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A Kansei evaluation approach based on the technique of computing with words

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ABSTRACT

Kansei evaluation plays a vital role in the implementation of Kansei engineering; however, it is difficult to quantitatively evaluate customer preferences of a product's Kansei attributes as such preferences involve human perceptual interpretation with certain subjectivity, uncertainty, and imprecision. An effective Kansei evaluation requires justifying the classification of Kansei attributes extracted from a set of collected Kansei words, establishing priorities for customer preferences of product alternatives with respect to each attribute, and synthesizing the priorities for the evaluated alternatives. Moreover, psychometric Kansei evaluation systems essentially require dealing with Kansei words. This paper presents a Kansei evaluation approach based on the technique of computing with words (CWW). The aims of this study were (1) to classify collected Kansei words into a set of Kansei attributes by using cluster analysis based on fuzzy relations; (2) to model Kansei preferences based on semantic labels for the priority analysis; and (3) to synthesize priority information and rank the order of decision alternatives by means of the linguistic aggregation operation. An empirical study is presented to demonstrate the implementation process and applicability of the proposed Kansei evaluation approach. The theoretical and practical implications of the proposed approach are also discussed.

1. Introduction

Successful new products contribute to financial and market performance measures and open up new opportunities for business. In today's highly competitive and uncertain market environment characterized by short product life cycles, new product strategies have transformed from a product-push type to a market-pull model [1]. Companies must develop every aspect of product quality to satisfy customer requirements and maintain market success. Previous research has argued that a better understanding of the process that designers use to incorporate customer requirements into a product design is needed [2]. However, customer requirements and preferences for a product often vary. More specifically, different groups of customers have different requirements, and even customers in the same target group frequently have distinct preferences. Customer preference is often referred to as the degree to which an individual likes a product, and is considered a psychological construct that might be composed of perceptive, affective, and behavioral dimensions [3]. Consequently, it is a challenge for companies to devise ways to identify and measure the elements of such preference decisions with any accuracy and reliability [4]. Further confounding this challenge, the psychological preferences a customer responds to are conceptually vague with uncertainty determined by his/her inner perceptions and frequently presented in linguistic forms. However, perceptions are not readily observable using external tools, and so how to precisely extract preference patterns from linguistic data as well as objectively evaluate such data is an important issue for both academia and industry.

The term "Kansei" is a Japanese word that covers the meanings of sensibility, impression, and emotion. It is related to a customer's physiological and psychological feelings and refers to the cognitive processes of human perception. Kansei engineering has been developed as a consumer-oriented technique to better understand customers' emotional responses and further translate them into the design elements of a product [5]. This technology has been widely employed in various design fields over the past few decades [6–8]. Kansei evaluation is an important step in determining and substantiating the degree of customer preferences prior to the utilization and application of Kansei engineering. Many studies have conducted Kansei evaluation in which statistical analysis associated with the semantic differential (SD) method is widely employed to quantify human perception and establish an understanding of Kansei preferences [9–12]. Conventional statistical

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analysis methods used with Kansei evaluation (e.g., correlation coefficient analysis, principal component analysis, factor analysis, and multiple regression analysis) assume that customer preferences increase or decrease linearly as improving or worsening product attributes. However, in many cases, these preferences can be a non-linear pattern due to uncertain, imprecise, or incomplete data caused by human error, recording error, or arbitrary guesses which may ultimately yield unreliable results. This non-linear behavior requires specific analytical techniques to identify the different effects that variations in Kansei attributes may have on customer preferences. To deal with the quantitative measures of perceptual information, a number of non-linear inference techniques have been developed and employed for modeling Kansei evaluation systems, including neural networks [13,14], fuzzy logic [15–17], and genetic algorithms [18–20].

Kansei evaluation is a systematic determination of customer preference significance using criteria against a set of Kansei attributes, where Kansei attributes refer to the criteria of emotional connotations. In practice, Kansei evaluation consists of three main operations, namely attribute classification, preference modeling, and priority analysis. A basic principle in Kansei evaluation is that valid results depend on justifying the classification of Kansei attributes extracted from a set of collected Kansei words, establishing priorities for the customer preferences of product alternatives with respect to each attribute, and synthesizing the priorities for the evaluated alternatives. Previous research has indicated that the main problem in constructing customer preference models with good predictive performance is how to deal with the inherent non-linear correlations between product attributes [15]. Kansei preferences refer to a non-quantifiable, subjective, and affective-based process involving the human perceptual interpretation of Kansei responses, which inevitably involves some imprecision or vagueness in terms of individual perceptual confidence. For example, the perceptual intensity of "very comfortable" is more than that of "comfortable", but by how much is unknown. Moreover, respondent bias occurs when customers are unable or unwilling to provide accurate answers in a Kansei evaluation survey. Fortunately, fuzzy set theory offers a powerful tool to deal with concepts and rules with uncertainty, imprecision, and non-linearity. This theory is based on the premise that the key points in human thinking are not numbers, but linguistic terms or labels of fuzzy sets [21]. Fuzzy logic incorporating computing with words (CWW) involves computers being activated by words, which are converted into a mathematical representation using fuzzy sets. These fuzzy sets are then mapped by means of a CWW engine into another fuzzy set, after which the latter is converted back into a word [22]. Over the last decade, CWW has been regarded as a very flexible technique for dealing with decision-making problems and evaluating human perceptions, and many different approaches for CWW using fuzzy sets have been proposed and used in the literature [23–28]. According to Wang and Hao [29], these approaches can be classified into three categories: (1) the Extension Principle based models, which operate on the underlying fuzzy set models of the linguistic terms using the Extension Principle [30]; (2) the symbolic model, which makes computations on the indices of the linguistic terms; and, (3) the 2-tuple representation based model, which is an improvement over the symbolic model. Franco et al. [24] indicated that CWW explores the brain's ability to handle and evaluate perceptions by means of the linguistic representation of information and knowledge. It can be used as a paradigm for developing reasoning mechanisms to improve solving processes of perception-based problems dealing with uncertainty, imprecision, and subjective vagueness [31–33]. The CWW paradigm deals with Kansei preferences through qualitative semantics instead of numbers. For Kansei evaluation situations in which customer preferences cannot be assessed precisely in a quantitative manner but can be approximated via a qualitative one, the use of the CWW paradigm is very appropriate.

With regard to existing Kansei evaluation approaches, Huang et al. [34] proposed a Kansei clustering method for Kansei attribute classification that combines the design/dependency structure matrix (DSM) with Pearson correlation analysis to measure the perceptual similarity of customers between the meanings of Kansei words. However, their method does not provide internal consistency verification for the customers' Kansei correlation matrix and also requires a heavy cognitive load to manage Kansei subsets. Although most Kansei evaluation studies have used quantification theory type I (QT1) to synthesize Kansei priority information [35], there are clear statistical limitations that can influence the synthesis results [18,36]. Based on the multi-attribute fuzzy target-oriented decision analysis, Yan et al. [17] proposed a Kansei evaluation model to improve the strength of Kansei evaluation systems. Their model uses a prioritized aggregation operator to aggregate the partial degrees of satisfaction for the evaluated alternatives. However, the prioritized aggregation includes three complex calculation processes for priority analysis and the OWA-based operator is a scoring type that focuses on the aggregation of crisp numbers rather than fuzzy numbers. Zhou et al. [37] argued that fuzzy numbers provide an efficient way of knowledge representation and can be applied to human preference modeling using linguistic terms. Accordingly, this paper presents a Kansei evaluation approach based on the CWW technique. The aims of this study were (1) to classify collected Kansei words into a set of Kansei attributes by using cluster analysis based on fuzzy relations; (2) to model Kansei preferences based on semantic labels for the priority analysis; and, (3) to synthesize priority information and rank the order of decision alternatives by means of a linguistic aggregation operation. This approach can be used to assist evaluators in assessing customer Kansei preferences of a product. The remainder of this paper is organized as follows. Section 2 introduces the theoretical fundamentals of Kansei preference modeling, Kansei clustering, and linguistic aggregation. Section 3 describes the proposed Kansei evaluation approach, while Section 4 presents an empirical study to demonstrate the implementation process and applicability of the proposed approach. A discussion is given in Section 5 and conclusions and recommendations for further research are offered in Section 6.

2. Theoretical fundamentals

In this section, some important fundamentals used in the proposed approach (see Section 3) are addressed. These fundamentals include Kansei preference modeling for the priority analysis, Kansei clustering for classifying collected Kansei words into a set of Kansei attributes, and linguistic aggregation for synthesizing Kansei priority information.

2.1. Kansei preference modeling

Kansei preferences are defined as customer preferences on a specific Kansei attribute of a product. In modeling such preferences, respondents are customarily asked in a questionnaire to indicate their appropriate choices from a set of self-report inventories. Likert-based and semantic differential-based scorings are two commonly used scales to quantify human perceptual interpretations. A Kansei attribute refers to a criterion of emotional connotation (e.g., elegant-positive feeling or inelegant-negative feeling) associated with different levels of intensity descriptors (e.g., very inelegant, inelegant, neutral, elegant, and very elegant) for quantifying customer preferences. To quantify Kansei preferences, the semantic differential (SD) method is often used. An SD consists of a number of scales, each of which is a bipolar adjective pair. Since the SD method requires cognitively positive and negative interpretations, one drawback is the increased cognitive demand, which can introduce errors in scores [38]. Although Likert-based scales contain only positively worded items and are conceptually proper for human psychological constructs, their use suffers from the bias of acquiescence in which respondents to a Kansei evaluation survey have a tendency to agree with all the questions or to indicate a positive connotation [38–40].

For human preference modeling, a 7-point labeled scale is commonly used to gather respondents' ratings for each perceptual item. Many researchers consider the psychometric rating scales as ordered-categorical data rather than interval-level data since one cannot assume that respondents perceive all pairs of adjacent levels as equidistant [41]. As shown in the linguistic format scale of Fig. 1, for example, a respondent perceives a product as medium but somewhat inelegant. In such a situation of response, what is the fundamental difference between "medium elegant" and "somewhat inelegant"? In Likert format, this perceptual interpretation may be approximately classified into "Neutral" preference with a numerical value of "0.5", while in SD format, the number "0.44" can perhaps more precisely indicate the value for the perceptual preference. Be that as it may, both numerical values do not exactly represent such a perceptual interpretation as human perceptual interpretation of Kansei responses involves inherent imprecision or vagueness to a certain extent, as mentioned above.

Fuzzy sets are a generalization of crisp sets for representing imprecision or vagueness in everyday life. The use of fuzzy sets is central to computing with words or labels as they provide a means of modeling the vagueness underlying most natural linguistic terms [22,42]. A fuzzy set is defined by its membership function, and the value of the membership grade indicates the degree to which the element belongs to the fuzzy set. A fuzzy set A is called normalized when at least one of its elements attains the maximum possible membership grade (i.e., $max_{x \in X} \mu_A(x) = 1$), and if the membership function $\mu_A(x)$ is a monotone increasing function for $x < b$ and a monotone decreasing function for $x > b$, where $\mu_A(b) = 1$, it can be considered as a convex fuzzy set. If a convex and normalized fuzzy set whose membership function is piecewise continuous is defined on $\mathcal{R}$, it can be classified as a fuzzy number. The concept of α-cut is a means to convert a fuzzy set into a

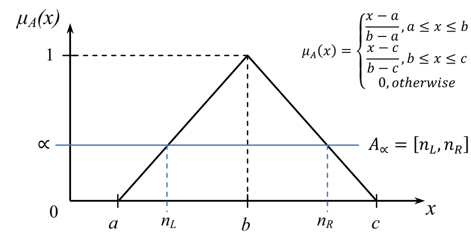

Fig. 2. Triangular membership function of fuzzy set A and its α-cut A_α.

universal set, which is very significant in the relationship between fuzzy sets and crisp sets, and is also useful for defining the arithmetic operations on fuzzy numbers. As shown in Fig. 2, the α-cut of fuzzy set A represented by a triangular membership function is the interval of real numbers $[n_L, n_R]$, and all the numbers in this interval have a degree of membership greater than or equal to the specified value of α. The α-cut of fuzzy set A can be expressed as $A_\alpha = \{\mu_A(x) \geqslant \alpha | x \in X, \alpha \in [0,1]\}$ [43,44].

In this paper, Kansei preferences are modeled by positively worded items with 7 levels of semantic labels to indicate respondents' perceptual intensity. As shown in the lower section of Fig. 1, Kansei preferences K in the semantic space S are characterized by triangular membership functions that associate each semantic element s of S with a real number, $\mu_K(s)$, in the interval $[0,1]$. The α-cut of a Kansei preference represented by a semantic label is a crisp set (interval) that contains all elements of the semantic space S that have a membership grade in the Kansei preference greater than or equal to the specified value of α ($\alpha \in [0,1]$). The above example of perceptual preference is thus interpreted as the degree of 0.64 (the value of the upper membership grade) belonging to the "Medium" preference and the degree of 0.36 (the value of the lower membership grade) belonging to the "Moderately Low" preference. A Kansei preference can be classified as a fuzzy number since it is a convex and normalized fuzzy set whose membership function is piecewise continuous defined on $\mathcal{R}$. Since triangular membership functions are a uniformly distributed ordered set of Kansei preferences in a semantic space, they provide an intuitive way to capture the vagueness of Kansei information. Each Kansei attribute comprises 7 sets of semantic terms

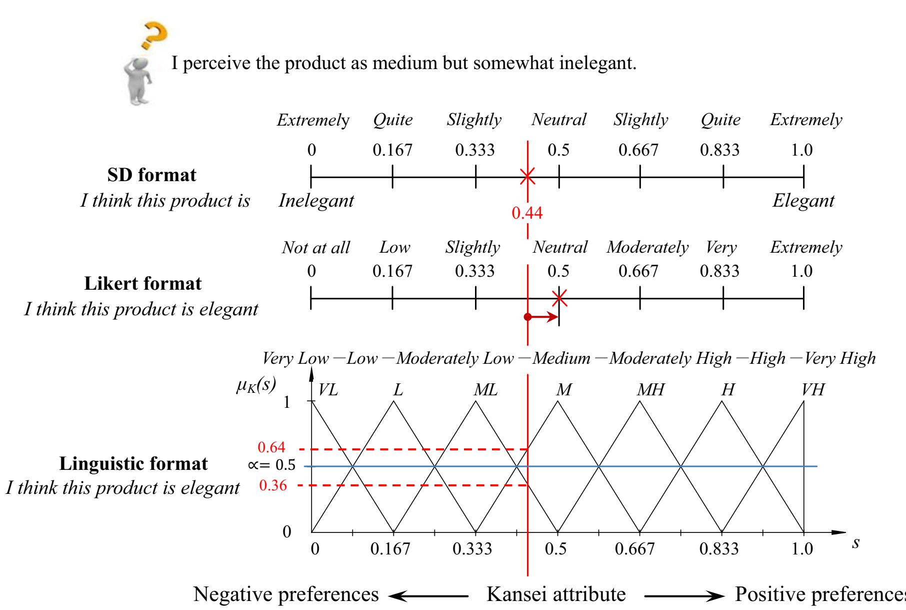

Fig. 1. Kansei preference modeling based on SD, Likert, and linguistic formats, respectively.

to indicate perceived preferences and perceived importance, as defined in Table 1.

These semantic terms allow customer Kansei preferences to be described and quantified with corresponding fuzzy numbers. The Kansei preferences K can also be crisp sets via interval numbers at $\propto = 0.5$ or cardinal numbers at $\propto = 1$ based on a norm of $[0, 1]$. In establishing priorities of preference relations, cardinal numbers confer a numerical value to the corresponding 7 semantic labels of the Kansei attribute for which the mean of the respondents' linguistic judgments (data points) is mapped into a corresponding interval number (interval line). Interval numbers are used to fuzzify the linguistic judgments into fuzzy numbers (symmetric triangular membership functions), thereby taking into account the fact that all respondents' judgments have some degree of inherent uncertainty. These fuzzy numbers are then used as fuzzy variables for the CWW engine to aggregate priority information. The CWW process based on the Kansei preference modeling is shown in Fig. 3.

2.2. Kansei clustering

Kansei clustering is an important process to justify that a set of much fewer selected Kansei words can be used as Kansei attributes to represent the whole meaning of all Kansei words collected from the customers [34]. Cluster analysis based on fuzzy relations has been widely studied and employed in the literature [45–47]. Moreover, it can be used as a mining technique to extract Kansei data by dividing a given set of Kansei words into an appropriate set of Kansei attributes for the evaluation.

Any relation between two sets X and Y is known as a binary relation. Similarly, fuzzy relations are fuzzy subsets of $X \times Y$. Let $X, Y \subseteq \mathcal{R}$ be universal sets; then, the fuzzy relation R on $X \times Y$ can be denoted by

$$R = \{((x, y), \mu_R(x, y)) | (x, y) \in X \times Y\} \tag{1}$$

which is characterized by the membership function $\mu_R(x, y),\ R : X \times Y \to [0, 1]$.

A fuzzy relation R on $X \times Y$ is called a fuzzy equivalence relation if it satisfies the following three properties [48,49]:

(1) Reflexivity: $\mu_R(x, y) = 1$, iff $x = y$, $\forall x, y \in X \times Y$.
(2) Symmetry: $\mu_R(x, y) = \mu_R(y, x)$, iff $x \neq y$, $\forall x, y \in X \times Y$.
(3) Transitivity: $R \circ R = R^{(2)} \subseteq R$, or more explicitly.

$$\mu_R(x, y) \geqslant \vee\{\wedge[\mu_R(x, \psi), \mu_R(\psi, y)]\}, \quad \forall x, \psi, y \in X \times Y$$

In Kansei attribute classification, human subjectivity provides important information. The measure among respondents' perceived preferences is a binary relation (a set of respondents and a corresponding set of their perceived preferences), which may be represented by a proximity relation. A *measure of subjective similarity* can be a fuzzy proximity relation that satisfies the properties of reflexivity and symmetry, but excludes the transitivity property [47,50–52].

Let $R(x, y), (x, y) \in X \times Y$ and $S(y, z), (y, z) \in Y \times Z$ be two fuzzy relations. The *max–min* composition of R and S is defined by

$$R \circ S = \{[(x, z), \vee\{\wedge\{\mu_R(x, y), \mu_S(y, z)\}\}] | (x, y) \in X \times Y,\ (y, z) \in Y \times Z\} \tag{2}$$

Table 1
Definitions of semantic terms.

Semantic label (S.L.)	Semantic term (perceived preference/perceived importance)	Fuzzy number (F.N.) $\propto \in [0.1]$	Interval number (I.N.) at $\propto = 0.5$	Cardinal number (C.N.) at $\propto = 1$
VL	Very low Kansei preference Very low importance	[0, 0.167]	[0, 0.083)	0
L	Low Kansei preference Low importance	[0, 0.333]	[0.083, 0.250)	0.167
ML	Moderately low Kansei preference Moderately low importance	[0.167, 0.5]	[0.250, 0.416)	0.333
M	Medium Kansei preference Medium importance	[0.333, 0.667]	[0.416, 0.583)	0.5
MH	Moderately high Kansei preference Moderately high importance	[0.5, 0.833]	[0.583, 0.750)	0.667
H	High Kansei preference High importance	[0.667, 1]	[0.750, 0.916)	0.833
VH	Very high Kansei preference Very high importance	[0.833, 1]	[0.916, 1]	1

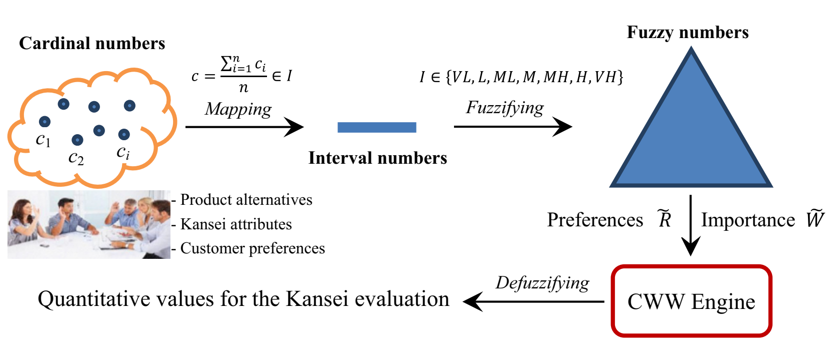

Fig. 3. CWW process based on Kansei preference modeling.

Tamura et al. [52] proposed an n-step procedure of *max–min* compositions initiated with a proximity relation. Given a *t-norm* and an initial fuzzy relation R, then $R^{(n)} = \{[(x,y), \vee\{t\{\mu_{R^{(n-1)}}(x,\psi), \mu_{R^{(n-1)}}(\psi,y)\}\}]|x,\psi,y \in X \times Y\}$ is called a *max-t* composition. Suppose R is a fuzzy proximity relation; then, we can obtain a transitive closure through n steps of *max-t* compositions as

$$I < R < R^{(2)} < \cdots < R^{(n)} = R^{(n+1)} = R^{(n+2)} = \cdots \tag{3}$$

The transitive closure $R^{(n)}$ is a *max–min* similarity relation used to define a fuzzy equivalence relation for partitioning the data set into clusters. If n is not finite, then $\lim_{n\to\infty} R^{(n)} = R^{(\infty)}$ with $R^{(\infty)}$ being a *max–min* similarity relation, i.e.

$$I < R < R^{(2)} < \cdots < R^{(n)} < R^{(n+1)} < R^{(n+2)} < \cdots < R^{(\infty)} \tag{4}$$

Let $R^{(n)}$ be a fuzzy equivalence relation on $X \times Y$, i.e. $R^{(n)} = \{((x,y), \mu_{R^{(n)}}(x,y))|(x,y) \in X \times Y\}$, the α-cut of $R^{(n)}$ is denoted by

$$R^{(n)}_{\alpha} = \left\{\left[(x,y), \mu_{R^{(n)}_{\alpha}}(x,y)\right]\middle|\mu_{R^{(n)}_{\alpha}}(x,y) = 1,\right.$$
$$\left.\text{iff } \mu_{R^{(n)}}(x,y) \geqslant \alpha;\ \mu_{R^{(n)}_{\alpha}}(x,y) = 0,\ \text{iff } \mu_{R^{(n)}}(x,y) < \alpha\right\} \tag{5}$$

The equivalence classes formed by the levels of refinement of a similarity relation can be interpreted as grouping elements that are similar to each other by a degree not less than α [45,50,52]. Based on the fuzzy equivalence relation, we can take an α-cut $R^{(n)}_{\alpha}$ for any value of α to create a crisp equivalence relation that represents the presence of similarity between the elements. Each of these equivalence relations forms a partition that represents the presence of similarity between the given Kansei words.

Determining the best number of clusters in a data set remains the most important application of cluster validity [53–57]. Once the partition is derived, the validity function can help verify whether the grouping accurately represents the data structure.

Let X be a data set of Kansei words and $C(x),\ x \in X$ be a cluster comprised of h elements (Kansei words); then, the intra-relational grade for cluster r can be defined as

$$c_r = \frac{1}{h(h-1)}\left(\sum_{u=1}^{h}\sum_{v=1}^{h}\gamma_{u,v}\right), \quad h > 1 \tag{6}$$

where

$\gamma_{u,v}$ is the relational grade between elements u and $v, \gamma_{u,v} \in R$; $\gamma_{u,v} = \gamma_{v,u},\ u,v = 1,2,\ldots,h$; and $\gamma_{u,v} = 0,\ u = v$ (i.e., changing the value of diagonal elements of R from 1 to 0).

Based on the intra-relational grades, the cluster validation index (*CVI*) can be expressed as

$$CVI = \frac{\left(\sum_{r=1}^{g} c_r\right) \cdot \ln g}{g} \tag{7}$$

where g is the number of clusters partitioned by $R^{(n)}_{\alpha}$.

Cluster validation refers to the quantitative evaluation of the clustering solution quality. The proposed *CVI* is based on the concept that elements (Kansei words) should be classified into appropriate clusters (Kansei attributes) with a low inter-group relation (discriminability of groups), where each cluster should have a high intra-element relation (homogeneity of elements). The former is achieved through weakening the extreme clusters on both sides of the hierarchy $\left(\text{i.e., } \frac{\ln g}{g}\right)$, while the latter is conducted by means of a summation of the intra-relational grades (i.e., $\sum_{r=1}^{g} c_r$). It should be noted that there is no intra-relational grade if the cluster only contains one element ($c_r = 0 \iff \gamma_{u,v} = 0,\ u = v$). Further, the *CVI* will be zero when the elements are classified into one single cluster (i.e., $g = 1$) or if they are all separate (i.e., $\sum_{r=1}^{g} c_r = 0$). A higher *CVI* indicates a clustering in which all clusters are more compact and distinct from each other. Thus, the highest *CVI* indicates a valid optimal clustering. After determining the best number of clusters, an appropriate set of Kansei attributes can be derived.

2.3. Linguistic aggregation

Aggregation operations on fuzzy sets are operations by which several fuzzy sets are combined in a desirable way to produce a single fuzzy set [43]. There are numerous computational models available for linguistic aggregation that have been investigated in the literature [25,58]. Since Kansei evaluation essentially requires synthesizing linguistic descriptors, this study used a linguistic aggregation model as a CWW engine to aggregate priority information and rank the order of decision alternatives.

Given a set of linguistic ratings variables $\widetilde{R} = [\![\widetilde{r_{jk}}]\!]$, and a set of linguistic variables of weights $\widetilde{W} = [\![\widetilde{w_k}]\!]$, the aggregation operator is formularized as

$$D_j(\tilde{r}\cdot\tilde{w}) = \frac{\sum_{k=1}^{m}[\![\widetilde{r_{jk}}]\!]\cdot[\![\widetilde{w_k}]\!]}{\sum_{k=1}^{m}[\![\widetilde{w_k}]\!]}$$
$$= \frac{\int_{\alpha=0}^{1}(\widetilde{r_{j1}}\times\widetilde{w_1})_{\alpha} + (\widetilde{r_{j2}}\times\widetilde{w_2})_{\alpha} + \cdots + (\widetilde{r_{jm}}\times\widetilde{w_m})_{\alpha}}{\int_{\alpha=0}^{1}(\widetilde{w_1})_{\alpha} + (\widetilde{w_2})_{\alpha} + \cdots + (\widetilde{w_m})_{\alpha}} \tag{8}$$

where

j is the number of alternatives; k is the number of criteria/attributes; and,
$D_j(\tilde{r}\cdot\tilde{w})$ represents the overall desirability of alternative j.

Linguistic variables $\widetilde{r_{jk}}$ and $\widetilde{w_k}$ are triangular fuzzy numbers, as given in Table 1. The aggregation with continuous α-cuts is a combination of extended algebraic operations based on interval arithmetic operations and requires that any fuzzy number can be represented by a continuous membership function and can be completely defined by its family of α-cuts [44,59–61]. For $\tilde{r}_{\alpha} = [a,b]$ and $\tilde{w}_{\alpha} = [c,d]$, the arithmetic operations can be expressed as

- $(\tilde{r}\times\tilde{w})_{\alpha} = \tilde{r}_{\alpha}\cdot\tilde{w}_{\alpha} = [a,b]\cdot[c,d] = [\wedge(ac,ad,bc,bd),\vee(ac,ad,bc,bd)] = [e,f] = \tilde{z}_{\alpha}$;
- $(\widetilde{z_1})_{\alpha} + (\widetilde{z_2})_{\alpha} + \cdots + (\widetilde{z_m})_{\alpha} = [e_1,f_1] + [e_2,f_2] + \cdots + [e_m,f_m] = [(e_1+e_2+\cdots+e_m),(f_1+f_2+\cdots+f_m)] = [\varepsilon,\eta]$;
- $(\widetilde{w_1})_{\alpha} + (\widetilde{w_2})_{\alpha} + \cdots + (\widetilde{w_m})_{\alpha} = [c_1,d_1] + [c_2,d_2] + \cdots + [c_m,d_m] = [(c_1+c_2+\cdots+c_m),(d_1+d_2+\cdots+d_m)] = [\rho,\sigma]$; and provided that $0 \notin [\rho,\sigma]$;
- $\frac{[\varepsilon,\eta]}{[\rho,\sigma]} = [\varepsilon,\eta]\cdot\left[\frac{1}{\sigma},\frac{1}{\rho}\right] = \left[\wedge\left(\frac{\varepsilon}{\rho},\frac{\varepsilon}{\sigma},\frac{\eta}{\rho},\frac{\eta}{\sigma}\right),\vee\left(\frac{\varepsilon}{\rho},\frac{\varepsilon}{\sigma},\frac{\eta}{\rho},\frac{\eta}{\sigma}\right)\right]$.

The result of the arithmetic operations is a crisp set (interval) that represents the α-cut of the fuzzy set obtained by operating on fuzzy numbers $\widetilde{r_{jk}}$ and $\widetilde{w_k}$. Through the aggregation operations, the family of α-cuts defined as the resultant membership function of the evaluated alternative can be presented as a convex and normalized fuzzy set (also classified as a fuzzy number). In order to obtain a quantitative value of the resultant fuzzy number, the center-of-gravity (COG) defuzzification method is employed as shown in Eq. (9). The higher the $\overline{s_j}$ value, the better is the evaluated alternative. An example of the linguistic aggregation result is shown in Fig. 4.

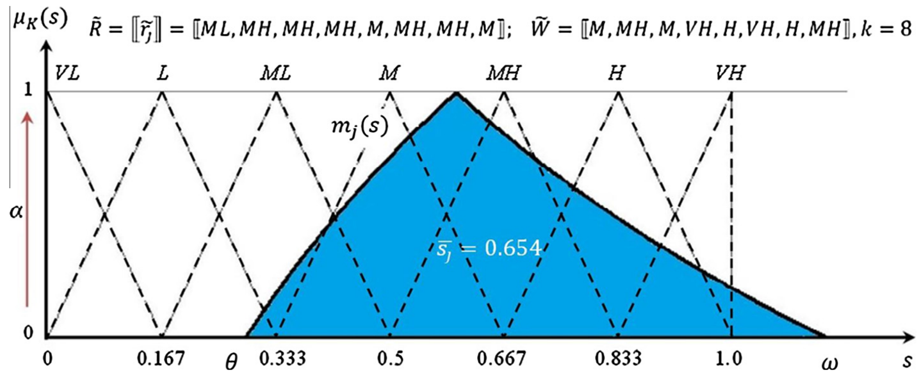

Fig. 4. Example of the linguistic aggregation result.

$$\bar{s_j} = \frac{\int_\theta^\omega m_j(s) \cdot s ds}{\int_\theta^\omega m_j(s) ds} \tag{9}$$

where

$m_j(s)$ represents the resultant membership function of the evaluated alternative j; while
θ and ω are the respective lower and upper limits of the fuzzy number support.

3. Proposed approach

Based on the theoretical fundamentals given in Section 2, the implementation steps of the Kansei evaluation approach are elaborated as follows:

Step 1. Select a set of sample products as decision alternatives for evaluation.

$$\mathrm{A} = \{A_j | j = 1, 2, \ldots, o\} \tag{10}$$

Step 2. Collect a set of Kansei words and construct a preference matrix.

According to customer feelings toward the sample products, evaluators collect as many emotional adjectives as possible from various sources such as magazines, academic literature, product manuals, product test reports, expert reviews, user opinions, and customer interviews. Through a preliminary analysis, a set of Kansei words is determined as

$$\mathrm{KW} = \{KW_l | l = 1, 2, \ldots, d\} \tag{11}$$

Let X be a discrete data set of Kansei words constructed from the evaluation of perceived preferences regarding a reference product using the semantic label scoring of cardinal numbers given in Table 1; then, the preference matrix can be constructed as

$$X_{t \times d} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \\ \vdots \\ x_t \end{bmatrix} = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(l) & \cdots & x_1(d) \\ x_2(1) & x_2(2) & \cdots & x_2(l) & \cdots & x_2(d) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_i(1) & x_i(2) & \cdots & x_i(l) & \cdots & x_i(d) \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_t(1) & x_t(2) & \cdots & x_t(l) & \cdots & x_t(d) \end{bmatrix} \tag{12}$$

where $x_i(l)$ represents the vector of scoring data; i is the number of respondents, $i = 1, 2, \ldots, t$; and l is the number of Kansei words, $l = 1, 2, \ldots, d$.

Step 3. Classify the collected Kansei words into a set of Kansei attributes.

Any valid metric can be used as a measure of similarity between pairs of objects (Kansei words). The choice of which clusters to merge or split is determined by a linkage criterion, which itself is a function of the pairwise distances/correlations between objects. Fuzzy clustering based on distance similarity measures has widely been used in the literature [62–64]. The concept of membership grades is used as a linkage criterion to indicate the similarity between data sets, and is substantiated by the definition and interpretation of fuzzy sets. Different membership functions may produce different clusters since the membership function is usually assumed as an indicator to form a partition of unity [65]. However, it is difficult to determine an appropriate membership function to fit the data properties and construct a rational fuzzy relation. Grey relational analysis (GRA) has been one of the most practical analytical tools to investigate order relation of given objects of data sets with similarity [66,67]. In this step, topology-based grey relational analysis (TGRA) is used as an indicator function to derive a set of relational grades for constructing a fuzzy proximity matrix.

Let X be a grey relation vector space, with x_i and x_f being d-dimensional vectors within X. The metric between two vectors (x_i and x_f) with the distinguishing coefficient, ζ, is defined as follows [68–70]:

$$\gamma_{i,f} = \gamma(x_i, x_f) = 1 - \frac{\Delta_{i,f}}{\Delta_{max}} \tag{13}$$

where

$$\Delta_{i,f} = \|x_i - x_f\|_\zeta = \sqrt[\zeta]{\textstyle\sum_{l=1}^d |x_i(l) - x_f(l)|^\zeta}, \ i, f = 1, 2, \ldots, t;$$
$$\Delta_{max} = \vee_{\forall i} \vee_{\forall f} \{\Delta_{i,f}\}; \ \zeta \geqslant 1.$$

Within matrix (12), each row is operated as a reference vector ($x_i(l)$) by turn, with the others acting as comparison vectors ($x_f(l)$). Letting $\zeta = 2$ (i.e., Euclidean distance), and respectively substituting the vector data into Eq. (13) to perform the TGRA operation, a set of global relational grades can be obtained, which is expressed as a relational matrix shown in Eq. (14). The relational grades are based on pairwise comparisons and have the following four properties: (1) Normality: $\gamma_{p,q} \in [0, 1]$; (2) Isolation: $\Delta_{i,f} = \Delta_{max} \Longleftrightarrow \gamma_{p,q} = 0$; (3) Coincidence: $\gamma_{p,q} = 1$ iff $p = q$; and, (4) Symmetry: $\gamma_{p,q} = \gamma_{q,p}$ iff $p \neq q$; $p, q = 1, 2, \ldots, d$.

$$R = \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & \cdots & \gamma_{1,q} & \cdots & \gamma_{1,d} \\ \gamma_{2,1} & \gamma_{2,2} & \cdots & \gamma_{2,q} & \cdots & \gamma_{2,d} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \gamma_{p,1} & \gamma_{p,2} & \cdots & \gamma_{p,q} & \cdots & \gamma_{p,d} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \gamma_{d,1} & \gamma_{d,2} & \cdots & \gamma_{d,q} & \cdots & \gamma_{d,d} \end{bmatrix} \tag{14}$$

The matrix R is a binary relation matrix (i.e., relations between any two Kansei words derived from the evaluation of the evaluators' perceived preferences) used as a measure of subjective similarity. It can be regarded as a fuzzy proximity matrix that satisfies both reflexivity ($\gamma_{p,q} = 1$ iff $p = q$) and symmetry ($\gamma_{p,q} = \gamma_{q,p}$ iff $p \neq q$) properties, but not transitivity. To ensure that the matrix is a fuzzy equivalence relation, it should also represent a transitive closure of R. By iterating matrix R's self-composition computation until the transitivity property is satisfied (i.e., $R^{(n)} \circ R^{(n)} \subseteq R^{(n)}$ or $\gamma_{p,q} \geqslant \vee(\gamma_{p,s} \wedge \gamma_{s,q}), \gamma_{p,q}, \gamma_{p,s}, \gamma_{s,q} \in R^{(n)}$), a fuzzy equivalence relation matrix, $R^{(n)}$, can be derived. Given an α value as a real number in the closed interval $[0, 1]$, we can create a class of equivalence relations by means of different levels of α-cuts $R^{(n)}_{\alpha}$. The Kansei words are then classified into some clusters through taking an appropriate α value.

By using Eqs. (6) and (7) to perform the cluster validation test, the optimal number of clusters can be determined, allowing a set of Kansei attributes to be classified as

$$\mathrm{K} = \{K_k | k = 1, 2, \ldots, m\}, \quad m < d, \ \mathrm{KW} \subset \mathrm{K} \tag{15}$$

Step 4. Establish priorities for obtaining Kansei variables.

According to the classified Kansei attributes, evaluators establish priorities for both the Kansei attributes and preferences for each alternative product with respect to each Kansei attribute. The evaluation scales are based on the Kansei preference modeling for the CWW process given in Section 2.1. After completing the priority analysis, two fuzzy linguistic sets of Kansei variables ($\widetilde{R}$ and $\widetilde{W}$) are obtained.

Step 5. Synthesize the priority information and rank the order of the alternative products.

By substituting the two sets of Kansei variables into Eq. (8) to perform the linguistic aggregation operation, the resultant membership functions of the evaluated alternatives can be obtained. Eq. (9) is then used to defuzzify these fuzzy numbers and subsequently rank the alternative products by their quantitative values. The higher the value is, the stronger the Kansei preferences of the alternative product.

4. Empirical study

A USB flash drive is a data storage device that combines flash memory with an integrated Universal Serial Bus (USB) interface, and is one of the most popular computer peripherals available today. In addition to storage capacity and data transfer speed, the Kansei quality is a vital consideration for customers when purchasing a USB flash drive. In this section, USB flash drives are used as sample products to illustrate the implementation process and applicability of the proposed Kansei evaluation approach. The aim of the illustrative case is to evaluate the most desirable alternatives from a set of selected USB flash drives in terms of the target customers' Kansei preferences. The empirical study consisted of two parts: (1) a pilot study to classify relevant Kansei words into a set of Kansei attributes; and, (2) the Kansei evaluation for the selected USB flash drives.

4.1. Determination of a set of Kansei attributes

This Kansei evaluation research involved 7 Ph.D. students (3 females and 4 males, with an average age of 33.4 years) who majored in Industrial Design and had at least 3 years of practical experience in product design. Based on the positively-worded formula for modeling Kansei preferences, the research team members collected as many emotional adjectives as possible in the domain of USB flash drives from the aforementioned sources. After completing the preliminary analysis, a total of 26 adjectives were selected as Kansei words (see Table 2) for assessing USB flash drives. In the pilot study, a reference product (Kingston DTSE9 USB drive) was used for deriving a set of Kansei attributes. This reference product received a Red Dot Design Award in 2012 and an iF Product Design Award in 2013. The 7 team members evaluated the product according to their perceived preferences against the 26 Kansei words. The evaluation scale was based on the 7-level semantic labels using cardinal numbers. The results are given in Table 2, with the Kansei data classified as the preference matrix presented in Eq. (16).

$$X_{7\times 26} = \begin{bmatrix} 0.667 & 0.833 & 1.000 & 1.000 & 0.500 & 0.833 & 0.500 & 0.667 & 0.667 & 0.500 & 0.833 & 0.833 & 0.500 & 0.333 & 0.333 & 0.333 & 0.667 & 0.500 & 1.000 & 0.333 & 0.833 & 1.000 & 0.000 & 0.667 & 0.833 & 0.333 \\ 0.500 & 1.000 & 0.833 & 1.000 & 0.667 & 1.000 & 1.000 & 0.833 & 0.667 & 0.833 & 0.833 & 0.833 & 0.833 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 & 0.667 & 1.000 & 1.000 & 0.833 & 1.000 & 1.000 & 0.833 \\ 0.833 & 0.667 & 1.000 & 1.000 & 0.167 & 0.833 & 0.833 & 0.833 & 1.000 & 0.500 & 0.500 & 1.000 & 0.167 & 0.833 & 0.667 & 0.833 & 0.500 & 0.833 & 0.833 & 0.500 & 0.833 & 1.000 & 0.000 & 0.833 & 0.833 & 0.667 \\ 0.667 & 0.667 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 & 0.833 & 0.833 & 1.000 & 1.000 & 0.333 & 0.333 & 0.333 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 & 1.000 & 0.000 & 1.000 & 1.000 & 1.000 \\ 0.500 & 0.667 & 0.833 & 1.000 & 0.000 & 0.333 & 0.333 & 0.833 & 0.500 & 0.667 & 0.500 & 0.833 & 0.500 & 1.000 & 0.667 & 0.833 & 0.833 & 0.500 & 0.833 & 0.500 & 1.000 & 1.000 & 0.167 & 0.833 & 1.000 & 0.667 \\ 0.500 & 0.667 & 0.667 & 0.667 & 0.167 & 0.500 & 0.500 & 0.500 & 0.667 & 0.500 & 0.500 & 0.667 & 0.500 & 0.500 & 0.333 & 0.500 & 0.667 & 0.500 & 0.667 & 0.333 & 0.500 & 0.667 & 0.167 & 0.500 & 0.667 & 0.500 \\ 0.833 & 0.667 & 0.833 & 1.000 & 1.000 & 0.667 & 0.833 & 0.833 & 0.833 & 0.833 & 1.000 & 0.500 & 0.333 & 0.500 & 0.333 & 0.667 & 1.000 & 1.000 & 1.000 & 0.167 & 0.833 & 0.833 & 0.167 & 0.833 & 1.000 & 1.000 \end{bmatrix} \tag{16}$$

Table 2
Evaluators' perceived preferences on the reference product against the 26 Kansei words.

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	x_{26}
E_1	*MH*	*H*	*VH*	*VH*	*M*	*H*	*M*	*MH*	*MH*	*M*	*H*	*H*	*M*	*ML*	*ML*	*ML*	*MH*	*M*	*VH*	*ML*	*H*	*VH*	*VL*	*MH*	*H*	*ML*
E_2	*M*	*VH*	*H*	*VH*	*MH*	*VH*	*VH*	*H*	*MH*	*H*	*H*	*H*	*H*	*VH*	*VH*	*VH*	*VH*	*VH*	*VH*	*MH*	*VH*	*VH*	*H*	*VH*	*VH*	*H*
E_3	*H*	*MH*	*VH*	*VH*	*L*	*H*	*H*	*H*	*VH*	*M*	*M*	*VH*	*L*	*H*	*MH*	*H*	*M*	*H*	*H*	*M*	*H*	*VH*	*VL*	*H*	*H*	*MH*
E_4	*MH*	*MH*	*VH*	*VH*	*VH*	*VH*	*VH*	*VH*	*H*	*H*	*VH*	*VH*	*ML*	*ML*	*ML*	*VH*	*VH*	*VH*	*VH*	*VH*	*VH*	*VH*	*VL*	*VH*	*VH*	*VH*
E_5	*M*	*MH*	*H*	*VH*	*VL*	*ML*	*ML*	*H*	*M*	*MH*	*M*	*H*	*M*	*VH*	*MH*	*H*	*H*	*M*	*H*	*M*	*VH*	*VH*	*L*	*H*	*VH*	*MH*
E_6	*M*	*MH*	*MH*	*MH*	*ML*	*M*	*M*	*M*	*MH*	*M*	*M*	*MH*	*M*	*M*	*ML*	*M*	*MH*	*M*	*MH*	*ML*	*M*	*MH*	*L*	*M*	*MH*	*M*
E_7	*H*	*MH*	*H*	*VH*	*VH*	*MH*	*H*	*H*	*H*	*H*	*VH*	*M*	*ML*	*M*	*ML*	*MH*	*VH*	*VH*	*VH*	*L*	*H*	*H*	*L*	*H*	*VH*	*VH*

Reference product (Kingston DTSE9)

Product features: 32 GB, USB 2.0 39 (L) × 12.35(W) × 4.55(H) mm, 6.7 g Stylish metal casing with a large ring.

Kansei words: x_1: Artistic, x_2: Classic, x_3: Compact, x_4: Contemporary, x_5: Cute, x_6: Delicate, x_7: Distinguished, x_8: Elegant, x_9: Exquisite, x_{10}: Eye-catching, x_{11}: Handy, x_{12}: Hard, x_{13}: Ingenious, x_{14}: Lustrous, x_{15}: Luxurious, x_{16}: Novel, x_{17}: Personalized, x_{18}: Plain, x_{19}: Portable, x_{20}: Precious, x_{21}: Quality, x_{22}: Simplificative, x_{23}: Soft, x_{24}: Stylish, x_{25}: Technological, x_{26}: Unique

By substituting the preference matrix data of Eq. (16) into Eq. (13) to perform the TGRA operation, a relational matrix R was derived as shown in Eq. (17).

$$R=\begin{bmatrix}
1.000 & 0.712 & 0.673 & 0.585 & 0.537 & 0.692 & 0.701 & 0.733 & 0.846 & 0.744 & 0.712 & 0.664 & 0.550 & 0.577 & 0.584 & 0.638 & 0.630 & 0.70 & 0.630 & 0.578 & 0.630 & 0.592 & 0.289 & 0.682 & 0.614 & 0.701\\
0.712 & 1.000 & 0.733 & 0.682 & 0.455 & 0.756 & 0.701 & 0.756 & 0.733 & 0.769 & 0.733 & 0.744 & 0.622 & 0.655 & 0.646 & 0.692 & 0.744 & 0.70 & 0.744 & 0.564 & 0.744 & 0.712 & 0.289 & 0.769 & 0.722 & 0.664\\
0.673 & 0.733 & 1.000 & 0.866 & 0.355 & 0.711 & 0.646 & 0.811 & 0.756 & 0.646 & 0.691 & 0.828 & 0.383 & 0.512 & 0.449 & 0.655 & 0.701 & 0.68 & 0.866 & 0.455 & 0.827 & 0.891 & 0.058 & 0.796 & 0.827 & 0.630\\
0.585 & 0.682 & 0.866 & 1.000 & 0.297 & 0.630 & 0.592 & 0.768 & 0.664 & 0.607 & 0.646 & 0.733 & 0.323 & 0.494 & 0.402 & 0.630 & 0.711 & 0.65 & 0.891 & 0.368 & 0.845 & 0.923 & 0.000 & 0.782 & 0.891 & 0.607\\
0.537 & 0.455 & 0.355 & 0.297 & 1.000 & 0.538 & 0.585 & 0.466 & 0.477 & 0.599 & 0.638 & 0.341 & 0.477 & 0.285 & 0.387 & 0.433 & 0.494 & 0.55 & 0.388 & 0.512 & 0.378 & 0.293 & 0.341 & 0.449 & 0.359 & 0.570\\
0.692 & 0.756 & 0.711 & 0.630 & 0.538 & 1.000 & 0.828 & 0.733 & 0.756 & 0.701 & 0.756 & 0.722 & 0.500 & 0.500 & 0.543 & 0.673 & 0.664 & 0.769 & 0.701 & 0.592 & 0.682 & 0.655 & 0.225 & 0.744 & 0.646 & 0.664\\
0.701 & 0.701 & 0.646 & 0.592 & 0.585 & 0.828 & 1.000 & 0.744 & 0.768 & 0.756 & 0.744 & 0.655 & 0.494 & 0.531 & 0.563 & 0.744 & 0.691 & 0.89 & 0.655 & 0.599 & 0.655 & 0.599 & 0.260 & 0.756 & 0.638 & 0.782\\
0.733 & 0.756 & 0.811 & 0.768 & 0.466 & 0.733 & 0.744 & 1.000 & 0.782 & 0.796 & 0.756 & 0.796 & 0.477 & 0.606 & 0.557 & 0.811 & 0.796 & 0.796 & 0.796 & 0.578 & 0.866 & 0.782 & 0.180 & 0.923 & 0.827 & 0.796\\
0.846 & 0.733 & 0.756 & 0.664 & 0.477 & 0.756 & 0.768 & 0.782 & 1.000 & 0.722 & 0.711 & 0.744 & 0.477 & 0.564 & 0.543 & 0.691 & 0.664 & 0.768 & 0.701 & 0.550 & 0.682 & 0.673 & 0.202 & 0.744 & 0.682 & 0.722\\
0.744 & 0.769 & 0.646 & 0.607 & 0.599 & 0.701 & 0.756 & 0.796 & 0.722 & 1.000 & 0.796 & 0.655 & 0.630 & 0.630 & 0.638 & 0.769 & 0.811 & 0.78 & 0.673 & 0.647 & 0.712 & 0.614 & 0.346 & 0.782 & 0.691 & 0.845\\
0.712 & 0.733 & 0.691 & 0.646 & 0.638 & 0.756 & 0.744 & 0.756 & 0.711 & 0.796 & 1.000 & 0.630 & 0.512 & 0.465 & 0.482 & 0.638 & 0.796 & 0.769 & 0.744 & 0.537 & 0.701 & 0.638 & 0.217 & 0.744 & 0.701 & 0.744\\
0.664 & 0.744 & 0.828 & 0.733 & 0.341 & 0.722 & 0.655 & 0.796 & 0.744 & 0.655 & 0.630 & 1.000 & 0.449 & 0.584 & 0.537 & 0.722 & 0.655 & 0.65 & 0.733 & 0.570 & 0.782 & 0.796 & 0.134 & 0.782 & 0.733 & 0.622\\
0.550 & 0.622 & 0.383 & 0.323 & 0.477 & 0.500 & 0.494 & 0.477 & 0.477 & 0.630 & 0.512 & 0.449 & 1.000 & 0.592 & 0.722 & 0.500 & 0.494 & 0.46 & 0.388 & 0.622 & 0.428 & 0.354 & 0.630 & 0.471 & 0.388 & 0.494\\
0.577 & 0.655 & 0.512 & 0.494 & 0.285 & 0.500 & 0.531 & 0.606 & 0.564 & 0.630 & 0.465 & 0.584 & 0.592 & 1.000 & 0.796 & 0.672 & 0.543 & 0.54 & 0.494 & 0.524 & 0.584 & 0.524 & 0.369 & 0.614 & 0.543 & 0.570\\
0.584 & 0.646 & 0.449 & 0.402 & 0.387 & 0.543 & 0.563 & 0.557 & 0.543 & 0.638 & 0.482 & 0.537 & 0.722 & 0.796 & 1.000 & 0.630 & 0.500 & 0.53 & 0.433 & 0.630 & 0.512 & 0.438 & 0.537 & 0.563 & 0.454 & 0.550\\
0.638 & 0.692 & 0.655 & 0.630 & 0.433 & 0.673 & 0.744 & 0.811 & 0.691 & 0.769 & 0.638 & 0.722 & 0.500 & 0.672 & 0.630 & 1.000 & 0.722 & 0.769 & 0.646 & 0.638 & 0.744 & 0.655 & 0.248 & 0.827 & 0.701 & 0.796\\
0.630 & 0.744 & 0.701 & 0.711 & 0.494 & 0.664 & 0.691 & 0.796 & 0.664 & 0.811 & 0.796 & 0.655 & 0.494 & 0.543 & 0.500 & 0.722 & 1.000 & 0.756 & 0.782 & 0.506 & 0.782 & 0.701 & 0.184 & 0.811 & 0.811 & 0.782\\
0.701 & 0.701 & 0.682 & 0.655 & 0.557 & 0.769 & 0.891 & 0.796 & 0.768 & 0.782 & 0.769 & 0.655 & 0.460 & 0.543 & 0.537 & 0.769 & 0.756 & 1.00 & 0.711 & 0.544 & 0.711 & 0.646 & 0.213 & 0.811 & 0.711 & 0.846\\
0.630 & 0.744 & 0.866 & 0.891 & 0.388 & 0.701 & 0.655 & 0.796 & 0.701 & 0.673 & 0.744 & 0.733 & 0.388 & 0.494 & 0.433 & 0.646 & 0.782 & 0.71 & 1.000 & 0.418 & 0.845 & 0.866 & 0.062 & 0.811 & 0.891 & 0.655\\
0.578 & 0.564 & 0.455 & 0.368 & 0.512 & 0.592 & 0.599 & 0.578 & 0.550 & 0.647 & 0.537 & 0.570 & 0.622 & 0.524 & 0.630 & 0.638 & 0.506 & 0.54 & 0.418 & 1.000 & 0.494 & 0.412 & 0.428 & 0.557 & 0.428 & 0.585\\
0.630 & 0.744 & 0.827 & 0.845 & 0.378 & 0.682 & 0.655 & 0.866 & 0.682 & 0.712 & 0.701 & 0.782 & 0.428 & 0.584 & 0.512 & 0.744 & 0.782 & 0.71 & 0.845 & 0.494 & 1.000 & 0.866 & 0.114 & 0.891 & 0.891 & 0.691\\
0.592 & 0.712 & 0.891 & 0.923 & 0.293 & 0.655 & 0.599 & 0.782 & 0.673 & 0.614 & 0.638 & 0.796 & 0.354 & 0.524 & 0.438 & 0.655 & 0.701 & 0.64 & 0.866 & 0.412 & 0.866 & 1.000 & 0.027 & 0.796 & 0.866 & 0.599\\
0.289 & 0.289 & 0.058 & 0.000 & 0.341 & 0.225 & 0.260 & 0.180 & 0.202 & 0.346 & 0.217 & 0.134 & 0.630 & 0.369 & 0.537 & 0.248 & 0.184 & 0.21 & 0.062 & 0.428 & 0.114 & 0.027 & 1.000 & 0.176 & 0.068 & 0.252\\
0.682 & 0.769 & 0.796 & 0.782 & 0.449 & 0.744 & 0.756 & 0.923 & 0.744 & 0.782 & 0.744 & 0.782 & 0.471 & 0.614 & 0.563 & 0.827 & 0.811 & 0.81 & 0.811 & 0.557 & 0.891 & 0.796 & 0.176 & 1.000 & 0.846 & 0.782\\
0.614 & 0.722 & 0.827 & 0.891 & 0.359 & 0.646 & 0.638 & 0.827 & 0.682 & 0.691 & 0.701 & 0.733 & 0.388 & 0.543 & 0.454 & 0.701 & 0.811 & 0.71 & 0.891 & 0.428 & 0.891 & 0.866 & 0.068 & 0.846 & 1.000 & 0.691\\
0.701 & 0.664 & 0.630 & 0.607 & 0.570 & 0.664 & 0.782 & 0.796 & 0.722 & 0.845 & 0.744 & 0.622 & 0.494 & 0.570 & 0.550 & 0.796 & 0.782 & 0.846 & 0.655 & 0.585 & 0.691 & 0.599 & 0.252 & 0.782 & 0.691 & 1.000
\end{bmatrix} \quad (17)$$

By iterating matrix R's self-composition computation until the transitivity property is satisfied, the equivalence relation matrix shown in Eq. (18) was derived, which satisfies the properties of reflexivity ($\gamma_{p,q} = 1$ iff $p = q$), symmetry ($\gamma_{p,q} = \gamma_{q,p}$ iff $p \neq q$), and transitivity ($R^{(16)} \circ R^{(16)} \subseteq R^{(16)}$).

$$R^{(16)}=\begin{bmatrix}
1.000 & 0.769 & 0.782 & 0.782 & 0.638 & 0.782 & 0.782 & 0.782 & 0.846 & 0.782 & 0.782 & 0.782 & 0.672 & 0.672 & 0.672 & 0.782 & 0.782 & 0.782 & 0.782 & 0.647 & 0.782 & 0.782 & 0.630 & 0.782 & 0.782 & 0.782\\
0.769 & 1.000 & 0.769 & 0.769 & 0.638 & 0.769 & 0.769 & 0.769 & 0.769 & 0.769 & 0.769 & 0.769 & 0.672 & 0.672 & 0.672 & 0.769 & 0.769 & 0.769 & 0.769 & 0.647 & 0.769 & 0.769 & 0.630 & 0.769 & 0.769 & 0.769\\
0.782 & 0.769 & 1.000 & 0.891 & 0.638 & 0.811 & 0.811 & 0.891 & 0.782 & 0.811 & 0.796 & 0.828 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 0.891 & 0.647 & 0.891 & 0.891 & 0.630 & 0.891 & 0.891 & 0.811\\
0.782 & 0.769 & 0.891 & 1.000 & 0.638 & 0.811 & 0.811 & 0.891 & 0.782 & 0.811 & 0.796 & 0.828 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 0.891 & 0.647 & 0.891 & 0.923 & 0.630 & 0.891 & 0.891 & 0.811\\
0.638 & 0.638 & 0.638 & 0.638 & 1.000 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.638 & 0.630 & 0.638 & 0.638 & 0.638\\
0.782 & 0.769 & 0.811 & 0.811 & 0.638 & 1.000 & 0.828 & 0.811 & 0.782 & 0.828 & 0.796 & 0.811 & 0.672 & 0.672 & 0.672 & 0.811 & 0.811 & 0.828 & 0.811 & 0.647 & 0.811 & 0.811 & 0.630 & 0.811 & 0.811 & 0.828\\
0.782 & 0.769 & 0.811 & 0.811 & 0.638 & 0.828 & 1.000 & 0.811 & 0.782 & 0.845 & 0.796 & 0.811 & 0.672 & 0.672 & 0.672 & 0.811 & 0.811 & 0.891 & 0.811 & 0.647 & 0.811 & 0.811 & 0.630 & 0.811 & 0.811 & 0.846\\
0.782 & 0.769 & 0.891 & 0.891 & 0.638 & 0.811 & 0.811 & 1.000 & 0.782 & 0.811 & 0.796 & 0.828 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 0.891 & 0.647 & 0.891 & 0.891 & 0.630 & 0.923 & 0.891 & 0.811\\
0.846 & 0.769 & 0.782 & 0.782 & 0.638 & 0.782 & 0.782 & 0.782 & 1.000 & 0.782 & 0.782 & 0.782 & 0.672 & 0.672 & 0.672 & 0.782 & 0.782 & 0.782 & 0.782 & 0.647 & 0.782 & 0.782 & 0.630 & 0.782 & 0.782 & 0.782\\
0.782 & 0.769 & 0.811 & 0.811 & 0.638 & 0.828 & 0.845 & 0.811 & 0.782 & 1.000 & 0.796 & 0.811 & 0.672 & 0.672 & 0.672 & 0.811 & 0.811 & 0.845 & 0.811 & 0.647 & 0.811 & 0.811 & 0.630 & 0.811 & 0.811 & 0.845\\
0.782 & 0.769 & 0.796 & 0.796 & 0.638 & 0.796 & 0.796 & 0.796 & 0.782 & 0.796 & 1.000 & 0.796 & 0.672 & 0.672 & 0.672 & 0.796 & 0.796 & 0.796 & 0.796 & 0.647 & 0.796 & 0.796 & 0.630 & 0.796 & 0.796 & 0.796\\
0.782 & 0.769 & 0.828 & 0.828 & 0.638 & 0.811 & 0.811 & 0.828 & 0.782 & 0.811 & 0.796 & 1.000 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 0.828 & 0.647 & 0.828 & 0.828 & 0.630 & 0.828 & 0.828 & 0.811\\
0.672 & 0.672 & 0.672 & 0.672 & 0.638 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 1.000 & 0.722 & 0.722 & 0.672 & 0.672 & 0.672 & 0.672 & 0.647 & 0.672 & 0.672 & 0.630 & 0.672 & 0.672 & 0.672\\
0.672 & 0.672 & 0.672 & 0.672 & 0.638 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 0.722 & 1.000 & 0.796 & 0.672 & 0.672 & 0.672 & 0.672 & 0.647 & 0.672 & 0.672 & 0.630 & 0.672 & 0.672 & 0.672\\
0.672 & 0.672 & 0.672 & 0.672 & 0.638 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 0.672 & 0.722 & 0.796 & 1.000 & 0.672 & 0.672 & 0.672 & 0.672 & 0.647 & 0.672 & 0.672 & 0.630 & 0.672 & 0.672 & 0.672\\
0.782 & 0.769 & 0.827 & 0.827 & 0.638 & 0.811 & 0.811 & 0.827 & 0.782 & 0.811 & 0.796 & 0.827 & 0.672 & 0.672 & 0.672 & 1.000 & 0.811 & 0.811 & 0.827 & 0.647 & 0.827 & 0.827 & 0.630 & 0.827 & 0.827 & 0.811\\
0.782 & 0.769 & 0.811 & 0.811 & 0.638 & 0.811 & 0.811 & 0.811 & 0.782 & 0.811 & 0.796 & 0.811 & 0.672 & 0.672 & 0.672 & 0.811 & 1.000 & 0.811 & 0.811 & 0.647 & 0.811 & 0.811 & 0.630 & 0.811 & 0.811 & 0.811\\
0.782 & 0.769 & 0.811 & 0.811 & 0.638 & 0.828 & 0.891 & 0.811 & 0.782 & 0.845 & 0.796 & 0.811 & 0.672 & 0.672 & 0.672 & 0.811 & 0.811 & 1.000 & 0.811 & 0.647 & 0.811 & 0.811 & 0.630 & 0.811 & 0.811 & 0.846\\
0.782 & 0.769 & 0.891 & 0.891 & 0.638 & 0.811 & 0.811 & 0.891 & 0.782 & 0.811 & 0.796 & 0.828 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 1.000 & 0.647 & 0.891 & 0.891 & 0.630 & 0.891 & 0.891 & 0.811\\
0.647 & 0.647 & 0.647 & 0.647 & 0.638 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 0.647 & 1.000 & 0.647 & 0.647 & 0.630 & 0.647 & 0.647 & 0.647\\
0.782 & 0.769 & 0.891 & 0.891 & 0.638 & 0.811 & 0.811 & 0.891 & 0.782 & 0.811 & 0.796 & 0.828 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 0.891 & 0.647 & 1.000 & 0.891 & 0.630 & 0.891 & 0.891 & 0.811\\
0.782 & 0.769 & 0.891 & 0.923 & 0.638 & 0.811 & 0.811 & 0.891 & 0.782 & 0.811 & 0.796 & 0.828 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 0.891 & 0.647 & 0.891 & 1.000 & 0.630 & 0.891 & 0.891 & 0.811\\
0.630 & 1.000 & 0.630 & 0.630 & 0.630\\
0.782 & 0.769 & 0.891 & 0.891 & 0.638 & 0.811 & 0.811 & 0.923 & 0.782 & 0.811 & 0.796 & 0.828 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 0.891 & 0.647 & 0.891 & 0.891 & 0.630 & 1.000 & 0.891 & 0.811\\
0.782 & 0.769 & 0.891 & 0.891 & 0.638 & 0.811 & 0.811 & 0.891 & 0.782 & 0.811 & 0.796 & 0.828 & 0.672 & 0.672 & 0.672 & 0.827 & 0.811 & 0.811 & 0.891 & 0.647 & 0.891 & 0.891 & 0.630 & 0.891 & 1.000 & 0.811\\
0.782 & 0.769 & 0.811 & 0.811 & 0.638 & 0.828 & 0.846 & 0.811 & 0.782 & 0.845 & 0.796 & 0.811 & 0.672 & 0.672 & 0.672 & 0.811 & 0.811 & 0.846 & 0.811 & 0.647 & 0.811 & 0.811 & 0.630 & 0.811 & 0.811 & 1.000
\end{bmatrix} \quad (18)$$

Subsequently, a class of equivalence relations was created via the α-cut operation. The Kansei words were then classified into groups according to their similarity based on the evaluators' perceived preferences toward the reference product. The classification under different α-cut levels was further analyzed using the cluster validation indices. As shown in Table 3, the top five partitions are P_5, P_9, P_8, P_4, and P_7 in descending order. In this case, most researchers may tend to select P_9 ($g = 5$) as the appropriate set of Kansei attributes for the Kansei evaluation; however, the *CVI* value of P_5 ($g = 12$) is greater than that of P_9. Further analysis of the results reveals that the discriminability of P_9 clusters $\left(\frac{\ln 5}{5} = 0.322\right)$ is superior to that of P_5 $\left(\frac{\ln 12}{12} = 0.207\right)$, but the homogeneity of elements of P_9 $\left(\sum_{r=1}^{5} c_r = 1.438\right)$ is inferior to that of P_5 $\left(\sum_{r=1}^{12} c_r = 2.439\right)$. This is due to the partition of P_5 containing much more effective clusters (i.e., a cluster with more than 2

Table 3
Clustering arrangements and cluster validation indices.

Partition	α	g	Clustering arrangement	CVI
P_1	1	26	$\{x_1\}; \{x_2\}; \{x_3\}; \{x_4\}; \{x_5\}; \{x_6\}; \{x_7\}; \{x_8\}; \{x_9\}; \{x_{10}\}; \{x_{11}\}; \{x_{12}\}; \{x_{13}\}; \{x_{14}\}; \{x_{15}\}; \{x_{16}\}; \{x_{17}\}; \{x_{18}\}; \{x_{19}\}; \{x_{20}\}; \{x_{21}\}; \{x_{22}\}; \{x_{23}\}; \{x_{24}\}; \{x_{25}\}; \{x_{26}\}$	0
P_2	0.923	24	$\{x_1\}; \{x_2\}; \{x_3\}; \{x_4, x_{22}\}; \{x_5\}; \{x_6\}; \{x_7\}; \{x_8, x_{24}\}; \{x_9\}; \{x_{10}\}; \{x_{11}\}; \{x_{12}\}; \{x_{13}\}; \{x_{14}\}; \{x_{15}\}; \{x_{16}\}; \{x_{17}\}; \{x_{18}\}; \{x_{19}\}; \{x_{20}\}; \{x_{21}\}; \{x_{23}\}; \{x_{25}\}; \{x_{26}\}$	0.244
P_3	0.891	18	$\{x_1\}; \{x_2\}; \{x_3, x_4, x_8, x_{19}, x_{21}, x_{22}, x_{24}, x_{25}\}; \{x_5\}; \{x_6\}; \{x_7, x_{18}\}; \{x_9\}; \{x_{10}\}; \{x_{11}\}; \{x_{12}\}; \{x_{13}\}; \{x_{14}\}; \{x_{15}\}; \{x_{16}\}; \{x_{17}\}; \{x_{20}\}; \{x_{23}\}; \{x_{26}\}$	0.279
P_4	0.845	15	$\{x_1, x_9\}; \{x_2\}; \{x_3, x_4, x_8, x_{19}, x_{21}, x_{22}, x_{24}, x_{25}\}; \{x_5\}; \{x_6\}; \{x_7, x_{10}, x_{18}, x_{26}\}; \{x_{11}\}; \{x_{12}\}; \{x_{13}\}; \{x_{14}\}; \{x_{15}\}; \{x_{16}\}; \{x_{17}\}; \{x_{20}\}; \{x_{23}\}$	0.453
P_5	0.827	12	$\{x_1, x_9\}; \{x_2\}; \{x_3, x_4, x_8, x_{12}, x_{16}, x_{19}, x_{21}, x_{22}, x_{24}, x_{25}\}; \{x_5\}; \{x_6, x_7, x_{10}, x_{18}, x_{26}\}; \{x_{11}\}; \{x_{13}\}; \{x_{14}\}; \{x_{15}\}; \{x_{17}\}; \{x_{20}\}; \{x_{23}\}$	0.505
P_6	0.811	10	$\{x_1, x_9\}; \{x_2\}; \{x_3, x_4, x_6, x_7, x_8, x_{10}, x_{12}, x_{16}, x_{17}, x_{18}, x_{19}, x_{21}, x_{22}, x_{24}, x_{25}, x_{26}\}; \{x_5\}; \{x_{11}\}; \{x_{13}\}; \{x_{14}\}; \{x_{15}\}; \{x_{20}\}; \{x_{23}\}$	0.367
P_7	0.782	7	$\{x_2\}; \{x_1, x_3, x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{16}, x_{17}, x_{18}, x_{19}, x_{21}, x_{22}, x_{24}, x_{25}, x_{26}\}; \{x_5\}; \{x_{13}\}; \{x_{14}, x_{15}\}; \{x_{20}\}; \{x_{23}\}$	0.426
P_8	0.769	6	$\{x_1, x_2, x_3, x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{16}, x_{17}, x_{18}, x_{19}, x_{21}, x_{22}, x_{24}, x_{25}, x_{26}\}; \{x_5\}; \{x_{13}\}; \{x_{14}, x_{15}\}; \{x_{20}\}; \{x_{23}\}$	0.457
P_9	0.722	5	$\{x_1, x_2, x_3, x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{16}, x_{17}, x_{18}, x_{19}, x_{21}, x_{22}, x_{24}, x_{25}, x_{26}\}; \{x_5\}; \{x_{13}, x_{14}, x_{15}\}; \{x_{20}\}; \{x_{23}\}$	0.463
P_{10}	0.672	4	$\{x_1, x_2, x_3, x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{21}, x_{22}, x_{24}, x_{25}, x_{26}\}; \{x_5\}; \{x_{20}\}; \{x_{23}\}$	0.237
P_{11}	0.647	3	$\{x_1, x_2, x_3, x_4, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{20}, x_{21}, x_{22}, x_{24}, x_{25}, x_{26}\}; \{x_5\}; \{x_{23}\}$	0.246
P_{12}	0.638	2	$\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{20}, x_{21}, x_{22}, x_{24}, x_{25}, x_{26}\}; \{x_{23}\}$	0.227
P_{13}	0.630	1	$\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{20}, x_{21}, x_{22}, x_{23}, x_{24}, x_{25}, x_{26}\}$	0

elements) than that of P_9. According to the results, the 26 Kansei words were classified into 12 groups, where Kansei words x_1 and x_9 were translated into the Kansei attribute of "Tasteful"; Kansei words $x_3, x_4, x_8, x_{12}, x_{16}, x_{19}, x_{21}, x_{22}, x_{24}$, and x_{25} were translated into "Minimalist"; and Kansei words x_6, x_7, x_{10}, x_{18}, and x_{26} were translated into "Appealing". The set of extracted Kansei attributes is expressed as follows.

$$\begin{aligned} \mathrm{K} = \{&K_1\ (\text{Tasteful}), K_2\ (\text{Classic}), K_3\ (\text{Appealing}), \\ &K_4\ (\text{Cute}), K_5\ (\text{Handy}), K_6\ (\text{Ingenious}), K_7\ (\text{Lustrous}), \\ &K_8\ (\text{Luxurious}), K_9\ (\text{Minimalist}), K_{10}\ (\text{Personalized}), \\ &K_{11}\ (\text{Precious}), K_{12}\ (\text{Soft})\} \end{aligned} \tag{19}$$

4.2. Kansei evaluation for the selected product alternatives

In this part of the experiment, 10 USB flash drives were selected to test the proposed approach for evaluating customers' Kansei preferences on these product alternatives. The product features of the selected USB flash drives are listed in Table 4. Since university students are an important group that purchase and use USB flash drives, they were regarded as the target customers for the Kansei evaluation in this empirical study. Twenty university students majoring in Product Design were recruited as experimental subjects to evaluate the product alternatives. These subjects consisted of 10 females and 10 males, ranging in age from 18 to 22 years (Mean = 20.1, SD = 1.1); each was rewarded with a Transcend 8 GB USB drive for his/her effort in responding to the questionnaire.

The questionnaire consisted of two phases according to the CWW process detailed in Section 2.1. In the first phrase, each subject was asked to provide his/her perceived importance to each Kansei attribute, the purpose of which was to establish attribute priorities. Subsequently, the second phase required subjects to scrutinize each of the 10 USB flash drives and insert/remove it into/from a laptop (HP PowerBook 4331s). After completing the tests, each subject indicated his/her perceived preferences according to the given Kansei attributes to establish priorities for the perceived preferences of each product alternative. The frequency distributions of the original linguistic judgments for Kansei importance and Kansei preferences are shown in Appendix A. The two sets of Kansei variables, expressed as the following 2 fuzzy linguistic matrixes, were categorized and are listed in Table 5.

$$\widetilde{R} = [\![\widetilde{r_{jk}}]\!] = \begin{bmatrix} M & M & M & L & M & M & H & M & MH & M & M & ML \\ MH & MH & H & ML & MH & MH & H & MH & MH & MH & M & ML \\ M & ML & MH & MH & ML & M & L & L & ML & MH & ML & MH \\ MH & MH & MH & M & ML & MH & H & M & H & MH & M & ML \\ M & M & M & MH & MH & M & L & L & M & M & ML & MH \\ MH & MH & H & M & MH & MH & MH & M & MH & H & M & ML \\ MH & MH & MH & ML & MH & MH & MH & M & H & MH & M & ML \\ M & M & M & MH & ML & M & M & ML & M & M & ML & ML \\ MH & MH & MH & M & M & MH & H & H & H & MH & H & ML \\ M & MH & M & ML & MH & M & M & ML & M & M & ML & ML \end{bmatrix} \tag{20}$$

$$\begin{aligned} \widetilde{W} = [\![\widetilde{w_k}]\!] = [&MH \quad MH \quad MH \quad M \quad VH \quad H \quad MH \quad M \quad MH \quad H \\ &ML \quad MH] \end{aligned} \tag{21}$$

By substituting the two sets of Kansei variables into Eq. (8) to perform the linguistic aggregation operation and further defuzzifying the resultant membership functions using Eq. (9), 10 sets of quantitative values as well as ranked product alternatives were derived. The final results of the Kansei evaluation are listed in Table 6. According to the evaluation results, the ranking of the product alternatives is $A_9 \succ A_6 \succ A_2 \succ A_7 \succ A_4 \succ A_1 \succ A_{10} \succ A_5 \succ A_8 \succ A_3$. In terms of the target customers' preferences on the Kansei attributes, the best example was Alternative 9 and the worst was Alternative 3. Alternative 9 has a tiny metallic design with a refined gold-plated casing, while Alternative 3 has a soft appearance of cotton candy with a rubberized casing. The results are reasonable and credible as customers prefer such a USB flash drive as a unique fashion accessory to a cute one in terms of university students' Kansei preferences. In comparison with the results derived from the traditional weighted average operation using crisp numbers, Alternative 9 is still the best example, with the exception that Alternative 2 and Alternative 6 are ranked in reverse order. Further analysis of the differences indicated that subjects gave divergent judgments on Alternative 2 against Kansei attributes K_5 and K_{11}, while the linguistic judgments of Alternative 6 follow a central tendency toward Kansei attributes K_4 and K_8. The results imply that the proposed linguistic aggregation model based on triangular fuzzy numbers is more valid and practical than the traditional weighted average method using crisp numbers. This is because the proposed model is able to handle psychometric Kansei evaluation problems involving uncertain and imprecise data likely caused by customers' arbitrary guesses, recording errors, or respondent biases.

Table 4
List of the 10 selected product alternatives for the Kansei evaluation study. (For interpretation of the references to color in this table legend, the reader is referred to the web version of this article.)

Alternative 1		Alternative 2	
Apacer AH450 	**Product features:** • 32 GB, USB 3.0 • 54.6(L) × 20.6(W) × 8.6(H) mm, 8 g • Plastic housing with silvery luster in a gradient pattern	HP v250w 	**Product features:** • 32 GB, USB 2.0 • 46.6(L) × 15.8(W) × 5.5(H) mm, 11.5 g • Durable steel metal housing with shiny mirror finish and a hook head design
Alternative 3		Alternative 4	
PNY Candy 	**Product features:** • 32 GB, USB 3.0 • 40.8(L) × 18.3(W) × 12.3(H) mm, 10.07 g • Cute candy form design in three colors with durable rubberized casing	PQI i-mini 	**Product features:** • 32 GB, USB 3.0 • 16.4(L) × 17.8(W) × 6.0(H) mm, 4.9 g • Ultra-small stylish design with a strong tensile Zinc-alloy unibody casing and high-quality matte silver finish
Alternative 5		Alternative 6	
RiDATA OD12 	**Product features:** • 32 GB, USB 2.0 • 42(L) × 18(W) × 8(H) mm, 10 g • Cute form design in a bright reddish-yellow color with durable rubberized casing	SanDisk CZ58 Cruzer Orbit 	**Product features:** • 32 GB, USB 2.0 • 35.17(L) × 21.5(W) × 6.72(H) mm, 3.94 g • A protective cover that combines a 360-degree swivel with pocket-sized portability
Alternative 7		Alternative 8	
Silicon Power Firma F80 	**Product features:** • 32 GB, USB 2.0 • 44(L) × 18(W) × 4.5(H) mm, 5.9 g • A ring shaped metallic unibody exterior in silver gray with a Zinc-alloy body	TOPMOREAS ALA 	**Product features:** • 32 GB, USB 3.0 • 23.6(L) × 15.1(W) × 7.4(H) mm, 4.2 g • Ultra-small body design with a stylish Baroque pattern and white piano lacquer finish
Alternative 9		Alternative 10	
Transcend JetFlash 510G 	**Product features:** • 32 GB, USB 2.0 • 21.8(L) × 12.2(W) × 4.55(H) mm, 2.7 g • Ultra-small metallic (gold) design with a refined Zinc-alloy body	SONY MicroVaultUSM32GU 	**Product features:** • 32 GB, USB 3.0 • 58.6(L) × 18.8(W) × 8.9(H) mm, 9 g • Plastic housing with a click style mechanism and a bright LED indicator

5. Discussion

Kansei evaluation aims to systematically determine the significance of customers' preferences of a product using criteria against a set of Kansei attributes. As Kansei evaluation involves human perceptual interpretation with subjectivity, uncertainty, and imprecision, quantitatively evaluating customer preferences on Kansei attributes of products is inherently difficult. In this paper, a Kansei evaluation approach based on the technique of CWW is proposed. Compared to existing Kansei evaluation methods, the proposed approach has distinct advantages in Kansei attribute classification, Kansei preference modeling, and Kansei priority analysis. The theoretical and practical implications of the Kansei evaluation approach are discussed in the following.

Conventional Kansei evaluation approaches rely heavily on the intuition that designers/engineers use to cluster the Kansei words; however, such classifications may be inconsistent with customer opinions as they are evaluated by designers/engineers rather than customers themselves. In order to derive a customer-consistent classification result, Huang et al. [34] proposed a Kansei clustering method based on a design structure matrix (DSM). This method breaks the Kansei words up into a number of subsets so that each participant deals with only a portion of the collected Kansei words. Pearson correlations are used to establish the distances among the Kansei words, and the subsets are then integrated by merging the identical correlation pairs for deriving an overall Kansei clustering result. The Pearson correlation coefficient is mainly sensitive to a linear relationship (linear dependence) between two variables; however, customer perception on Kansei preferences can manifest as a non-linear pattern, as mentioned above. Huang et al.'s proposed method does not provide internal consistency verification for the customers' Kansei correlation matrix, for which they assume the meaning of a Kansei word is a crisp set with no overlap between any two Kansei words. Their method requires a heavy cognitive load to manage Kansei subsets and also lacks a cluster validation test to verify whether the Kansei clusters accurately represent the data structure. The proposed Kansei evaluation approach applies cluster analysis based on fuzzy relations to classify collected Kansei words into a set of Kansei attributes. In this approach, topology-based grey relational analysis (TGRA) is used as an indicator function to derive a set of global relational grades for constructing a fuzzy proximity matrix. This matrix is based

Table 5
List of linguistic judgments for Kansei importance and Kansei preferences.

Kansei attribute		K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}	K_{11}	K_{12}
Kansei importance													
w	C.N.	0.667	0.683	0.742	0.475	0.925	0.842	0.658	0.425	0.708	0.800	0.345	0.583
	I.N.	[0.583, 0.750)	[0.583, 0.750)	[0.583, 0.750)	[0.416, 0.583)	[0.916, 1]	[0.750, 0.916)	[0.583, 0.750)	[0.416, 0.583)	[0.583, 0.750)	[0.750, 0.916)	[0.250, 0.416)	[0.583, 0.750)
	S.L.	*MH*	*MH*	*MH*	*M*	*VH*	*H*	*MH*	*M*	*MH*	*H*	*ML*	*MH*
Kansei preference													
A_1	C.N.	0.417	0.525	0.525	0.242	0.458	0.533	0.817	0.508	0.583	0.500	0.425	0.275
	I.N.	[0.416, 0.583)	[0.416, 0.583)	[0.416, 0.583)	[0.083, 0.250)	[0.416, 0.583)	[0.416, 0.583)	[0.750, 0.916)	[0.416, 0.583)	[0.583, 0.750)	[0.416, 0.583)	[0.416, 0.583)	[0.250, 0.416)
	S.L.	*M*	*M*	*M*	*L*	*M*	*M*	*H*	*M*	*MH*	*M*	*M*	*ML*
A_2	C.N.	0.700	0.658	0.750	0.317	0.592	0.725	0.900	0.600	0.683	0.733	0.575	0.358
	I.N.	[0.583, 0.750)	[0.583, 0.750)	[0.750, 0.916)	[0.250, 0.416)	[0.583, 0.750)	[0.583, 0.750)	[0.750, 0.916)	[0.583, 0.750)	[0.583, 0.750)	[0.583, 0.750)	[0.416, 0.583)	[0.250, 0.416)
	S.L.	*MH*	*MH*	*H*	*ML*	*MH*	*MH*	*H*	*MH*	*MH*	*MH*	*M*	*ML*
A_3	C.N.	0.417	0.375	0.617	0.658	0.375	0.442	0.183	0.225	0.383	0.592	0.267	0.675
	I.N.	[0.416, 0.583)	[0.250, 0.416)	[0.583, 0.750)	[0.583, 0.750)	[0.250, 0.416)	[0.416, 0.583)	[0.083, 0.250)	[0.083, 0.250)	[0.250, 0.416)	[0.583, 0.750)	[0.250, 0.416)	[0.583, 0.750)
	S.L.	*M*	*ML*	*MH*	*MH*	*ML*	*M*	*L*	*L*	*ML*	*MH*	*ML*	*MH*
A_4	C.N.	0.583	0.592	0.617	0.575	0.400	0.683	0.758	0.542	0.767	0.683	0.525	0.350
	I.N.	[0.583, 0.750)	[0.583, 0.750)	[0.583, 0.750)	[0.416, 0.583)	[0.250, 0.416)	[0.583, 0.750)	[0.750, 0.916)	[0.416, 0.583)	[0.750, 0.916)	[0.583, 0.750)	[0.416, 0.583)	[0.250, 0.416)
	S.L.	*MH*	*MH*	*MH*	*M*	*ML*	*MH*	*H*	*M*	*H*	*MH*	*M*	*ML*
A_5	C.N.	0.433	0.442	0.492	0.592	0.583	0.450	0.217	0.217	0.542	0.542	0.283	0.700
	I.N.	[0.416, 0.583)	[0.416, 0.583)	[0.416, 0.583)	[0.583, 0.750)	[0.583, 0.750)	[0.416, 0.583)	[0.083, 0.250)	[0.083, 0.250)	[0.416, 0.583)	[0.416, 0.583)	[0.250, 0.416)	[0.583, 0.750)
	S.L.	*M*	*M*	*M*	*MH*	*MH*	*M*	*L*	*L*	*M*	*M*	*ML*	*MH*
A_6	C.N.	0.700	0.650	0.783	0.508	0.650	0.692	0.733	0.558	0.592	0.767	0.575	0.350
	I.N.	[0.583, 0.750)	[0.583, 0.750)	[0.750, 0.916)	[0.416, 0.583)	[0.583, 0.750)	[0.583, 0.750)	[0.583, 0.750)	[0.416, 0.583)	[0.583, 0.750)	[0.750, 0.916)	[0.416, 0.583)	[0.250, 0.416)
	S.L.	*MH*	*MH*	*H*	*M*	*MH*	*MH*	*MH*	*M*	*MH*	*H*	*M*	*ML*
A_7	C.N.	0.650	0.692	0.700	0.408	0.608	0.625	0.708	0.558	0.758	0.708	0.567	0.392
	I.N.	[0.583, 0.750)	[0.583, 0.750)	[0.583, 0.750)	[0.250, 0.416)	[0.583, 0.750)	[0.583, 0.750)	[0.583, 0.750)	[0.416, 0.583)	[0.750, 0.916)	[0.583, 0.750)	[0.416, 0.583)	[0.250, 0.416)
	S.L.	*MH*	*MH*	*MH*	*ML*	*MH*	*MH*	*MH*	*M*	*H*	*MH*	*M*	*ML*
A_8	C.N.	0.467	0.425	0.508	0.683	0.383	0.525	0.417	0.317	0.567	0.575	0.367	0.358
	I.N.	[0.416, 0.583)	[0.416, 0.583)	[0.416, 0.583)	[0.583, 0.750)	[0.250, 0.416)	[0.416, 0.583)	[0.416, 0.583)	[0.250, 0.416)	[0.416, 0.583)	[0.416, 0.583)	[0.250, 0.416)	[0.250, 0.416)
	S.L.	*M*	*M*	*M*	*MH*	*ML*	*M*	*M*	*ML*	*M*	*M*	*ML*	*ML*
A_9	C.N.	0.683	0.692	0.742	0.550	0.467	0.675	0.817	0.800	0.750	0.667	0.767	0.367
	I.N.	[0.583, 0.750)	[0.583, 0.750)	[0.583, 0.750)	[0.416, 0.583)	[0.416, 0.583)	[0.583, 0.750)	[0.750, 0.916)	[0.750, 0.916)	[0.750, 0.916)	[0.583, 0.750)	[0.750, 0.916)	[0.250, 0.416)
	S.L.	*MH*	*MH*	*MH*	*M*	*M*	*MH*	*H*	*H*	*H*	*MH*	*H*	*ML*
A_{10}	C.N.	0.458	0.625	0.483	0.392	0.642	0.483	0.483	0.367	0.508	0.483	0.342	0.383
	I.N.	[0.416, 0.583)	[0.583, 0.750)	[0.416, 0.583)	[0.250, 0.416)	[0.583, 0.750)	[0.416, 0.583)	[0.416, 0.583)	[0.250, 0.416)	[0.416, 0.583)	[0.416, 0.583)	[0.250, 0.416)	[0.250, 0.416)
	S.L.	*M*	*MH*	*M*	*ML*	*MH*	*M*	*M*	*ML*	*M*	*M*	*ML*	*ML*

Table 6
Final results of the Kansei evaluation.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
Quantitative value	0.581	0.720	0.523	0.679	0.560	0.724	0.694	0.530	0.737	0.564
Rank	6	3	10	5	8	2	4	9	1	7
Weighted average	0.495	0.650	0.442	0.595	0.473	0.646	0.629	0.472	0.657	0.489
Rank	6	2	10	5	8	3	4	9	1	7

on the measure of subjective similarity among respondents' perceived preferences of the reference product and satisfies the properties of reflexivity and symmetry. With respect to the application of pairwise correlations, "transitivity" is a critical requirement for deriving an equivalence relation which ensures that all respondents' judgments are consistent in the preference matrix. By use of the *n*-step procedure of *max*–*min* compositions [52], a fuzzy equivalence relation matrix can be derived. The Kansei words are then classified into clusters via different values of α-cuts. Based on the formulation of high discriminability of clusters (Kansei attributes) and high homogeneity of elements (Kansei words), a cluster validation index (*CVI*) is also proposed to assist evaluators in determining the best number of clusters and extracting an appropriate set of Kansei attributes for the Kansei evaluation.

In modeling Kansei evaluation systems, the semantic differential (SD) method is often used as a measure to quantify human perception for an understanding of Kansei preferences [10,11,71]. The use of the SD method is based on the premise that any two products can be differentiated semantically by a set of a limited number of emotional antonym scales [72]. However, some emotional adjectives are difficult to match with an exclusively corresponding antonym and some Kansei attributes are difficult to define absolutely with a bipolar pair of Kansei words, since the semantics of emotional adjectives may not have clearly distinguishable connotations of emotions in the contexts of different languages like Japanese, Chinese, and English. A drawback with the SD format is the increased cognitive demand, which could introduce errors in scores and weaken the psychometric Kansei evaluation quality [38]. The SD method includes three basic dimensions of response, namely evaluation, potency, and activity (EPA); however, almost all applications of the SD method to Kansei evaluation have relied only on evaluation measurements, particularly on the evaluation of positive Kansei preferences. For example, customers tend to prefer perceiving how beautiful a product is to how ugly the product is in terms of the bipolar pair of Kansei words "Beautiful-Ugly". To facilitate the Kansei evaluation implementation, Kansei preferences are modeled by positively worded items with 7 levels of semantic labels. The 7-point label scale renders judgments easier and more intuitive, allowing respondents to feel more confident about giving their perceptual interpretations in the form of semantic terms rather than numerical ratings. Nevertheless, a limitation is that the semantic scale is a pattern of bipolar intensity descriptors, measuring either a positive or negative response to a Kansei preference. Consequently, it may be subject to distortion from several uncertain causes, such as central tendency bias, acquiescence bias, or social desirability bias. To overcome this, the proposed approach treats the semantic scale as 7 semantic label sets described by triangular membership functions. These semantic label sets are defined respectively by fuzzy numbers, interval numbers, and cardinal numbers according to different α-cut levels. Different defined numbers are used for different processes to establish priorities of preference/importance relations for the CWW engine, while simultaneously taking into account the inherent uncertainty and imprecision of Kansei responses in the Kansei evaluation.

Most Kansei evaluation studies have used quantification theory type I (QT1) to synthesize Kansei priority information [35]. QT1 is a technique of multiple regression analysis used to summarize Kansei data as well as model the functional relationships between quantification and characterization of Kansei research. However, a multiple regression model has several shortcomings: for instance, it imprecisely assumes that all predictors are linearly related to each other, and also has a statistical limitation on the number of explanatory variables [18,36]. As aforementioned, customer Kansei preferences refer to non-quantifiable, subjective, and affective-based processes, involving human perceptual interpretations with some uncertainty and imprecision. To improve the strength of Kansei evaluation systems, Yan et al. [17] proposed a Kansei evaluation model based on multi-attribute fuzzy target-oriented decision analysis and prioritized aggregation. In their model, Kansei attributes are based on the bipolar pairs of Kansei words derived from the SD method. They are intuitively assessed by respondents' voting statistics and are represented as linguistic variables using triangular fuzzy numbers. Customer preferences are modeled by three types of fuzzy targets used as fuzzy numbers to derive the degrees of satisfaction for the evaluated products through the α-cut operation. Besides, Yan et al.'s model uses a prioritized aggregation operator to aggregate the partial degrees of satisfaction for the evaluated product alternatives. The operator is a scoring type based on Yager's OWA operator [73], and the prioritized aggregation includes three complex calculation processes for priority analysis. However, Zhou et al. [37] indicated that Yager's OWA operator focuses exclusively on the aggregation of crisp numbers, and also suggested that fuzzy numbers provide an efficient way of knowledge representation which can be applied to human preference modeling using linguistic terms. Kansei evaluation essentially requires synthesizing linguistic descriptors. In addition to the improvement in Kansei attribute extraction and Kansei preference modeling, the proposed Kansei evaluation approach has other advantages over Yan et al.'s model. Based on computing with words, the proposed approach uses a linguistic aggregation model as a CWW engine to synthesize priority information and rank the order of decision alternatives. This approach can be regarded as an Extension Principle based model [29] that enables fuzzy numbers to be aggregated through the four arithmetic operations on closed intervals. The Kansei preference and Kansei importance variables are fuzzified into fuzzy numbers represented by 7-level semantic labels. These two sets of Kansei variables are aggregated by means of the linguistic aggregation operation. The resultant fuzzy numbers are then defuzzified to derive the corresponding quantitative values for the evaluated product alternatives. As a whole, the use of the CWW technique allows for the incorporation of unquantifiable information, incomplete information, non-obtainable information, and partially ignorant facts into a decision model; hence, this approach is capable of capturing customers' ambiguous appraisals and is valid for dealing with psychometric Kansei evaluation problems.

6. Conclusions

Kansei studies refer to an interdisciplinary research field that focuses on understanding what Kansei is, how the Kansei process works, and how designers/engineers can apply valid domain knowledge to relevant Kansei implementation. This study aimed at implementing the psychological measures of Kansei responses via a mathematical model. In this paper, a Kansei evaluation approach based on computing with words (CWW) was presented to assess customer Kansei attribute preferences of products. Kansei preferences were modeled by positively worded items with 7 levels of semantic labels defined by fuzzy, interval, and cardinal numbers for establishing Kansei priorities. Kansei attributes were extracted from a set of collected Kansei words using fuzzy relation-based clustering associated with a cluster validation index (*CVI*). A linguistic aggregation model was used as a CWW engine to synthesize Kansei priority information and rank the order of product alternatives. The implementation process and applicability of the proposed Kansei evaluation approach were illustrated through a product evaluation example of USB flash drives.

In conclusion, this study contributes to our domain knowledge by using fuzzy cluster analysis associated with CWW in Kansei evaluation research areas. It also introduces a cluster validation index for determining the best number of clusters. Kansei refers to a cognitive function, for which the Kansei process begins with gathering human sensory functions such as feelings, emotions, and intuitions via vision, hearing, smell, taste, and touch. Further research could focus on developing a physiometric Kansei evaluation system for measuring customer Kansei responses to a product by means of physiological measurement technologies such as heart rate and blood pressure, eye tracking, electromyography (EMG), electroencephalography (EEG), event-related potential (ERP), and functional magnetic resonance imaging (fMRI).

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Appendix A. Frequency distributions of the original linguistic judgments for Kansei importance and Kansei preferences

Kansei attribute		K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}	K_{11}	K_{12}
Kansei importance													
w	*VL*	0	0	0	0	0	0	0	1	0	0	1	0
	L	1	0	0	4	0	0	0	1	0	0	3	0
	ML	0	0	0	4	0	0	0	8	0	0	9	3
	M	5	6	6	6	0	2	8	8	5	1	7	9
	MH	8	7	5	4	2	5	6	1	6	7	0	5
	H	4	6	3	1	5	3	5	0	8	7	0	1
	VH	2	1	6	1	13	10	1	1	1	5	0	2
Kansei preference													
A_1	*VL*	0	0	0	2	2	0	0	0	0	0	0	3
	L	4	2	3	9	3	1	0	3	0	3	6	5
	ML	8	4	3	8	3	5	0	4	4	3	2	8
	M	4	6	7	0	6	6	1	5	5	7	7	4
	MH	3	6	3	1	2	5	6	5	8	5	5	0
	H	0	1	3	0	4	3	7	3	3	2	0	0
	VH	1	1	1	0	0	0	6	0	0	0	0	0
A_2	*VL*	0	0	0	2	1	0	0	0	0	0	0	1
	L	0	0	0	6	1	0	0	2	0	1	1	3
	ML	0	0	2	7	2	1	0	0	2	0	3	8
	M	5	7	1	2	4	1	0	6	3	4	7	8
	MH	7	7	6	3	7	10	2	9	6	4	6	0
	H	7	6	7	0	4	6	8	2	9	7	1	0
	VH	1	0	4	0	1	2	10	1	0	4	2	0
A_3	*VL*	1	0	0	0	3	0	6	3	1	1	2	0
	L	3	5	1	2	4	2	8	10	6	1	9	0
	ML	6	8	1	0	6	8	4	4	4	3	4	3
	M	5	4	7	3	3	5	2	3	4	4	5	4
	MH	5	3	7	8	0	5	0	0	5	5	0	4
	H	0	0	2	6	4	0	0	0	0	4	0	7
	VH	0	0	2	1	0	0	0	0	0	2	0	2
A_4	*VL*	0	0	0	1	1	0	0	1	0	0	1	2
	L	1	0	1	1	3	0	0	1	0	1	1	4
	ML	3	3	2	3	8	3	0	3	2	0	2	6
	M	3	6	6	4	4	1	1	5	1	5	7	6
	MH	11	8	5	6	3	8	9	7	5	5	8	2
	H	2	3	5	4	1	7	8	3	7	8	1	0
	VH	0	0	1	1	0	1	2	0	5	1	0	0

(*continued on next page*)

Appendix A (*continued*)

Kansei attribute		K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}	K_{11}	K_{12}
A_5	*VL*	1	1	0	1	1	0	6	3	1	1	1	0
	L	0	1	2	1	0	1	5	9	2	0	9	1
	ML	10	9	6	2	3	7	6	7	1	4	6	1
	M	6	5	5	3	8	9	3	1	7	7	3	4
	MH	2	2	6	9	2	3	0	0	6	5	1	5
	H	0	1	0	3	4	0	0	0	2	2	0	5
	VH	1	1	1	1	2	0	0	0	1	1	0	4
A_6	*VL*	0	0	0	0	0	0	0	0	0	0	0	2
	L	0	0	0	1	0	0	0	0	2	0	0	5
	ML	0	0	0	5	2	1	1	4	1	1	5	5
	M	3	7	0	8	3	4	0	8	6	2	5	5
	MH	10	8	9	4	10	8	9	5	6	5	6	3
	H	7	5	8	2	5	5	10	3	5	8	4	0
	VH	0	0	3	0	0	2	0	0	0	4	0	0
A_7	*VL*	0	0	0	0	1	0	0	0	0	0	0	2
	L	0	0	0	4	2	0	0	0	0	0	0	3
	ML	1	1	0	6	2	1	0	4	0	0	2	5
	M	5	3	6	7	4	8	3	7	3	4	10	7
	MH	9	9	5	3	3	7	11	7	6	8	6	2
	H	5	6	8	0	5	3	4	2	8	7	2	1
	VH	0	1	1	0	3	1	2	0	3	1	0	0
A_8	*VL*	0	0	0	0	0	1	1	2	1	0	0	1
	L	1	1	1	0	5	0	3	6	1	1	6	6
	ML	8	10	6	1	6	6	5	7	4	3	6	6
	M	6	6	6	4	7	4	8	3	3	8	7	5
	MH	4	3	5	8	2	6	2	1	5	4	0	0
	H	1	0	2	6	0	3	1	1	6	2	1	2
	VH	0	0	0	1	0	0	0	0	0	2	0	0
A_9	*VL*	0	0	0	0	1	0	0	0	0	0	0	2
	L	0	0	0	1	3	0	0	0	0	0	0	4
	ML	2	2	1	5	5	0	0	0	1	2	0	7
	M	4	3	1	6	4	5	1	2	2	3	3	4
	MH	7	6	7	4	4	9	5	7	5	8	5	1
	H	4	8	10	3	3	6	9	4	10	7	9	2
	VH	3	1	1	1	0	0	5	7	2	0	3	0
A_{10}	*VL*	0	0	1	0	0	0	1	1	1	1	1	2
	L	1	1	0	3	4	4	1	4	1	0	6	5
	ML	8	1	6	9	0	2	5	7	4	6	7	5
	M	9	7	8	6	2	9	7	6	8	7	4	4
	MH	0	5	3	2	7	3	4	2	3	5	1	2
	H	1	5	2	0	3	1	2	0	2	1	1	1
	VH	1	1	0	0	4	1	0	0	1	0	0	1

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