]$

   (a) For each $\mathbf{w}_{n_l}^* \in W$, compute $\mathbb{P}(\mathbf{p}_m^{n_l} \succeq \mathbf{p}_{n_l})$, the probability that the Kansei profile of O_m meets the consumer's target $\mathbf{p}_{n_l}$ on attribute A_{n_l}, by

   $$\mathbb{P}(\mathbf{p}_m^{n_l} \succeq \mathbf{p}_{n_l}) = \sum_{g=1}^{G} \mathbf{p}_m^{n_l}(L_g^{n_l}) P(L_g^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) \triangleq \mathbb{P}_m^{n_l} \tag{4.5}$$

   where $P(L_g^{n_l} \succeq_{n_l} \mathbf{p}_{n_l})$ is the cumulative probability function defined by

   $$P(L_g^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) = \sum_{L_g^{n_l} \succeq_{n_l} L_h^{n_l}} \mathbf{p}_{n_l}(L_h^{n_l}) \tag{4.6}$$

   (b) Then, the obtained probabilities $\mathbb{P}(\mathbf{p}_m^{n_l} \succeq \mathbf{p}_{n_l}) = \mathbb{P}_m^{n_l}$, for $l = 1, \dots, q$, will be aggregated into an overall value by taking the linguistic quantifier LQ into account, making use of the so-called ordered weighted averaging (OWA) operator [133]. This is done as follows.

An OWA operator of dimension q is a mapping

$$\mathcal{F} : [0,1]^q \to [0,1]$$

associated with a weighting vector $[w_1, \ldots, w_q]$ such that (i) $w_l \in [0,1]$ and (ii) $\sum_l w_l = 1$, and

$$\mathcal{F}(a_1, \ldots, a_q) = \sum_{l=1}^{q} w_l b_l \tag{4.7}$$

where b_l is the l-th largest element in the collection $[a_1, \ldots, a_q]$ and weights w_l can be obtained directly using fuzzy set-based semantics of a linguistic quantifier LQ involved in the aggregation process (see, e.g., [133], [2]).

In this thesis, we use fuzzy linguistic quantifiers as the weights. The fuzzy linguistic quantifiers were introduced in [134]. We focus on the relative quantifiers such as *most* and *at least half*. A relative quantifier F is defined as a mapping

$$\mathcal{F} : [0,1]^q \rightarrow [0,1]$$

Where:

$$\begin{aligned} F(0) &= 0 \\ \exists r \in [0,1] &\ \text{that } Q(r) = 1 \\ \text{Q} &\ \text{is a nondecreasing function} \end{aligned}$$

In [135], the generic membership function define as

$$Q(r) = \begin{cases} 0 \text{ if } r < a \\ \frac{r-a}{b-a} \text{ if } a \leqslant r \leqslant b \\ 1 \text{ if } \ \text{if } r > b \end{cases} \tag{4.8}$$

Where:

$a, b \in [0,1]$

Figure 4.3 illustrates the generic membership function from equation 4.8

Then, Yager [133] propose to compute the weights w_i's based on the linguistic quantifier represented by Q as follows:

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right), \text{ for } i = 1, ..., n. \tag{4.9}$$

Eqaution 4.10-4.15 are examples of linguistic quantifiers associate with their membership functions from [135, 133].

Linguistic quantifier: *there exists*

$$Q(r) = \begin{cases} 0 \text{ if } r = 0 \\ 1 \text{ if } r > 0 \end{cases} \tag{4.10}$$

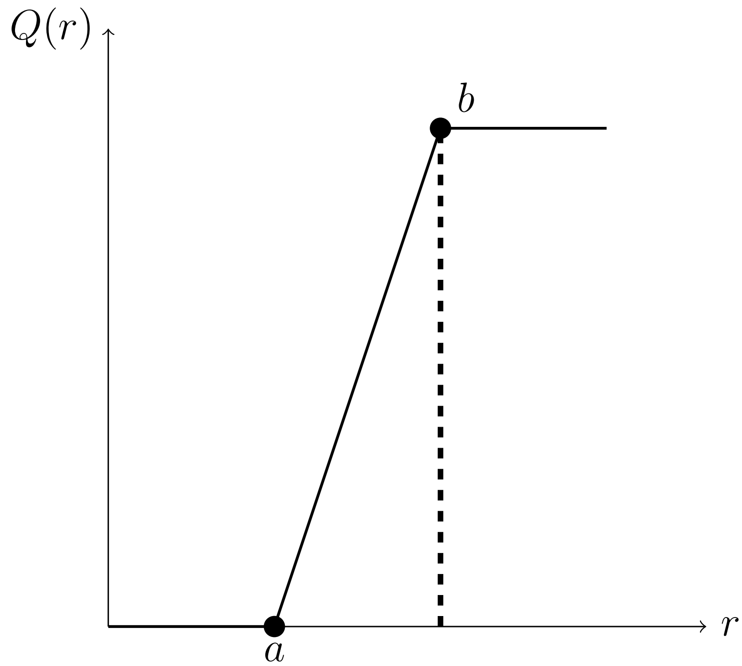


Figure 4.3: Generic membership function

Linguistic quantifier: *for all*

$$Q(r) = \begin{cases} 1 \text{ if } r = 1 \\ 0 \text{ if } r \neq 1 \end{cases} \tag{4.11}$$

Linguistic quantifier: *identity*

$$Q(r) = r \tag{4.12}$$

Linguistic quantifier: *at least half*

$$Q(r) = \begin{cases} 2r & \text{if } 0 \leqslant r \leqslant 0.5 \\ 1 & \text{if } 0.5 \leqslant r \leqslant 1 \end{cases} \tag{4.13}$$

Linguistic quantifier: *as many as possible*

$$Q(r) = \begin{cases} 0 & \text{if } 0 \leqslant r \leqslant 0.5 \\ 2r - 1 & \text{if } 0.5 \leqslant r \leqslant 1 \end{cases} \tag{4.14}$$

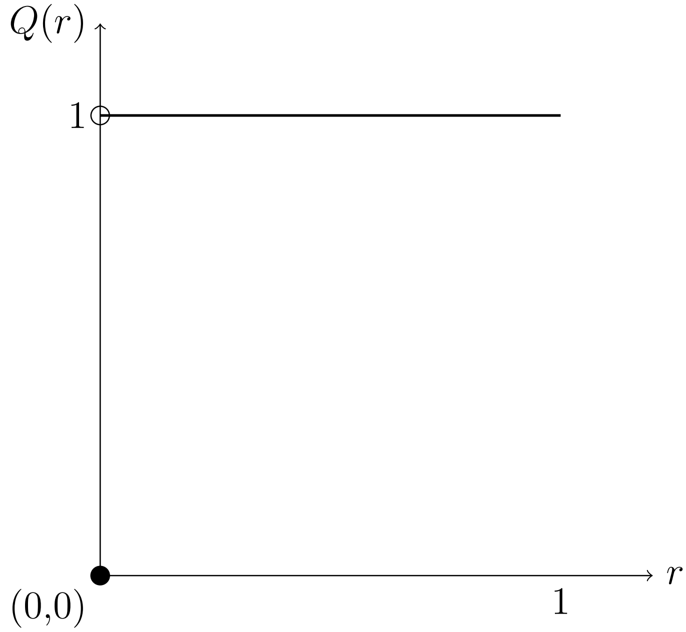


Figure 4.4: *There exists* membership function

Linguistic quantifier: *most*

$$Q(r) = \begin{cases} 0 & \text{if } 0 \leqslant r \leqslant 0.3 \\ 2r - 0.6 & \text{if } 0.3 \leqslant r \leqslant 0.8 \\ 1 & \text{if } 0.8 \leqslant r \leqslant 1 \end{cases} \tag{4.15}$$

Figure 4.4-4.9 illustrate the membership function from equation 4.10 - 4.15

There are additional measures *"orness"* and *"andness"* for OWA operator $\mathcal{F}$ associated with weighting vector $w = [w_1, ..., w_n]$ are defined as

$$orness(\mathcal{F}) = \frac{1}{n-1}\sum_{i=1}^{n}((n-i)w_i) \tag{4.16}$$

$$andness(\mathcal{F}) = 1 - orness(\mathcal{F}) \tag{4.17}$$

Table 4.2 and 4.3 show linguistic quatifiers and the aggreagation behavior of corresponding OWA $\mathcal{F}$ for the case $n = 5$ respectively.

With OWA operator $\mathcal{F}$ encoding the semantics of linguistic quantifier LQ, we now define the evaluation function, for any $O_m \in \mathcal{O}$, as follows

$$V(O_m) = \mathcal{F}\left(\mathbb{P}_m^{n_1}, \ldots, \mathbb{P}_m^{n_q}\right) \tag{4.18}$$

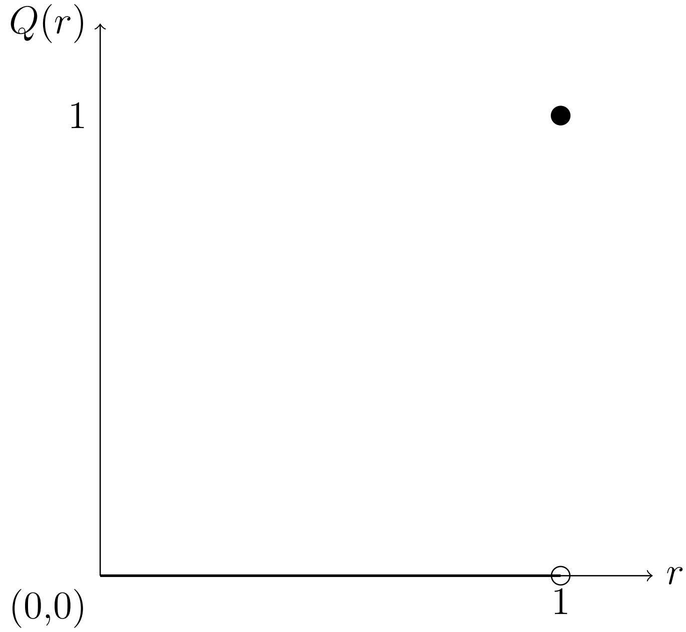


Figure 4.5: *For all* membership function

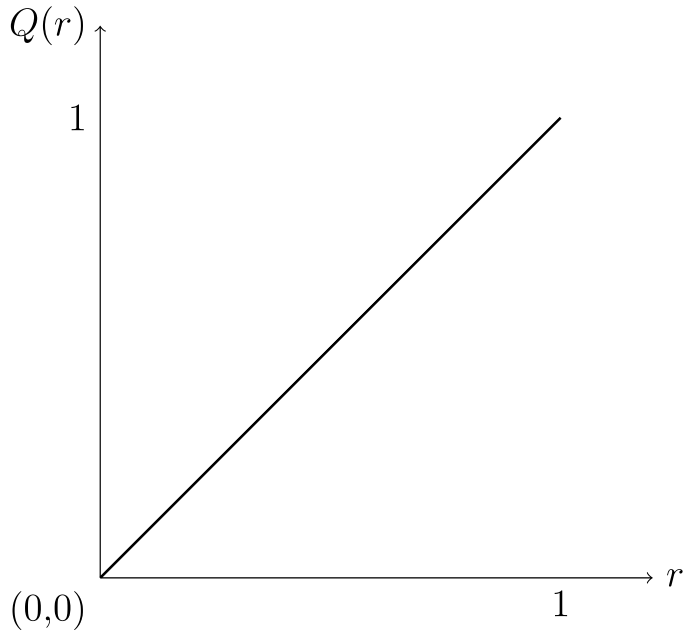


Figure 4.6: *Identity* membership function

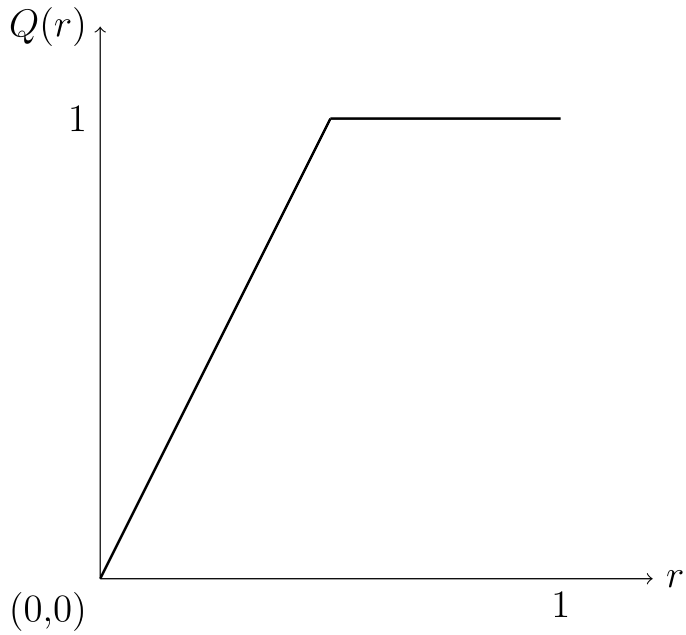


Figure 4.7: *At least half* membership function

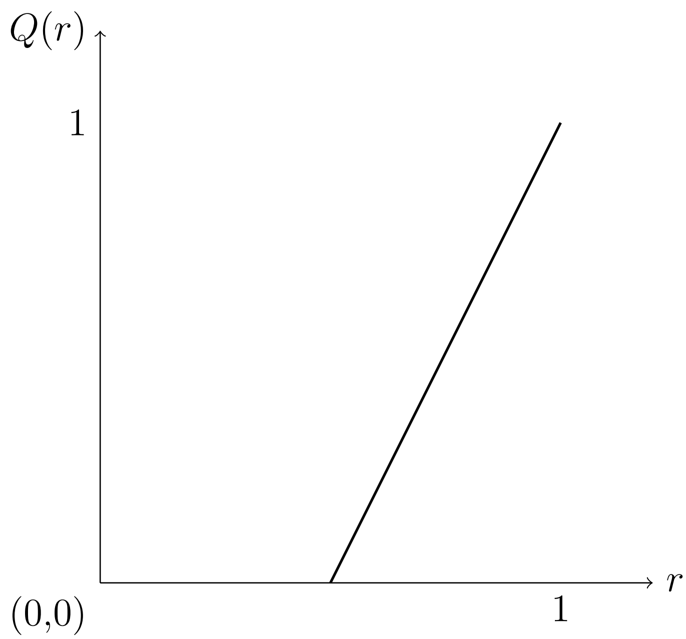


Figure 4.8: *As many as possible* membership function

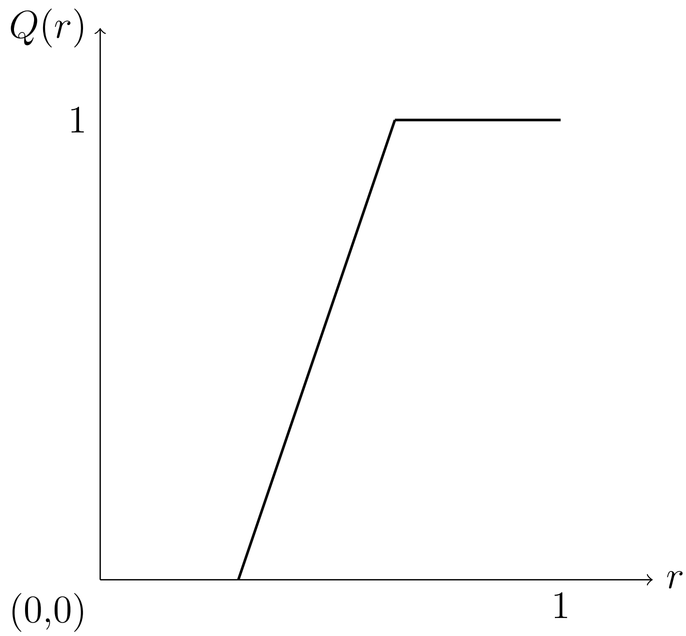


Figure 4.9: *Most* membership function

Table 4.2: Linguistic quantifiers of correponding $\mathcal{F}$

Linguistic quantifier	Weighting vector
there exists	$[1, 0, 0, 0, 0]$
for all	$[0, 0, 0, 0, 1]$
identity	$[0.2, 0.2, 0.2, 0.2, 0.2]$
at least half	$[0.4, 0.4, 0.2, 0, 0]$
as many as possible	$[0, 0, 0.2, 0.4, 0.4]$
most	$[0, 0.2, 0.4, 0.4, 0]$

Table 4.3: Aggregation behavior of correponding $\mathcal{F}$

Linguistic quantifier	Aggregation befavior of $\mathcal{F}$	
	$orness(\mathcal{F})$	$andness(\mathcal{F})$
there exists	1	0
for all	0	1
identity	0.5	0.5
at least half	0.8	0.2
as many as possible	0.2	0.8
most	0.45	0.55

The aggregated value $V(O_m)$ is interpreted as the degree to which product O_m meets the consumer's Kansei preference specified as $[W, LQ]$.

4.4 Summary

In the first section of this chapter, we introduce a consumer-oriented evaluation model. Assuming that there is a predefined set of Kansei attributes, a consumer then uses a subset of this predefined set to specify his preferences. The model also incorporates the concept of "Linguistic Quantifier" into the model. In the second section, we formulate the consumer's target. We implement the least prejudiced distribution to represent the preference of the consumer. In the last section, we present the target-based evaluation of a product item. This evaluation uses the Kansei profile generated using the linguistic representation of Kansei data in Chapter 3 and the preference of the consumer specified by the model described earlier.

In the next chapter, we conduct a case study of the proposed Kansei data modeling and consumer-oriented evaluation on Kutani-cup.

Chapter 5

Case study: Consumer-oriented evaluation of Kutani cups

In this chapter, we conduct a case study to illustrate proposed Kansei data model. We use the Kansei data collected by Professor Yoshiteru Nakamori, Associate Professor Mina Ryoke, Associate Professor Yukihiro Yamashita and their team. Next, we create Kansei profile from Kansei data using proposed Kansei data model. Then, we evaluate products using *"A Consumer-Oriented Kansei Evaluation Method."*

After the Kansei profile creation and consumer-oriented evaluation are demonstrated, We have a discussion about the evaluation result, sensitivity analysis of membership function and the effect of consumer oriented evaluation method on proposed model.

5.1 Experiment data: Traditional Japanese Crafts

Professor Yoshiteru Nakamori, Associate Professor Mina Ryoke from the University of Tsukuba, Associate Professor Yukihiro Yamashita from the Nagoya University of Economics and their team have conducted a Kansei experiment of traditional Japanese hand-painted Kutani cups. We use their data in our case study.

Kunita cups are a traditional Japanese hand-painted craft of Ishikawa prefecture, Japan. In the experiment, they carefully selected 35 patterns of Kutani cups to be evaluated. Pictures of Kutani cups are shown in Figure 5.1. The participants identified 26 Kansei attributes used for assessment of the Kutani cups. This list of the 26 Kansei attributes translated into English is shown in Table 5.1. A 7-point SD scale was used to evaluate the Kutani cups with respect to the 26 Kansei attributes such that $\mathcal{V} = \{1, 2, 3, 4, 5, 6, 7\}$.

Finally, a total of 60 subjects from the selected population including relevant researchers of KE, senior residents and certified masters of traditional crafts, were chosen as evaluators. They were invited to provide their judgment for 35 patterns of Kutani cups on using the 26 Kansei attributes, simultaneously.

5.2 Kansei profile generation using the proposed approach

As discussed in Section 3.2, for each Kansei attribute, we can define a Kansei linguistic variable with the set of seven Kansei labels. We use triangular fuzzy numbers as a semantical representation of Kansei labels for the purpose of simplicity. Formally, the Kansei label set $\mathcal{L}_n$ for Kansei attribute A_n $(n = 1, \ldots, 26)$ is defined as shown in Equation (5.1). Figure 5.2 shows the fuzzy numbers of Kansei linguistic variables for Kansei attribute.

Given the fuzzy set representation of Kansei linguistic labels in $\mathcal{L}_n$ with respect to each Kansei attribute A_n $(n = 1, \ldots, 26)$, as discussed in Section 3.3, making use of Equation 3.8-3.9 we can easily derive a 7-tuple of linguistic representations of all possible prototype Kansei labels in $\mathcal{L}_n$. Here, with the triangular membership functions of Kansei linguistic labels of $\mathcal{L}_n$ as given in (5.1), we obtain the semantic overlapping amongst the Kansei labels according to (3.8)-(3.9) as shown in Table 5.2.

For example, if a subject selects L_2^n as his/her Kansei judgment for a product on Kansei attribute A_n, the linguistic representation of L_2^n defined as a probability distribution on $\mathcal{L}_n$ is

$$\left[\frac{0.109}{L_1^n}, \frac{0.782}{L_2^n}, \frac{0.109}{L_3^n}, \frac{0.0}{L_4^n}, \frac{0.0}{L_5^n}, \frac{0.0}{L_6^n}, \frac{0.0}{L_7^n}\right]$$

This means that, even if the subject chooses L_2^n, his confident is only 78.2% that L_2^n is the only appropriate label to describe his Kansei judgment, The other labels escpecially L_1^n and L_3^n are also possible to represent his Kansei judgment. In this case label L_1^n and L_3^n are appropriate with an equal probability of 10.9% each. This phonomenal interestingly represents the individual uncertainty and semantic overlapping of Kansei labels.

Figure 5.1: Hand-painted Kutani cups

Table 5.1: The Kansei attributes used in the experiment

A_n	Left Kansei word $\langle \mathbf{w}_n^- \rangle$	7-scale Kansei linguistic variable							Right Kansei word $\langle \mathbf{w}_n^+ \rangle$
		L_n^1	L_n^2	L_n^3	L_n^4	L_n^5	L_n^6	L_n^7	
A_1	conventional	☐	☐	☐	☐	☐	☐	☐	unconventional
A_2	simple	☐	☐	☐	☐	☐	☐	☐	compound
A_3	solemn	☐	☐	☐	☐	☐	☐	☐	funny
A_4	formal	☐	☐	☐	☐	☐	☐	☐	casual
A_5	serene	☐	☐	☐	☐	☐	☐	☐	forceful
A_6	still	☐	☐	☐	☐	☐	☐	☐	moving
A_7	pretty	☐	☐	☐	☐	☐	☐	☐	austere
A_8	friendly	☐	☐	☐	☐	☐	☐	☐	unfriendly
A_9	soft	☐	☐	☐	☐	☐	☐	☐	hard
A_{10}	blase	☐	☐	☐	☐	☐	☐	☐	attractive
A_{11}	flowery	☐	☐	☐	☐	☐	☐	☐	quiet
A_{12}	happy	☐	☐	☐	☐	☐	☐	☐	normal
A_{13}	elegant	☐	☐	☐	☐	☐	☐	☐	loose
A_{14}	delicate	☐	☐	☐	☐	☐	☐	☐	large-hearted
A_{15}	luxurious	☐	☐	☐	☐	☐	☐	☐	frugal
A_{16}	gentle	☐	☐	☐	☐	☐	☐	☐	pithy
A_{17}	bright	☐	☐	☐	☐	☐	☐	☐	dark
A_{18}	reserved	☐	☐	☐	☐	☐	☐	☐	imperious
A_{19}	free	☐	☐	☐	☐	☐	☐	☐	regular
A_{20}	level	☐	☐	☐	☐	☐	☐	☐	indented
A_{21}	lustered	☐	☐	☐	☐	☐	☐	☐	matte
A_{22}	transpicous	☐	☐	☐	☐	☐	☐	☐	dim
A_{23}	warm	☐	☐	☐	☐	☐	☐	☐	cool
A_{24}	moist	☐	☐	☐	☐	☐	☐	☐	arid
A_{25}	colorful	☐	☐	☐	☐	☐	☐	☐	sober
A_{26}	plain	☐	☐	☐	☐	☐	☐	☐	gaudy-loud

$$
\begin{aligned}
\mathcal{L}_n &= \{L_1^n, L_2^n, L_3^n, L_4^n, L_5^n, L_6^n, L_7^n\} \\
&= \{\textit{very}\ \mathbf{w}_n^-,\ \mathbf{w}_n^-,\ \textit{fairly}\ \mathbf{w}_n^-,\ \textit{neutral},\ \textit{fairly}\ \mathbf{w}_n^+,\ \mathbf{w}_n^+,\ \textit{very}\ \mathbf{w}_n^+\} \qquad (5.1) \\
&= \{(1,1,2),(1,2,3),(2,3,4),(3,4,5),(4,5,6),(5,6,7),(6,7,7)\}.
\end{aligned}
$$

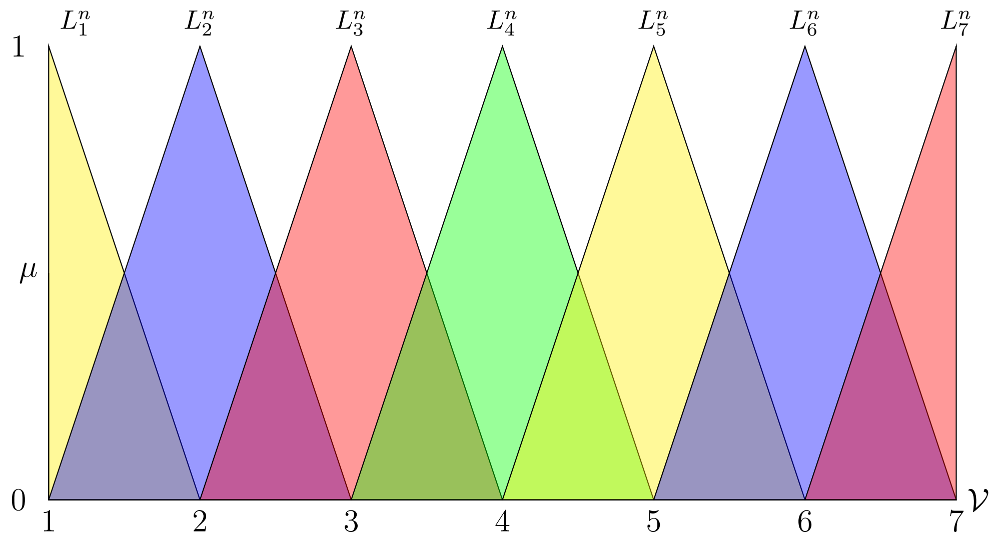


Figure 5.2: Linguistic varibles for Kansei attribute

Table 5.2: Semantic overlapping among Kansei labels in $\mathcal{L}_n$

Prototype Kansei L	Linguistic representation of L on $\mathcal{L}^n$						
	L_1^n	L_2^n	L_3^n	L_4^n	L_5^n	L_6^n	L_7^n
L_1^n	0.782	0.218	0.0	0.0	0.0	0.0	0.0
L_2^n	0.109	0.782	0.109	0.0	0.0	0.0	0.0
L_3^n	0.0	0.109	0.782	0.109	0.0	0.0	0.0
L_4^n	0.0	0.0	0.109	0.782	0.109	0.0	0.0
L_5^n	0.0	0.0	0.0	0.109	0.782	0.109	0.0
L_6^n	0.0	0.0	0.0	0.0	0.109	0.782	0.109
L_7^n	0.0	0.0	0.0	0.0	0.0	0.218	0.782

Table 5.3: Population distribution of Kutani cup O_{31} on Kansei attributes A_7 and A_8, respectively

Attribute	$\mathbf{E}_{31}^n(\cdot)$						
	L_1^n	L_2^n	L_3^n	L_4^n	L_5^n	L_6^n	L_7^n
A_7	10	19	17	1	7	6	0
A_8	5	16	30	1	5	3	0

Assume that all the 60 subjects are equally important, we can use Equation (3.12) to generate the Kansei profile for product O_m on Kansei attribute A_n. For $h = 1, \ldots, 7$, let denote

$$\mathbf{E}_m^n(L_h^n) = \{e_k \in \mathbf{E} | x_m^n(e_k) = L_h^n\} \tag{5.2}$$

and

$$\pi_m^n(L_h^n) = \frac{|\mathbf{E}_m^n(L_h^n)|}{60} \tag{5.3}$$

To illustrate and simplify the discussion, we use the result of Kutani cup O_{31} on Kansei attributes $A_7 = \langle\text{pretty, austere}\rangle$ and $A_8 = \langle\text{friendly, unfriendly}\rangle$. Then the population distribution of evaluations of Kutani cup O_{31} on Kansei attributes A_7 and A_8 is obtained by (5.2) shown in Table 5.3.

Accordingly, the weighting vectors with respect to the Kansei labels are obtained by (5.3) as

$$\begin{aligned}
\pi_{31}^7 &= \left[\frac{10/60}{L_1^7}, \frac{19/60}{L_2^7}, \frac{17/60}{L_3^7}, \frac{1/60}{L_4^7}, \frac{7/60}{L_5^7}, \frac{6/60}{L_6^7}, \frac{0/60}{L_7^7}\right] \\
&= \left[\frac{0.17}{L_1^7}, \frac{0.32}{L_2^7}, \frac{0.28}{L_3^7}, \frac{0.02}{L_4^7}, \frac{0.12}{L_5^7}, \frac{0.1}{L_6^7}, \frac{0.0}{L_7^7}\right] \\
\pi_{31}^8 &= \left[\frac{5/60}{L_1^8}, \frac{16/60}{L_2^8}, \frac{30/60}{L_3^8}, \frac{1/60}{L_4^8}, \frac{5/60}{L_5^8}, \frac{3/60}{L_6^8}, \frac{0/60}{L_7^8}\right] \\
&= \left[\frac{0.08}{L_1^8}, \frac{0.27}{L_2^8}, \frac{0.5}{L_3^8}, \frac{0.02}{L_4^8}, \frac{0.08}{L_5^8}, \frac{0.05}{L_6^8}, \frac{0.0}{L_7^8}\right]
\end{aligned} \tag{5.4}$$

Now taking the semantic overlapping amongst Kansei labels (Table 5.2) into consideration, we can obtain the Kansei profiles of Kutani cup O_{31} on Kansei attributes A_7 and A_8 as

$$\begin{aligned}
\mathbf{p}_{31}^7 &= \left[p_{31}^7(L_1^7), p_{31}^7(L_2^7), p_{31}^7(L_3^7), p_{31}^7(L_4^7), p_{31}^7(L_5^7), p_{31}^7(L_6^7), p_{31}^7(L_7^7)\right] \\
\mathbf{p}_{31}^8 &= \left[p_{31}^8(L_1^8), p_{31}^8(L_2^8), p_{31}^8(L_3^8), p_{31}^8(L_4^8), p_{31}^8(L_5^8), p_{31}^8(L_6^8), p_{31}^8(L_7^8)\right]
\end{aligned} \tag{5.5}$$

where as

$$
\begin{aligned}
p_{31}^7(L_1^7) &= \frac{(0.17 * 0.782) + (0.32 * 0.218)}{L_1^7} \\
p_{31}^7(L_2^7) &= \frac{(0.17 * 0.109) + (0.32 * 0.782) + (0.28 * 0.109)}{L_2^7} \\
p_{31}^7(L_3^7) &= \frac{(0.32 * 0.109) + (0.28 * 0.782) + (0.02 * 0.109)}{L_3^7} \\
p_{31}^7(L_4^7) &= \frac{(0.28 * 0.109) + (0.02 * 0.782) + (0.12 * 0.109)}{L_4^7} \\
p_{31}^7(L_5^7) &= \frac{(0.02 * 0.109) + (0.12 * 0.782) + (0.1 * 0.109)}{L_5^7} \\
p_{31}^7(L_6^7) &= \frac{(0.12 * 0.109) + (0.1 * 0.782) + (0.0 * 0.109)}{L_6^7} \\
p_{31}^7(L_7^7) &= \frac{(0.1 * 0.218) + (0.0 * 0.782)}{L_7^7} \\
p_{31}^8(L_1^8) &= \frac{(0.08 * 0.782) + (0.27 * 0.218)}{L_1^8} \\
p_{31}^8(L_2^8) &= \frac{(0.08 * 0.109) + (0.27 * 0.782) + (0.5 * 0.109)}{L_2^8} \\
p_{31}^8(L_3^8) &= \frac{(0.27 * 0.109) + (0.5 * 0.782) + (0.02 * 0.109)}{L_3^8} \\
p_{31}^8(L_4^8) &= \frac{(0.5 * 0.109) + (0.02 * 0.782) + (0.08 * 0.109)}{L_4^8} \\
p_{31}^8(L_5^8) &= \frac{(0.02 * 0.109) + (0.08 * 0.782) + (0.05 * 0.109)}{L_5^8} \\
p_{31}^8(L_6^8) &= \frac{(0.08 * 0.109) + (0.05 * 0.782) + (0.0 * 0.109)}{L_6^8} \\
p_{31}^8(L_7^8) &= \frac{(0.05 * 0.218) + (0.0 * 0.782)}{L_7^8}
\end{aligned}
\tag{5.6}
$$

Therefore,

$$
\begin{aligned}
\mathbf{p}_{31}^7 &= \left[\frac{0.16}{L_1^7}, \frac{\mathbf{0.31}}{L_2^7}, \frac{0.26}{L_3^7}, \frac{0.06}{L_4^7}, \frac{0.1}{L_5^7}, \frac{0.09}{L_6^7}, \frac{0.01}{L_7^7}\right] \\
\mathbf{p}_{31}^8 &= \left[\frac{0.09}{L_1^8}, \frac{0.28}{L_2^8}, \frac{\mathbf{0.42}}{L_3^8}, \frac{0.08}{L_4^8}, \frac{0.07}{L_5^8}, \frac{0.05}{L_6^8}, \frac{0.01}{L_7^8}\right]
\end{aligned}
\tag{5.7}
$$

which the indication that Kansei labels L_2^7 and L_3^8 have the highest probabilities (0.31 and 0.42) describing the profile of Kutani cup O_{31} on Kansei attributes A_7 and A_8, respectively.

As described above, in the proposed approach the SD scale $\mathcal{V}$ is treated as a linguistic variable consisting of 7 linguistic labels for each Kansei attribute. In this sense, our approach can capture the fuzziness inherent in Kansei data. In addition, as we can

Table 5.4: The possibility distribution for attribute $\mathbf{w}_8^-$, $\mathbf{w}_{17}^-$ and $\mathbf{w}_{25}^-$

	$\mu_{T_{n_l}}(L_1^{n_l})$	$\mu_{T_{n_l}}(L_2^{n_l})$	$\mu_{T_{n_l}}(L_3^{n_l})$	$\mu_{T_{n_l}}(L_4^{n_l})$	$\mu_{T_{n_l}}(L_5^{n_l})$	$\mu_{T_{n_l}}(L_6^{n_l})$	$\mu_{T_{n_l}}(L_7^{n_l})$
$\mu_{T_{n_l}}(L_g^{n_l})$	$\frac{(7-1)}{(7-1)}$	$\frac{(7-2)}{(7-1)}$	$\frac{(7-3)}{(7-1)}$	$\frac{(7-4)}{(7-1)}$	$\frac{(7-5)}{(7-1)}$	$\frac{(7-6)}{(7-1)}$	$\frac{(7-7)}{(7-1)}$
result	1.00	0.83	0.67	0.50	0.33	0.17	0.00

Table 5.5: The possibility distribution for attribute $\mathbf{w}_2^+$ and $\mathbf{w}_{10}^+$

	$\mu_{T_{n_l}}(L_1^{n_l})$	$\mu_{T_{n_l}}(L_2^{n_l})$	$\mu_{T_{n_l}}(L_3^{n_l})$	$\mu_{T_{n_l}}(L_4^{n_l})$	$\mu_{T_{n_l}}(L_5^{n_l})$	$\mu_{T_{n_l}}(L_6^{n_l})$	$\mu_{T_{n_l}}(L_7^{n_l})$
$\mu_{T_{n_l}}(L_g^{n_l})$	$\frac{(1-1)}{(7-1)}$	$\frac{(2-1)}{(7-1)}$	$\frac{(3-1)}{(7-1)}$	$\frac{(4-1)}{(7-1)}$	$\frac{(5-1)}{(7-1)}$	$\frac{(6-1)}{(7-1)}$	$\frac{(7-1)}{(7-1)}$
result	0.00	0.17	0.33	0.50	0.67	0.83	1.00

observe, there is no subject assessing O_{31} on A_7 and A_8 using v_7. However, the collective linguistic representations of Kansei judgments of O_{31} on A_7 and A_8 respectively have L_7^7 and L_7^8 as appropriate labels but with small probabilities, due to the semantic overlapping of Kansei linguistic judgments.

5.3 Consumer-oriented evaluation

Let us illustrate how the evaluation model proposed in the preceding section works, for example, with consumer's request formally specified as follows:

$$[\{\mathbf{w}_2^+, \mathbf{w}_8^-, \mathbf{w}_{10}^+, \mathbf{w}_{17}^-, \mathbf{w}_{25}^-, \}, \textit{as many as possible}]$$

That is, the consumer is looking for Kutani cups that would meet *as many as possible* of her feeling preferences of *compound*, *friendly*, *attractive*, *bright* and *colorful*.

Then, according to (4.1) we have preference orders defined on Kansei attributes A_2, A_8, A_{10}, A_{17} and A_{25} as $\succeq_2 = \succeq_{10}$ and $\succeq_8 = \succeq_{17} = \succeq_{25}$, where

$$L_7 \succeq_2 \ldots \succeq_2 L_1 \text{ and } L_1 \succeq_8 \ldots \succeq_8 L_7$$

The possibility distributions defined by 4.2 for Kansei target $\mathbf{w}_8^-$, $\mathbf{w}_{17}^-$ and $\mathbf{w}_{25}^-$ and by (4.4) for Kansei targets $\mathbf{w}_2^+$ and $\mathbf{w}_{10}^+$ are depicted in table 5.4 and 5.5, respectively.

We can obtain the least prejudiced distributions defined by (4.3) for Kansei targets $\mathbf{w}_8^-$, $\mathbf{w}_{17}^-$ and $\mathbf{w}_{25}^-$ as

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_1^{n_l}) &= \sum_{T_{n_l}^g | L_1^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=1}^{7} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{1/6}{1} + \frac{1/6}{2} + \frac{1/6}{3} + \frac{1/6}{4} + \frac{1/6}{5} + \frac{1/6}{6} + \frac{0}{7} \\
&= 0.41
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_2^{n_l}) &= \sum_{T_{n_l}^g | L_2^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=2}^{7} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{1/6}{2} + \frac{1/6}{3} + \frac{1/6}{4} + \frac{1/6}{5} + \frac{1/6}{6} + \frac{0}{7} \\
&= 0.24
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_3^{n_l}) &= \sum_{T_{n_l}^g | L_3^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=3}^{7} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{1/6}{3} + \frac{1/6}{4} + \frac{1/6}{5} + \frac{1/6}{6} + \frac{0}{7} \\
&= 0.16
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_4^{n_l}) &= \sum_{T_{n_l}^g | L_4^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=4}^{7} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{1/6}{4} + \frac{1/6}{5} + \frac{1/6}{6} + \frac{0}{7} \\
&= 0.1
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_5^{n_l}) &= \sum_{T_{n_l}^g | L_5^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=5}^{7} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{1/6}{5} + \frac{1/6}{6} + \frac{0}{7} \\
&= 0.06
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_6^{n_l}) &= \sum_{T_{n_l}^g | L_6^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=6}^{7} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{1/6}{6} + \frac{0}{7} \\
&= 0.03
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_7^{n_l}) &= \sum_{T_{n_l}^g | L_7^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=7}^{7} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{0}{7} \\
&= 0.0
\end{aligned}
$$

and by (4.4) for Kansei targets $\mathbf{w}_2^+$ and $\mathbf{w}_{10}^+$ as

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_1^{n_l}) &= \sum_{T_{n_l}^g | L_1^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=1}^{1} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{0}{7} \\
&= 0.0
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_2^{n_l}) &= \sum_{T_{n_l}^g | L_2^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=1}^{2} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{0}{7} + \frac{1/6}{6} \\
&= 0.03
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_3^{n_l}) &= \sum_{T_{n_l}^g | L_3^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=1}^{3} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{0}{7} + \frac{1/6}{6} + \frac{1/6}{5} \\
&= 0.06
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_4^{n_l}) &= \sum_{T_{n_l}^g | L_4^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=1}^{4} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{0}{7} + \frac{1/6}{6} + \frac{1/6}{5} + \frac{1/6}{4} \\
&= 0.1
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{p}_{n_l}(L_5^{n_l}) &= \sum_{T_{n_l}^g | L_5^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=1}^{5} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{0}{7} + \frac{1/6}{6} + \frac{1/6}{5} + \frac{1/6}{4} + \frac{1/6}{3} + \\
&= 0.16
\end{aligned}
$$

(a) $\mathbf{w}_8^-$, $\mathbf{w}_{17}^-$ and $\mathbf{w}_{25}^-$ (b) $\mathbf{w}_2^+$ and $\mathbf{w}_{10}^+$

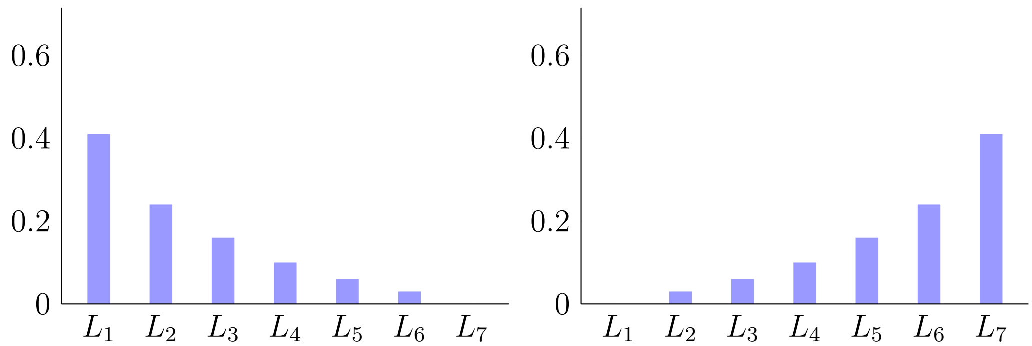


Figure 5.3: The least prejudiced distributions induced by fuzzy Kansei targets

$$\begin{aligned}
\mathbf{p}_{n_l}(L_6^{n_l}) &= \sum_{T_{n_l}^g | L_6^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=1}^{6} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{0}{7} + \frac{1/6}{6} + \frac{1/6}{5} + \frac{1/6}{4} + \frac{1/6}{3} + \frac{1/6}{2} \\
&= 0.24
\end{aligned}$$

$$\begin{aligned}
\mathbf{p}_{n_l}(L_7^{n_l}) &= \sum_{T_{n_l}^g | L_7^{n_l} \in T_{n_l}^g} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} = \sum_{g=1}^{7} \frac{\mathbf{m}_{n_l}(T_{n_l}^g)}{|T_{n_l}^g|} \\
&= \frac{0}{7} + \frac{1/6}{6} + \frac{1/6}{5} + \frac{1/6}{4} + \frac{1/6}{3} + \frac{1/6}{2} + \frac{1/6}{1} \\
&= 0.41
\end{aligned}$$

The least prejudiced distributions defined by (4.3) for Kansei targets $\mathbf{w}_8^-$, $\mathbf{w}_{17}^-$ and $\mathbf{w}_{25}^-$ and by (4.4) for Kansei targets $\mathbf{w}_2^+$ and $\mathbf{w}_{10}^+$ are depicted in Figure 5.3 (a) and (b), respectively.

Assume that the membership function of the quantifier '*as many as possible*' is defined as a mapping $Q : [0, 1] \to [0, 1]$ such that [135]

$$Q(r) = \begin{cases} 0 & \text{if } 0 \leqslant r \leqslant 0.5 \\ 2r - 1 & \text{if } 0.5 \leqslant r \leqslant 1 \end{cases}$$

Then we can obtain the weighting vector $w = [w_1, w_2, w_3, w_4, w_5]$ making use of Yager's method proposed in [133] by

$$w_l = Q\left(\frac{l}{5}\right) - Q\left(\frac{l-1}{5}\right), \text{ for } l = 1, \ldots, 5$$

which yields $w = [0, 0.0.2, 0.4, 0.4]$.

Now, by (4.5) and (4.6) we compute probabilities $\mathbb{P}_m^2$, $\mathbb{P}_m^8$, $\mathbb{P}_m^{10}$, $\mathbb{P}_m^{17}$ and $\mathbb{P}_m^{25}$ of meeting corresponding Kansei targets $\mathbf{w}_2^+$, $\mathbf{w}_8^-$, $\mathbf{w}_{10}^+$, $\mathbf{w}_{17}^-$ and $\mathbf{w}_{25}^-$ for each Kutani cup O_m ($m = 1, \ldots, 35$). For illustration, we compute probability $\mathbb{P}_{31}^7$ of meeting Kansei target $\mathbf{w}_7^+$ as an example in equaltion 5.8 - 5.10 .

From 4.5,

$$\mathbb{P}_{31}^7 = \sum_{g=1}^{7} \mathbf{p}_m^{n_l}(L_g^{n_l}) P(L_g^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) \tag{5.8}$$

and from 4.6,

$$
\begin{aligned}
P(L_1^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) &= \sum_{h=1}^{1} \mathbf{p}_{n_l}(L_h^{n_l}) \\
&= 0.0 \\
P(L_2^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) &= \sum_{h=1}^{2} \mathbf{p}_{n_l}(L_h^{n_l}) \\
&= 0.0 + 0.03 \\
&= 0.03 \\
P(L_3^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) &= \sum_{h=1}^{3} \mathbf{p}_{n_l}(L_h^{n_l}) \\
&= 0.0 + 0.03 + 0.06 \\
&= 0.09 \\
P(L_4^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) &= \sum_{h=1}^{4} \mathbf{p}_{n_l}(L_h^{n_l}) \\
&= 0.0 + 0.03 + 0.06 + 0.1 \\
&= 0.19 \\
P(L_5^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) &= \sum_{h=1}^{5} \mathbf{p}_{n_l}(L_h^{n_l}) \\
&= 0.0 + 0.03 + 0.06 + 0.1 + 0.16 \\
&= 0.35 \\
P(L_6^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) &= \sum_{h=1}^{6} \mathbf{p}_{n_l}(L_h^{n_l}) \\
&= 0.0 + 0.03 + 0.06 + 0.1 + 0.16 + 0.24 \\
&= 0.59 \\
P(L_7^{n_l} \succeq_{n_l} \mathbf{p}_{n_l}) &= \sum_{h=1}^{7} \mathbf{p}_{n_l}(L_h^{n_l}) \\
&= 0.0 + 0.03 + 0.06 + 0.1 + 0.16 + 0.24 + 0.41 \\
&= 1.00
\end{aligned}
\tag{5.9}
$$

Thus,

$$\begin{aligned}\mathbb{P}_{31}^{7} &= (0.16 * 0.0) + (0.31 * 0.03) + (0.26 * 0.09) + \\ &\quad (0.06 * 0.19) + (0.1 * 0.35) + (0.09 * 0.59) + (0.01 * 1.0) \\ &= 0.1436\end{aligned} \tag{5.10}$$

Then, using (4.18) we have

$$V(O_m) = \mathcal{F}(\mathbb{P}_m^2, \mathbb{P}_m^8, \mathbb{P}_m^{10}, \mathbb{P}_m^{17}, \mathbb{P}_m^{25})$$

where $\mathcal{F}$ is the OWA operator of dimension 5 associated with the weighting vector $w = [0, 0, 0.2, 0.4, 0.4]$.

Finally, the target achievements of Kutani cups for selected attributes as well as their aggregate values using linguistic qualifier *'as many as possible'* are shown in Table 5.6. The obtained ranking is then considered as the recommendation according to consumer's request specified by

$$[\{\mathbf{w}_2^+, \mathbf{w}_8^-, \mathbf{w}_{10}^+, \mathbf{w}_{17}^-, \mathbf{w}_{25}^-, \}, \textit{as many as possible}]$$

5.4 Discussions

5.4.1 The evaluation result

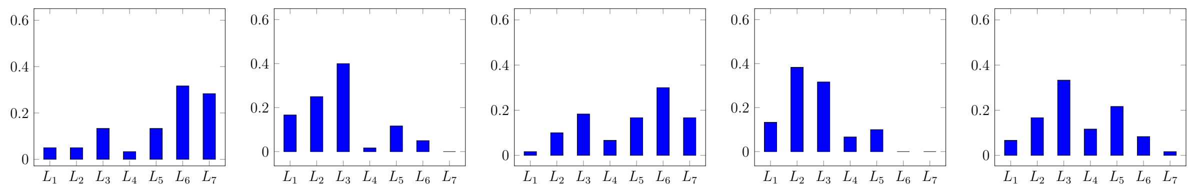
Let us consider the top three Kutani cups O_4, O_{35} and O_{24} those profiles on selected attributes are shown in Figure 5.4, Figure 5.5 and Figure 5.6, respectively. Matching the least prejudiced distributions induced by Kansei targets (Figure 5.3) and Kansei profiles on selected attributes of Kutani cups, we can see that the obtained result reflects rather well consumer's attitudes towards Kansei targets and aggregation behavior induced by linguistic quantifier used in consumer's request.

It is worth noting that aggregation operator $\mathcal{F}$ with weighting vector corresponding to linguistic qualifier *'as many as possible'* behaves toward an 'AND' aggregation, due to the requirement of meeting as many as possible of the five Kansei targets {*compound*, *friendly*, *attractive*, *bright*, *colorful*}. As such, the cup O_4 is the most recommended product as having the highest aggregate value which is the weighted sum of its three lowest degrees of

Table 5.6: Target achievements for selected attributes of Kutani cups and their aggregate values using linguistic qualifier *'as many as possible'*

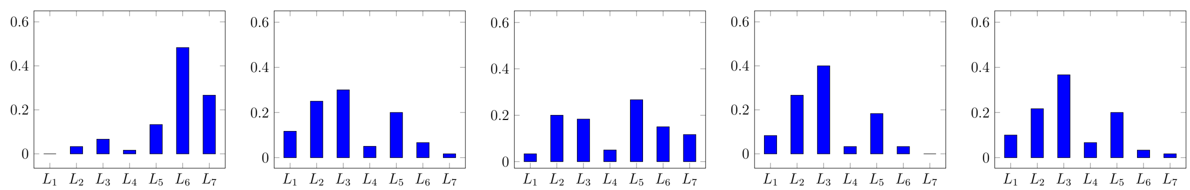
Rank	Product	$\mathbf{w}_2^+$	$\mathbf{w}_8^-$	$\mathbf{w}_{10}^+$	$\mathbf{w}_{17}^-$	$\mathbf{w}_{25}^-$	Aggregate value
#1	O_4	0.520025	0.463688	0.428180	0.491468	0.328095	0.395248
#2	O_{35}	0.596131	0.397232	0.327011	0.406938	0.387908	0.365414
#3	O_{24}	0.411411	0.475931	0.248224	0.609647	0.508942	0.359040
#4	O_{31}	0.606135	0.430731	0.199804	0.521938	0.491729	0.350560
#5	O_{33}	0.630634	0.310095	0.254294	0.551102	0.508058	0.327367
#6	O_{10}	0.287541	0.541899	0.330383	0.549422	0.314617	0.306940
#7	O_{30}	0.441292	0.297133	0.365229	0.308980	0.294748	0.298549
#8	O_6	0.255884	0.519287	0.235527	0.613633	0.493179	0.295200
#9	O_3	0.510061	0.305776	0.216592	0.425776	0.446414	0.294102
#10	O_{22}	0.492550	0.298177	0.226551	0.409206	0.481328	0.291733
#11	O_{21}	0.357500	0.333546	0.259473	0.345926	0.278075	0.281729
#12	O_{26}	0.325861	0.360088	0.198079	0.447475	0.425584	0.281594
#13	O_{16}	0.300772	0.389261	0.438541	0.315843	0.232551	0.276498
#14	O_1	0.655496	0.157949	0.332237	0.367259	0.508967	0.269526
#15	O_{17}	0.494190	0.236384	0.283391	0.304185	0.349587	0.268747
#16	O_{14}	0.363552	0.467553	0.070515	0.473052	0.475452	0.267138
#17	O_9	0.210845	0.522853	0.391129	0.497356	0.261397	0.267123
#18	O_{11}	0.204253	0.548827	0.356622	0.543505	0.281062	0.265450
#19	O_{29}	0.234915	0.600222	0.279530	0.541064	0.274480	0.259664
#20	O_{25}	0.255883	0.437307	0.392516	0.369947	0.193790	0.253858
#21	O_{32}	0.590928	0.259255	0.238994	0.269248	0.384168	0.253149
#22	O_{18}	0.734643	0.098814	0.301928	0.450055	0.739662	0.250308
#23	O_2	0.486821	0.399237	0.353703	0.269711	0.174682	0.248498
#24	O_{13}	0.248530	0.675964	0.206608	0.627204	0.261551	0.234365
#25	O_{27}	0.269952	0.318525	0.461769	0.270028	0.178210	0.233271
#26	O_{28}	0.463018	0.274604	0.297284	0.226134	0.210591	0.229611
#27	O_8	0.162538	0.541821	0.399338	0.511993	0.207917	0.228049
#28	O_7	0.100144	0.575727	0.364353	0.533313	0.248855	0.212470
#29	O_{15}	0.143998	0.468843	0.330074	0.455888	0.189727	0.199505
#30	O_{20}	0.617130	0.141927	0.285565	0.136840	0.297460	0.168620
#31	O_{12}	0.606500	0.120144	0.201230	0.196468	0.359102	0.166891
#32	O_{19}	0.341159	0.251189	0.192023	0.135147	0.168105	0.159705
#33	O_{34}	0.472042	0.222790	0.326899	0.129327	0.153691	0.157765
#34	O_{23}	0.376296	0.205596	0.450828	0.099145	0.084618	0.114624
#35	O_5	0.122027	0.293308	0.475549	0.117959	0.090160	0.107653

target achievement for *friendly*, *attractive* and *colorful*, while having good performance on other two targets *compound* and *bright*. Interestingly, the second recommended product



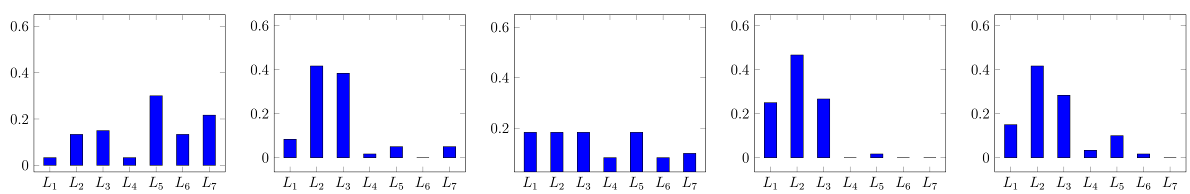
(a) $\mathbf{w}_2^+$ (b) $\mathbf{w}_8^-$ (c) $\mathbf{w}_{10}^+$ (d) $\mathbf{w}_{17}^-$ (e) $\mathbf{w}_{25}^-$

Figure 5.4: Kansei profile of Kutani cup O_4 on selected attributes



(a) $\mathbf{w}_2^+$ (b) $\mathbf{w}_8^-$ (c) $\mathbf{w}_{10}^+$ (d) $\mathbf{w}_{17}^-$ (e) $\mathbf{w}_{25}^-$

Figure 5.5: Kansei profile of Kutani cup O_{35} on selected attributes



(a) $\mathbf{w}_2^+$ (b) $\mathbf{w}_8^-$ (c) $\mathbf{w}_{10}^+$ (d) $\mathbf{w}_{17}^-$ (e) $\mathbf{w}_{25}^-$

Figure 5.6: Kansei profile of Kutani cup O_{24} on selected attributes

O_{35} has the second highest aggregate value of target achievement also for *friendly*, *attractive* and *colorful*. This is because, as we can observe graphically, the profiles on selected attributes of these two products are quite similar to each other. Although the cup O_{24} has quite good performance on *bright* and *colorful* as well as comparable performance on *compound* and *friendly*, its performance on *attractive* is much lower in comparison with O_4 and O_{35}, this significantly lowers the aggregate value of its three lowest degrees of target achievement for *compound*, *friendly*, *attractive* and consequently makes it thirdly recommended.

5.4.2 Effect of proposed model on Kansei profile

In Figure 3.6 and 3.7, we show the effect of proposed Kansei data model in Kansei profile. proposed Kansei data model make the histogram of Kansei profile smoother.

The uncertainty of consumer's judgment decreases the confidence of his judgment. The maximum point of the histogram is also decrease. However, the minimum point of the histogram is increase. The difference of Kansei profile between proposed method and normal method can be shown in the following

$$\triangle p_m^n(L_g^n) = 0.109 p_m^n(L_{g-1}^n) - 0.109 p_m^n(L_g^n) + 0.109 p_m^n(L_{g+1}^n) - 0.109 p_m^n(L_g^n) \tag{5.11}$$

For simplicity, we ignore the notation for product m and attributes n, and focus on linguistic label L_2. The difference of Kansei profile is

$$\triangle p(L_2) = 0.109 p(L_1) - 0.109 p(L_2) + 0.109 p(L_3) - 0.109 p(L_2) \tag{5.12}$$

if L_2 is local maximum ($L_2 > L_1$ and $L2 > L3$), the value of Equation 5.12 is negative. The local maximum point is decreased.

if L_2 is local minimum ($L_2 < L_1$ and $L2 < L3$), the value of Equation 5.12 is positive. The local minimum point is increased.

Therefore, the peak for Kansei profile histogram is decreased, overall histogram is smoother and the the difference between two adjacent labels is decreased. As we incorporate the concept of semantic overlapping of Kansei label into the model, the confidence of subject's judgment acquired in Kansei experiment is lower.

5.4.3 Sensitivity analysis of membership function

In this section, we perform a sensitivity analysis of membership functions used in proposed model. In proposed Kansei data model, we model Kansei data from Kansei assessment of products as a *Kansei linguistic variable* denoted by Equation 3.3

We define the linguistic representation of Kansei value using the least prejudiced distribution (see Chapter 3) as in Equation 3.6.

In our thesis, the Kansei label set $\mathcal{L}_n$ for Kansei attribute A_n ($n = 1, \ldots, 26$) and membership functions of linguistic variables are defined as shown in Equation (5.1). Figure 5.2 shows the triangular membership functions of linguistic variables of Kansei attribute.

With the triangular membership functions of Kansei linguistic labels of $\mathcal{L}_n$ as given in Equation 5.1, we obtain the semantic overlapping of Kansei labels according to Equation 3.8- 3.9 as shown in Table 5.2.

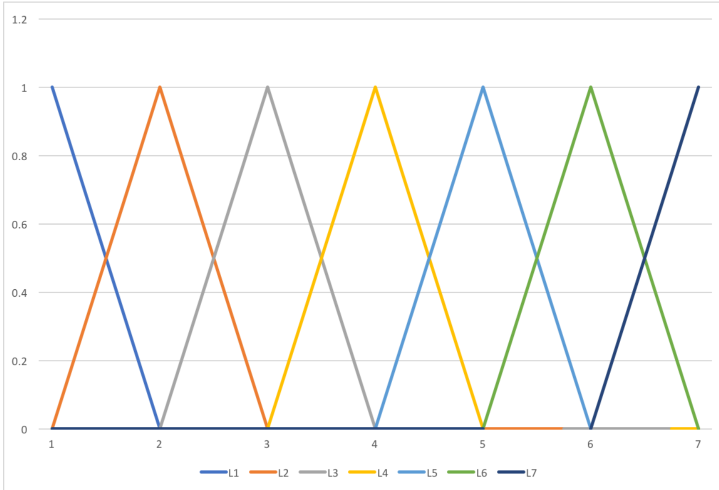


Figure 5.7: Triangular membership functions

We perform sensitivity analysis of membership function using difference membership functions of Kansei linguistic labels of $\mathcal{L}_n$ and their effect on semantic overlapping. First, we can rearrange the Equation 3.6 into

$$p_{\mathcal{L}_n}(L_g^n|\omega) = \frac{1}{(1 - \mathbf{m}_\omega(\varnothing)} \sum_{F_j : L_g^n \in F_j} \frac{\mathbf{m}_\omega(F_j)}{|F_j|} \tag{5.13}$$

In normal fuzzy set

$$\frac{1}{(1 - \mathbf{m}_\omega(\varnothing))} = 1$$

and

$$\sum_{F_j : L_g^n \in F_j} \frac{\mathbf{m}_\omega(F_j)}{|F_j|}$$

is the least prejudiced distribution. For simplicity, we analyze the difference membership functions using their least prejudiced distribution.

The triangular membership functions and their prejudiced distribution function are shown in Figure 5.7 and 5.8 respectively.

If we use trapezoid membership functions (Equation 5.14) instead of triangular membership functions. The membership functions and their least prejudiced distribution are shown in Figure 5.9 and Figure 5.10 respectively.

The shape of the least prejudiced distribution of trapezoid membership function in Figure 5.10 is similar to the shape of the least prejudiced distribution of triangular function in Figure 5.8.

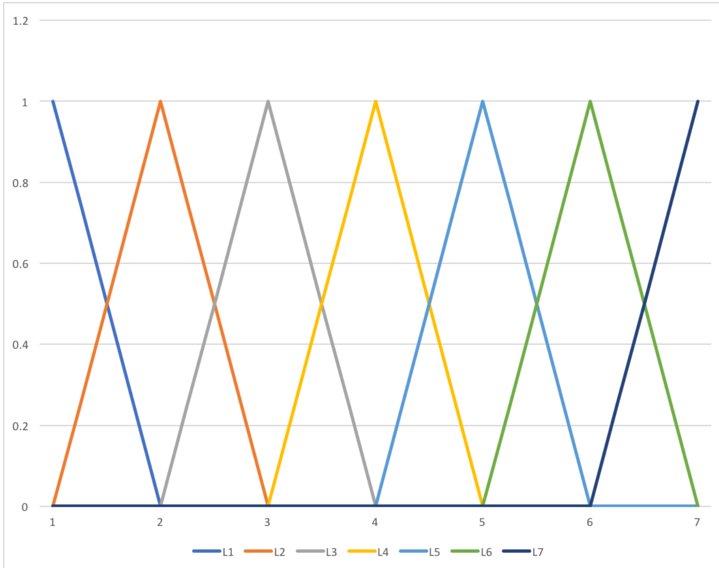


Figure 5.8: The least prejudiced distributions

$$
\begin{aligned}
\mathcal{L}_n &= \{L_1^n, L_2^n, L_3^n, L_4^n, L_5^n, L_6^n, L_7^n\} \\
&= \{(0, 0, 1.5, 2), (1, 1.5, 2.5, 3), (2, 2.5, 3.5, 4), (3, 3.5, 4.5, 5), (4, 4.5, 5.5, 6), \\
&\quad (5, 5.5, 6.5, 7), (6, 6.5, 7, 7)\}.
\end{aligned} \tag{5.14}
$$

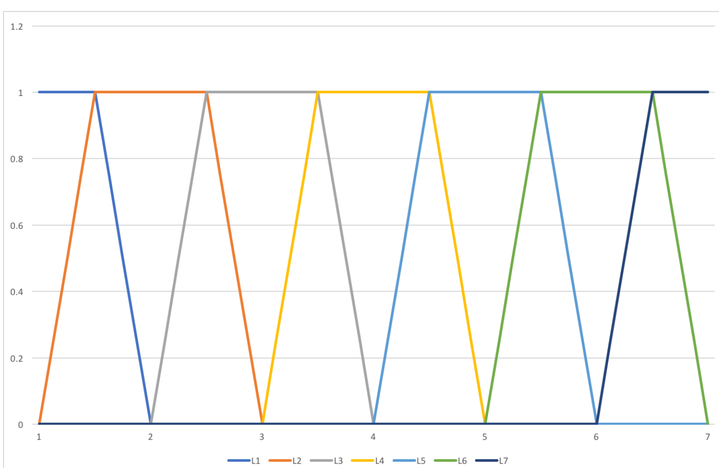


Figure 5.9: Trapezoid membership functions

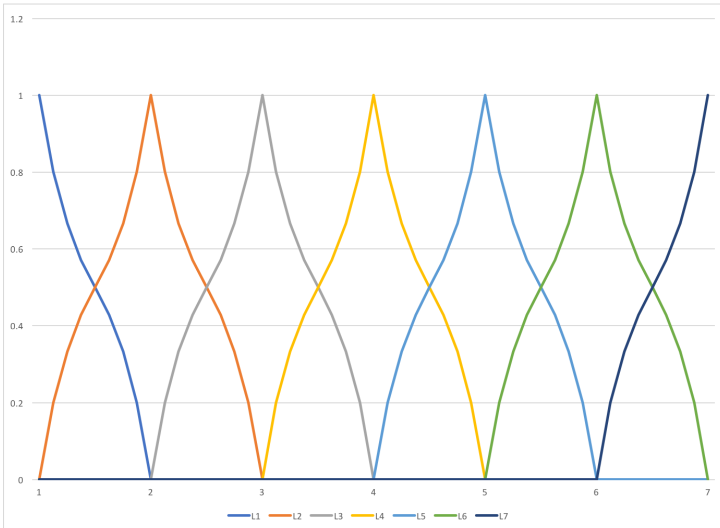


Figure 5.10: The least prejudiced distributions

$$
\begin{aligned}
\mathcal{L}_n &= \{L_1^n, L_2^n, L_3^n, L_4^n, L_5^n, L_6^n, L_7^n\} \\
&= \{(0, 0, 1.75, 2), (1, 1.25, 2.75, 3), (2, 2.25, 3.75, 4), (3, 3.25, 4.75, 5), (4, 4.25, 5.75, 6), \\
&\quad (5, 5.25, 6.75, 7), (6, 6.25, 7, 7)\}.
\end{aligned} \tag{5.15}
$$

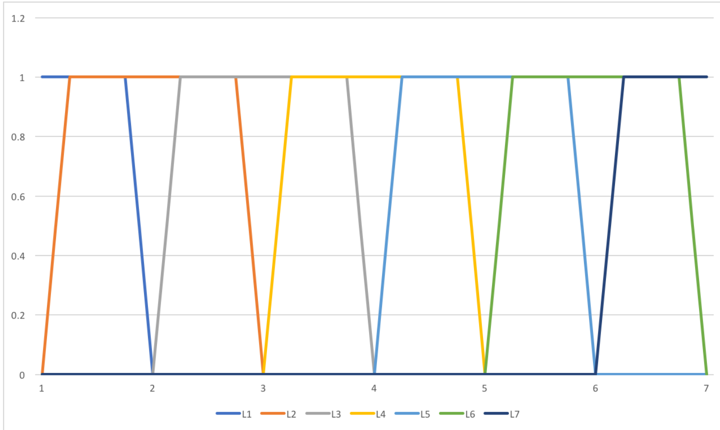


Figure 5.11: Trapezoid membership functions

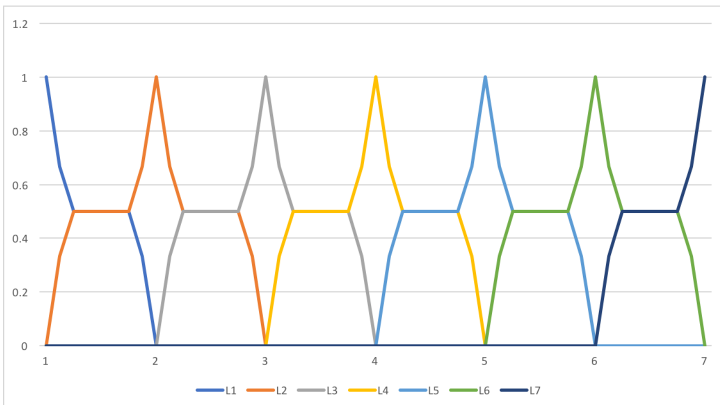


Figure 5.12: The least prejudiced distributions

If we further increase the size of trapezoid in Equation 5.14 to Equation 5.15.

The extended trapezoid membership functions and their least prejudiced distribution are shown in Figure 5.11 and Figure 5.12 respectively.

The extension of overlapped area of between adjacent membership function effect the least prejudiced distribution. In practical, the membership value of $\mu_{L_1}(\omega)$ and $\mu_{L_2}(\omega)$ cannot be both 1.0 at the same time.

In the case of trapezoid and extended trapezoid membership function, the boundary of the least prejudiced distributions are intact. Therefore, there are some effects in semantic overlapping in Table. 5.2, but the effects came from the adjacent Kansei labels only.

In case of widen the size of triangular membership functions from Equation 5.1 to Equation 5.16

The widen triangular membership functions and their least prejudiced distribution are shown in Figure 5.13 and Figure 5.14 respectively.

$$
\begin{aligned}
\mathcal{L}_n &= \{L_1^n, L_2^n, L_3^n, L_4^n, L_5^n, L_6^n, L_7^n\} \\
&= \{\textit{very } \mathbf{w}_n^-,\ \mathbf{w}_n^-,\ \textit{fairly } \mathbf{w}_n^-,\ \textit{neutral},\ \textit{fairly } \mathbf{w}_n^+,\ \mathbf{w}_n^+,\ \textit{very } \mathbf{w}_n^+\} \qquad (5.16) \\
&= \{(1,1,3),(0,2,4),(1,3,5),(2,4,6),(3,5,7),(4,6,8),(5,7,7)\}.
\end{aligned}
$$

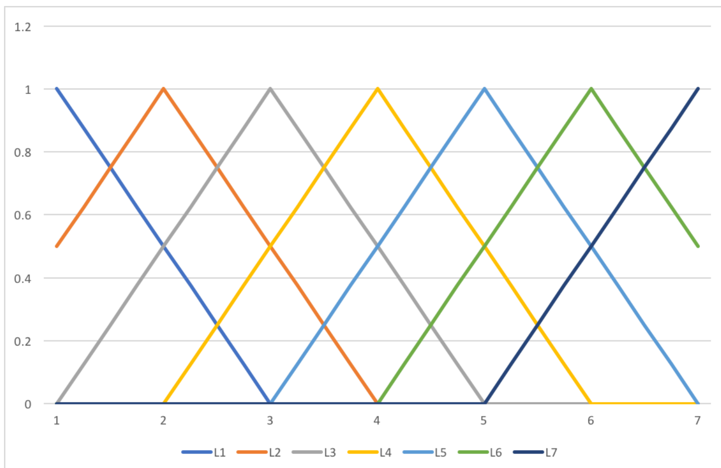


Figure 5.13: Widen triangular membership functions

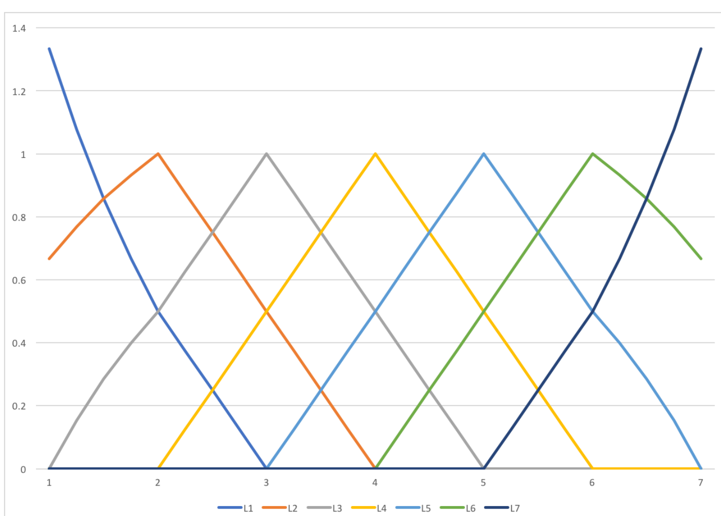


Figure 5.14: The least prejudiced distributions

In the case of widen triangular membership function, the boundary of the least prejudiced distributions are also widen. The effect of semantic overlapping spreads wider than the effect from Equation 5.1.

In summary, the shape of the membership function has a little effect on semantic overlapping of Kansei data, as long as the support of membership function is intact. However, the change of support of membership function has a great impact on the least prejudiced distribution.

5.4.4 Effect of consumer oriented evaluation method on proposed model

We use Kansei profile as a knowledge in evaluation process. In this thesis, we use evaluation techqniued called *"Consumber-Oriented Target-based Kansei Evaluation"* as described in Section 4.3. The probability that the Kansei profile of O_m meets the consumer's target $\mathbf{p}_{n_l}$ on attribute A_{n_l}, by

$$\mathbb{P}(\mathbf{p}_m^{n_l} \geq \mathbf{p}_{n_l}) = \sum_{g=1}^{G} \mathbf{p}_m^{n_l}(L_g^{n_l}) P(L_g^{n_l} \geq_{n_l} \mathbf{p}_{n_l}) \triangleq \mathbb{P}_m^{n_l} \tag{5.17}$$

where $P(L_g^{n_l} \geq_{n_l} \mathbf{p}_{n_l})$ is the cumulative probability function defined by

$$P(L_g^{n_l} \geq_{n_l} \mathbf{p}_{n_l}) = \sum_{L_g^{n_l} \geq_{n_l} L_h^{n_l}} \mathbf{p}_{n_l}(L_h^{n_l}) \tag{5.18}$$

The difference between using the cumulative probability function and the regular method is illustrated in Figure 5.15.

From the shape of Kansei profile in Figure 3.8, we assume that generally Kansei profile has local minimum at L_1, L_4, and L_7. The result of using the proposed Kansei data model in Target-based evaluation is shown as follows:

1. The local minimum L_7 is increased with very high cumulative probability
2. The local maximum (L_6) is changed with high cumulative probability
3. The local maximum (L_5) is changed with low cumulative probability
4. The local minimum L_4 in increased with low cumulative probability

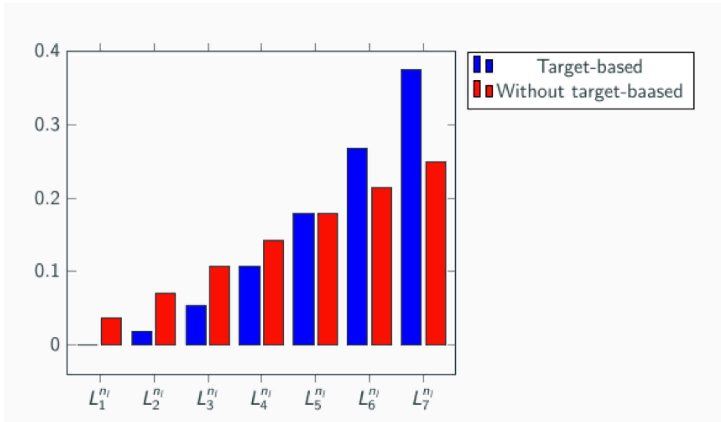


Figure 5.15: Effect of Target-based Evaluation Method

5. The rest of the label $(L_1 - L_3)$ is changed with very low cumulative probability

We can assume that there is the probability that overall aggregated score of the most product is higher. Thus, the result of evaluation could be unchanged.

5.5 Summary

In this chapter, we conduct a case study using Kansei data of hand-painted Kutani cups. We use the proposed model to generate Kansei profile of product from Kansei database of product. Then, the Kansei profile is used as knowledge for product evaluation. The objective of our proposed model is to include uncertainty of consumer's judgment into the consideration. Since it is hard to justify the evaluation result, therefore we analyze the effect of proposed model on Kansei profile, the sensitivity analysis of membership function of Kansei linguistic labels, and the effect of evaluation method.

The proposed model smooths the value of Kansei profile along the universe of discourse (Ω). The maximum of Kansei profile histogram decrease while the minimum increase. This phenomenon is intuitive because the uncertainty in consumer's judgment lowers the maximum value in histogram. The smoother histogram represent the effect of consumer's uncertainty in his judgment. Then, we analyze the effect of proposed model on the consumer-oriented Kansei evaluation method.

In the last section, we perform the sensitivity analysis of membership function of Kansei linguistic labels. For simplicity, we conduct a sensitivity analysis on the least prejudiced distribution. The analysis states that the shape and the magnitude of membership function of Kansei linguistic labels has a little effect on the prejudiced distribution as long as the each Kansei linguistic label has the same shape and magnitude. Changing in support of membership function has a great effect in the least prejudiced distribution.

Chapter 6

Conclusion and future works

In this chapter, we summarize our work in this thesis. The first section presents the summary of the thesis. The second section presents the contribution and impact of this study. The last section concludes this thesis and suggests some direction for future works.

6.1 Conclusion

As state in **research objectives**(Section 1.4), the main objective of this thesis are

As stated in the research objectives (Section 1.4), the main objectives of this thesis are to:

1. Propose a method to model Kansei data. This modeling can represent the vagueness and ambiguity in Kansei data. Additionally, the proposed method can handle the semantic overlapping of consumers' judgment.

2. Develop a target-based model for consumer-oriented evaluation of traditional products using the proposed Kansei data modeling approach.

6.1.1 Linguistic representation approach to modeling Kansei data

In Chapter 3, we propose a modeling method for representing Kansei data. This method is based on the linguistic interpretation of Kansei judgment and the probabilistic semantics of fuzzy sets. We conduct a case study in Chapter 5 to demonstrate the proposed model using available Kansei data (see Chapter 5). We interpret and model this consumer's assessment using the proposed model. Thus, the Kansei values of the products are transformed to linguistic labels which correspond to Kansei attributes. We implement linguistic interpretation further to represent the overlapping of Kansei judgment between Kansei labels. Finally, we generate a Kansei profile of the products.

6.1.2 Target-based model for consumer-oriented evaluation

In the research, we propose an evaluation method for traditional products in Chapter 4. Our approach calculates the fitness of the product. First, we justify the measurement of how products meet the specific feelings of consumers. Since there is some degree of uncertainty and vagueness, we represent the measurement using probability. In Chapter 5, we evaluate the fitness of products that match the consumer's requirement on specific attributes. This approach itself is intuitively natural. However, some extensions are required to adapt our proposed evaluation method into a real application. In a real-world recommendation system, functional and quantitative features of traditional products are also important factors in the decision-making process of the consumer. These factors should be considered in the evaluation framework. Second, the ambiguous and uncertainty of human judgments regarding Kansei features of Kansei data are not considered because we represent consumers' judgments as categorical data. In the target-oriented studies [132], fuzzy sets and their extensions can be used to solve this problem.

6.2 Thesis contributions

This section discusses the contributions of this thesis to both social impact and academic impact.

6.2.1 Social impact

In Section 2.1, Kansei Engineering (KE) has been applied to many fields [14]. Kansei Engineering has created many new products. Nagamachi designed a refrigerator for Sharp in which the vegetable compartment is at the top and the freezer at the bottom. He also supported the Sharp Kansei team to invent a video camcorder in which the camera lens can rotate 350 degrees with a liquid crystal display. This is the prototype of the current digital camera [37].

Our Kansei data model can represent the vagueness and uncertainty of customers from the Kansei database. Traditional craft producers will have better knowledge of the Kansei attributes of their products. Understanding the Kansei attributes in traditional crafts helps producers to design products which match current customers' lifestyles. Therefore, the contribution of this study will affect traditional craft industries both locally and nationally.

6.2.2 Academic impact

The linguistic representation approach to modeling Kansei data which is proposed in this thesis is based on data from SD scales. Since the SD scale is one of the most widely used scales in the measurement of attitudes [136], the proposed model can be implemented using the current data with minimal modification.

Another academic impact of this research is to embed a semantic overlapping into Kansei profiles. This method not only manages the vague and qualitative nature of Kansei attributes but also considers the uncertainty of a subject's answers acquired from SD scales.

6.3 Future works

In this section, some possible directions for future research are discussed.

6.3.1 Kansei data model

Gathering Kansei data is very important as the garbage input causes garbage output. There are two aspects of data modeling to study.

- Subjective information: The challenge of this aspect is how to model consumers' feelings mathematically. It begins with the data collection process. Some of the suggestions for improving the collecting process are to:
  - Extend the SD method in the design questionnaire process to capture consumers' feelings more precisely
  - Optimize the Kansei keywords to reduce the complexity of the questionnaires

  - Identify users' context to improve the understanding of the decision-making factors

- Objective information: Some objective information is hidden in the products. For example, we can extract hidden features from products using techniques of computer vision [137, 138] and bag-of-words models [139]. We can find the relationship between Kansei keywords and image features [140].

6.3.2 Target-based model for consumer-oriented evaluation

Some possible directions for a target-based model for the consumer-oriented evaluation model are:

- Consider users' context in the evaluation model. Sometimes, preferences of users change from one context to another.

- Implement the concept of Kansei keywords using *Ontology* [141].

- Extend linguistic quantifiers from predicate or first-order logic to support higher order logic.

6.3.3 Software-based application

Implementation of the study has a great impact on social and traditional craft industries. However, there are some limitations:

- Calculation formulas are complex.

- Available product patterns are fixed.

Thus, a software-based decision support system overcomes these limitations. The advantages of software-based decision support systems are listed as follows:

- Calculation power: Even in a mobile device or single-board computer, the calculation power of a central processing unit is very high. A calculation process uses concise time.

- Accessibility: With the development of a mobile device and user experience design, it is easier for traditional craft producers, sellers, and consumers to access and use the recommendation system. This is true even if the consumers are elderly people.
- Adaptive: New products can be evaluated (with some limitations due to lack of supervision from experts), and available product patterns are virtually unlimited.

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