Kansei clustering for emotional design using a combined design structure matrix

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A B S T R A C T

Consumers’ emotional requirements, or so-called Kansei needs, have become one of the most important concerns in designing a product. Conventionally, Kansei engineering has been widely used to co-relate these requirements with product parameters. However, a typical Kansei engineering approach relies heavily on the intuition of the person who uses the method in clustering the Kansei adjectives, who may be the engineer or designer. As a result, the selection of Kansei adjectives may not be consistent with the consumers’ opinions. In order to obtain a consumer-consistent result, all of the collected Kansei adjectives (usually hundreds) need to be evaluated by every survey participant, which is impractical in most design cases. Therefore, a Kansei clustering method based on a design structure matrix (DSM) is proposed in this work. The method breaks the Kansei adjectives up into a number of subsets so that each participant deals with only a portion of the words collected. Pearson correlations are used to establish the distances among the Kansei adjectives. The subsets are then integrated by merging the identical correlation pairs for an overall Kansei clustering result. The details of the proposed approach are presented and illustrated using a case study on wireless battery drills. The case study reveals that the proposed method is promising in handling Kansei adjective clustering problems.

Relevance to industry: This study presents a generic method to deal with consumers’ Kansei requirements for emotional design in new product development. It appears that the proposed method can be utilized to capture and analyze consumers’ Kansei needs as well as to facilitate decision making in practical industrial design cases.

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1. Introduction

It is well-known that a successful product is one that has the highest quality, the lowest cost, and the shortest time-to-market. This has been widely advocated by most product manufacturers in their new product development (NPD) endeavors. On top of this, in recent years, product design and development has shifted its emphasis to the experiences gained from users’ interaction with products (Norman, 2008). The studies of users’ experiences (or user-centered design) may tackle different problems in various perspectives. In this regard, the Kansei engineering approach (Nagamachi, 1995, 1999, 2002, 2008; Nagamachi et al., 2006) is considered to be the most reliable and useful methodology to handle consumers’ emotional requirements (Chen et al., 2008). It has been successfully applied in various design domains, such as domestic commodities (Hsiao et al., 2010), interior decorating (Hsiao and Tsai, 2005), seat comfort (Goonetilleke, 1998; Goonetilleke and Song, 2001), machine tools (Mondragón et al., 2005), home appliances (Demirtas et al., 2009), and trade show booth (Huang et al., 2011).

A conventional approach to studying Kansei involves the following nine consecutive steps (Grimsæth, 2005): (1) collecting as many Kansei adjectives as possible from various sources (about 300–500 Kansei adjectives for a product); (2) pre-processing/clustering the collected Kansei adjectives in such a way that a small number of Kansei adjectives can be used to represent the whole unit (about 25–30 clustered Kansei adjectives); (3) collecting product samples; (4) listing product attributes and attribute variables; (5) surveying and evaluating representative products using the clustered Kansei adjectives; (6) representing the survey results in a proper format; (7) identifying the correlations among the Kansei adjectives using factor analysis (FA), followed by a cluster analysis to further cluster the Kansei adjectives; (8) identifying the correlations between the clustered Kansei adjectives and the product attributes, using such methods as quantification theory type I or cross tabs analysis; and (9) presenting the results, using such tools as bar and/or radar charts to interpret, explain, and check the results. Although relatively less studied, the first two steps deserve more in-depth investigation, because the results obtained from the early steps may significantly affect the later steps.

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Based on the literature, it appears that the semantic differential (SD) method (Osgood, 1962; Osgood et al., 1967) has been widely adopted by most conventional approaches in studying Kansei adjectives, such as car wheel hub study (Luo et al., 2012), ladies’ dress shoes design (Au and Goonetilleke, 2007), and customer preferences on real estate (Llinares and Page, 2011). Osgood postulated that any two concepts can be differentiated semantically by a set of a limited number of antonym scales. Following Osgood’s idea of the SD method, Nagamachi (1999) suggested that any two products can be differentiated semantically by a set of a limited number of emotional antonym scales (Kansei adjectives). Therefore, choosing the antonym scales (Kansei adjectives) is of great importance to the success of Kansei engineering implementations. A typical Kansei engineering approach collects as many Kansei adjectives as possible from customers. However, it depends on the user(s) of the method to decide how the Kansei adjectives should be pre-clustered (Step 2). The question is how to justify that a set of much fewer selected Kansei adjectives can be used to represent the whole meaning of all of the Kansei adjectives collected from the customers. For example, a case study from Grimsaeth’s work (2005) shows that two words “freedom” and “comfort” were reduced to one, “freedom,” by the researcher’s subjective judgments. However, to ensure researchers, “freedom” and “comfort” in the head to “comfort,” “fun” and “comfort” does not necessarily refer only to “freedom.” The elimination of “comfort” is debatable. Therefore, this work proposes a Kansei clustering method to deal with such problems.

A large number of data clustering methods have been proposed to date. These methods can be categorized into two major categories, namely hierarchical methods and partitional methods (Xu and Wunsch, 2008). Hierarchical methods group data with a sequence of nested partitions, either in a bottom-up or top-down manner. Partitional methods organize data sets into clusters, while maximizing or minimizing a pre-specified criterion function without any hierarchical structure. Some representative hierarchical clustering algorithms are average linkage clustering for shape similarity (Rodrigo et al., 2012); balanced iterative reducing and clustering using hierarchies (BIRCH) for clustering very large numerical data sets in Euclidean spaces (Zhang et al., 1996; Gan et al., 2007); clustering using representatives (CURE), which can identify non-spherical shapes in large databases with a wide variance in size (Guha et al., 2001); Chameleon, a two-phase agglomerative hierarchical clustering algorithm (Karypis et al., 1999); DISMEA, a divisive hierarchical clustering algorithm that uses the k-means algorithm to subdivide a cluster into two (Späth, 1980); and so on. Hierarchical clustering methods are able to break data objects up into several levels of nested partitions (or a tree of clusters). Despite the many advantages, the weaknesses of hierarchical clustering methods make them unsuitable to cluster Kansei data. For instance, deploying Kansei adjectives hierarchically may ignore relatively weak connections among Kansei clusters, which might result in an unreliable clustering solution.

On the other hand, partitional clustering methods aim to organize data sets into many clusters while maximizing or minimizing a pre-specified criterion function without any hierarchical structure (Xu and Wunsch, 2008). Typical partitional clustering algorithms include the standard k-means, which works best on data that contains spherical clusters (Macqueen, 1967); variations of k-means, which improve some aspects of the standard k-means (Likas et al., 2003; Kaufman and Rousseuw, 1990); and a mixture density-based clustering method in which each data object is assumed to be generated from one of the k underlying probability distributions (Law et al., 2004). Additional clustering algorithms include the graph theory-based clustering method, which treats clusters as highly connected subgraphs and uses a minimum weight cut procedure to identify the subgraphs recursively (Hartuv and Shamir, 2000; Shamir and Tsur, 2007); fuzzy c-means, in which the object can belong to all of the clusters with a certain degree of membership (Bezdek, 1981; Zhou and Schaefer, 2009); the constrained agglomerative algorithm, which is a combination of hierarchical and partitional methods (Zhao and Karypis, 2005); search techniques-based clustering methods (Hall et al., 1999; Brown and Huntley, 1992; Al-Sultan, 1995); and so on.

Unfortunately, partitional clustering methods are not suitable for handling Kansei clustering problems either. This is mainly due to three reasons. First, Kansei adjectives are vague to be manipulated using existing partitional clustering algorithms. Guha and Munagala (2009) suggested clustering uncertain data using approximation algorithms. Nonetheless, Kansei data cannot be easily represented using probability distributions. Second, the meaning or mapping of the Kansei adjectives may not be a continuous region, which might hinder the use of partitional methods. Third, although fuzzy clustering algorithms are capable of dealing with vague data such as Kansei, it may be difficult to define a membership function for each Kansei adjective. In summary, the existing data clustering methods and algorithms are not fully capable of handling the Kansei adjective clustering problems. A new clustering method is thus needed.

The design/dependency structure matrix (DSM) proposed by Steward in the 1980s has a distinct advantage in showing the information cycles or connections among all units in a system in a visual and traceable way (Steward, 1981). Each unit in a DSM is assigned to a row and a corresponding column of the matrix. The off-diagonal entries correspond to the information dependencies between two units (Jiao et al., 2004). In this sense, an entry below the diagonal stands for a feed-forward information flow while that above the diagonal indicates a feedback information flow. By changing the sequence of units in a DSM, it is possible to identify loops or iterated connections among units. More specifically, a DSM is rearranged into a lower triangular form, and iterations located along the diagonal line can be minimized. For example, it is possible to trace forward manually until a unit is encountered twice. All units between the first and second occurrence of the unit constitute a loop and should be placed together. This process is known as partitioning a DSM. A number of DSM partitioning algorithms have been proposed, for example, binary matrix algebra (Warfield, 1973), the powers of adjacency matrix method (Gebala and Eppinger, 1991), a loop tracing procedure (Steward, 1981), and a triangularization algorithm (Kusiak and Wang, 1993), to name a few. These algorithms are rather similar in a sense. The major difference among them lies in how the iterations are identified. In addition to binary entries, numerical entries have been adopted in DSMs to offer more information about the units so that more complex situations can be handled. For example, repeat probabilities incurred (Smith and Eppinger, 1997) and two-dimensional variables (Yassine et al., 1999) make use of single or multiple numerical entries to measure the strengths of the unit dependencies in a DSM. Nonetheless, the lower triangular form is not suitable for dealing with Kansei clustering problems, because a Kansei DSM is symmetrical and heavy weighted units should be placed close and along the diagonal. In addition, conventional partitioning algorithms are capable of handling a single DSM only. Therefore, a method to establish relationships among multiple DSMs so as to enable a holistic analysis on a combined DSM is required. Accordingly, a new DSM partitioning method, DSM for Kansei partitioning, is proposed in this work.

The proposed Kansei clustering method uses a complete set of Kansei adjectives during a product evaluation. In order to facilitate the evaluation, the set is divided into several Kansei subsets. Then, a combined DSM is built accordingly. Subsequently, the DSM is partitioned, which results in clusters of Kansei adjectives based on the customers’ viewpoints. Thereby, a smaller number of Kansei...
adjectives can be used in Kansei engineering implementations. The next section, Section 2, describes the proposed method. Section 3 illustrates the proposed method with a case study and Section 4 discusses the experiment’s results. The work concludes in Section 5.

2. A Kansei clustering method

The proposed method intends to improve the second step of a conventional Kansei engineering implementation (Grimsæth, 2005) in such a way that the Kansei adjectives are clustered based on the customers’ voices/opinions. Therefore, the resulting design may better reflect the customers’ emotional requirements.

The method consists of eight steps, namely, collecting Kansei adjectives, building Kansei subsets, collecting product samples, evaluating survey questionnaires, building a DSM for each Kansei subset, establishing the combined DSM, processing the combined DSM, and analyzing and manipulating the results (Fig. 1). A step by step description of the method is presented as follows.

2.1. Step 1: collecting Kansei adjectives

Kansei adjectives are collected from all available sources where words (mainly adjectives) are used to describe the product under study. Sources may include magazines, academic literature, product manuals, experts, experienced users, and so on. As many Kansei adjectives as possible should be collected in this step. Usually, the number (n) can reach 300–500 words for a product.

2.2. Step 2: building Kansei subsets

The collected Kansei adjectives are divided into a number of subsets. Each subset contains a portion of the Kansei adjectives. The Kansei subset-forming process involves three substeps:

1) List all of the Kansei adjectives on paper in a random sequence.
2) Define the number of adjectives in one subset. Each subset may contain 10–25 Kansei adjectives, depending on the design of the survey questionnaires and the total number of Kansei adjectives. (Note: The higher the number of subsets, the more participants are required.)
3) Fill each subset with the Kansei adjectives from the list. When a subset has reached the pre-set number of Kansei adjectives, proceed to fill up the next subset. In doing this, any two adjacent subsets share half (50%) of the same Kansei adjectives. (Note: If more than 50% are overlapping, e.g., 75%, it may not be effective to conduct the survey due to too many subsets; in the case of less than 50% overlapping, e.g., 25%, some adjectives might not be clustered. Therefore, in this study, 50% overlapping was used.)

2.3. Step 3: collecting product samples

In this step, products are collected for evaluation. The purpose is to examine as many products (in the same category) as possible in

![Fig. 1. A framework of the Kansei clustering method.](image-url)
the market. Virtual models, for example, future or ideal products depicted by photorealistic renderings, can be used too. Product attributes, such as color, shape, and texture, and the corresponding attribute variables can be defined by product designers or Kansei researchers according to the objectives of the Kansei experiments. The number of product attributes and corresponding variables are dependent on the scale and complexity of the case. However, too many product attributes (and variables) will result in an extremely tedious process of customer evaluation. Therefore, a complex case should be broken up into several small ones. In so doing, one problem is that the results of studying several small ones separately might not be the same as that of studying them as a whole. In other words, the absence or presence of additional product attributes may change the current results. Product attributes may interact among themselves and hence affect the final emotions. For example, a study that focuses only on a sports car’s windshield suggests that a particular type of windshield satisfies a desired Kansei. However, a study concerning the overall appearance of the sports car may tell a different story, that the selected windshield does not fit well. After the product attributes and attribute variables are identified, representative products, which possess the identified attribute values, can then be collected. The purpose of choosing representative products is to reduce the number of products in the evaluation process while considering the required product attributes and variables. This may reduce the mental workload of the survey participants. In addition, sufficient product attributes and variables, such as product features and images, can be studied. It is important that the products are different so as to explore their output performance and the emotional responses that the users may have toward different combinations of product attributes. Therefore, a proper number of representative products should be determined.

2.4. Step 4: evaluating survey questionnaires

The representative products are evaluated with respect to every Kansei subset by the corresponding customer groups. The evaluation involves four substeps as follows.

1) **Prepare evaluation forms.** Place the representative products together with each Kansei subset. Therefore, if there are $s$ Kansei subsets and $p$ representative products to be evaluated, $sp$ different evaluation forms would be required. A seven-point scale is employed in this step. The scale uses a uniform bipolar system for evaluating the antonym pairs of the Kansei adjectives. In this system, one extreme of the scale indicates that there is no such feeling (Kansei) at all, while the other extreme reverses it (Schütte, 2005).

2) **Manage the participants.** If there are $s$ Kansei subsets, the participants are randomly divided into $s$ groups. Each group should include at least 30 people. Owing to the use of the 50% overlap, there are actually 60 survey participants for the overlapping parts of the subsets.

3) **Evaluate the forms.** Each group evaluates one Kansei subset for every representative product. The meanings of the Kansei adjectives should be clarified explicitly by the researcher(s)/designer(s), that is, the Kansei adjectives are explained to the survey participants before the evaluation.

4) **Collect the evaluation results and calculate the mean values using Eq. (1), where $ASxya$ is the average score of the $a$-th Kansei adjective in the $y$-th Kansei subset corresponding to the $x$-th representative product ($1 \leq ASxya \leq 7$), $Sxyaz$ is the score of the $a$-th Kansei adjective in the $y$-th Kansei subset corresponding to the $x$-th representative product by the $z$-th evaluator in a group ($1 \leq Sxyaz \leq 7$), and $k$ is the total number of evaluators in a group ($k \geq 30$).

$$ASxya = \frac{\sum_{z=1}^{k} Sxyaz}{k}$$ (1)

All notations used in this paper and their descriptions are shown in Fig. 3.

2.5. Step 5: building a DSM for each Kansei subset

In this step, statistical methods are employed to compute the correlation coefficients of the Kansei adjectives within each subset. The Pearson product-moment correlation (Moore, 2006) is utilized to measure the distance (similarities) between Kansei adjectives. The correlation coefficients obtained are used to construct a correlation matrix for each Kansei subset, that is, the DSM subset. Compared with other types of correlation measurement, the Pearson method provides the most well-known and widely used way to exhibit the similarity relationships between any two Kansei adjectives in a standardized interval (−1 to 1). The value of 1 (or close to 1) indicates that the two Kansei adjectives are positively correlated. On the contrary, the value of −1 (or close to −1) denotes a negative correlation between the two Kansei adjectives.

2.6. Step 6: establishing the combined DSM

A combined DSM can be obtained by merging the sub-DSMs for each Kansei subset. Three cases have to be considered before establishing the combined DSM: 1) for the Kansei adjective pairs that appear in both sub-DSMs, the corresponding Pearson correlations should be re-calculated based on the merged evaluation data; 2) for the Kansei adjective pairs that appear in one sub-DSM, the correlation coefficients obtained in Step 5 are used; and 3) for the Kansei adjective pairs that are not available, the corresponding values are filled with zeros. Hence, all Kansei adjectives are placed in a combined DSM for clustering in later steps. An example is shown in Fig. 4.
2.7. Step 7: processing the combined DSM

The combined DSM is partitioned in this step to cluster the Kansei adjectives. Obviously, positively correlated Kansei adjectives should be kept in one block (or cluster), while negatively correlated ones should be separated into different partitions. Here, a DSM for Kansei partitioning (DSMKP) algorithm is proposed to partition a DSM in which all of the evaluation data of the Kansei adjective pairs are available (Fig. 5a), while a combined DSM for Kansei partitioning (CDSMKP) algorithm is used for a combined

\begin{align*}
\text{s:} & \quad \text{The total number of Kansei subsets (usually } 6 \leq \text{s} \leq 20) \\
\text{p:} & \quad \text{The total number of representative products (usually } 5 \leq \text{p} \leq 15) \\
\text{n:} & \quad \text{The total number of Kansei adjectives (usually } n \text{ can reach to hundreds)} \\
\text{k:} & \quad \text{The total number of evaluators in a group (} k \geq 30) \\
\text{x:} & \quad \text{The } x\text{-th representative product (} 1 \leq x \leq p) \\
\text{y:} & \quad \text{The } y\text{-th Kansei subset (} 1 \leq y \leq s) \\
\text{y}_a: & \quad \text{The } a\text{-th Kansei adjective in the } y\text{-th Kansei subset (} 1 \leq a \leq 2n/s) \\
\text{z:} & \quad \text{The } z\text{-th evaluator in a group (} 1 \leq z \leq k) \\
S_{xy}\zeta & \quad \text{The score of the } a\text{-th Kansei adjective in the } y\text{-th Kansei subset corresponding to the } x\text{-th representative product by the } z\text{-th evaluator in a group (} 1 \leq S_{xy}\zeta \leq 7) \\
A_{Sxy}\alpha & \quad \text{The average score of the } a\text{-th Kansei adjective in the } y\text{-th Kansei subset corresponding to the } x\text{-th representative product (} 1 \leq A_{Sxy}\alpha \leq 7) \\
i, j: & \quad \text{Integers, e.g., the } i\text{-th row and the } j\text{-th column in a DSM } \{ 1 \leq i \text{ (or } j \text{) } \leq n \text{ (DSMKP) or } 2n/s \text{ (CDSMKP)} \}
\end{align*}

\begin{align*}
l, L: & \quad \text{Integers, e.g., the } l\text{-th row and the } L\text{-the column in a combined DSM } \{ 1 \leq l \text{ (or } L \text{) } \leq n \} \\
m, w: & \quad \text{Integers, e.g., the } m\text{-th row and the } w\text{-th column in a DSM or combined DSM } \{ 1 \leq m \text{ (or } w \text{) } \leq n \text{ (DSMKP) or } 2n/s \text{ (CDSMKP)} \}
\end{align*}

\begin{align*}
v_{ij} & \quad \text{The value of the element (row } i, \text{ column } j\text{) in a DSM (used in DSMKP) } (-1 \leq v_{ij} \leq 1) \\
v_{ij} & \quad \text{The value of the element (row } i, \text{ column } j\text{) in the } y\text{-th DSM (used in CDSMKP) } (-1 \leq v_{ij} \leq 1) \\
\max(v_{ij}) & \quad \text{The maximum } v \text{ among the } j\text{-th column in a DSM (used in DSMKP)} \\
\max(v_{ij}) & \quad \text{The maximum } v \text{ among the } J\text{-th column in a combined DSM (used in CDSMKP)} \\
v_{ij} & \quad \text{The value of the element (row } i, \text{ column } J\text{) in a combined DSM, the value is obtained based on one group's evaluations} \\
v_{ij} & \quad \text{The value of the element (row } i, \text{ column } J\text{) in a combined DSM, the value is obtained based on two groups' evaluations}
\end{align*}
DSM in which some of the correlations are assumed to be zeros (Fig. 5b), where \( i, j, I, J, m, \) and \( w \) are integers denoting a row or column in a DSM or combined DSM, \( v_{ij}, v_{ij-y}, v_{IJ}, \) and \( v_{IJ*} \) are the values of the corresponding element (row \( i \) or \( I \), column \( j \) or \( J \)) in a DSM or combined DSM based on one or two groups' evaluations, and \( \max(v_j) \) is the maximum value among the \( j \)-th column in a DSM or combined DSM. Basically, the two proposed algorithms arrange Kansei adjectives from column 1 to \( n \) in such a way that the corresponding values follow a descending sequence in the top-down direction. This is due to the fact that, in tackling Kansei clustering problems using DSMs, similar Kansei adjectives should be placed closely together. More specifically, the Kansei adjective with the maximum value of correlations in a column is placed on the diagonal level first, followed by the rest of the Kansei adjectives according to the value of correlations until a column is reordered. The reordering procedure repeats for the rest of the columns. As a result, those Kansei adjectives with the larger values of correlations are kept in a block along the diagonal line. It is noted that the DSMKP differs from the CDSMKP in the way that it considers the combination effect of the Kansei subsets. In other words, the values of the former Kansei adjectives are added together and the summations are compared. For CDSMKP, the combination effect of the Kansei subsets will not be considered for those values that are not available in the combined DSM. Nevertheless, for both algorithms, large correlation values are located as close to the diagonal line as possible, while small ones are placed on the sides (Fig. 6).

2.8. Step 8: analyzing and manipulating the results

After partitioning the combined DSM, possible Kansei clusters are formed. Advanced DSM techniques (e.g., tearing and binding), can then be employed to analyze and manipulate the existing Kansei clusters. The purpose of this step is to refine the Kansei clusters obtained in the previous step. The refinement helps to eliminate insignificant Kansei adjectives and reach a balance among the clusters.

3. Results

A case study based on Grimsæth's work (2005) is used to illustrate the proposed Kansei clustering method. The case study starts with a brief introduction to Grimsæth's work. Subsequently, the capability of the proposed method is demonstrated using the same case.

![Fig. 5. Pseudo-code of proposed Kansei clustering algorithms (a) DSM for Kansei partitioning, (b) Combined DSM for Kansei partitioning.](image-url)
3.1. A brief introduction to Grimsæth’s case

In Grimsæth’s work, wireless battery drills were studied using a conventional Kansei engineering approach, which involved nine steps as follows.

1. Collected as many Kansei adjectives as possible in the domain of wireless battery drills from sources like magazines, manuals, advertisements, product reviews, Internet user forums, brochures, and users. One hundred fifty-six Kansei adjectives were collected.

2. Pre-processed the Kansei adjectives based on the researcher’s own intuition, so that a small number of adjectives (25 in this case) could be used for the survey.

3. Fifty-one wireless battery drills found in the market were employed to study product attributes and attribute variables.

4. Thirteen representative wireless battery drills were selected and a list of product attributes and variables was prepared.

5. A set of survey questionnaires on the representative wireless battery drills using the 25 selected Kansei adjectives with a seven-point scale were prepared. Ten participants were asked to evaluate the drills and answer the questionnaires.

6. The answers were collected in Excel files and presented graphically.

7. A factor analysis was performed between the 25 Kansei adjectives using SPSS software. Three principal components, namely, user mood, practical purpose, and plastic, were identified after the data analysis. Based on these three components, a coordinate system was built for the cluster analysis of the 25 adjectives. Using the system, the researcher visually clustered these adjectives into eight clusters: 1 – classic and conventional; 2 – plastic; 3 – neat and elegant; 4 – fresh and modern; 5 – lifestyle, futuristic, fun, personal, and freedom; 6 – reliable, functional, safe, and professional; 7 – power, rugged, aggressive, confidence, and exclusive; and 8 – aesthetic and ergonomic.

8. Correlations between the eight clustered Kansei and the product attributes were studied using the cross tabs analysis method.

9. The results were analyzed and some design suggestions were listed. For example, a “classic/traditional” drill should have one type of material in the engine house, a straight rear, and a cylindrical chuck.

The proposed Kansei clustering method mainly deals with Step 2, which is considered the most critical step. A common objective of the proposed method and Grimsæth’s method is to reduce the large number of Kansei adjectives collected from customers to a small and controllable number in order for further Kansei engineering studies. Two key tasks need to be executed to meet this objective. One is to identify the locations of the clusters as if all of the Kansei adjectives are positioned on a map with the distances determined by their meanings. The other is to determine the radii of the clusters so that the number of Kansei adjectives in each cluster can be controlled. Grimsæth’s method requires the researchers to estimate the locations of the various clusters based on their intuition. Similarly, the proposed method also identifies the locations of the clusters on a map that contains all of the Kansei adjectives, but, the map is created based on the customers’ opinions (i.e., customers’ ranking scores). Therefore, the essential difference between the two approaches lies in who creates the map of Kansei adjectives: one customer (who may be the researcher) in the conventional approach, or a group of customers in the proposed method. If there was a case where only one subject was involved in a Kansei engineering study using the proposed method, this would actually be equivalent to using the conventional approach. Thus, in this special case, the results obtained from the proposed method should be identical to those obtained from a conventional approach (e.g., Grimsæth’s method). The next section illustrates the proposed method using the same case that Grimsæth’s work used.

3.2. Illustration of the proposed approach

To illustrate how the proposed method works, a number of participants (customers) were involved in the case study. It is

![Fig. 6. The partitioning result of Kansei adjectives.](image-url)

<table>
<thead>
<tr>
<th>Kansei subset</th>
<th>Kansei adjectives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subset 1</td>
<td>Control #1 Functional #9 Plastic #9 Rugged #9 Expensive #9 Control</td>
</tr>
<tr>
<td>Subset 2</td>
<td>Control #1 Functional #9 Plastic #9 Rugged #9 Expensive #9 Control</td>
</tr>
</tbody>
</table>
highly possible that the final Kansei clusters were not the same as those obtained by Grimsæth due to group opinion versus personal opinion. As a portion of the 156 Kansei adjectives were sufficient to illustrate the proposed method, 32 adjectives were randomly chosen for the study, as shown in Table 1. The Kansei adjectives were randomly divided into four subsets with 50% overlapping in each subset.

Table 2 shows the product attributes and attribute variables of the wireless battery drills. The representative drills were evaluated by four groups of participants using the four Kansei subsets, respectively. In other words, only a portion of the Kansei adjectives were evaluated by each participant. Each group consisted of 30 university students. A brief introduction that included the purpose of the survey was given to the subjects. The survey procedures and the meaning of the Kansei adjectives were explained, and then the subjects marked the survey forms according to their own feelings.

The average scores given by the 30 participants in each group were calculated using Eq. (1), and the survey results are shown in Fig. 7.

Based on the survey results, the Pearson product-moment correlations were calculated to measure the distance (similarities) between the Kansei adjectives in each subset. Each DSM subset was partitioned using the proposed DSMKP algorithm. The results are shown in Fig. 8, where there are four, four, five, and three major Kansei clusters under subsets 1, 2, 3, and 4, respectively.

The combined DSM was partitioned using the proposed CDSMKP algorithm (Fig. 9). Eight major Kansei clusters were identified based on the partitioned DSM: 1 — control and speed; 2 — functional and elegant; 3 — comfort and futuristic; 4 — boring and safe; 5 — professional, ergonomic, masculine, and torque; 6 — reliable, aggressive, and sturdy; 7 — modern, personal, expensive, smooth, power, clean, and stable; and 8 — rugged and cartoono. Other Kansei adjectives were stand-alone. These results were compared with the results obtained using another approach, in which the 30 survey participants were asked to evaluate all 32 Kansei adjectives for each representative product (13 products in total). In this case, the participants needed much more time and greater patience to complete the survey. The data were collected and processed after the survey, as shown in Fig. 10. The correlations among the Kansei adjectives were calculated and then a DSM was constructed. The DSMKP algorithm was used to partition the DSM as shown in Fig. 11, in which eight Kansei clusters

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**Table 2**

Attributes and corresponding variables of battery drills.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engine House</td>
<td>Shape</td>
</tr>
<tr>
<td></td>
<td>Details</td>
</tr>
<tr>
<td>Shaft</td>
<td>Material</td>
</tr>
<tr>
<td>Battery House</td>
<td>Rear Pos</td>
</tr>
<tr>
<td></td>
<td>Rear Prof</td>
</tr>
<tr>
<td>Chuck</td>
<td>Material</td>
</tr>
<tr>
<td></td>
<td>Details</td>
</tr>
<tr>
<td></td>
<td>Battery Pos</td>
</tr>
<tr>
<td>Chuck</td>
<td>R Button</td>
</tr>
<tr>
<td></td>
<td>Color</td>
</tr>
<tr>
<td>Form</td>
<td>Ratio</td>
</tr>
<tr>
<td></td>
<td>Joining</td>
</tr>
</tbody>
</table>

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**Fig. 7.** The survey results for each Kansei adjective of the four subsets.
identical to those obtained using the proposed method were identified. The comparison suggests that both methods achieve the same results, yet the proposed method reduces effort and length of time in surveying.

4. Discussion

As mentioned above, two key tasks need to be executed using the proposed method for all of the Kansei adjectives to be positioned on a map with the distances determined by their meanings. One task is to identify the locations of the Kansei clusters. The case study shows that the conventional method requires the researchers/designers to estimate the locations of the various clusters using their intuition. In contrast, the proposed method identifies the locations of the clusters based on the customers’ evaluations. More specifically, the proposed method uses correlation coefficients between the Kansei adjectives as the distances for each subset and, hence, the locations of the clusters are calculated. The other key task is to determine the radii of the clusters, so that the number of Kansei adjectives in each cluster can be controlled. This task is handled in Step 8 of the proposed method, which analyzes the partitioned DSM. Assuming that the 32 Kansei adjectives in the case study are positioned on a two-dimensional map with the distances between two adjectives determined by their meanings, and based on the correlation coefficient matrix, these adjectives can thus be displayed in a plane using the multidimensional scaling method (Fig. 12).

The customers’ Kansei correlations matrix can be used to obtain the relative distance between any two Kansei adjectives. This assumes that the meaning of a Kansei adjective is a crisp set and that there is no overlap between any two words. However, in reality, overlapping meaning between different adjectives is not uncommon. For example, in clustering the colors red, pink, and black, people tend to cluster red and pink together because they have something in common, that is, the hue. Similarly, Kansei adjectives with overlapping meaning should be grouped into the same cluster. Therefore, even if the locations of the clusters are known, the researchers still need to estimate the scope (or boundary) of each word in order to cluster them properly. As an example, the distance from “power” to “stable” and from “stable” to “heavy” is about the same (Fig. 13). It happens that a cluster located nearby can possibly encompass the three adjectives using the proposed method, if the radius of that cluster is slightly bigger. Otherwise, it would only contain two of the adjectives. In this case, the researchers have to appraise the boundary of each word subjectively. According to the researchers’ understanding of the three adjectives, “stable” and “heavy” might have some overlapping meaning.
area in their meanings. Therefore, these two adjectives should belong to the same cluster, but not “power.”

Although using the multidimensional scaling method is a convenient way to visualize the Kansei adjectives and the distances among them, it has a major weakness in clustering the Kansei adjectives when compared with the DSM method. Fig. 14 shows the 32 Kansei adjectives in a three-dimensional space. Higher dimensions are also possible. Obviously, different dimensions could result in different Kansei clusters.

In contrast, a DSM does not need to view data from one particular perspective. It provides the basic information about the correlations between any two Kansei adjectives. In this respect, the correlations should be analyzed from various viewpoints in order to cluster the adjectives. For example, because of the existence of many positive correlations, adjectives A and B might be grouped into a cluster. From another perspective, because adjective C and D are negatively correlated with a common word E, it would be rational to group C and D into one cluster.

To elaborate the relationship between the number of subsets, the number of participants needed, and the percentage of overlapping in the subsets, first, the number of Kansei subsets is dependent on the total number of Kansei adjectives to be clustered.

![Fig. 9. The combined DSM before and after CDSMKP partitioning.](image)

![Fig. 10. Mean values of product evaluation.](image)
In this regard, each subset should not contain more than 25 words to avoid effort and length of time in conducting Kansei experiments. Second, the number of participants needed for each Kansei subset should be equal to or more than 30 for statistical reasons. Third, 50% overlapping in the subsets is employed. If more than 50% overlapping is used, it may not be effective to conduct the survey due to too many subsets; in the case of less than 50% overlapping, some adjectives might be excluded in the clustering process. With 50% overlapping, an effective number of survey participants for each subset during the overlapping part is in fact equal to or more than 60 (30 or more \( \times 2 \)). Compared with a full-range survey without overlapping, the proposed method obtains the same results, yet takes a much shorter time, as stated in Section 3. However, the proposed clustering method requires many more evaluators (sometimes more than hundreds) in order to reduce each subject’s mental workload and time spent on the test. For example, in the case of 20 Kansei subsets, the researchers will need to invite a subject sample size that is twenty times larger than the one using traditional methods. This could be a challenge for some designers and researchers who cannot easily get support from communities with large populations, such as those with nearby universities and large shopping malls. In addition, because the number of Kansei adjectives in each subset is limited, the situation becomes even more serious when a large number of product samples are used. It is therefore important for designers and researchers to balance the possible tradeoffs among the number of Kansei adjectives and subsets used, product samples collected, evaluators involved, resulting clusters preferred, time and funds allowed, manpower available, and so forth. All of the above factors vary for different cases. A careful analysis of the issue before conducting Kansei experiments is thus needed.

In summary, the DSM creates a map which positions all of the Kansei adjectives based on their similarities of meanings. The map is depicted according to the customers’ opinions. Without the DSM-based map of Kansei relationships, the study has to rely fully on the intuition of the person who uses the method to cluster the Kansei adjectives, which might not be consistent with the customers’ opinions.
5. Conclusions

A Kansei clustering method is proposed and described in this work. The method takes customer's voices and opinions (i.e., Kansei needs) into consideration for emotional design. It incorporates a DSM in creating the map of Kansei adjectives, which positions all of the Kansei adjectives based on their similarity of meanings. The proposed method breaks a large number of Kansei adjectives up into manageable subsets so that each participant deals with only a portion of the words collected, reducing participart effort and time, while obtaining the same results as those obtained using a full-range survey. The proposed method's performance is illustrated using a case study on wireless battery drills. The results show that, compared with a conventional Kansei engineering approach, the proposed method is promising in handling Kansei adjective clustering problems. Future work would focus on improving the effectiveness and accuracy of identifying the radius of the Kansei clusters. In this respect, it is envisioned that a fully customer-oriented DSM-based Kansei clustering method can be realized.

References


