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Author(s)	Huynh, Van-Nam; Nakamori, Yoshiteru; Yan, Hongbin
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A Comparative Study of Target-Based Evaluation of Traditional Craft Patterns using Kansei Data

Van-Nam Huynh, Yoshiteru Nakamori, and Hongbin Yan

School of Knowledge Science
Japan Advanced Institute of Science and Technology
Nomi, Ishikawa, 923-1292, JAPAN
Email: huynh@jaist.ac.jp

Abstract. Evaluation for ranking is very useful for users in their decision-making process when they want to select some item(s) from a large number of items using their personal preferences. In this paper, we will focus on the evaluation of Japanese traditional crafts, in which product items are assessed according to the so-called *Kansei* features by means of the semantic differential method. In particular, two decision analysis based evaluation procedures, which take consumer-specified preferences on kansei features of traditional products into consideration, will be discussed and compared.

1 Introduction

Nowadays, in an increasingly competitive world market, it is important for manufacturers to have a customer-focused approach in order to improve attractiveness in development of new products, which should satisfy not only requirements of physical quality, defined objectively, but also consumers' psychological needs, by essence subjective [9]. This approach has actually received much attention since the 1970s from the research community of consumer-focused design and Kansei engineering, which is defined as "translating technology of a consumer's feeling and image for a product into design elements" [7]. Kansei engineering has been developed and successfully applied to a variety of industries, especially, in Japan. *Kansei* is a Japanese term which, according to Mitsuo Nagamachi – the founder of Kansei engineering, is 'the impression somebody gets from a certain artefact, environment or situation using all her senses of sight, hearing, feeling, smell, taste [and sense of balance] as well as their recognition' as quoted from [11]. For building a kansei database on psychological feelings regarding products, the most commonly-used method is to choose (adjectival) kansei words first, and then ask people to express their feelings using those kansei words by means of the semantic differential (SD) method [8].

The focus of this paper is on the evaluation of traditional craft products for personalized recommendation using kansei data, taking consumer-specified preferences on kansei features of traditional products into consideration. It should be emphasized here that artistic and aesthetic aspects play a crucial role in perception of traditional crafts, therefore kansei data are essential and necessary for evaluation. Such evaluation would be helpful for marketing or personalized recommendation, which is particularly important in the current service-oriented economy where recommender systems are gaining widespread acceptance in e-commerce applications [1, 3]. In [6], we have developed a consumer-oriented evaluation model for traditional Japanese crafts based on the appealing idea of target-based decision analysis [2]. Particularly, given a consumer's request, using available kansei assessment data the developed model aims to define an evaluation function that quantifies how well a product item meets the consumer's feeling preferences.

Recently, Martínez [12] has proposed to use linguistic decision analysis for sensory evaluation based on the linguistic 2-tuple representation model [4]. Note that the knowledge used for sensory evaluation is also acquired by means of human senses of *sight*, *taste*, *touch*, *smell* and *hearing*. Basically, Martínez's model considers the evaluation problem as a multi-expert/multi-criteria decision-making problem and assumes a consistent order relation over the qualitative evaluation scale treated as linguistic term set of a linguistic variable [16]. In fact, Martínez's model yields an overall ranking of evaluated objects, which is therefore inappropriate for the purpose of personalized recommendations.

In this paper we will first customize the linguistic 2-tuple representation model to make it applicable to the consumer-oriented evaluation problem for traditional Japanese crafts using kansei data, and then conduct a comparative study of these two methods. The rest of this paper is organized as follows. Section 2 describes the consumer-oriented evaluation problem using kansei data for traditional crafts. Section 3 introduces two decision analysis based methods for solving the consumer-oriented evaluation problem, one is based on fuzzy target-based decision analysis and the other is based on the linguistic decision analysis using the 2-tuple linguistic representation model. Section 4 then provides an illustration of these methods to evaluation of Kutani coffee cups along with a comparative analysis of the obtained results. Finally, some conclusions are presented in Section 5.

2 Kansei-based Evaluation Problem

For traditional crafts, decisions on which items to buy or use are usually influenced by personal feelings/characteristics, so an evaluation targeting those specific requests by consumers would be very useful, particularly for the purpose of personalized recommendation. In this section, we will describe such a consumer-oriented evaluation problem using kansei data for traditional crafts [13]. Let us denote $\mathcal{O}$ the collection of craft patterns to be evaluated and N is the cardinality of $\mathcal{O}$, i.e. $N = |\mathcal{O}|$.

The first task in the Kansei-based evaluation process is to identify what kansei features people often use to express their feelings regarding traditional crafts. Each kansei feature is defined by an opposite pair of (adjectival) kansei words, for example the *fun* feature determines the pair of kansei words *solemn* and *funny*. Let

1. $\{F_1, \ldots, F_K\}$ be the set of kansei features selected,
2. $\mathbf{w}_k^+$ and $\mathbf{w}_k^-$ be the opposite pair of kansei words corresponding to F_k, for $k = 1, \ldots, K$. Denote $\mathbf{W}$ the set of kansei words, i.e. $\mathbf{W} = \{\mathbf{w}_k^+, \mathbf{w}_k^- | k = 1, \ldots, K\}$.

Then, the SD method [8] is used as a measurement instrument to design the questionnaire for gathering kansei evaluation data. Particularly, the questionnaire using the SD method for gathering information consists in listing the kansei features, each of which corresponds to an opposite pair of kansei words that lie at either end of a qualitative M-point scale, where M is an odd positive integer as used, for example, in 5-point scale, 7-point scale or 9-point scale. Let us symbolically denote the M-point scale by

$$\mathbb{V} = \{v_1, \ldots, v_M\} \tag{1}$$

where $\mathbf{w}_k^+$ and $\mathbf{w}_k^-$ are respectively assumed to be at the ends v_1 and v_M.

The questionnaire is then distributed to a population $\mathcal{P}$ of subjects who are invited to express their emotional assessments according each kansei feature of craft patterns in $\mathcal{O}$ by using the M-point scale. Formally, we can model the kansei data of each craft pattern $o_i \in \mathcal{O}$ according to kansei features obtained from the assessment of subjects s_j in $\mathcal{P}$ as shown in Table 1, where $x_{jk}(o_i) \in \mathbb{V}$, for $j = 1, \ldots, P = |\mathcal{P}|$ and $k = 1, \ldots, K$.

Table 1. The kansei assessment data of pattern o_i

	Kansei Features			
Subjects	F_1	F_2	$\cdots$	F_K
s_1	$x_{11}(o_i)$	$x_{12}(o_i)$	$\cdots$	$x_{1K}(o_i)$
s_2	$x_{21}(o_i)$	$x_{22}(o_i)$	$\cdots$	$x_{2K}(o_i)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
s_P	$x_{P1}(o_i)$	$x_{P2}(o_i)$	$\cdots$	$x_{PK}(o_i)$

The kansei assessment database built, as described above, will be utilized to generate the knowledge serving for the following evaluation problem. Assume that an agent as a potential consumer is interested in looking for a craft pattern which would meet her preference given by a proper subset W of the set $\mathbf{W}$ of kansei words as defined below. She may then want to rate craft patterns available in $\mathcal{O}$ according to her preference. In particular, we are concerned with consumer-specified requests which can be stated generally in forms of the following statement:

> "I should like craft items which would best meet LQ (of) my preference specified in $W \subset \mathbf{W}$" $(\bigstar)$

where LQ is a linguistic quantifier such as *all*, *most*, *at least half*, *as many as possible*, etc. Formally, the problem can be formulated as follows.

Given $W = \{\mathbf{w}^*_{k_1}, \ldots, \mathbf{w}^*_{k_n}\}$ and LQ corresponding to the request specified by an agent as linguistically stated in ($\bigstar$), where $*$ stands for either $+$ or $-$, and $\{k_1, \ldots, k_n\} \subseteq \{1, \ldots, K\}$, the problem now is how to evaluate craft patterns in $\mathcal{O}$ using kansei data and the request specified as the pair $[W, LQ]$? Here, by $*$ standing for either $+$ or $-$ as above, it indicates that only one of the two $\mathbf{w}^+_{k_l}$ and $\mathbf{w}^-_{k_l}$ $(l = 1, \ldots, n)$ presents in W, which may be psychologically reasonable to assume. For example, if the agent is interested in craft items being *funny* according to kansei feature of *fun*, then she is not interested in those being *solemn*, the opposite kansei word of *funny*.

In the following section, we will introduce two decision analysis based procedures for solving this consumer-oriented evaluation problem. Namely, the first evaluation procedure is based on fuzzy target-based decision analysis approach, and the second one is based on the linguistic decision analysis approach with the 2-tuple linguistic representation model [12].

3 Two Decision Analysis Based Evaluation Procedures

3.1 Evaluation Method using Target-Based Decision Analysis

Viewing multi-person assessments as uncertain judgments regarding kansei features of traditional craft items, the above-mentioned evaluation problem can be solved by applying the fuzzy target-based decision model recently developed in [5] as follows.

First, let us denote $\mathbf{D}$ the kansei assessment database about a finite set $\mathcal{O}$ of craft patterns using SD method as mentioned previously, and $\mathbf{D}[o_i]$ the data of pattern o_i $(i = 1, \ldots, N)$ as shown in Table 1.

For each pattern o_i, we define for each kansei feature F_k, $k = 1, \ldots, K$, a probability distribution $f_{ik} : \mathbb{V} \to [0, 1]$ as follows:

$$f_{ik}(v_h) = \frac{|\{s_j \in \mathcal{P} : x_{jk}(o_i) = v_h\}|}{|\mathcal{P}|} \tag{2}$$

This distribution f_{ik} is considered as an uncertain judgment of craft pattern o_i according to kansei feature F_k. By the same way, we can obtain a K-tuple of distributions $[f_{i1}, \ldots, f_{iK}]$ regarding the kansei assessment of o_i and call the tuple the kansei profile of o_i. Similarly, kansei profiles of all patterns in $\mathcal{O}$ can be generated from $\mathbf{D}$.

Having generated kansei profiles for all patterns $o_i \in \mathcal{O}$ as above, we now define the evaluation function V corresponding to the request ($\bigstar$) symbolically specified as $[W, LQ]$, where $W = \{\mathbf{w}^*_{k_1}, \ldots, \mathbf{w}^*_{k_n}\}$ and LQ is a linguistic quantifier.

Intuitively, if a consumer expresses her preference on a kansei feature such as *color contrast* with kansei word *bright*, she may implicitly assume a preference order on the semantic differential scale corresponding to *color contrast* towards the end v_1 where *bright* is placed. Conversely, if the consumer's preference on *color contrast* was *dark*, i.e. the opposite kansei word of *bright*, she would assume an inverse preference order on the scale towards the end v_M where *dark* is placed. In other words, in consumer-oriented evaluation using kansei data, the preference order on the semantic differential scale corresponding to a kansei feature should be determined adaptively depending on a particular consumer's preference. This can be formally formulated as below.

For each $\mathbf{w}^*_{k_l} \in W$, we define a linear preference order $\succeq_l$ on $\mathbb{V}$ according to the kansei feature F_{k_l} as follows

$$v_h \succeq_l v_{h'} \Leftrightarrow \begin{cases} h' \geq h, & \text{if } \mathbf{w}^*_{k_l} = \mathbf{w}^+_{k_l} \\ h \geq h', & \text{if } \mathbf{w}^*_{k_l} = \mathbf{w}^-_{k_l} \end{cases} \tag{3}$$

In addition, due to vagueness inherent in consumer's expression of preference in terms of kansei words, each $\mathbf{w}^*_{k_l}$ is considered as the feeling target, denoted by T_{k_l}, of the consumer according to kansei feature F_{k_l}, which can be represented as a possibility variable (Zadeh, 1978) on $\mathbb{V}$ whose possibility distribution is defined as

$$\pi_{k_l}(v_h) = \begin{cases} \left(\frac{M-h}{M-1}\right)^m, & \text{if } \mathbf{w}^*_{k_l} = \mathbf{w}^+_{k_l} \\ \left(\frac{h-1}{M-1}\right)^m, & \text{if } \mathbf{w}^*_{k_l} = \mathbf{w}^-_{k_l} \end{cases} \tag{4}$$

where $m \geq 0$ expresses the degree of intensity of the consumer's feelings about the target. Intuitively, when a consumer expresses her feeling targets using kansei words combined with linguistic modifiers such as *very*, *slightly*, etc., to emphasize her intensity about targets, the degree of intensity m can then be determined similarly as in Zadeh's method of modelling linguistic modifiers via power functions in approximate reasoning [16]. Fig. 1 graphically illustrates these concepts for the case $m = 1$, which exhibits a neutral-intensity toward targets.

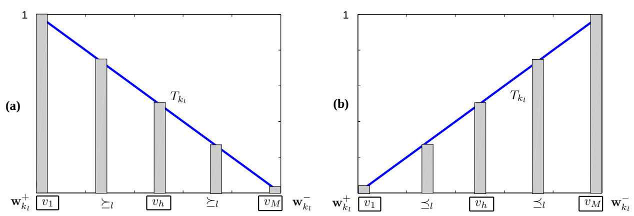


Fig. 1. The preference order $\succeq_l$ and the possibility distribution of feeling target T_{k_l}: (a) $\mathbf{w}^*_{k_l} = \mathbf{w}^+_{k_l}$; (b) $\mathbf{w}^*_{k_l} = \mathbf{w}^-_{k_l}$

As such, with the consumer's preference specified by W, we obtain n feeling targets T_{k_l} $(l = 1, \ldots, n)$ accompanying with n preference orders $\succeq_l$ $(l = 1, \ldots, n)$ on the semantic differential scale of kansei features F_{k_l} $(l = 1, \ldots, n)$, respectively. Recall that, for each $l = 1, \ldots, n$, the uncertain judgment of each craft pattern o_i regarding the kansei feature F_{k_l} is represented by the probability distribution f_{ik_l} over $\mathbb{V}$, as defined previously. Now we are able to evaluate, for each $l = 1, \ldots, n$, how the feeling performance of a pattern o_i on F_{k_l}, denoted by $F_{k_l}(o_i)$ and represented by f_{ik_l}, meets the feeling target T_{k_l} representing consumer's preference on F_{k_l}. This can be done as follows.

Firstly, making use of the possibility-probability conversion method [15] we can transform the possibility distribution of feeling target T_{k_l} into an associated probability distribution, denoted by $\hat{p}_{k_l}$, via the simple normalization as follows

$$\hat{p}_{k_l}(v_h) = \frac{\pi_{k_l}(v_h)}{\sum\limits_{v \in \mathbb{V}} \pi_{k_l}(v)} \tag{5}$$

Then, by accepting the assumption that the feeling target T_{k_l} is stochastically independent of feeling performance on F_{k_l} of any pattern o_i, we can work out the probability that the feeling performance $F_{k_l}(o_i)$ meets the feeling target T_{k_l}, denoted by $\mathbf{P}(F_{k_l}(o_i) \succeq T_{k_l})$, in terms of the preference order $\succeq_l$ as

$$\begin{aligned} \mathbf{P}(F_{k_l}(o_i) \succeq T_{k_l}) &\triangleq P(f_{ik_l} \succeq_l \hat{p}_{k_l}) \\ &= \sum_{h=1}^{M} f_{ik_l}(v_h) P(v_h \succeq_l \hat{p}_{k_l}) \end{aligned} \tag{6}$$

where $P(v_h \succeq_l \hat{p}_{k_l})$ is the cumulative probability function defined by

$$P(v_h \succeq_l \hat{p}_{k_l}) = \sum_{v_h \succeq_l v_{h'}} \hat{p}_{k_l}(v_{h'}) \tag{7}$$

Intuitively, the quantity $\mathbf{P}(F_{k_l}(o_i) \succeq T_{k_l})$ defined above could be interpreted as the probability of "the feeling performance on F_{k_l} of o_i meeting the feeling target T_{k_l} specified by a consumer on F_{k_l}". Then, after having these probabilities $\mathbf{P}(F_{k_l}(o_i) \succeq T_{k_l}) = \mathbf{P}_{k_l i}$, for $l = 1, \ldots, n$, we are able to aggregate all of them to obtain an aggregated value with taking the linguistic quantifier LQ into account, making use of the so-called ordered weighted averaging (OWA) aggregation operator [14].

Under such a semantics of OWA operators, now we are ready to define the evaluation function, for any $o_i \in \mathcal{O}$, as follows

$$\begin{aligned} V(o_i) &= \mathcal{F}(\mathbf{P}_{k_1 i}, \ldots, \mathbf{P}_{k_n i}) \\ &= \sum_{l=1}^{n} w_l \mathbf{P}_{li} \end{aligned} \tag{8}$$

where $\mathbf{P}_{li}$ is the l-th largest element in the collection $\mathbf{P}_{k_1 i}, \ldots, \mathbf{P}_{k_n i}$ and weighting vector $[w_1, \ldots, w_n]$ is determined directly by using a fuzzy set-based semantics of the linguistic quantifier LQ. As interpreted previously on quantities $\mathbf{P}_{k_l i}$ ($l = 1, \ldots, n$), the aggregated value $V(o_i)$ therefore indicates the degree to which craft pattern o_i meets the feeling preference derived from the request specified by a consumer as $[W, LQ]$.

3.2 Evaluation Method using Linguistic Decision Analysis

Now we will develop in this section another evaluation method, making use of linguistic decision analysis with the 2-tuple linguistic representation model [4]. The main reason for using the 2-tuple based evaluation approach is due to its advantage over conventional fuzzy set-based and symbolic approaches; it overcomes the limitations of the loss of information yielded by the process of linguistic approximation, and the lack of precision in final results inherently faced by these conventional approaches.

To make the 2-tuple linguistic representation model applicable to the evaluation problem at hand, we will treat qualitative assessments regarding each kansei feature given in the 7-point scale as linguistic assessments accordingly taken from the set $\mathcal{S}$ of seven linguistic terms as described in Fig. 2.

F_k

$\mathbf{w}_k^+$	s_0	s_1	s_2	s_3	s_4	s_5	s_6	$\mathbf{w}_k^-$

Fig. 2. Linguistic values and their relation to a pair of kansei words

In the 2-tuple representation model, linguistic information is represented by a linguistic 2-tuple (s, α) composed of a linguistic term $s \in \mathcal{S}$ and a number $\alpha \in [-0.5, 0.5)$. More particularly, let $\mathcal{S} = \{s_0, \ldots, s_g\}$ be a linguistic term set on which a total order is defined as: $s_i \leq s_j \Leftrightarrow i \leq j$. In addition, a negation operator Neg can be defined by: $\mathrm{Neg}(s_i) = s_j$ such that $j = g - i$. In general, applying a symbolic method for aggregating linguistic information often yields a value $\beta \in [0, g]$, and $\beta \notin \{0, \ldots, g\}$, then a symbolic approximation must be used to get the result expressed in $\mathcal{S}$.

In order to avoid any approximation process which causes a loss of information in the processes of computing with words, alternatively the 2-tuple linguistic representation model takes $\mathcal{S} \times [-0.5, 0.5)$ as the underlying space for representing information. In this representation space, if a value $\beta \in [0, g]$ represents the result of a linguistic aggregation operation, then the 2-tuple (s_i, α) that expresses the information equivalent to β is obtained by means of the following transformation:

$$\begin{aligned} \Delta : [0, g] &\longrightarrow \mathcal{S} \times [-0.5, 0.5) \\ \beta \quad &\longmapsto (s_i, \alpha), \end{aligned}$$

with

$$\begin{cases} i = \mathrm{round}(\beta) \\ \alpha = \beta - i \end{cases}$$

and then α is called a *symbolic translation*, which supports the "difference of information" between the value $\beta \in [0, g]$ obtained after a symbolic aggregation operation, and the closest value in $\{0, \ldots, g\}$ indicating the index of the best matched term in $\mathcal{S}$.

Inversely, a 2-tuple $(s_i, \alpha) \in \mathcal{S} \times [-0.5, 0.5)$ can also be equivalently represented by a numerical value in $[0, g]$ by means of the following transformation:

$$\begin{aligned} \Delta^{-1} : \mathcal{S} \times [-0.5, 0.5) &\longrightarrow [0, g] \\ (s_i, \alpha) &\longmapsto \Delta^{-1}(s_i, \alpha) = i + \alpha. \end{aligned}$$

Under such transformations, it should be noticed here that any original linguistic term s_i in S is then represented by its equivalent 2-tuple $(s_i, 0)$ in the 2-tuple linguistic model.

The comparison of linguistic information represented by 2-tuples is defined as follows. Let (s_i, α_1) and (s_j, α_2) be two 2-tuples, then

- if $i < j$ then (s_i, α_1) is less than (s_j, α_2),
- if $i = j$ then
  1. if $\alpha_1 = \alpha_2$ then (s_i, α_1) and (s_j, α_2) represent the same information,
  2. if $\alpha_1 < \alpha_2$ then (s_i, α_1) is less than (s_j, α_2),
  3. if $\alpha_1 > \alpha_2$ then (s_i, α_1) is greater than (s_j, α_2).

Using two 2-tuple transformations defined above, the negation operator over 2-tuples is defined as follows:

$$\mathrm{Neg}((s_i, \alpha)) = \Delta(g - (\Delta^{-1}(s_i, \alpha))) \tag{9}$$

Now the consumer-oriented evaluation method based on the 2-tuple representation model can be formulated as follows.

Given a request $[W, LQ]$ with $W = \{\mathbf{w}^*_{k_1}, \ldots, \mathbf{w}^*_{k_n}\}$ and LQ as a linguistic quantifier, let us decompose the set of indices $I = \{k_1, \ldots, k_n\}$ into two disjoint subsets I^+ and I^- such that

$$I^+ = \{k_j \in I | \mathbf{w}^*_{k_j} = \mathbf{w}^+_{k_j}\} \text{ and } I^- = \{k_j \in I | \mathbf{w}^*_{k_j} = \mathbf{w}^-_{k_j}\} \tag{10}$$

Then, for each object $o_i \in \mathcal{O}$, the performance of o_i on the kansei feature F_{k_j} is evaluated by

$$V_{k_j}(o_i) = \Delta\left(\sum_{s \in \mathcal{S}} f_{ik_j}(s) \Delta^{-1}(s, 0)\right), \text{ if } k_j \in I^- \tag{11}$$

and

$$V_{k_j}(o_i) = \Delta\left(\sum_{s \in \mathcal{S}} f_{ik_j}(s) \Delta^{-1}(\mathrm{Neg}((s, 0)))\right), \text{ if } k_j \in I^+ \tag{12}$$

where $f_{ik_j}(s)$ is defined by

$$f_{ik_j}(s) = \frac{|\{s_h \in \mathcal{P} : x_{hk_j}(o_i) = s\}|}{|\mathcal{P}|} \tag{13}$$

That is, $V_{k_j}(o_i)$ is the mean value of uncertain linguistic assessment of o_i regarding the kansei feature F_{k_j} computed by means of linguistic 2-tuples. Once values $V_{k_j}(o_i)$ have been computed for all features $F_{k_j}, k_j \in I$, the overall performance of o_i is calculated by aggregating all of them using an OWA operator $\mathcal{F}$ of dimension n similar to (8), such as

$$V(o_i) = \mathcal{F}(V_{k_1}(o_i), \ldots, V_{k_n}(o_i)) \tag{14}$$

with the associated weighting vector $[w_1, \ldots, w_n]$ determined by using the fuzzy set-based semantics of linguistic quantifier LQ.

4 Illustration to Evaluation of Kutani Coffee Cups

For illustration, we shall apply the proposed model to evaluating Kutani porcelain, a traditional craft industry in Japan, historically back to the seventeenth century, of Kutani Pottery Village in Ishikawa prefecture[1]. A total of 35 patterns of Kutani coffee cup have been collected for the Kansei-based evaluation, and 26 opposite pairs of kansei words were used to design the answer sheet for gathering kansei assessment data of these items (i.e., Kutani coffee cups) for evaluation. Kansei words are approximately translated into English as shown in Table 2.

A total of 60 subjects were invited to participate in the kansei assessment process. The data obtained is 3-way data of which each Kutani coffee cup $\#i$ ($i = 1, \ldots, 35$) is assessed by all participated subjects on all kansei features F_k, $k = 1, \ldots, 26$. The 3-way data is then used to generate kansei profiles for patterns via (2) as mentioned previously. These kansei profiles are considered as (uncertain) feeling assessments of items serving as the knowledge for consumer-oriented evaluation.

4.1 Obtained Results of Two Methods

Assuming a consumer's request is specified as

$$[\{\mathbf{w}_7^+, \mathbf{w}_{10}^-, \mathbf{w}_{11}^+, \mathbf{w}_{17}^+, \mathbf{w}_{25}^-, \}, \textit{as many as possible}]$$

That is, verbally, she would ask for items meeting *as many as possible* of her feeling preferences of *pretty*, *attractive*, *flowery*, *bright* and *pale*.

We first determine preference orders on $\mathbb{V} = \{v_1, \ldots, v_7\}$ for features F_7, F_{10}, F_{11}, F_{17} and F_{25}. Using (3), we have $\succeq_{10}=\succeq_{25}$ and $\succeq_7=\succeq_{11}=\succeq_{17}$, where

$$v_1 \succeq_7 \ldots \succeq_7 v_7 \text{ and } v_7 \succeq_{10} \ldots \succeq_{10} v_1$$

Then, using (4) for $m = 2$, we define feeling targets T_7, T_{10}, T_{11}, T_{17} and T_{25} for features F_7, F_{10}, F_{11}, F_{17} and F_{25} respectively. In this case we have $T_{10} \equiv T_{25}$ and $T_7 \equiv T_{11} \equiv T_{17}$ with possibility distributions shown in Fig. 3.

We now determine the weighting vector of dimension 5, denoted by $w = [w_1, w_2, w_3, w_4, w_5]$, according to the fuzzy set-based semantics of linguistic quantifier '*as many as possible*'. Assume that, for example, the membership function

[1] http://shofu.pref.ishikawa.jp/shofu/intro_e/HTML/H_S50402.html

Table 2. Opposite pairs of kansei words used for the evaluation

F_k	*Left kansei word*	v_1	$\cdots$	v_7	*Right kansei word*
1	conventional($\mathbf{w}_1^+$)	□	$\cdots$	□	unconventional($\mathbf{w}_1^-$)
2	simple($\mathbf{w}_2^+$)	□	$\cdots$	□	compound($\mathbf{w}_2^-$)
3	solemn($\mathbf{w}_3^+$)	□	$\cdots$	□	funny($\mathbf{w}_3^-$)
4	formal($\mathbf{w}_4^+$)	□	$\cdots$	□	causal($\mathbf{w}_4^-$)
5	serene($\mathbf{w}_5^+$)	□	$\cdots$	□	forceful($\mathbf{w}_5^-$)
6	still($\mathbf{w}_6^+$)	□	$\cdots$	□	moving($\mathbf{w}_6^-$)
7	pretty($\mathbf{w}_7^+$)	□	$\cdots$	□	austere($\mathbf{w}_7^-$)
8	friendly($\mathbf{w}_8^+$)	□	$\cdots$	□	unfriendly($\mathbf{w}_8^-$)
9	soft($\mathbf{w}_9^+$)	□	$\cdots$	□	hard($\mathbf{w}_9^-$)
10	blase($\mathbf{w}_{10}^+$)	□	$\cdots$	□	attractive($\mathbf{w}_{10}^-$)
11	flowery($\mathbf{w}_{11}^+$)	□	$\cdots$	□	quiet($\mathbf{w}_{11}^-$)
12	happy($\mathbf{w}_{12}^+$)	□	$\cdots$	□	normal($\mathbf{w}_{12}^-$)
13	elegant($\mathbf{w}_{13}^+$)	□	$\cdots$	□	loose($\mathbf{w}_{13}^-$)
14	delicate($\mathbf{w}_{14}^+$)	□	$\cdots$	□	large-hearted($\mathbf{w}_{14}^-$)
15	luxurious($\mathbf{w}_{15}^+$)	□	$\cdots$	□	frugal($\mathbf{w}_{15}^-$)
16	gentle($\mathbf{w}_{16}^+$)	□	$\cdots$	□	pithy($\mathbf{w}_{16}^-$)
17	bright($\mathbf{w}_{17}^+$)	□	$\cdots$	□	dark($\mathbf{w}_{17}^-$)
18	reserved($\mathbf{w}_{18}^+$)	□	$\cdots$	□	imperious($\mathbf{w}_{18}^-$)
19	free($\mathbf{w}_{19}^+$)	□	$\cdots$	□	regular($\mathbf{w}_{19}^-$)
20	level($\mathbf{w}_{20}^+$)	□	$\cdots$	□	indented($\mathbf{w}_{20}^-$)
21	lustered($\mathbf{w}_{21}^+$)	□	$\cdots$	□	matte($\mathbf{w}_{21}^-$)
22	transpicuous($\mathbf{w}_{22}^+$)	□	$\cdots$	□	dim($\mathbf{w}_{22}^-$)
23	warm($\mathbf{w}_{23}^+$)	□	$\cdots$	□	cool($\mathbf{w}_{23}^-$)
24	moist($\mathbf{w}_{24}^+$)	□	$\cdots$	□	arid($\mathbf{w}_{24}^-$)
25	colorful($\mathbf{w}_{25}^+$)	□	$\cdots$	□	sober($\mathbf{w}_{25}^-$)
26	plain($\mathbf{w}_{26}^+$)	□	$\cdots$	□	gaudy, loud($\mathbf{w}_{26}^-$)

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

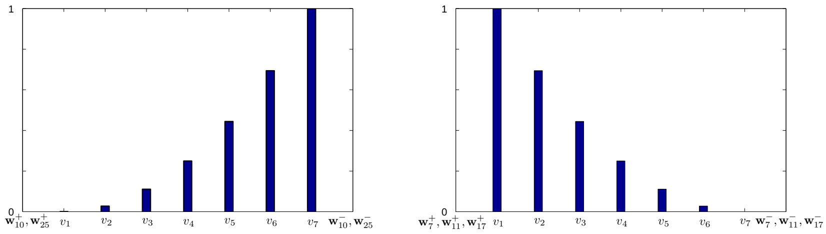
$$Q(r) = \begin{cases} 0 & \text{if } 0 \le r \le 0.5 \\ 2r - 1 & \text{if } 0.5 \le r \le 1 \end{cases}$$

We then obtain the weighting vector as $w = [0, 0, 0.2, 0.4, 0.4]$ using Yager's method proposed in [14].

With these preparations we are now ready to apply the target based evaluation method for ranking items Kutani_cup#i, $i = 1, \ldots, 35$, as follows. First, we use (5) and (6) for computing probabilities $\mathbf{P}_{7i}$, $\mathbf{P}_{10i}$, $\mathbf{P}_{11i}$, $\mathbf{P}_{17i}$ and $\mathbf{P}_{25i}$ of meeting corresponding feeling targets T_7, T_{10}, T_{11}, T_{17} and T_{25} for each item Kutani_cup#i ($i = 1, \ldots, 35$). Then, using (8) we have

$$V(\text{Kutani\_cup}\#i) = \mathcal{F}(\mathbf{P}_{7i}, \mathbf{P}_{10i}, \mathbf{P}_{11i}, \mathbf{P}_{17i}, \mathbf{P}_{25i})$$

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



a) Targets T_{10} and T_{25} $(m = 2)$ b) Targets T_7, T_{11} and T_{17} $(m = 2)$

Fig. 3. Possibility distribution of feeling targets

Table 3 shows the top three patterns that would best meet the feeling preferences *pretty*, *attractive*, *flowery*, *bright* and *pale*, with different typical linguistic quantifiers used.

Table 3. Quantifiers used and corresponding top 3 patterns

Linguistic quantifier	Weighting vector	The top 3 patterns
As many as possible (AMAP)	$[0, 0, 0.2, 0.4, 0.4]$	$\#4 \succeq \#8 \succeq \#11$
All	$[0, 0, 0, 0, 1]$	$\#8 \succeq \#7 \succeq \#30$
There exists	$[1, 0, 0, 0, 0]$	$\#13 \succeq \#18 \succeq \#29$
At least haft (ALH)	$[0.4, 0.4, 0.2, 0, 0]$	$\#13 \succeq \#6 \succeq \#24$

On the other hand, using the 2-tuple based evaluation method described above, we also obtain results of the top 3 recommended items with different linguistic quantifiers applied as shown in Table 4.

Table 4. Top 3 items recommended using the 2-tuple based method

Linguistic quantifier	Weighting vector	The top 3 patterns
As many as possible (AMAP)	$[0, 0, 0.2, 0.4, 0.4]$	$\#8 \succeq \#11 \succeq \#4$
All	$[0, 0, 0, 0, 1]$	$\#7 \succeq \#9 \succeq \#8$
There exists	$[1, 0, 0, 0, 0]$	$\#13 \succeq \#29 \succeq \#18$
At least haft (ALH)	$[0.4, 0.4, 0.2, 0, 0]$	$\#13 \succeq \#6 \succeq \#24$

4.2 Comparative Analysis

For the sake of facilitating the discussion of obtained results, all the recommended items by the target based evaluation method (according to typical linguistic quantifiers used) as well as their uncertain assessments on selected features F_7, F_{10}, F_{11}, F_{17} and F_{25} are depicted in Fig. 4.

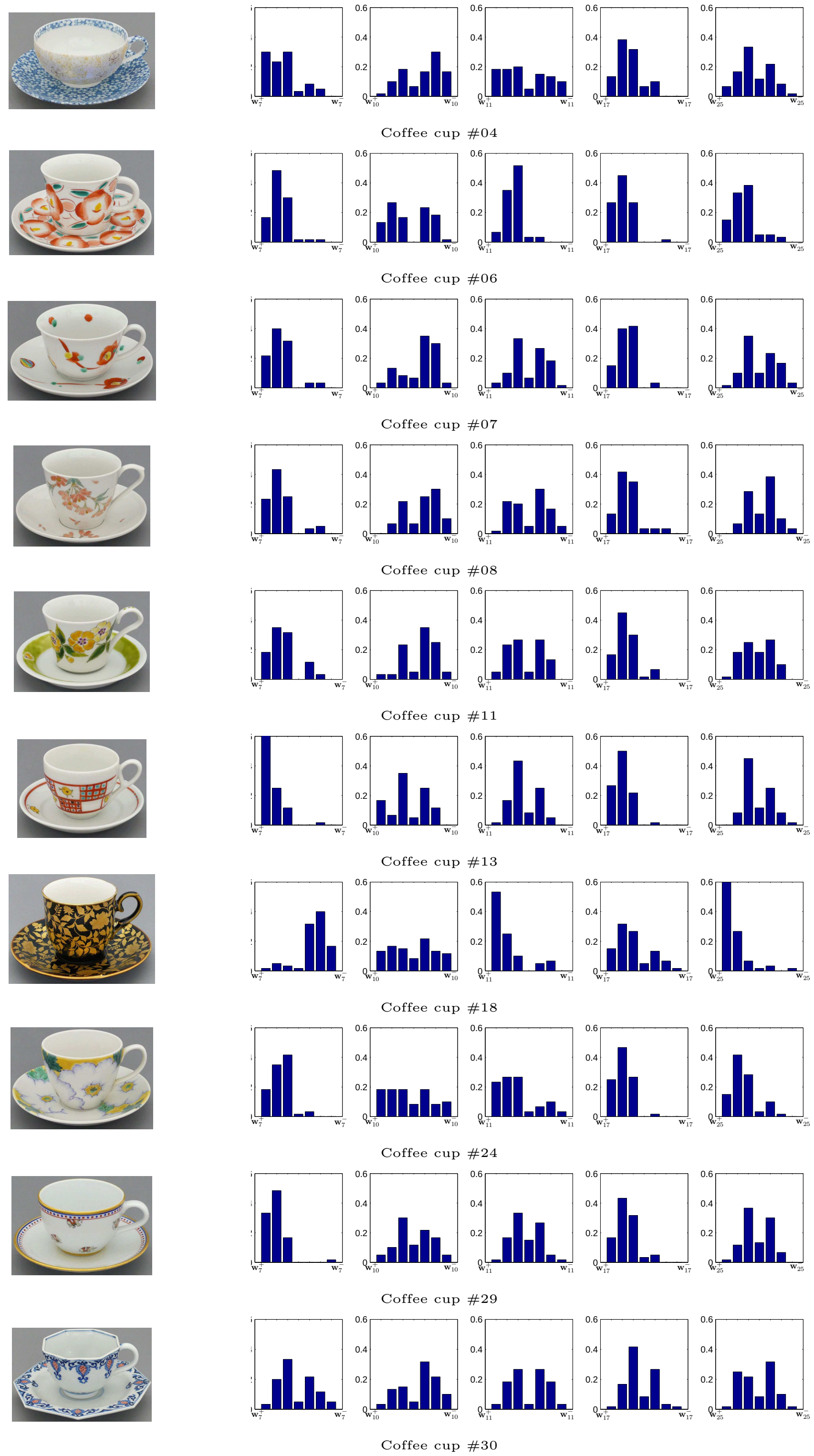


Fig. 4. Recommended items and those uncertain judgments for selected features

As we have seen from Tables 3 and 4, the results yielded by two methods are quite different, except the case of quantifier '*at least half*'. Particularly, in the first case of quantifier '*as many as possible*', though two methods produced the same top 3 items but these items were ranked differently. Item #4 was ranked first by the target-based method while it appears as the third by the 2-tuple based method. For the case of quantifier '*all*', it is worth noting here that the uncertain judgments of items #7 and #8 on correspondingly selected features are somewhat similar. However, item #8 was ranked third by the 2-tuple based method and dominated by item #9 as the second and item #7 as the first, while it was ranked first by the target-based method. In the case of quantifier '*there exists*', a position interchange of items #18 and #29 happens, in particular item #18 was dominated by item #29 with the 2-tuple based method and vice-versa with the target-based method. In fact, the target achievement of item #18 on target *flowery* ($\mathbf{w}_{11}^{+}$) is 0.7209 which is better than that of item #29 on target *pretty* ($\mathbf{w}_{7}^{+}$) as 0.6804. This can be observed as illustrated in Fig. 4.

The difference in ranking results of the two methods can be explained as follows. In the 2-tuple based method, only preferences over the linguistic term set $\mathcal{S}$ induced from the consumer's request are taken into account. While in the target-based method, not only these preferences but also feeling targets specified by the consumer are considered simultaneously. From a decision analysis point of view, after determining consumer-specified preferences the 2-tuple based method applies the expected value model (refer to (11) and (12)) to evaluate the performance of an object regarding each kansei feature specified by the consumer. Thus, as discussed in Huynh *et al.* [5], the 2-tuple based method works similarly to the target-based method when the 'neutral target' is used. In particularly, if we define targets as

$$\pi_{k_l}(v_h) = 1$$

instead of the targets defined in (4), then the result obtained by the target-based method is the same as that produced by the 2-tuple based method. This means that the target-based method can provide recommendations which would interestingly reflect attitudes of consumer towards feeling targets as graphically illustrated by Fig. 4, whilst those recommended by the 2-tuple based method would not do so.

5 Conclusions

In this paper we have conducted a comparative study of two decision analysis based evaluation methods for the evaluation problem of Japanese traditional crafts, which take consumer-specified preferences on kansei features of traditional products into consideration. In doing so, we have first customized the linguistic 2-tuple representation model in linguistic decision analysis in order to apply it to the consumer-oriented evaluation problem using kansei data. It has been shown that the 2-tuple based evaluation method can be seen as a special case of the target-based evaluation method which would interestingly provide the evaluated results reflecting attitudes of consumers about feeling targets.

References

1. G. Adomavicius, A. Tuzhilin, Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions, *IEEE Trans. Know. Data Eng.* **17** (2005) 734–749.
2. R. Bordley, C. Kirkwood, Multiattribute preference analysis with performance targets, *Operations Research* **52** (2004) 823–835.
3. N. Manouselis, C. Costopoulou, Analysis and classification of multi-criteria recommender systems, *World Wide Web* **10** (2007) 415–441.
4. F. Herrera, L. Martínez, A 2-tuple fuzzy linguistic representation model for computing with words, *IEEE Trans. Fuzzy Syst.*8 (2000) 746–752.
5. V.N. Huynh, Y. Nakamori, M. Ryoke, T.B. Ho, Decision making under uncertainty with fuzzy targets, *Fuzzy Optim. Decis. Making* **6** (2007) 255–278.
6. V.N. Huynh, H.B. Yan, Y. Nakamori, A target-based decision making approach to consumer-oriented evaluation model for Japanese traditional crafts, *IEEE Trans. Eng. Manag.* (in press).
7. M. Nagamachi, "Kansei Engineering: a new ergonomic consumer-oriented technology for product development," *Inter. J. Indus. Ergo.* 15 (1995) 3–11.
8. C. E. Osgood, G. J. Suci, P. H. Tannenbaum, *The Measurement of Meaning.* Urbana, USA: University of Illinois Press, 1957.
9. J.-F. Petiot, B. Yannou, Measuring consumer perceptions for a better comprehension, specification and assessment of product semantics, *Inter. J. Indus. Ergo.* **33** (2004) 507–525.
10. D. Ruan, X. Zeng (Eds.), *Intelligent Sensory Evaluation: Methodologies and Applications.* Berlin: Springer-Verlag, 2004.
11. S. Schütte, *Engineering Emotional Values in Product Design – Kansei Engineering in Development.* Linköpings Universitet, Dissertation 951, 2005.
12. L. Martínez, Sensory evaluation based on linguistic decision analysis, *Inter. J. Approx. Reason.***44** (2007) 148–164.
13. H.B. Yan, V.N. Huynh, Y. Nakamori, A probability-based approach to consumer oriented evaluation of traditional craft items using kansei data, in: V.N. Huynh et al. (Eds.), *Interval/Probabilistic Uncertainty and Non-Classical Logics*, Springer-Verlag, 2008, pp. 326–340.
14. R.R. Yager, On ordered weighted averaging aggregation operators in multicriteria decision making, *IEEE Trans. Syst.*, *Man*, *Cybern.***18** (1988) 183–190.
15. R.R. Yager, On the instantiation of possibility distributions, *Fuzzy Sets Syst.***128** (2002) 261–266.
16. L. A. Zadeh, The concept of a linguistic variable and its applications to approximate reasoning, *Inf. Sci.***8** (1975) 199–249; 310–357.