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Author(s)	Yan, Hong-Bin; Huynh, Van-Nam; Murai, Tetsuya; Nakamori, Yoshiteru
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Description	

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Kansei Evaluation Based on Prioritized Multi-Attribute Fuzzy Target-Oriented Decision Analysis

Hong-Bin Yan [1] Van-Nam Huynh [1] Tetsuya Murai [2]
Yoshiteru Nakamori [1]

[a] *Graduate School of Knowledge Science*
Japan Advanced Institute of Science and Technology
Nomi City, Ishikawa 923-1292, Japan

[b] *Graduate School of Information Science and Technology*
Hokkaido University
Kita-ku, Sapporo 060-0814, Japan

Abstract

This paper deals with Kansei evaluation focusing on consumers' psychological needs and personal taste. To do so, a preparatory study is conducted beforehand to obtain Kansei data of the products to be evaluated, in which products are assessed according to Kansei attributes by means of the semantic differential method and linguistic variables. These Kansei data are then used to generate Kansei profiles for evaluated products by means of the voting statistics. As consumers' preferences on Kansei attributes of products vary from person to person and target-oriented decision analysis provides a good description of individual preference, the target-oriented decision analysis has been used and extended to quantify how well a product meets consumers' preferences. Due to the vagueness and uncertainty of consumers' preferences, three types of fuzzy targets are defined to represent the consumers' preferences. Considering the priority order of Kansei attributes specified by consumers, a so-called prioritized scoring aggregation operator is utilized to aggregate the partial degrees of satisfaction for the evaluated products. As the aesthetic aspect plays a crucial role in human choice of traditional crafts, an application to evaluate Kanazawa gold leaf, a traditional craft in Ishikawa, Japan, has also been provided to illustrate how the proposed model works in practice.

Key words: Kansei evaluation; Fuzzy target-oriented decision analysis; Multi-attribute; Prioritized aggregation; Traditional crafts.

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[1] {hongbinyan,huynh,nakamori}@jaist.ac.jp
[2] murahiko@main.ist.hokudai.ac.jp

1 Introduction

In today's increasingly competitive market place, satisfying consumers' needs and tastes has become a great concern of almost every company [15,19,44]. Consumers put more emphasis not only on functional requirements of products, defined objectively, but also on psychological needs and feelings, by essence subjective [39]. Moreover, with the development of global markets and modern technologies, it is likely that many similar products will be functionally equivalent [19], thus consumers may find that it is difficult to distinguish and choose their desired product(s). In this regard, consumers' psychological needs and feelings must be considered in choice of products [2].

Kansei engineering has been developed as a methodology to deal with consumers' subjective impressions (called Kansei in Japanese) regarding a product into the design elements of a product [33,34,35]. According to Nagamachi [33], "Kansei is an individual subjective impression from a certain artifact, environment or situation using all the senses of *sight, hearing, feeling, smell, taste, recognition and balance*". Kansei engineering is also sometimes referred to as "*sensory engineering*" or "*emotional usability*" [10]. Kansei engineering can be either used by designers as a design aid to develop products that are able to match consumers' Kansei or used by consumers to select products based on their Kansei requirements [33]. To obtain Kansei data for the products to be evaluated, the most commonly used method is to identify and measure Kansei attributes (attributes having a bipolar pair of Kansei words) first and then ask people to assess their feelings regarding these Kansei attributes, in which semantic differential [38](SD) method is often used. Among Kansei engineering, Kansei evaluation is an important process in which a product design may be selected for production or design [7,25,26,28,39,44]. In this paper, we focus on Kansei evaluation process based on consumers' Kansei requirements, the very early process in Kansei engineering.

Many studies have attempted to solve Kansei evaluation [2,7,25,26,28,32,39] in the literature. Statistical analysis plays an important role and is widely accepted as the most systematic tool for Kansei evaluation. For example, Hsu et al. [15] used multivariate analysis to analyze consumers' perceptions and to build conceptual models for telephone design. Llinares and Page [28] performed statistical analysis to quantify purchaser perceptions in housing assessment to identify main attributes which describe consumers' perception. To reduce dimensionality, principal component analysis (PCA) and fuzzy PCA are also used [28,36] in Kansei evaluation. Moreover, Barone et al. [2] proposed a weighted regression approach by means of conjoint analysis, in which attribute importance weights are estimated by using respondent choice time in controlled interviews. Petiot and Yannou [39] proposed an integrated approach which rates and ranks the new product prototypes according to their closeness to the specified "ideal product", in which three types of satisfaction utility functions are defined and a multi-additive model is used to obtain the global satisfaction utility. In addition to these methods, in closely similar and related studies on sensory evaluation or subjective evaluation, decision analysis has also been utilized in the evaluation problems [5,18,20,24,29,30,31,40,53]. For example, Martínez [29] proposed a sensory evaluation model based on linguistic decision analysis by using the linguistic 2-tuple representation model [13,14], in which knowledge used for sensory evaluation is acquired from a panel of experts by means of the five senses of *sight, taste, touch, smell and hearing*. The sensory evaluation model [29] considers the evaluation problem as a multi-expert/multi-attribute decision problem, assuming a consistent order relation on the quantitative evaluation scale treated as the linguistic term set of a linguistic variable [51,52]. More studies of sensory evaluation based on the linguistic 2-tuple representation model [13,14] can be found in the literature [30,40,53]. The additive or multiplicative utility model has also been used for subjective evaluations [20,39].

Previous studies have significantly advanced the issue of Kansei and Kansei-related evaluations. However,

(1) consumers' preferences on Kansei attributes vary from person to person according to character, feeling, aesthetic and so on. For example, a Kansei attribute *fun* having left and right Kansei words as <solemn, funny>. Some consumers may prefer *solemn*, others may prefer *funny*, and there are also some consumers preferring *neither solemn nor funny*. In this regard, in contrast to the sensory evaluation model [29,30,40,53], we will have *inconsistent order relations* on Kansei attributes.
(2) Furthermore, as pointed out by Bordley and Kirkwood [3], empirical evidence indicates that conventional concave attribute utility function often does not provide a good description of individual preference, and usually it is difficult for consumers to determine their utility functions for Kansei attributes.
(3) Finally, a consumer usually may have a priority order of the Kansei attributes, i.e., some Kansei attributes may be necessary to be satisfied.

These considerations lead us to solve Kansei evaluation based on multi-attribute fuzzy target-oriented decision analysis and prioritized aggregation. In their pioneering work Kahneman and Tversky [21] proposed an S-shaped value function to substitute for utility function. Heath et al. [11] suggested that the reference point in this S-shaped value function can be interpreted as a target. Developing this concept further, target-oriented decision analysis [4] suggested that instead of maximizing the utility, the decision makers try to maximize the probability of meeting target. In general, target-oriented decision analysis lies in the philosophical root of Simon's bounded rationality [42] as well as represents the S-shaped value function [21]. Particularly, in Kansei evaluation, due to vagueness and uncertainty of consumers' preferences, fuzzy targets can be used to represent consumers' uncertain preferences. In addition, multiple Kansei attributes are usually considered. To model the prioritization of Kansei attributes, Yager [46,47] proposed the prioritized aggregation operator by using importance weights in which the weights associated with the lower priority attributes are related to the satisfaction of the higher priority attributes.

In order to propose a Kansei evaluation model based on multi-attribute fuzzy target-oriented decision analysis and prioritized aggregation, firstly, like the traditional Kansei evaluation method, a preparatory experiment study is conducted in advance to select Kansei attributes by means of SD [38] method. In order to obtain Kansei data of products, a number of people are selected to assess products regarding these Kansei attributes. Secondly, these Kansei data are used to generate Kansei profiles for evaluated products by making use of the voting statistics. Thirdly, according to consumer-specified preferences on Kansei attributes, three main types of fuzzy targets are defined, to represent the consumers' preferences. Based on the principle of target-oriented decision analysis [3,4], we can obtain the degrees of satisfaction (probabilities of meeting targets) regarding the Kansei attributes selected by consumers for all the evaluated products, by means of an α-cuts based method. Finally, considering prioritization of the Kansei attributes, a so-called prioritized scoring aggregation operator [47] is used to aggregate the partial degrees of satisfaction for the evaluated products.

The organization of this paper is as follows. In Section 2 a Kansei evaluation model based on multi-attribute fuzzy target-oriented decision analysis and prioritized aggregation is proposed. In Section 3 an application to evaluation of Kanazawa gold leaf, a traditional craft in Kanazawa, Japan, is given to illustrate how the proposed Kansei evaluation model works in practice. Finally, some concluding remarks are presented in Section 4.

2 A Kansei Evaluation Model Based on Prioritized Multi-Attribute Fuzzy Target-Oriented Decision Analysis

In this section we shall propose a Kansei evaluation model, based on the assumption that a consumer will be only interested in products that best meet her/his psychological needs from an aesthetic point of view. Our proposed Kansei evaluation model consists of the following steps, as shown in Fig. 1.

The dashed rectangle I in Fig. 1 shows the preparatory experiment study phase, a common process in Kansei engineering, which is used to identify and measure Kansei attributes first and then to obtain Kansei data of the products to be evaluated. The dashed rectangle II in Fig. 1 shows the target-oriented decision analysis phase, in which fuzzy target-oriented decision analysis is used to compute degrees of satisfaction for the Kansei attributes selected by consumers, and a prioritized aggregation operator is used to aggregate partial degrees of satisfaction under a given priority hierarchy. In the following subsections, we will describe our model in more detail.

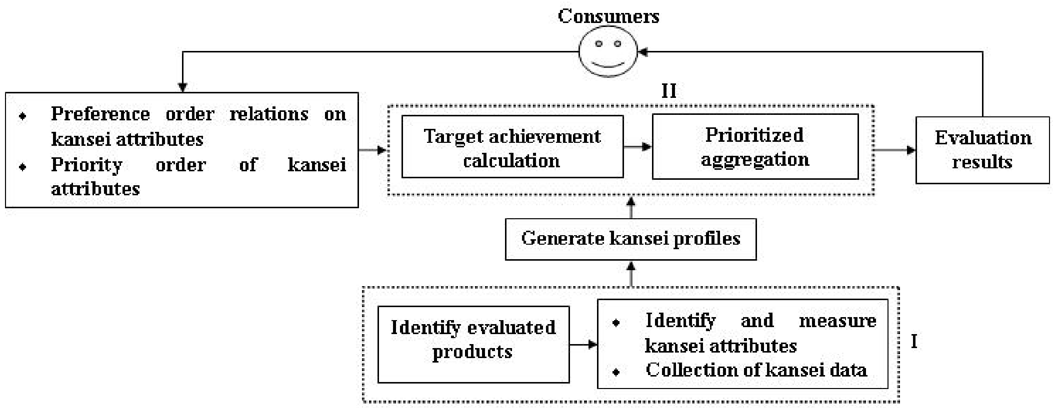

Fig. 1. Kansei evaluation process

2.1 Identification and measurement of Kansei attributes

Let $\mathcal{O}$ be set of products to be evaluated and M is the cardinality of products, i.e., $M = |\mathcal{O}|$. Once having identified and selected the products to be evaluated, we have to identify and measure Kansei attributes used by people to express their psychological feelings regarding the products to be evaluated. Usually Kansei attributes are identified by a panel of experts (experts means people familiar with the product type and Kansei engineering) via a brainstorming process [10]. Each Kansei attribute is defined by a bipolar pair of Kansei words. The bipolar pairs of Kansei words describing the product domain can be collected from many sources, such as magazines, manuals, product reviews, and users [10]. Although identification of Kansei words in practice is a difficult task, it is a necessary and important process in Kansei engineering. The Kansei attributes can be expressed as follows:

(1) Let $X = [X_1, \cdots, X_n, \cdots, X_N]$ be set of Kansei attributes of products, where N denotes the total number of Kansei attributes;
(2) Let $W_n =< W_n^-, W_n^+ >$ be the opposite pair of Kansei words with respect to Kansei attribute $X_n, n = 1, 2, \cdots, N$. For example, a Kansei attribute *fun* can be denoted as bipolar Kansei words as <solemn, funny>.

In addition, a questionnaire is designed by means of the semantic differential (SD) method [38] to collect subjective assessments provided by a number of subjects (respondents for the questionnaire). The questionnaire consists of listing Kansei attributes, each of which corresponds to a bipolar pair of Kansei words with a $2K+1$-point odd qualitative scale. For example, the odd qualitative scale of Kansei attributes can be 5-point scale [36], 7-point scale [32], and 9-point scale [10].

The subjective assessments provided by the subjects are usually conceptually vague, with uncertainty that is frequently represented in linguistic forms [44]. To help people easily express their subjective assessments, the linguistic variables [51,52] are used to linguistically assess the products to be evaluated. In order to establish the linguistic term set for each Kansei attribute, we have to choose syntax and semantics [12,13] as follows

(1) The cardinality of each linguistic term set for each Kansei attribute corresponds to the semantic scale of each Kansei attribute, i.e., the cardinality of each linguistic term set is $2K+1$.
(2) Similar to the linguistic decision analysis [12,13], ordered structure approach has been used to choose linguistic descriptors for Kansei attributes. For example, the linguistic terms "*fairly*" and "*very*" are used to describe the Kansei linguistic variables.
(3) Fuzzy numbers are used to represent the Kansei linguistic variables. Fuzzy numbers can have a variety of shapes. In practical applications, for simplicity, the triangular or trapezoidal form of the membership function is used most often for representing fuzzy numbers [14,23,48]. In this study, triangular fuzzy numbers are used to represent the Kansei linguistic variables.

In this way, we can establish a linguistic term set for each Kansei attribute, denoted as $V_n = \{V_n^{-K}, \cdots, V_n^k, \cdots, V_n^K\}$, where $k = -K, -(K-1), \cdots, 0, \cdots, (K-1), K$.

Example Assume a Kansei attribute *fun* having left and right Kansei words <solemn, funny> with a 7-point ($K = 3$) scale, similar to the linguistic variables in [26,29], the linguistic term set for this Kansei attribute can be defined as

$$\begin{aligned} V &= \{V^{-3}, V^{-2}, V^{-1}, V^0, V^1, V^2, V^3\} \\ &= \{\text{Very solemn, Solemn, Fairly solemn, Neutral, Fairly funny, Funny, Very funny}\} \\ &= \{(-3,-3,-2), (-3,-2,-1), (-2,-1,0), (-1,0,1), (0,1,2), (1,2,3), (2,3,3)\} \end{aligned}$$

Fig. 2 shows the semantics and fuzzy numbers of Kansei linguistic variables for Kansei attribute *fun*.

It should be noted that the Kansei linguistic term set V_n for each Kansei attribute X_n here we used is different from that used in the sensory evaluation model [29,30,40,53]. The sensory evaluation model considers the linguistic term set having a *consistent order relation*. However, for the linguistic term set of a Kansei attribute, the order relation depends on the consumers' preferences, in this sense, we have *inconsistent order relations*. Now we will take the Kansei attribute *fun* represented in Fig. 2, as an example to illustrate the *inconsistent order relations*. Generally, three types of order relations can be considered

(1) Some consumers may prefer *solemn*, then the linguistic order relation is

$$V^{-3} \succeq V^{-2} \succeq V^{-1} \succeq V^{0} \succeq V^{1} \succeq V^{2} \succeq V^{3};$$

(2) Other consumers prefer *neutral*, then the linguistic order relation is

$$V^{-3} \preceq V^{-2} \preceq V^{-1} \preceq V^{0} \succeq V^{1} \succeq V^{2} \succeq V^{3};$$

(3) There are also some consumers preferring *funny*, then the linguistic order relation is

$$V^{-3} \preceq V^{-2} \preceq V^{-1} \preceq V^{0} \preceq V^{1} \preceq V^{2} \preceq V^{3}.$$

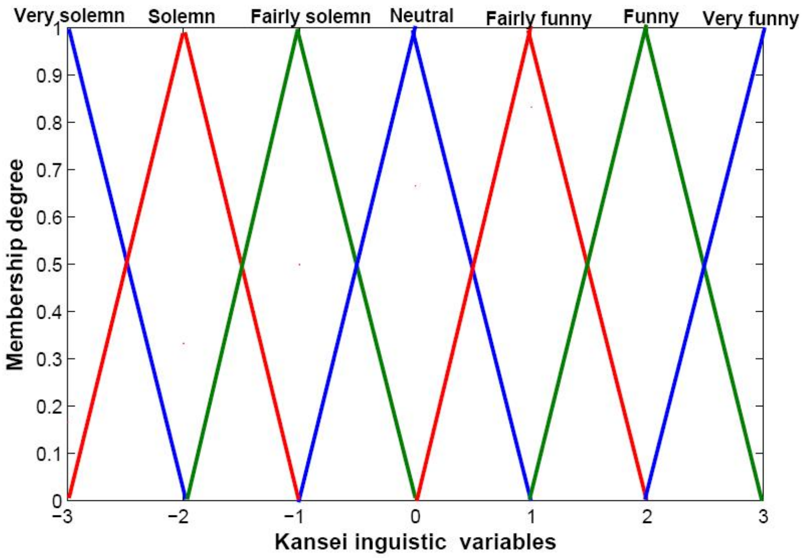

Fig. 2. Linguistic variables for Kansei attribute *fun*

2.2 Generation of Kansei profiles

The questionnaire is then assigned to a number P of subjects $\mathcal{S}$, who are selected to linguistically express their subjective assessments regarding the Kansei attributes in a simultaneous way. Having obtained the Kansei assessments given by the subjects, based on our previous work [50], we can obtain Kansei profiles as follows. For evaluated product $O_m, m = 1, 2, \cdots, M$, we define for Kansei attribute X_n, $n = 1, 2, \cdots, N$, a probability distribution function $f_{mn} : \mathbb{V} \to [0, 1]$ as follows

$$f_{mn}(V_n^k) = \frac{|\{S_p \in \mathcal{S} : X_{pn}(O_m) = V_n^k\}|}{|\mathcal{S}|} \tag{1}$$

where $k = -K, -(K-1), \cdots, 0, \cdots, (K-1), K$, and $X_{pn}(O_m)$ denotes the Kansei assessment for product O_m with respect to Kansei attribute X_n given by subject $S_p, p = 1, \cdots, P$. In the same way, we can obtain a 2K+1-tuple of probability distributions for product O_m with respect to Kansei attribute X_n,

$$\left[f_{mn}(V_n^{-K}), f_{mn}(V_n^{-(K-1)}), \cdots, f_{mn}(V_n^0), \cdots, f_{mn}(V_n^{(K-1)}), f_{mn}(V_n^K)\right]$$

and call this tuple as *Kansei profile* of O_m with respect to Kansei attribute X_n. The 2K+1-tuple of probability distributions, as shown in Table 1, can be viewed as a general multi-attribute decision matrix, where each Kansei attribute has $2K+1$ states of nature. For Kansei attribute X_n at the state of nature k, where $k = -K, -(K-1), \cdots, 0, \cdots, (K-1), K$, all the products have the same attribute values (fuzzy numbers), but different probability distributions and semantics.

Table 1
Kansei profiles of evaluated products: probability distributions of Kansei assessments

Products	Kansei attributes										
	X_1					$\cdots$	X_N				
	$-K$	$\cdots$	0	$\cdots$	K	$\cdots$	$-K$	$\cdots$	0	$\cdots$	K
O_1	$f_{11}(V_1^{-K})$	$\cdots$	$f_{11}(V_1^0)$	$\cdots$	$f_{11}(V_1^K)$	$\cdots$	$f_{1N}(V_N^{-K})$	$\cdots$	$f_{1N}(V_N^0)$	$\cdots$	$f_{1N}(V_N^K)$
O_2	$f_{21}(V_1^{-K})$	$\cdots$	$f_{21}(V_1^0)$	$\cdots$	$f_{21}(V_1^K)$	$\cdots$	$f_{2N}(V_N^{-K})$	$\cdots$	$f_{2N}(V_N^0)$	$\cdots$	$f_{2N}(V_N^K)$
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
O_M	$f_{M1}(V_1^{-K})$	$\cdots$	$f_{M1}(V_1^0)$	$\cdots$	$f_{M1}(V_1^K)$	$\cdots$	$f_{MN}(V_N^{-K})$	$\cdots$	$f_{MN}(V_N^0)$	$\cdots$	$f_{MN}(V_N^K)$

2.3 Specification of consumers' preferences

Having generated Kansei profiles for all evaluated products $O_m \in \mathcal{O}, m = 1, 2, \cdots, M$ as above, we now consider the preferences of consumers. Assume that a potential consumer is interested in a collection of Kansei attributes $X = \{X_1, \cdots, X_n, \cdots, X_N\}$ [3]. As mentioned previously, order relations of Kansei linguistic term sets regarding Kansei attributes vary from person to person according to their character, feeling, aesthetic and so on, a preference function for Kansei attribute $X_n, n = 1, 2, \cdots, N$ is needed.

In the context of multi-attribute decision making, usually there are two types of goal preferences [22,43].

- Target goal values are adjustable: "more is better" or "less is better";

[3] The number of Kansei attributes selected by consumers may be different from the total number of Kansei attributes. Here for simplicity of denotation we shall use the same number, N.

- Target goal values are fairly fixed and not subject to much change, i.e., too much or too little is not acceptable.

To model consumers' preference order relations on Kansei linguistic term set, we shall define three main types of target preferences [4] as follows:

- *Less is better*: Left Kansei words preferred;
- *More is better*: Right Kansei word preferred;
- *Target goal values are fairly fixed*: Neutral preferred.

Due to the vagueness and uncertainty of Kansei preference values, fuzzy targets are used to represent consumers' preferences. Fig. 3 shows the three types of preferences represented by fuzzy targets.

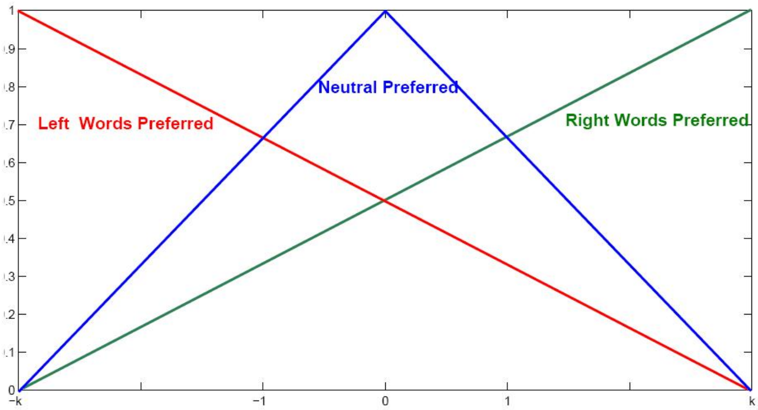

Fig. 3. Target-oriented preferences

Based on consumer-specified preferences, a collection of fuzzy targets, such that $T = \{T_1, \cdots, T_n, \cdots, T_N\}$, can be obtained with respect to the collection of Kansei attributes $X = \{X_1, \cdots, X_n, \cdots, X_N\}$.

In addition to the preference order relations on Kansei linguistic term set, consumers may have a priority order of the Kansei attributes. Simply speaking, by saying Kansei attribute X_1 has a higher priority than Kansei attribute X_2, it means that the consumers are not willing to trade off satisfaction to Kansei attribute X_2 until they attain some level of satisfaction of Kansei attribute X_1 [46,47].

Considering these two types of consumer-specified preferences, we divide the evaluation process into two phases

(1) Calculate degree of satisfaction for Kansei attribute X_n;

[4] Generally speaking, any target can be defined by consumers. However, as consumers are not so specific about their own personal preference, here we just provide three types of targets.

(2) Aggregate partial degrees of satisfaction under the prioritized hierarchy.

Fuzzy target-oriented decision analysis [16,17] has been extended to calculate the degree of satisfaction for Kansei attribute X_n, and then Yager's prioritized scoring aggregation operator [47] is used to aggregate the partial degrees of satisfaction. In this regard, we shall view our research problem as *prioritized multi-attribute fuzzy target-oriented decision analysis*. In the following two subsections, we shall discuss these two steps in further detail.

2.4 Satisfaction degree calculation based on an alpha-cuts method

According to the principle of target-oriented decision analysis [3], for our general decision matrix as shown in Table 1, we can define the probability of product O_m meeting the fuzzy target T_n with respect to Kansei attribute X_n as follows:

$$\mathrm{P}(X_{mn} \succeq T_n) = \sum_{k=-K}^{K} f_{mn}(V_n^k) \cdot \mathrm{P}(V_n^k \succeq T_n) \tag{2}$$

where V_n^k denotes the k-th linguistic variable for Kansei attribute X_n, $k = \{-K, -(K-1), \cdots, 0, \cdots, (K-1), K\}$, $f_{mn}(V_n^k)$ denotes the probability distribution of Kansei attribute X_n at linguistic variable V_n^k, and $\mathrm{P}(V_n^k \succeq T_n)$ is the probability of V_n^k meeting target T_n.

Central to this problem is how to compute the probability $\mathrm{P}(V_n^k \succeq T_n)$ of V_n^k meeting fuzzy target T_n. Recently, two methods of computing target achievement have been proposed. One is the normalization-based method, in which fuzzy targets can be represented as linguistic variables and Yager's possibility-probability transformation function has been used (for more detail, see Huynh et al. [17]). The other method is based on α-cuts to compare two fuzzy numbers [16,49]. In these two methods, two types of preferences have been considered, *more is better and less is better*. Besides these two types of preferences, there exists another type of preference, such that the *target goal values are fairly fixed*. In this subsection, we shall extend the target-based model to a broader context, and apply it to the context of general multi-attribute decision matrix as shown in Table 1 of Subsection 2.2 based on an α-cuts method.

Before discussing how to compute $\mathrm{P}(V_n^k \succeq T_n)$, let us first consider a special case. Assume that both the attribute and target values are interval numbers, denoted as $X = [x_l, x_u]$ and $T = [t_l, t_u]$, where x_l and t_l denotes the lower values, x_u and t_u denotes the upper values. Here we want to utilize an approach to compare intervals motivated by a probabilistic view of the underlying uncertainty. More formally, we aim at defining a probability-based comparison relation over intervals, denoted by $P(X \succeq T)$. Toward this end, similar to Huynh et al. [16] and Yager [49], we consider intervals X and T having uniform distributions $f(x)$ and $f(t)$ over $[x_l, x_u]$ and $[t_l, t_u]$, respectively. We can define the uniform probability distribution for attribute and target as follows:

$$f(x) = \begin{cases} \frac{1}{x_u - x_l}, & x_l \leq x \leq x_u; \\ 0, & \text{otherwise.} \end{cases} \text{ and } f(t) = \begin{cases} \frac{1}{t_u - t_l}, & t_l \leq t \leq t_u; \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

The target-oriented decision model [3] suggests using the following function

$$\mathrm{P}(X \succeq T) = \int_{-\infty}^{\infty} f(x) \int_{-\infty}^{\infty} \mu(x,t) f(t) dt dx \quad (4)$$

where $\mu(x,t)$ is used to denote consumers' preference type, $f(x)$ is the probability density function over attribute X, and $f(t)$ is the probability density function over target T. Similar to the target-oriented principle proposed by Bordley and Kirkwood [3], we can define $\mu(x,t)$ as:

(1) *More is better*:

$$\mu(x,t) = \begin{cases} 1, \ x \geq t; \\ 0, \ \text{otherwise.} \end{cases} \quad (5)$$

(2) *Less is better*:

$$\mu(x,t) = \begin{cases} 1, \ x \leq t; \\ 0, \ \text{otherwise.} \end{cases} \quad (6)$$

(3) *Ideal or Range Level*:

$$\mu(x,t) = \begin{cases} 1, \ x \in [t_l, t_u]; \\ 0, \ \text{otherwise.} \end{cases} \quad (7)$$

According to Eq. (4) and Eqs. (5)-(7) we can calculate the probability of attribute X meeting target T for different types of preferences in case of interval numbers. Obviously, the result of computation depends on the relative positions of x_l and x_u with respect to t_l and t_u.

Now let us consider the case where both attribute value and target value are fuzzy numbers represented by the canonical form [23], denoted by

$$\mu_X(x) = \begin{cases} f_X(x), & x_1 \leq x \leq x_2, \\ 1, & x_2 \leq x \leq x_3, \\ g_X(x), & x_3 \leq x \leq x_4 \\ 0, & \text{otherwise.} \end{cases} \text{ and } \mu_T(t) = \begin{cases} f_T(t), & t_1 \leq t \leq t_2, \\ 1, & t_2 \leq t \leq t_3, \\ g_T(t), & t_3 \leq t \leq t_4 \\ 0, & \text{otherwise.} \end{cases} \quad (8)$$

respectively. Then we can obtain their α-cuts expressions as follows

$$X_\alpha = [x_l(\alpha), x_r(\alpha)] = \begin{cases} [f_X^{-1}(\alpha), g_X^{-1}(\alpha)], & \text{when } \alpha \in (0,1), \\ [x_2, x_3], & \text{when } \alpha = 1. \end{cases} \tag{9}$$

and

$$T_\alpha = [t_l(\alpha), t_r(\alpha)] = \begin{cases} [f_T^{-1}(\alpha), g_T^{-1}(\alpha)], & \text{when } \alpha \in (0,1), \\ [t_2, t_3], & \text{when } \alpha = 1. \end{cases} \tag{10}$$

where f^{-1} and g^{-1} are the inverse functions of f and g. In case of interval numbers, for example, $T = [t2, t3]$, we define $T_\alpha = T$ for all $\alpha \in (0, 1]$. A crisp number can be viewed as one special case of interval number.

As the family $\{X_\alpha | \alpha \in (0, 1]\}$ can be viewed as a uniformly distributed random set [16], then the membership function μ_X can be represented as an integral

$$\mu_X(x) = \int_0^1 \mu_{X_\alpha}(x) d\alpha. \tag{11}$$

Based on the comparison relation on intervals defined above and the α-cuts representations of fuzzy numbers, we now define a comparison relation on fuzzy numbers, denoted by $\mathrm{P}(X \succeq T)$, as follows:

$$\mathrm{P}(X \succeq T) = \int_0^1 \mathrm{P}(X^\alpha \succeq T^\alpha) d\alpha \tag{12}$$

If a consumer prefers '"*more is better*" or "*less is better*" preference, then equation (12) reduces to a fuzzy number comparison method proposed in [16,49]. It should be noted that, for any crisp number X, we can define its probability distribution as $f(x) = 1,\ \text{if } x = X; 0, \text{otherwise}$.

For evaluated product O_m in our general multi-attribute decision matrix, according to Eqs. (2) and (12) we can get the probability of product O_m meeting fuzzy target T_n with respect to Kansei attribute X_n as follows:

$$\mathrm{P}(X_{mn} \succeq T_n) = \sum_{k=-K}^{K} f_{mn}(V_n^k) \cdot \left[\int_0^1 \mathrm{P}\left(V_n^k(\alpha) \succeq T_n(\alpha) \right) d\alpha \right] \tag{13}$$

where $V_n^k(\alpha)$ and $T_n(\alpha)$ are the α-cut representations of Kansei linguistic variable V_n^k and fuzzy target T_n respectively, and $\mathrm{P}\left(V_n^k(\alpha) \succeq T_n(\alpha)\right)$ can be calculated according to Eqs. (4)-(7) based on consumers' preference types.

2.5 *Prioritized aggregation of target achievements*

Having computed the probability of meeting consumers' specified fuzzy target-oriented preferences for Kansei attributes selected by consumers, we have to aggregate partial degrees of satisfaction (target achievements) $\mathrm{P}(X_{mn} \succeq T_n)$. One commonly used approach is to calculate for product O_m a value $\mathrm{Val}(O_m)$ by using an aggregation function F as

$$F\left(\mathrm{P}(X_{m1} \succeq T_1), \cdots, \mathrm{P}(X_{mn} \succeq T_n), \cdots, \mathrm{P}(X_{mN} \succeq T_N)\right)$$

and then order the evaluated products according to these values $\mathrm{Val}(O_m)$. In many types of applications, people usually associate importance weights with the attributes [6,47]. A commonly used form for F is a weighted average of the O_m. In this case we calculate

$$\mathrm{Val}(O_m) = \sum_{n=1}^{N} w_n \cdot \mathrm{P}(X_{mn} \succeq T_n), \text{ where } \sum_{n=1}^{N} w_n = 1.$$

Central to this types of aggregation operators is the ability to trade off between attributes [46]. In some situations, the consumers may not need this kind of tradeoffs between Kansei attributes. In this case, we will have a prioritization hierarchy. Assume that the collection of Kansei attributes $X = \{X_1, \cdots, X_n, \cdots, X_N\}$ are partitioned into Q distinct priority levels, $H = \{H_1, \cdots, H_q, \cdots, H_Q\}$ such that $H_q = \{X_{q1}, \cdots, X_{qi}, \cdots, X_{qN_q}\}$, where N_q is the Kansei attribute number in priority level H_q, and X_{qi} is the i-th Kansei attribute in category H_q. We also assume a prioritization of these Kansei attributes is $H_1 > \cdots > H_q > \cdots > H_Q$. The total set of Kansei attributes is $X = \bigcup_{q=1}^{Q} H_q$. The total number of Kansei attributes is $N = \sum_{q=1}^{Q} N_q$. For simplicities of denotations, we shall use $\mathrm{P}_{qi}(O_m)$ to express the degree of satisfaction for the i-th Kansei attribute in priority level H_q with respect to evaluated product O_m. Table 2 shows the priority hierarchy structure of the Kansei attributes.

Table 2
Prioritization of Kansei attributes specified by consumers

H_1	$X'_{11}, \cdots, X'_{1i}, \cdots, X'_{XN_1}$
$\vdots$	$\vdots$
H_q	$X'_{q1}, \cdots, X'_{qi}, \cdots, X'_{qN_q}$
$\vdots$	$\vdots$
H_Q	$X'_{Q1}, \cdots, X'_{Qi}, \cdots, X'_{QN_Q}$

Recently, Yager [46,47] proposed a prioritized aggregation operator based on the assumption that prioritized aggregation can be modeled by using a kind of importance weight in which the importance of a lower priority attribute will be based on its satisfaction to the higher priority attribute. The prioritized aggregation operator suggested using the following steps:

(1) For Kansei attributes in priority level H_q regarding product O_m, a degree of satisfaction $S_q(O_m)$ is calculated as follows

$$S_q(O_m) = F\left(\mathrm{P}_{qi}(O_m), \cdots, \mathrm{P}_{qi}(O_m), \cdots, \mathrm{P}_{qi}(O_m)\right) \tag{14}$$

(2) Then an importance weight $Z_q(O_m)$ for priority level H_q is calculated as follows

$$\begin{aligned} Z_q(O_m) &= \prod_{l=1}^{q} S_{l-1}(O_m) \\ &= Z_{q-1}(O_m) \cdot S_{q-1}(O_m) \end{aligned} \tag{15}$$

where $Z_0(O_m) = S_0(O_m) = 1$.

(3) To calculate the overall degree of satisfaction for product O_m as follows

$$\mathrm{Val}(O_m) = \sum_{q=1}^{Q} \left[\sum_{i=1}^{N_q} Z_q(O_m) \cdot \mathrm{P}_{qi}(O_m) \right] \tag{16}$$

This prioritized aggregation operator is a scoring type operator. The main reason for this scoring type operator rather than an averaging operator is that the averaging operator does not always guarantee a monotonic aggregation (for more details see Yager [46,47]).

Central to this problem is how to compute the degree of satisfaction for product O_m in priority level H_q. According to Yager [46,47], the ordered weighted averaging (OWA) [45] operator can be used to obtain the degree of satisfaction for priority level H_q. The OWA operator is generally composed of the following three steps [27,48]:

(1) Reorder the input arguments in descending order,
(2) Determine the weights associated with the OWA operator by using a proper method, and
(3) Utilize the OWA weights to aggregate these reordered arguments.

Many of the techniques available for calculating the OWA weights can be tailored for this particular application. We can resolve a mathematical programming problem [6,9], associate it with a linguistic quantifier [6,9,45], or obtain OWA weights via analytic method [8]. We shall use the weights determining method proposed by O'Hagan [37]. In this case we would supply a desired level of tolerance Ω_q and solve the following constrained optimization problem for the i-the element in priority hierarchy level H_q a weight u_{qi}.

$$\text{Maximize} - \sum_{i=1}^{N_q} u_{qi} \cdot \ln u_{qi} \tag{17a}$$

$$\text{subject to } \sum_{i=1}^{N_q} \left[\frac{N_q - i}{N_q - 1} \cdot u_{qi} \right] = \Omega_q,\ 0 \leq \Omega_q \leq 1 \tag{17b}$$

$$\sum_{i=1}^{N_q} u_{qi} = 1,\ 0 \leq u_{qi} \leq 1. \tag{17c}$$

An Operations Research software package called *LINDO* [5] can be used to solve this mathematical programming problem.

Once having calculated $\mathrm{Val}(O_m)$ for all the evaluated products, we then select as our optimal choice, the product O^* which satisfy

$$\mathrm{Val}(\mathcal{O}^*) = \max_{O_m \in \mathcal{O}} [\mathrm{Val}(O_m)]. \tag{18}$$

3 An Application: Kansei Evaluation of Kanazawa Gold Leaf

Kansei evaluation has been applied to consumer products with successful results, e.g., table glasses [39], housing assessment [28], telephones [15], cars [7], and mobile phones [25,26] and so on. However, Kansei evaluation of commercial products has received less attention [32], in particular, Kansei evaluation of traditional crafts has not been addressed yet, according to our knowledge [50]. In Japan, there are many traditional crafts such as fittings, textile, etc. These beautiful, elegant and delicate products are closely related to and have played an important role in Japanese culture and life. Evaluations of these traditional crafts would be of great help for marketing or recommendation purposes.

As the aesthetic aspect (brand image, pattern, personal aesthetics, current trends of fashion etc.) plays a crucial role in consumers' perceptions of traditional crafts, Kansei information is essential and necessary for this evaluation problem. We will use the Kanazawa gold leaf [6], a traditional craft material with a history of over 400 years, as a case study to illustrate the proposed Kansei evaluation model. A total of thirty products of Kanazawa gold leaf have been collected for Kansei evaluation, as shown in Fig. 4.

[5] http://www.lindo.com/
[6] http://www.kougei.or.jp/english/crafts/1503/f1503.html

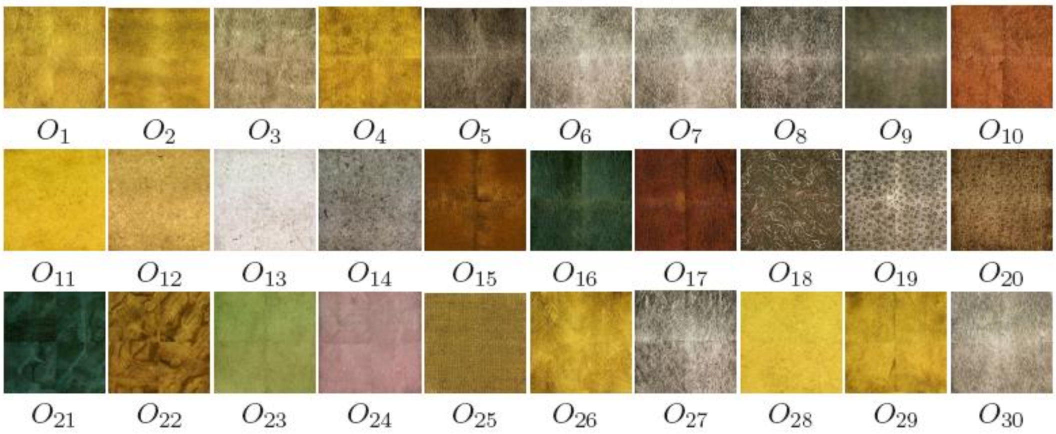

Fig. 4. The thirty products of Kanazawa gold leaf used for Kansei evaluation

3.1 Identification and measurement of Kansei attributes

To obtain Kansei data of these traditional crafts, a preliminary study was conducted to select Kansei attributes with a 7-point scale, in which Kansei attributes are selected through a brainstorming process by consulting local manufactures and selling shops. Finally 26 opposite pairs of Kansei words were selected at the end of the brainstorming process. Linguistic variables [51,52] are used to express the 7-scale Kansei data and triangular fuzzy numbers are used to represent the Kansei linguistic variables for each Kansei attribute. Table 3 shows the Kansei attributes with linguistic variables and triangular fuzzy numbers, where Kansei words were used in Japanese at first and approximately translated into English (adapted from [41]) in this study.

3.2 Generation of Kansei profiles

In order to gather Kansei data of the traditional crafts $O_m, m = 1, 2, \cdots, 30$, a total of 211 subjects, including relevant researchers of Kansei engineering, senior residents in Kanazawa, and certificated masters of traditional crafts, were invited to assess the thirty traditional crafts regarding Kansei attributes $X_n, n = 1, 2, \cdots, 26$ in a simultaneous way. It should be emphasized that, in order to enhance the reliability of subjective assessments for traditional crafts, all subjects were invited to participate in a centralized evaluation session on an appointed day. Moreover, in many studies of Kansei engineering, the number of subjects involved in experimental studies usually ranges from 10 to 35 [7,25,26,28]. For purposes of our Kansei evaluation, such a small number of subjects may not provide enough information from various points of view, and may bring a statistical bias. To possibly reduce the subjectiveness of the assessments, a number of subjects, with a larger size, 211, were invited to

Table 3
Kansei attributes of traditional crafts, shown using linguistic variables and triangular fuzzy numbers.

X_n	Left adj. W_n^-	V_n^{-3} Very W_n^- (-3,-3,-2)	V_n^{-2} W_n^- (-3,-2,-1)	V_n^{-1} Fairly W_n^- (-2,-1,0)	V_n^0 Neutral (-1,0,1)	V_n^{+1} Fairly W_n^+ (0,1,2)	V_n^{+2} W_n^+ (1,2,3)	V_n^{+3} Very W_n^+ (2,3,3)	Right adj. W_n^+
X_1	conventional	☐	☐	☐	☐	☐	☐	☐	unconventional
X_2	simple	☐	☐	☐	☐	☐	☐	☐	compound
X_3	solemn	☐	☐	☐	☐	☐	☐	☐	funny
X_4	formal	☐	☐	☐	☐	☐	☐	☐	casual
X_5	serene	☐	☐	☐	☐	☐	☐	☐	forceful
X_6	still	☐	☐	☐	☐	☐	☐	☐	moving
X_7	pretty	☐	☐	☐	☐	☐	☐	☐	austere
X_8	friendly	☐	☐	☐	☐	☐	☐	☐	unfriendly
X_9	soft	☐	☐	☐	☐	☐	☐	☐	hard
X_{10}	blase	☐	☐	☐	☐	☐	☐	☐	attractive
X_{11}	flowery	☐	☐	☐	☐	☐	☐	☐	quiet
X_{12}	happy	☐	☐	☐	☐	☐	☐	☐	normal
X_{13}	elegant	☐	☐	☐	☐	☐	☐	☐	loose
X_{14}	delicate	☐	☐	☐	☐	☐	☐	☐	large-hearted
X_{15}	luxurious	☐	☐	☐	☐	☐	☐	☐	frugal
X_{16}	gentle	☐	☐	☐	☐	☐	☐	☐	pithy
X_{17}	bright	☐	☐	☐	☐	☐	☐	☐	dark
X_{18}	reserved	☐	☐	☐	☐	☐	☐	☐	imperious
X_{19}	free	☐	☐	☐	☐	☐	☐	☐	regular
X_{20}	level	☐	☐	☐	☐	☐	☐	☐	indented
X_{21}	lustered	☐	☐	☐	☐	☐	☐	☐	matte
X_{22}	transpicuous	☐	☐	☐	☐	☐	☐	☐	dim
X_{23}	warm	☐	☐	☐	☐	☐	☐	☐	cool
X_{24}	moist	☐	☐	☐	☐	☐	☐	☐	arid
X_{25}	colorful	☐	☐	☐	☐	☐	☐	☐	sober
X_{26}	plain	☐	☐	☐	☐	☐	☐	☐	gaudy, loud

give their Kansei assessments for products regarding the Kansei attributes. These Kansei data are then used to generate Kansei profiles of the evaluated products according to Eq. (1).

3.3 Evaluation based on consumer-specified preferences

Assume that a consumer has selected seven Kansei attributes she/he cares about, such that $X = [X_4, X_{10}, X_{11}, X_{15}, X_{21}, X_{25}, X_{26}]$. Corresponding to these seven Kansei attributes, the consumer specifies seven targets such that $\mathrm{T} = [T_4, T_{10}, T_{11}, T_{15}, T_{21}, T_{25}, T_{26}]$. Table 4 shows the seven selected Kansei attributes and the seven specified targets.

According to the *alpha*-cuts based method for target-oriented decision analysis discussed in Subsection 2.4, we can calculate the probability of product O_m meeting the targets with respect to the Kansei attributes selected by consumers, as shown in Table 5.

Table 4
Target-oriented preferences for the seven selected Kansei attributes.

Kansei attributes	Preferred Kansei word	Target value
X_4	T_4: Neutral preferred	(-3,0,3)
X_{10}	T_{10}: Attractive preferred	(-3,3,3)
X_{11}	T_{11}: Flowery preferred	(-3,-3,3)
X_{15}	T_{15}: Luxurious preferred	(-3,-3,3)
X_{21}	T_{21}: Matte preferred	(-3,3,3)
X_{25}	T_{25}: Colorful preferred	(-3,-3,3)
X_{26}	T_{26}: Neutral preferred	(-3,0,3)

Table 5
Degree of satisfaction for each Kansei attribute: the probability of target achievement.

Products	Target achievement						
	T_4	T_{10}	T_{11}	T_{15}	T_{21}	T_{25}	T_{26}
	X_4	X_{10}	X_{11}	X_{15}	X_{21}	X_{25}	X_{26}
O_1	0.4666	0.2715	0.5210	0.5437	0.0902	0.5040	0.6639
O_2	0.4413	0.3025	0.4980	0.5203	0.0809	0.4746	0.6623
O_3	0.5532	0.2977	0.2820	0.3293	0.0853	0.2900	0.6565
O_4	0.4502	0.2841	0.5638	0.6140	0.0719	0.5749	0.6436
O_5	0.5483	0.2489	0.2410	0.2780	0.1431	0.2054	0.6802
O_6	0.4976	0.3157	0.3669	0.4509	0.0953	0.3704	0.6664
O_7	0.5410	0.2854	0.2438	0.2881	0.1267	0.2125	0.6294
O_8	0.5435	0.2562	0.2653	0.3061	0.1267	0.2577	0.6483
O_9	0.5385	0.3167	0.1613	0.2784	0.1549	0.1844	0.6573
O_{10}	0.5681	0.2314	0.2959	0.3291	0.1031	0.3256	0.6950
O_{11}	0.5099	0.2942	0.4945	0.5032	0.1019	0.4784	0.6672
O_{12}	0.5328	0.2922	0.3938	0.4348	0.1206	0.3930	0.7032
O_{13}	0.5263	0.2927	0.1885	0.2476	0.2122	0.2082	0.6327
O_{14}	0.5614	0.2904	0.2163	0.3098	0.1504	0.2414	0.6638
O_{15}	0.5664	0.2404	0.3043	0.3447	0.1181	0.3506	0.6515
O_{16}	0.5508	0.2621	0.1105	0.1609	0.1336	0.1431	0.6606
O_{17}	0.5688	0.1947	0.2206	0.2390	0.1755	0.2455	0.6606
O_{18}	0.5068	0.1382	0.2022	0.2533	0.2235	0.2506	0.5192
O_{19}	0.4562	0.2561	0.3047	0.2275	0.1322	0.2409	0.7057
O_{20}	0.4185	0.2688	0.2669	0.2133	0.1508	0.2324	0.704
O_{21}	0.5346	0.1743	0.2098	0.2657	0.1457	0.2521	0.6156
O_{22}	0.5133	0.1660	0.3810	0.4554	0.1052	0.4976	0.4881
O_{23}	0.4765	0.2220	0.3407	0.2992	0.0997	0.3746	0.6531
O_{24}	0.4169	0.2670	0.4715	0.3379	0.0875	0.4093	0.6671
O_{25}	0.4523	0.2352	0.2737	0.2977	0.4519	0.2758	0.6492
O_{26}	0.4511	0.2920	0.5162	0.5444	0.0775	0.5267	0.6705
O_{27}	0.5238	0.3286	0.2610	0.3183	0.1056	0.2615	0.6359
O_{28}	0.4952	0.2805	0.4893	0.5210	0.0945	0.4696	0.6557
O_{29}	0.4462	0.3100	0.5380	0.5676	0.0768	0.5320	0.6450
O_{30}	0.5001	0.2962	0.2336	0.3243	0.1211	0.2541	0.6515

3.4 Prioritized aggregation of target achievement

Assume the seven selected Kansei attriubtes are partitioned into 3 distinct priority levels H_1, H_2, H_3. In Table 6 we show the positioning of the Kansei attributes. In this prioritization hierarchy structure, Kansei attributes X_4 and X_{26} have the highest priority level, i.e., the consumer is not willing to trade off satisfaction with other Kansei attributes in hierarchy level H_2 and H_3, until she/he has attained some level of satisfaction regarding X_4 and X_{26}.

Table 6
Prioritization of the seven selected Kansei attributes

H_1	$X_4(X'_{11}), X_{26}(X'_{12})$
H_2	$X_{11}(X'_{21}), X_{15}(X'_{22}), X_{21}(X'_{23})$
H_3	$X_{10}(X'_{31}), X_{25}(X'_{32})$

In order to aggregate the partial degrees of satisfaction under this prioritization hierarchy structure, we have to compute the OWA weighting vector for each priority level under the attitudinal character Ω_q. It should be noted that, for each priority level $H_q, q = 1, 2, 3$, the prioritized aggregation operator mentioned in Subsection 2.5 allows a different attitudinal character Ω_q. Here, for the sake of simplicity, we assume that for each priority level $H_q, q = 1, 2, 3$, the same attitudinal character Ω is used, i.e., $\Omega_q = \Omega, q = 1, 2, 3$. Following the prioritized aggregation process which used Eqs. (14)-(16) and the OWA weighting determination method in Eq. (17), we can obtain the aggregated value for each product.

To illustrate the prioritized aggregation process, we shall take product O_{11} as an example. From Table 5, we know that the partial degrees of satisfaction are as follows:

$$\mathrm{P}_{11}(O_{11}) = 0.5099, \mathrm{P}_{12}(O_{11}) = 0.6672$$

$$\mathrm{P}_{21}(O_{11}) = 0.4945, \mathrm{P}_{22}(O_{11}) = 0.5032, \mathrm{P}_{23}(O_{11}) = 0.1019$$

$$\mathrm{P}_{31}(O_{11}) = 0.2942, \mathrm{P}_{32}(O_{11}) = 0.4784$$

Assume that the consumer specified her/his attitudinal character $\Omega = 0.5$. The OWA weighting vectors for priority hierarchy $H_q, q = 1, 2, 3$, are $U_1 = [0.5, 0.5]$, $U_2 = [\frac{1}{3}, \frac{1}{3}, \frac{1}{3}]$, and $U_3 = [0.5, 0.5]$. The prioritized aggregation process is as follows:

(1) To calculate a degree of satisfaction for each priority hierarchy level:

$$S_1(O_{11}) = \mathrm{OWA}_{0.5}(0.5099, 0.6672) = 0.5886$$

$$S_2(O_{11}) = \mathrm{OWA}_{0.5}(0.4945, 0.5032, 1019) = 0.3665$$

$$S_3(O_{11}) = \mathrm{OWA}_{0.5}(0.2942, 0.4784) = 0.3845$$

(2) To calculate the induced importance weight for each priority hierarchy

level:

$Z_1(O_{11}) = Z_0(O_{11}) * S_0(O_{11}) = 1.0$

$Z_2(O_{11}) = Z_1(O_{11}) * S_1(O_{11}) = 0.5886$

$Z_3(O_{11}) = Z_2(O_{11}) * S_2(O_{11}) = 0.2157$

(3) To calculate the global value of satisfaction for product O_{11}:
$\mathrm{Val}(O_{11}) = Z_1(O_{11}) * (0.5099 + 0.6672) + Z_2(O_{11}) * (0.4945 + 0.5032 + 0.1019) + Z_3(O_{11}) * (0.2942 + 0.4784) = 1.9907$

It is easily seen that, lower degree of satisfaction for Kansei attributes in higher priority level will induce lower importance weights for the attributes in lower priority level. The induced importance weights are product dependent. This is the fundamental feature of prioritized aggregation operator proposed by Yager [47]. Table 7 shows the ranking list of the top 5 products that best meet consumer's preferences with 11 attitudinal characters.

Table 7
Prioritized aggregation of the partial target achievements with 11 attitudinal characters Ω: the top 5 products.

Attitudinal character Ω	Ranking order of top 5 traditional crafts
$\Omega = 0.0$	$O_{12} \succeq O_{11} \succeq O_{28} \succeq O_{10} \succeq O_1$
$\Omega = 0.1$	$O_{11} \succeq O_{12} \succeq O_{28} \succeq O_1 \succeq O_4$
$\Omega = 0.2$	$O_{11} \succeq O_{12} \succeq O_{28} \succeq O_1 \succeq O_4$
$\Omega = 0.3$	$O_{11} \succeq O_{12} \succeq O_{28} \succeq O_4 \succeq O_1$
$\Omega = 0.4$	$O_{11} \succeq O_{12} \succeq O_4 \succeq O_{28} \succeq O_1$
$\Omega = 0.5$	$O_{11} \succeq O_4 \succeq O_{12} \succeq O_1 \succeq O_{28}$
$\Omega = 0.6$	$O_{11} \succeq O_4 \succeq O_1 \succeq O_{12} \succeq O_{26}$
$\Omega = 0.7$	$O_4 \succeq O_{11} \succeq O_1 \succeq O_{26} \succeq O_{28}$
$\Omega = 0.8$	$O_4 \succeq O_{11} \succeq O_1 \succeq O_{26} \succeq O_{29}$
$\Omega = 0.9$	$O_4 \succeq O_{11} \succeq O_{26} \succeq O_1 \succeq O_{29}$
$\Omega = 1.0$	$O_4 \succeq O_{26} \succeq O_1 \succeq O_{11} \succeq O_{29}$

There exists one case where only one Kansei attribute in each priority level is considered, i.e., the consumer does not need the tradeoffs between the Kansei attributes. In this case, the attitudinal character Ω will not affect the aggregation value for each priority level, thus the aggregation results depend only upon priority hierarchy of Kansei attributes. For purposes of simplicity, we assume that the attribute priority hierarchy has been made in order of the index of Kansei attributes, denoted as $X_4 > X_{10} > X_{11} > X_{15} > X_{21} > X_{25} > X_{26}$. Then the ranking list of the top 5 products that best meet consumer's preferences is: $O_3 \succeq O_{12} \succeq O_{11} \succeq O_{14} \succeq O_{15}$.

4 Conclusion

Usually consumers purchase or select products according to their functional requirements or psychological needs. In this paper we concerned ourselves with Kansei evaluation focusing on consumers' psychological needs and feelings according to so-called Kansei attributes, which reflect aesthetic aspects of human perception on products. In particular, a preliminary study is conducted beforehand to obtain Kansei data of products, by means of the semantic differential method and linguistic variables. These Kansei data are then used to generate Kansei profiles for evaluated products by means of the voting statistics. Because consumers' preferences on Kansei attributes of products vary from person to person and target-oriented decision analysis provides a good description of individual preference, the target-oriented decision analysis is used to quantify how well a product meets consumers' Kansei preferences. Due to the vagueness and uncertainty of consumers' preferences, three types of fuzzy targets are defined to represent consumers' preferences. Because consumers usually may prioritize Kansei attributes, i.e., a prioritization hierarchy of Kansei attributes, a prioritized scoring aggregation operator is utilized to aggregate the partial degrees of satisfaction for the evaluated products. As the aesthetic aspect plays a crucial role in human choice of traditional crafts, an application to evaluate Kanazawa gold leaf, a traditional craft in Ishikawa, Japan, has also been provided to illustrate how the proposed model works in practice. By using the proposed methodology, consumers can purchase or select their preferred traditional crafts according to their preferences.

Like most studies on Kansei evaluation, one preparatory step in our proposed methodology is to identify and measure Kansei attributes and then conduct a questionnaire to collect Kansei data. In practical application, the preparatory study is time-consuming, difficult and subjective. This bottleneck lies in most studies of Kansei evaluation. In addition, consumers may pay attention to both functional and Kansei requirements regarding products. In this study, we focus only on Kansei attributes. Despite these two limitations, the proposed Kansei evaluation model suggested a consumer-oriented approach for Kansei evaluations in Kansei engineering. Furthermore, the proposed model would be of great help for marketing or recommendation purposes, particularly more important in the area of e-commerce, where recommender systems have become an important research area [1].

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