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ORIGINAL PAPER

A fuzzy mapping method for Kansei needs interpretation considering the individual Kansei variance

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Abstract
Having an accurate understanding of the individual's Kansei needs and afterwards designing products that match these needs are particularly important in the era of mass personalisation. Although customers' Kansei needs have been addressed by Kansei engineering, difficulties remain in handling the differences of individual Kansei. In this paper, individual Kansei variance is considered to transform the Kansei words into multisensory design elements, to help designers better understand the individual's Kansei needs. First, a fuzzy cognitive model is proposed to identify the individual Kansei differences in Kansei words by taking customers' characteristics and purchasing motives into consideration. Second, a fuzzy cognitive model-based mapping method is proposed to interpret Kansei words into multisensory design elements. The method incorporates a fuzzy clustering method and basic-emotion systems to identify Kansei variance and to determine design elements' membership of Kansei words dynamically. Finally, the prototype application of the proposed method on a compact SUV is illustrated. The results suggest that individual differences in Kansei terms do exist among customers in the same market segment, and the proposed method has good feasibility and practicability in handling individual Kansei differences in emotional design. Those Kansei dimensions that are more prominent in individual Kansei variance are highly recommended for further digging, which would benefit carrying out personalised customisation and differentiated design.

Keywords Kansei needs interpretation · Fuzzy cognitive · Motives · Kansei engineering · Fuzzy mapping

1 Introduction

1.1 Motivations and technical challenges

In the age of diversification and personalisation, keen competitions have resulted in profuse product alternatives in the market and an increasing number of consumers like to express their individual expectations about a product (Shimizu et al. 2004). Mass customisation (Pine and Pine 1992) was widely used by many companies to combine the low unit costs of mass production processes with the flexibility of individual customisation. As human society gradually entered the era of Experience Economy (Pine et al. 1999), consumers are no longer merely satisfied with functional use of products. The individual's emotional needs, or the so-called Kansei needs, have become one of the most important concerns in product design nowadays (Huang et al. 2012b). This demand has triggered the research dealing with individual's Kansei needs and further translating them into the domain of product design. Although a large number of approaches which are more or less relevant to Kansei engineering have been proposed, difficulties remain in handling the differences of individual Kansei (Wang and Yang 2012).

The challenge for designers to accurately handle the diversified and personalised Kansei mainly comes from two aspects. First, the human emotions are extremely subjective, circumstance-related and individual. It would be influenced by culture, personality, motives and by the socio-economic status of the consumer. There are still many difficulties in dealing with the fuzzy and uncertainty of human thought under multi-granularity linguistic environment (He et al. 2017). Even if the target customers describe their Kansei needs with the same words, their real thoughts may vary

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from person to person. Second, customers, marketing folks and designers employ different sets of context to express their understanding of affect information (Gologlu and Zurnaci 2016). Differences in semantics and terminology impair the coherence of transferring Kansei needs effectively from customers to designers (Jiao et al. 2006). For example, product exterior features are generally determined by the subjective aesthetic sense of designers with little attention paid to individual's affective responses. This leads to a cognitive gap between designers and customers, resulting in a performance failure in the marketplace (Shieh et al. 2016).

Against this background, this paper aims to establish a set of fuzzy mapping method to transform the individual's Kansei needs into more clear and comprehensible design elements, helping designers to better understand the individual's Kansei needs. By taking customers' characteristics, purchasing motives and basic-emotion system into consideration, a fuzzy cognitive model (FCM) is proposed to characterise the individual's latent perception pattern and to identify the individual Kansei differences in Kansei words. Then fuzzy clustering method is employed to find groups with similar perception patterns to the individual from the Kansei evaluation data sets. Finally, fuzzy logic (Zadeh 1988) is used to deal with Kansei variance and the design elements whose membership degree is greater than a specified threshold are selected for designers.

1.2 Literature review

A number of studies have been conducted to investigate emotions in the psychological realm. For example, based on four basic components (cognition, evaluation, motivation and feelings), Ben-Ze'ev (2000) suggested that emotions are an integrated and complex process that involves human intentional activities as well as a feeling domain. The word "Kansei" can be interpreted as people's feelings or impressions of an object, representing their psychological expectations and perceptions (Chang and Chen 2016; Lai et al. 2005). In emotional design, it may be evoked by such attributes as product form, style, colour, function and price, and affected by consumer emotions and personal senses of values (Stappers et al. 2002). These emotions and attitudes reflect latent variables or constructs which cannot be directly observed, and which cannot be measured as easily as other objective aspects of the product. They reflect aspects of the total product experience which go beyond the products' functionality or usability, and are associated with the emotional benefits provided using the product. Consequently, they are influenced by culture, personality, experience and by the socio-economic status of the consumer (Childs et al. 2006).

Owing to the fact that human emotions are extremely subjective, circumstance-related and individual, an accurate measurement of Kansei needs is generally impractical. In this regard, Kansei engineering (Nagamachi 1995) advocators suggested an effective way to represent human emotions, i.e. the use of Kansei words or adjectives to represent various emotions (Ota and Aoyama 2002). Then these Kansei words are clustered into several Kansei clusters (Huang et al. 2012a), which can then be used to represent consumer's Kansei needs in the next stages. In previous studies, the semantic differential (SD) method has been widely used in Kansei engineering to address the relationship between emotions and design elements. Many sophisticated methods and models (Chang and Chen 2016; Yang 2011) have been established based on the conventional SD method. However, the conventional SD method assumes that the survey participants' understanding of Kansei words is consistent, which might not be true for all design cases (Huang et al. 2012b). Moreover, the expectations for the same product could be varied according to different customers. Thus the reflection of individual customer preferences in product design is essential (Hong et al. 2010). Therefore, the collected data involve complicated interactions and relationships between design elements and consumer affections, inherent with imprecision, uncertainty and fuzziness (Zhai et al. 2009b).

To overcome these difficulties, many approaches have been proposed in Kansei engineering. The basic assumption of Kansei engineering studies is that there exists a cause-and-effect relationship between affective responses and a product's attributes (Yang 2011). Rough set theory, a rule-based knowledge acquisition method capable of targeting imprecise, non-linear human perceptions, has been adapted to discover the mapping pattern between consumer affections and product design elements from raw design data (Shi et al. 2012; Shieh et al. 2016; Takenouchi and Tokumaru 2017; Zhai et al. 2009b). Zhai et al. (2009a) proposed a systematic approach to Kansei engineering based on the dominance-based rough set theory, which can identify and analyse two types of inconsistencies caused by indiscernibility relations and dominance principles respectively. Yang et al. (2011) extended the work of Nagamachi by introducing three concepts to reinforce Kansei Engineering System: consumer segmentation (CS), affective response dimension selection, and product form feature selection. Wang and Chin (2017) employed Kansei engineering to capture user attitude toward affective features and constructed a classification tree to carry out effective market partitioning. Meng-Dar and Fang-Chen (2013) adopted a fuzzy c-means clustering to separate the consumers with heterogeneous preference evaluation into homogenous groups, and demonstrate that fuzzy clustering is a suitable method for the application of CS. Jiao et al. (2006) considered the heterogeneous nature of customer needs and implemented rule refinement at the segment level to utilise valuable affect information latent in customers' impressions of existing affective designs. Considering that the consumers' affective response changes with social trends, Li et al. (2018) proposed a machine learning-based affective design dynamic mapping approach (MLADM) to collect consumers' affective responses extensively, dynamically and automatically. Kim et al. (2019) developed an affective variable extraction methodology that can reflect users' implicit needs. Wang et al. (2019) proposed a heuristic deep learning method that extracts affective opinions from customer product reviews, and classified them into seven pairs of affective attributes. Guo et al. (2020) investigated whether N400 can be used as an electrophysiological measurement to effectively identify Kansei words for assessing product design features in Kansei engineering research. Li et al. (2019) proposed a posterior preference articulation approach to Kansei engineering system aimed at optimizing product form design to deal with MARs simultaneously. However, these research still assumes that customers in the same market segmentation are likely to present a more homogeneous response to products.

In this regard, Huang et al. (2012b) incorporated basic-emotion systems to identify Kansei variance and mapping functions in determining transformed values on Kansei-tag dimensions and proposed a basic-emotion-based semantic differential method. To identify emotion-related product attributes, Huang et al. (2014) developed the customer's mind map for each Kansei tag and used a means-value chain to generate targets based on the personal construct theory. Camargo and Henson (2015) pointed out the disadvantage of rating scales is that they rely on the honesty and awareness of the respondent for their validity. The principal components analysis method, which is used for analysing the ratings, is often difficult to relate the resulting semantic space to the constructs that the manufacturer wishes to know about. They use Rasch measurement theory to measure the affective impression and state the benefits of using the Rasch approach are in the ability to obtain reliable results from small samples of consumers. Gologlu and Zurnaci (2016) indicated that the reflection of individual customer preferences in product design is essential. They present a methodology combining Kansei engineering for determining the relationships between customer preference and products with the fuzzy logic approach for evaluating customer preferences. Mata et al. (2017) established a methodology to identify the relationships between perceptions, aesthetic features, desire to own and background of consumers. Zhou et al. (2017) proposed a personalized recommendation model based on Kansei engineering for online apparel shopping. Sakornsathien et al. (2019) combined the data mining technique with Kansei Engineering technique to predict possible design elements of a product which is appropriate for users. The style and preference of each user were used as a categorizing factor clustering the database into groups with K-means technique.

1.3 Outline of paper

The remainder of the paper proceeds as follows. In Sect. 2, the fuzzy cognitive model of Kansei needs and its modelling process are presented. Section 3 describes the methodology of interpreting the individual's Kansei needs into related design elements. Sect reports the prototype application of the proposed method on a compact SUV. Validation of the proposed model is also discussed in term of individual Kansei variance. Discussions on managerial implications and conclusions are drawn in Sects. 5 and 6 respectively.

2 Kansei needs modelling

2.1 Generation of Kansei needs

People's understanding towards objective things starts from sensation. It is a process of explaining things after processing of perception, understanding and inferring of the sensory information. Compared to sensation, perception involves participation of individual's experience of knowledge, as well as effects of individual's psychological characteristics and subjective factors, such as cognition, motivation and interests. The combination of sensory stimulation and cognitive processing composes the customer's complete emotional understanding of a product. As shown in Fig. 1, considering their personal characteristics, desires, motives and interests, the customer obtained a complete emotional understanding of the product through interaction with the product. Then the customer cognised the product in an inferential way with metaphor and reasoning like 'what is the product like', 'how is this kind of product', and described their cognition with certain abstract Kansei adjectives, such as 'convenient', 'modern', 'beautiful' and 'noble' etc..

It can be seen that Kansei needs are the outcome of a series of cognitive activities of sensation and perceptions. In other words, Kansei can be seen as a process, which is a multidimensional and comprehensive psychological reaction from sensory stimulation to perception. And this reaction can be guided to express through Kansei words (including body language) and behaviours. Due to the heterogeneous nature in cognitive processes of different subjects (including customer and customer, customer and designer), designers are often not aware of the underlying coupling and interrelationships between Kansei words and various design elements with regard to customers' affective satisfaction. It is necessary to convert the Kansei words to more clear, comprehensible and less ambiguous design elements, which could enable the bridging of designers' creativity and customers' Kansei needs and facilitates the development of competitive new products.

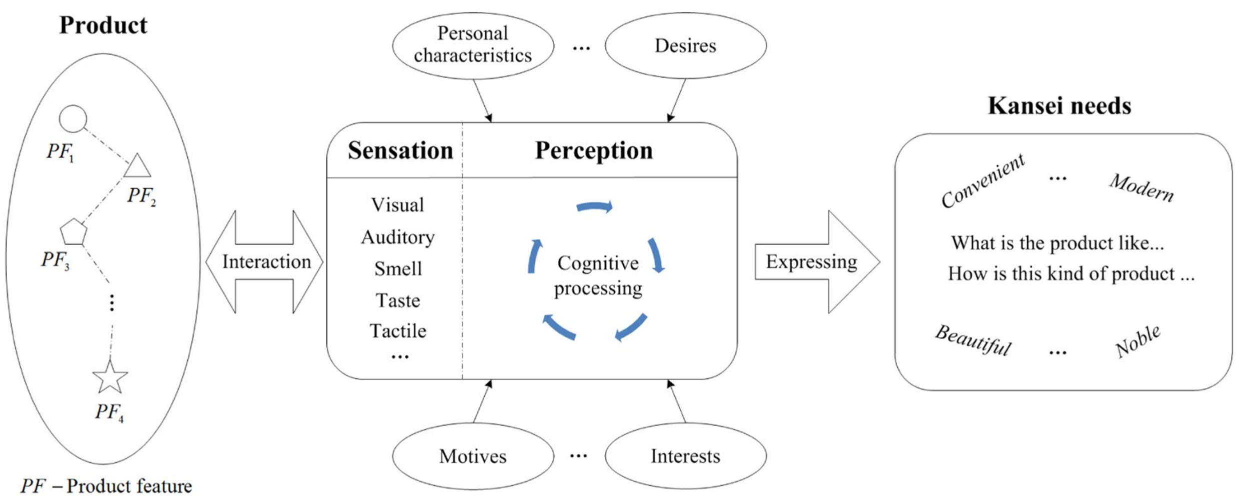

Fig. 1 The generation of Kansei needs

2.2 Fuzzy cognitive model of Kansei needs

According to Maslow's hierarchy of needs theory, a product satisfies different levels of customer's needs with its function, usability, appearance and so on. In addition to the customer's personal characteristics (lifestyle, values, education, personality, occupation, race, age, gender, family, etc.) and life experiences, the purchasing motives are also important factors affecting the customer's emotional perception of a product. These motives can usually be understood as 'having this product should make me fashionable' or 'this product should help me complete …' or 'this product makes me feel happy'. Different customers have different characteristics and different purchasing motives, and this kind of difference also exists between the user and the designer.

Although different customers may use the same Kansei words to describe their emotional needs, due to the heterogeneous nature of their emotional cognitive process, the Kansei needs that the words represent are different. When designers interpret Kansei needs and develop emotional design in accordance with the perceptual pattern of their own or part of the leading user, the design results may not be able to meet the target customer's Kansei needs. Based on characteristics of the emotional cognitive process, this paper sets up a fuzzy cognitive model (FCM) to characterise the individual's latent perception pattern and to identify the individual Kansei differences in Kansei words. As shown in Fig. 2, the FCM is a directed graph composed of consumer, motives of purchasing, multisensory design elements, Kansei words and basic-emotion system nodes. To be more specific, multisensory design elements described here are those design features which can be directly perceived and understood by the user's senses, including line, shape, form, space, colour, texture, material, sound, odour and ways of interacting, etc., or can be a combination of the above elements. Free association is the advanced function of mankind and can express the deepest desire and ideas of mankind. Things that exist in people's minds can bring a lot of inspiration to the designer, so multisensory design elements in Fig. 2 include not only those product-related but also some samples obtained by metaphor extraction techniques.

For a specific customer c_n, there are three different types of paths in FCM to characterise the customer's latent perception pattern. The first type of $c_n \rightarrow m_l$ path indicates what kind of purchase motives the customer have. The second type of $c_n \rightarrow \mathrm{de}_p \rightarrow \mathrm{kw}_q$ path represents the Kansei evaluation of design element de_p in the Kansei words kw_q dimension by customer c_n, and the evaluation value $v_{\mathrm{de}_p}^{c_n}(\mathrm{kw}_q)$ is the weight of the $c_n \rightarrow \mathrm{de}_p \rightarrow \mathrm{kw}_q$ path. The third type of $c_n \rightarrow \mathrm{kw}_q \rightarrow \mathrm{Be}$ path represents the subjective evaluation of Kansei words kw_q in the basic-emotion system by customer c_n, the evaluation value $V_{\mathrm{kw}_q}^{c_n}(\mathrm{Be})$ is the weight of the $c_n \rightarrow \mathrm{kw}_q \rightarrow \mathrm{Be}$ path.

As shown in Fig. 3, the steps of building the fuzzy cognitive model are as follows:

Step 1: Collect product-related semantic adjective pairs and cluster into a Kansei words library, which is denoted as:

$$\mathrm{Kw} = \{\mathrm{kw}_1, \mathrm{kw}_2, \dots, \mathrm{kw}_q\} \tag{1}$$

Step 2: Invite a group of leading target customers, senior designers and user researchers to do free association of the Kansei words, and use multisensory elements to describe ideas on their minds. Collect these elements, together with those extracted from the actual product, and form the multisensory design element library, denoted as:

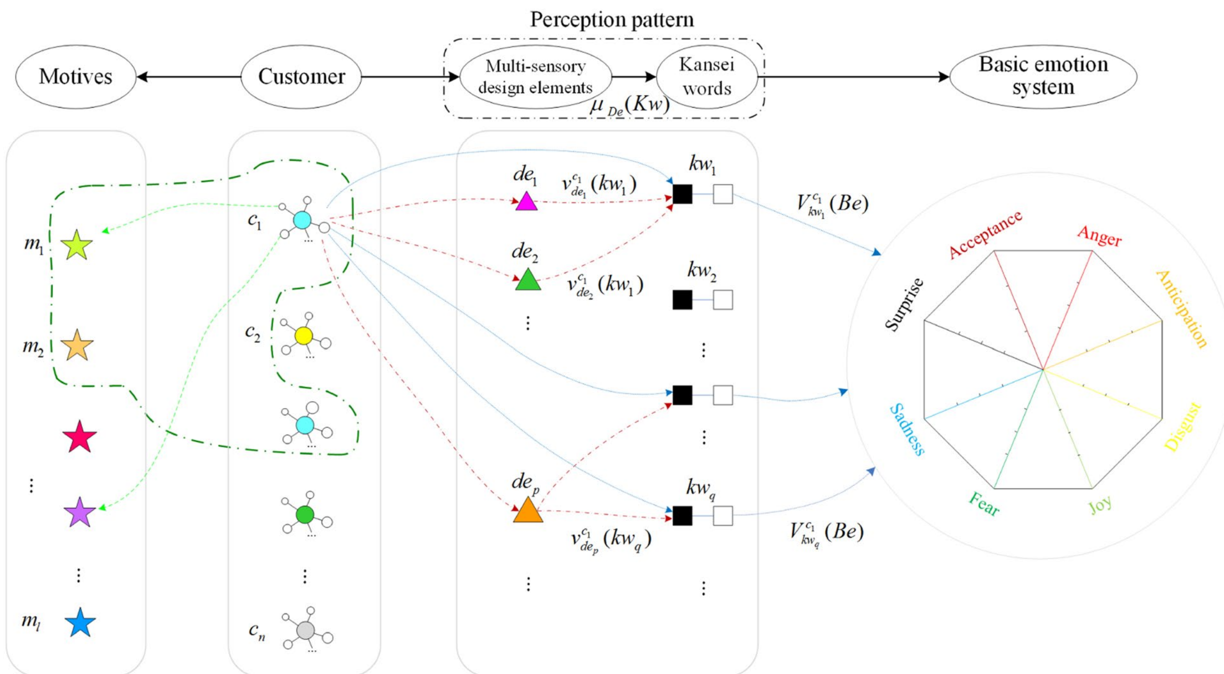

Fig. 2 The fuzzy cognitive model of customer's Kansei needs

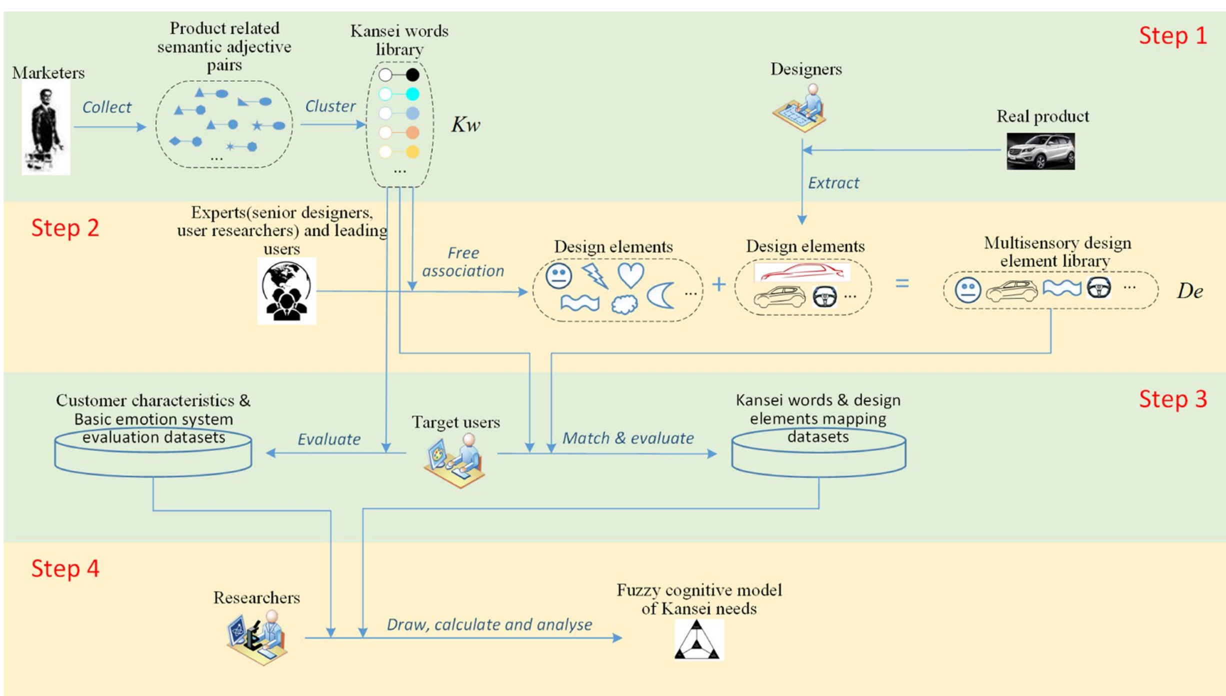

Fig. 3 The steps to build the fuzzy cognitive model

$$\mathrm{De} = \{\mathrm{de}_1, \mathrm{de}_2, \ldots, \mathrm{de}_p\}. \tag{2}$$

Step 3: Invite the target customer to evaluate multisensory design elements with Kansei words using a Likert-type scale, and then evaluate Kansei words with basic emotions (Huang et al. 2012b; Plutchik 1991). During the evaluation process, they can freely select those words that can represent their emotional dimensions in the Kansei words library. For the convenience of subsequent data mining, the number of words used for evaluating each design element is generally not less than five. Collect these evaluations to form a dataset D, which can be used for subsequent mining of the fuzzy mapping relationship between the multisensory design elements and Kansei words. The data related to customer c_n in the dataset is denoted as follows:

$$D\left(c_n\right)=\left\{X\left(c_n\right),M\left(c_n\right),V_{\mathrm{De}}^{c_n}(\mathrm{Kw}),V_{\mathrm{Kw}}^{c_n}(\mathrm{Be})\right\},$$

$$V_{\mathrm{De}}^{c_n}(\mathrm{Kw})=\{\langle \mathrm{de}_p,\mathrm{kw}_q,v_{\mathrm{de}_p}^{c_n}(\mathrm{kw}_q)\rangle \big| \mathrm{de}_p\in \mathrm{De},\mathrm{kw}_q\in \mathrm{Kw}\},$$

$$V_{\mathrm{Kw}}^{c_n}(\mathrm{Be})=\{\langle \mathrm{kw}_q,\mathrm{Be},v_{\mathrm{kw}_q}^{c_n}(\mathrm{Be})\rangle \big| \mathrm{kw}_q\in \mathrm{Kw}\}.$$

In which, $X\left(c_n\right)$ represents the personal characteristics of customer c_n, $M\left(c_n\right)$ represents the purchase motives of customer c_n.

Step 4: Draw a fuzzy cognitive map. First, generate c_n, m_l, de_p, kw_q and Be nodes, and then connect related nodes to form several paths according to the Kansei evaluation data of each customer, and mark the corresponding weights. With the accumulation of Kansei evaluation data, a complete fuzzy cognitive map of the target customer group on the emotional aspect of a certain product is formed. This fuzzy cognitive map can then be used to predict the customer's latent perception pattern based on their personal characteristics and purchasing motives.

3 Kansei needs interpretation considering the individual Kansei variance

3.1 Purchasing motives involved customer fuzzy clustering

Generally speaking, interpreting an individual's Kansei needs requires a deeper understanding of the individual's personal characteristics and purchase motives. However, it is not economical or necessary for mass personalisation. This paper predicts the perception pattern of an individual by analysing the Kansei evaluation data of customers with similar characteristics and purchase motives to the individual in the fuzzy cognitive map. First, fuzzy clustering method is employed to divide the target customers into several groups with similar perception pattern. As shown in Fig. 4, the steps of fuzzy clustering are as follows:

Step 1: Assume that the domain $C=\left\{c_1,c_2,\dots,c_n\right\}$ is the to-be-classified target customer group, and characterise the i-th customer c_i with m indicators:

$$c_i=\left\{x_{i1},x_{i2},\dots,x_{il},x_{i(l+1)},\dots,x_{im}\right\},i=1,2,\dots,n \tag{6}$$

In particular, $x_{ik}(k>l)$ refers to the purchasing motives of the customer c_i.

Hereafter, the original data matrix is:

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m}\\ x_{21} & x_{22} & \cdots & x_{2m}\\ \vdots & \vdots & \ddots & \vdots\\ x_{n1} & x_{n2} & \cdots & x_{nm}\end{bmatrix}. \tag{7}$$

Step 2: Determine the weight vector of these indicators as $\omega=\left(\omega_1,\omega_2,\dots,\omega_l,\omega_{l+1},\dots,\omega_m\right)^T$. These weights can be obtained by the AHP method or by expert experience. Generally, the purchasing motives occupy a higher weight than the others. Then the original data matrix X is weighted to obtain a new data matrix $X'=\left(x'_{ik}\right)_{n\times m}$.

$$x'_{ik}=\omega_i\cdot x_{ik}. \tag{8}$$

Step 3: Get normalized data matrix $X''=\left(x''_{ik}\right)_{n\times m}$ by performing range transformation on X'.

$$x''_{ik}=\frac{x'_{ik}-\min_{1\le i\le n}\left\{x'_{ik}\right\}}{\max_{1\le i\le n}\left\{x'_{ik}\right\}-\min_{1\le i\le n}\left\{x'_{ik}\right\}}. \tag{9}$$

Step 4: Establish the fuzzy similarity matrix $R=\left(r_{ij}\right)_{n\times n}$ using the correlation coefficient method.

$$r_{ij}=\frac{\sum_{k=1}^{m}\left|x''_{ik}-\overline{x''_i}\right|\left|x''_{jk}-\overline{x''_j}\right|}{\sqrt{\sum_{k=1}^{m}\left(x''_{ik}-\overline{x''_i}\right)^2}\sqrt{\sum_{k=1}^{m}\left(x''_{jk}-\overline{x''_j}\right)^2}}. \tag{10}$$

In which $\overline{x''_i}=\frac{1}{m}\sum_{k=1}^{m}x''_{ik}$, $\overline{x''_j}=\frac{1}{m}\sum_{k=1}^{m}x''_{jk}$.

Step 5: Get the fuzzy equivalence matrix R^* by computing the transitive closure (Guoyao 1992) of fuzzy similarity matrix R.

Step 6: Determine the optimal threshold λ for classification, calculate the λ-cut matrix of the fuzzy equivalent matrix R^* and obtain the equivalent classification at the λ level. Assume the number of categories that corresponding

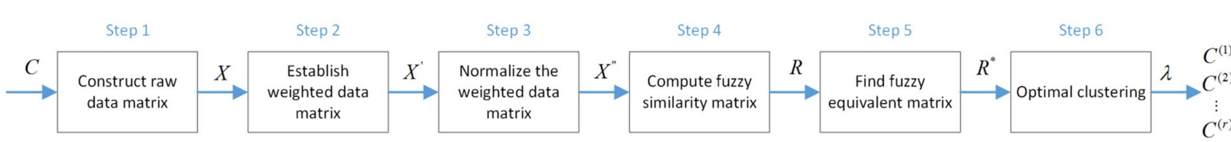

Fig. 4 The steps of purchasing motives involved customer fuzzy clustering

to value λ is r, and the number of customers in the s-th category is n_s.

The centre vector of the total samples is:

$$\overline{c} = (\overline{x'_1}, \overline{x'_2}, \ldots, \overline{x'_m}). \tag{11}$$

In which, $\overline{x'_k} = \frac{1}{n}\sum_{i=1}^{n} x'_{ik}, (k = 1, 2, \ldots, m)$ refers to the average of the k-th feature of all samples.

The centre vector of the s-th category is:

$$\overline{c}^{(s)} = \left(\overline{x'_1}^{(s)}, \overline{x'_2}^{(s)}, \ldots, \overline{x'_m}^{(s)}\right). \tag{12}$$

In which, $\overline{x'_k}^{(s)} = \frac{1}{n_s}\sum_{i=1}^{n_s} x'^{(s)}_{ik}, (k = 1, 2, \ldots, n_s)$ refers to the average of the k-th feature in the s-th category.

Construct the F statistics as follows:

$$F = \frac{\sum_{s=1}^{r} n_s \left\| \overline{c}^{(s)} - \overline{c} \right\|^2 \Big/ (r-1)}{\sum_{s=1}^{r}\sum_{i=1}^{n_s} \left\| c_i^{(s)} - \overline{c}^{(s)} \right\|^2 \Big/ (n-r)} \sim F(r-1, n-r). \tag{13}$$

In which, $\left\|\overline{c}^{(s)} - \overline{c}\right\| = \sqrt{\sum_{k=1}^{m}\left(\overline{x'_k}^{(s)} - \overline{x'_k}\right)^2}$ refers to the distance between $\overline{c}^{(s)}$ and $\overline{c}$, $\left\|c_i^{(s)} - \overline{c}^{(s)}\right\|$ refers to the distance between $c_i^{(s)}$ and the centre vector $\overline{c}^{(s)}$ in s-th category. The numerator in formula (13) represents the distance between two categories, and the denominator represents the distance between the customers in the same category. Since $F \sim F(r-1, n-r)$, the larger the value of F, the greater the distance between the two categories, and the better the result is. The λ that maximizes the F statistic is the optimal classification threshold. To ensure the statistical significance and operability of the clustering results, referring to the VALS2 (Novak and MacEvoy 1990), the recommended number of clusters is 3–14.

3.2 Fuzzy mapping of Kansei needs based on FCM

Different customer categories have different perception patterns. After fuzzy clustering, the target customers are divided into several categories with different perception pattern. Then the membership function between the design elements and the Kansei words of each category can be calculated.

Assume that the number of samples in s-th category is n_s. The evaluation of p-th design element from i-th customer c_i in s-th category is:

$$V_{\mathrm{de}_p}^{c_i^{(s)}}(\mathrm{Kw}) = \{(\mathrm{de}_p, \mathrm{kw}_1, v_{\mathrm{de}_p}^{c_i^{(s)}}(\mathrm{kw}_1)), (\mathrm{de}_p, \mathrm{kw}_2, v_{\mathrm{de}_p}^{c_i^{(s)}}(\mathrm{kw}_2)), \ldots, (\mathrm{de}_p, \mathrm{kw}_q, v_{\mathrm{de}_p}^{c_i^{(s)}}(\mathrm{kw}_q))\}. \tag{14}$$

For the s-th category, the membership degree of the design element de_p to the Kansei words kw_q is:

$$\mu_{\mathrm{de}_p}^{(s)}(\mathrm{kw}_q) = \frac{2}{x-1} \cdot \left(\frac{1}{n_s}\sum_{i=1}^{n_s} v_{\mathrm{de}_p}^{c_i^{(s)}}(\mathrm{kw}_q) - f\left(\mathrm{KV}_q^{(s)}\right)\right). \tag{15}$$

In which, x refers to the number of points in the Likert scale. $\mathrm{KV}_q^{(s)}$ refers to the total Kansei variance of s-th category for kw_q in basic-emotion dimensions, and it measures the difference in understanding each Kansei words by a group of customers. $f(\cdot)$ refers to the mapping function for adjusting the Kansei mean value to better reflect consumer's genuine opinions on the multisensory design elements, and the linear mapping function in literature (Huang et al. 2012b) is employed in this paper. Generally, it indicates that de_p and kw_q have strong positive or negative correlation when the membership degree $0.7 \le |\mu| \le 1$, relatively high correlation when $0.4 \le |\mu| \le 0.7$, weak correlation when $|\mu| < 0.4$.

Correspondingly, the membership matrix $\mu_{\mathrm{De}}^{(s)}(\mathrm{Kw})$ represents the perception pattern of s-th category on the design element library De, denoted as:

$$\mu_{\mathrm{De}}^{(s)}(Kw) = \begin{bmatrix} \mu_{\mathrm{de}_1}^{(s)}(\mathrm{kw}_1) & \mu_{\mathrm{de}_1}^{(s)}(\mathrm{kw}_2) & \cdots & \mu_{\mathrm{de}_1}^{(s)}(\mathrm{kw}_q) \\ \mu_{\mathrm{de}_2}^{(s)}(\mathrm{kw}_1) & \mu_{\mathrm{de}_2}^{(s)}(\mathrm{kw}_2) & \cdots & \mu_{\mathrm{de}_2}^{(s)}(\mathrm{kw}_q) \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{\mathrm{de}_p}^{(s)}(\mathrm{kw}_1) & \mu_{\mathrm{de}_p}^{(s)}(\mathrm{kw}_2) & \cdots & \mu_{\mathrm{de}_p}^{(s)}(\mathrm{kw}_q) \end{bmatrix}. \tag{16}$$

When the above membership matrix is established, the model can be used to interpret the Kansei needs of the new target customer. First, add the new individual into the existing target customer group and then recluster the sample using the fuzzy clustering algorithm in Sect. 3.1. The new individual can be classified into a certain category s which may have a similar perception pattern with them. Second, set α as the membership threshold of design element library De to Kansei words library Kw, and the designers can adjust it according to their own needs. If the new individual uses Kansei words kw_q to describe their Kansei needs, all the design elements that meet the criteria $\mu_{\mathrm{de}_p}^{(s)}(\mathrm{kw}_q) \ge \alpha$ will be selected to interpret their Kansei needs together with their Persona. Through the above steps, the new individual's Kansei needs can be converted to a visualised way to reduce the distortion of Kansei needs due to cognitive differences, thereby reducing the risk of new product development.

4 Case study

To verify the feasibility of the fuzzy mapping method mentioned in this paper, the author applied this method to the Kansei needs interpretation of a compact SUV in C Company. According to previous market research, the customers of this kind of vehicle were targeted at young people between 25 and 35 years old who love to play and pay more attention to the cross-country ability of vehicle, and their Kansei needs can be described by Kansei words such as “fashionable, sportive and high-tech”.

At first, according to the step 1 in Sect. 2.2, 63 Kansei adjectives that are often used to describe the styling of the vehicle were collected and clustered into 16 pairs of Kansei words with positive and negative poles, which are shown in Table 1. Then, according to the step 2 in Sect. 2.2, 67 design elements were collected and encoded through the focus group, in which including 52 visual elements, 8 material elements, 4 sound elements and 3 odour elements. In particular, the fuzzy mapping of Kansei needs will be explained only through visual elements in this case. As shown in Fig. 5 are 52 visual elements, mainly including shape, characters, interests and ways of interacting.

After the Kansei words and design elements were ready, a semantic difference questionnaire was formed according to the step 3 in Sect. 2.2. Also, 100 respondents who fit the target market positioning were invited and encoded to participate in the evaluation by working with the brand’s 4 s shop in about 40 days, of which male to female ratio is 54:46 and the age range is from 25 to 35 years old ($M = 31.17$, $SD = 2.82$). They consist of customers who come to the store (32%), customers who were invited by phone (49%), and graduate students who major in industrial design (19%). Among them, 24% are already the existing owners of the vehicle. To alleviate the negative impact of the large numbers of questions and to improve the reliability of the data,

Table 1 16 pairs of Kansei words with positive and negative poles

Thin—Thick	Imbalance—Coordinated	Dull—Sportive	Intermittent—Smooth
Vulgar—Elegant	Bulky—Light	Rough—Delicate	Ugly—Beauty
Reserved—Swanky	Rustic—Fashion	Soft—Masculine	Loose—Rigorous
Public—Personality	Complicated—Simple	Conservative—Advanced	Outdated—Novelty

Fig. 5 Part of the collected design elements

participants were asked to select only 5–8 Kansei words for each design element that can best describe it from the 16 pairs and gave corresponding scores, respectively. The average number of Kansei words selected to describe the design element was 5.62 with a standard deviation of 0.49. Then 37,654 lines of raw data were obtained. At the same time, the participants' personal characteristics information (including age, gender, race, occupation, education, personality, income level, family structure, lifestyle, etc.) and purchasing motives were also collected with their consent. These participants' motives to purchase this kind of compact SUV mainly including commuting, self-driving travel, business reception, taking of children to school, weekend picnic and cargo transport. Then the FCM was obtained according to the step 4 in Sect. 2.2. The above data lay the foundation for interpreting Kansei needs into multisensory design elements according to individual characteristics.

Then 12 new target customers were invited as participants to validate the fuzzy mapping method. Figure 6 shows the procedure for verifying the prediction accuracy of the method and whether there are individual Kansei variances, where UM and MO represent participants' own evaluation and the model's prediction results, respectively. Due to the space limit, the validation process is illustrated by only 3 sets of sample data here. First of all, "Fashion, Sportive and High-tech" three Kansei words and 15 random selected design elements were combined to form an 11-points Likert Scale. The evaluation data of three participants on the fifteen design elements were collected, and also the prediction results of membership obtained by inputting the participant's personal characteristics and motives to the model.

As shown in Table 2 and Fig. 7 are the model's prediction results (MO) and participants' own evaluation (UM) on the membership of fifteen design elements to 'Fashion, Sportive and high-tech'. As can be seen from the data, apart from the No.05, No.20 and No.23 design elements in the "Fashion" dimension are quite different, the MO and UM are basically consistent on the other design elements. Further correlation and comparative analysis of these data were made by the paired-samples T test method. As shown in Tables 3 and 4, the MO and UM show a high correlation ($r_{\text{Pair1}} = 0.985$, $r_{\text{Pair2}} = 0.994$, $r_{\text{Pair3}} = 0.892$) and their mean, statistically, have no significant difference ($t_{\text{Pair1}} = 1.230$, $P_{\text{Pair1}}(\text{Sig.}(2-\text{tailed})) = 0.239 > 0.05$; $t_{\text{Pair2}} = -0.150$, $P_{\text{Pair2}}(\text{Sig.}(2-\text{tailed})) = 0.883 > 0.05$; $t_{\text{Pair3}} = -1.848$, $P_{\text{Pair3}}(\text{Sig.}(2-\text{tailed})) = 0.086 > 0.05$). On the other hand, although the three participants have a high correlation ($r_{\text{Pair4}} = 0.871$, $r_{\text{Pair5}} = 0.633$, $r_{\text{Pair6}} = 0.925$) in the perceptual evaluation data, their perceptual mean were statistically inconsistent ($t_{\text{Pair4}} = -2.184$, $P_{\text{Pair4}}(\text{Sig.}(2-\text{tailed})) = 0.046 < 0.05$; $t_{\text{Pair5}} = -2.210$, $P_{\text{Pair5}}(\text{Sig.}(2-\text{tailed})) = 0.044 < 0.05$; $t_{\text{Pair6}} = -2.153$, $P_{\text{Pair6}}(\text{Sig.}(2-\text{tailed})) = 0.049 < 0.05$).

The above data indicate that the customers in the same market segment do exist individual differences in Kansei terms. Also, the model proposed in this paper has good feasibility and practicability in dealing with individual Kansei variance. It appears that this method could accurately interpret Kansei needs represented by Kansei words into design elements, which is easier to be understood by the designer according to the previous Kansei evaluation data.

5 Discussion

Nowadays, how to deal with the individual's Kansei differences is a key issue that modern company must think about in response to the challenge of mass personalisation. In traditional emotional design, Kansei words are usually used for delivering Kansei needs and measuring products in Kansei aspects. As mentioned, the Semantic Difference method assumes that participants would understand the

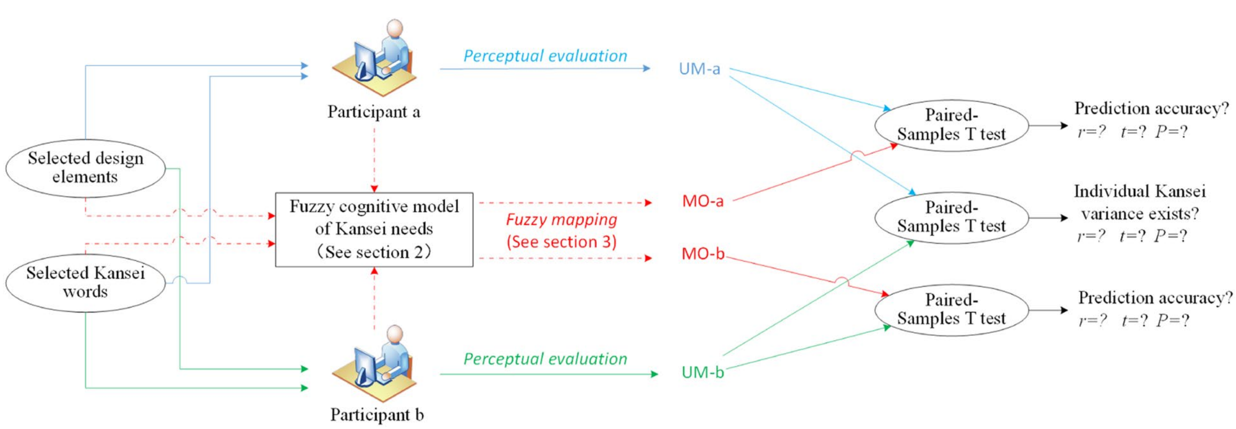

Fig. 6 the procedure for verifying the prediction accuracy and individual Kansei variances

Table 2 the model's prediction results and participants' own evaluation on the membership of fifteen design elements to 'Fashion, Sportive and high-tech'

Kansei words	The number of design elements	Participant 1			Participant 2			Participant 3		
		MO1	US1	UM1	MO2	US2	UM2	MO3	US3	UM3
Fashion	30	0.64	3.5	0.70	0.77	3.9	0.78	0.79	4.0	0.8
	48	0.78	3.7	0.74	0.72	3.4	0.68	0.72	3.3	0.66
	05	0.36	2.0	0.40	0.59	3.1	0.61	0.78	3.9	0.77
	20	0.23	1.0	0.20	0.51	2.7	0.53	0.78	4.3	0.85
	23	– 0.04	0.0	0.00	0.43	2.1	0.41	0.77	3.8	0.76
Sportive	28	0.84	3.9	0.78	0.8	4.2	0.84	0.9	4.5	0.89
	13	0.65	3.2	0.63	0.72	3.8	0.75	0.94	4.9	0.98
	18	0.29	1.5	0.30	0.46	2.1	0.42	0.49	2.9	0.57
	08	0.28	1.0	0.20	0.2	1.1	0.22	0.14	1.0	0.19
	19	0.13	0.3	0.05	– 0.12	– 0.4	– 0.08	– 0.2	– 1.3	– 0.25
High-tech	33	0.79	3.8	0.76	0.79	3.8	0.76	0.75	3.9	0.78
	34	0.75	3.5	0.70	0.74	3.7	0.73	0.86	4.0	0.79
	14	0.24	1.6	0.32	0.56	2.5	0.49	0.85	4.0	0.8
	04	0.13	0.5	0.10	– 0.02	– 0.1	– 0.01	– 0.2	– 0.9	– 0.17
	15	0.15	0.5	0.10	0.08	0.6	0.12	0.15	0.9	0.18

Note: MO and UM, respectively, refer to the model's prediction and participants' own evaluation on the membership of design elements to Kansei words, the US refers to the participants' ratings of design elements on Kansei words

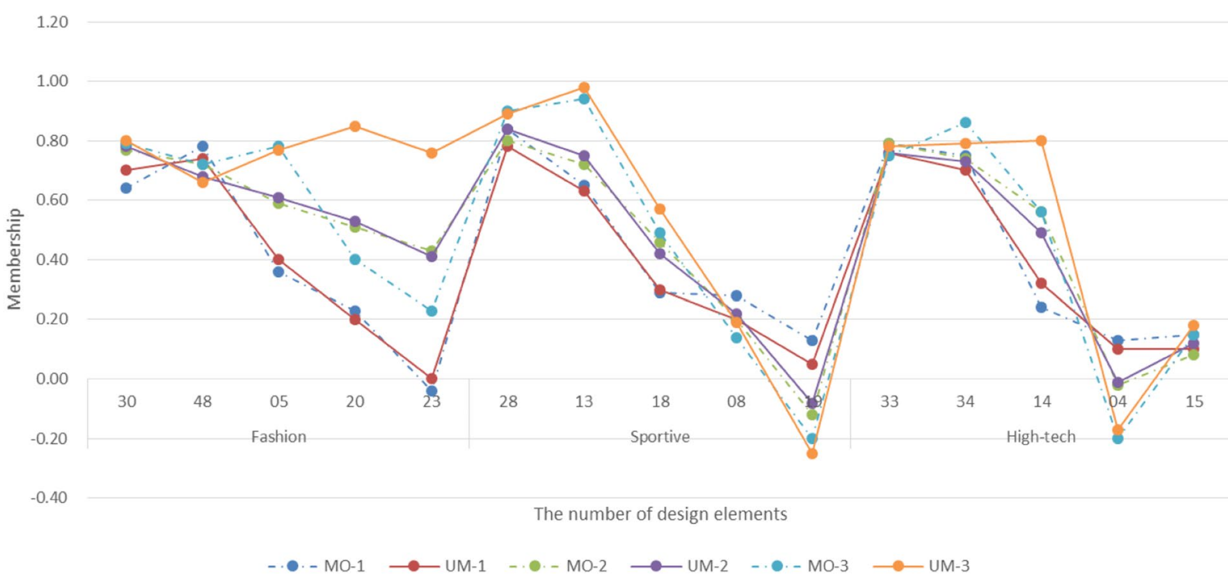

Fig. 7 The model's prediction results and participants' own evaluation on the membership of fifteen design elements to 'Fashion, Sportive and High-tech'

Kansei words in a consistent manner. However, it is a well-known fact that the same Kansei words may be understood differently by different people. Therefore, the Kansei words mean values that do not take the effect of the variance of Kansei words into considerations may not reflect a consumer's genuine opinions. The conversion or mapping of user's Kansei needs based on such methods can also pose risks to subsequent design. Since fuzzy logic is very suitable for dealing with the ambiguity and diversity of individual Kansei. This paper first introduces personal characteristics and basic-emotion system to establish the fuzzy cognitive model of Kansei needs, which is used to describe and identify individual Kansei variance. At the same time, fuzzy logic is introduced on the basis of the traditional Semantic Difference method, thereby establishing the fuzzy membership relationship of design elements to Kansei words. Then,

Table 3 Paired-samples correlations the model's prediction results and participants' own evaluation

	N	Correlation	Sig
Pair 1			
MO1 & UM1	15	0.985	0.000
Pair 2			
MO2 & UM2	15	0.994	0.000
Pair 3			
MO3 & UM3	15	0.892	0.000
Pair 4			
UM1 & UM2	15	0.871	0.000
Pair 5			
UM1 & UM3	15	0.633	0.011
Pair 6			
UM2 & UM3	15	0.925	0.000

through dynamic fuzzy clustering, a specific group with similar perception patterns to the individual is obtained, and the membership degree of the design elements to the Kansei words is calculated based on the Kansei evaluation data of the group and their Kansei variance in the basic-emotion dimensions. Finally, fuzzy logic operations are introduced to transform the individual's Kansei needs into visual design elements. The results show that the proposed method has high accuracy and great potential in handling the differences of individual Kansei.

In the case study, the data confirm that the customers in the same market segment do exist individual differences in Kansei terms. Although the validation process has only twelve participants, combining the participants in previous evaluation data, the results are still statistically significant and can illustrate the problem of individual Kansei variance. And the successful prototype application of this method in an actual project also illustrates this point. Regarding the difference between participant 3's Kansei evaluation and model's output in the "fashion" dimension, the interviews after the experiment found that participant 3's occupation is a fashion designer and has his own unique insights into "fashion". There are fewer samples in the existing data set that have similar personal characteristics to participant 3, which results in the model's failure to accurately predict the participant 3's perception pattern. The follow-up can be solved by enlarging the sample size. In addition, the interviews found that customers generally have a strong sense of design elements with distinctive styles (such as design element No. 30), and Kansei evaluation data in this part often have a better degree of distinction. However, there may be "passivation" phenomenon for more common or well-regulated design elements (such as design element No. 19), which leads to insufficient discrimination of Kansei evaluation data for this part of design elements. To further improve the practicality of the model, it is strongly recommended to dynamically remove some design elements that are not highly distinguishable through multiple iterations.

Needless to say, this method also has some limits. The interpretation accuracy of Kansei needs is more dependent on the completeness and coverage of the Kansei evaluation data, and the perception pattern of the customer may also gradually change with the social development and changes in the market environment. It is very time-consuming to obtain Kansei evaluation data by means of traditional market research and cannot guarantee the timeliness of the data. In the future, we can use the social platform or crowdsourcing to achieve rapid data collection in a reasonable business

Table 4 Paired-samples *T* test of the model's prediction results and participants' own evaluation

	Paired differences					*t*	*df*	Sig. (2-tailed)
	Mean	Std. deviation	Std. error mean	95% confidence interval of the difference				
				Lower	Upper			
Pair 1								
MO1—UM1	0.01600	0.05040	0.01301	− 0.01191	0.04391	1.230	14	0.239
Pair 2								
MO2—UM2	− 0.00133	0.03441	0.00888	− 0.02039	0.01772	− 0.150	14	0.883
Pair 3								
MO3—UM3	− 0.08600	0.18019	0.04652	− 0.18579	0.01379	− 1.848	14	0.086
Pair 4								
UM1—UM2	− 0.08467	0.15014	0.03877	− 0.16781	− 0.00152	− 2.184	14	0.046
Pair 5								
UM1—UM3	− 0.17467	0.30608	0.07903	− 0.34417	− 0.00517	− 2.210	14	0.044
Pair 6								
UM2—UM3	− 0.09000	0.16186	0.04179	− 0.17964	− 0.00036	− 2.153	14	0.049

model, which can also serve the entire design industry and has broad application prospects. On the other hand, the proposed method only solves the visual presentation of the individual's Kansei needs, and how designers understand these design elements and correctly use them for experience design needs more research in the future.

Also, everything has two sides. Although individual Kansei variance does bring trouble to the Kansei mapping patterns mining, the Kansei dimensions or design elements that are more prominent in individual Kansei variance just provide references for the further digging of user's needs through focus groups. And these are also places that designer can put forth the effort to carry out personalised customisation or differentiated design.

This paper mainly takes the automotive industry as the research background, while the issue of individual Kansei variance is often common. For those non-automotive consumer electromechanical products, although it should be possible to use the same steps to establish a domain-related FCM, domain-related expertise and regional culture may still affect FCM's ability to deal with the individual Kansei variance in other industries. In summary, those new product development companies and design teams who were conducting emotional design based on Kansei Engineering can gain the following managerial insights: ① They need to pay more attention to the individual Kansei variance in target Kansei needs to avoid inaccurate design directions. ② The perceptual evaluation data collected during the market research and design concept evaluation phase should include not only the mapping relationship between Kansei words and design elements, but also the customers' characteristics and purchasing motives. In addition, the timeliness of the data should be considered in the analysis process. ③ They need to focus on those Kansei needs with individual Kansei variance, as these places contain potential market opportunities.

6 Conclusions

This study aims to establish a set of fuzzy mapping method to transform the individual's Kansei needs into more clear and comprehensible design elements. Considering the individual Kansei variance, a fuzzy mapping method for Kansei needs interpretation is proposed in this work. The method improves the conventional Kansei mapping method by taking customer's characteristics and purchasing motives into consideration for better identifying the individual Kansei variance on Kansei words. It incorporates a fuzzy clustering method and basic-emotion systems to identify Kansei variance and dynamically determine the membership of design elements to Kansei words based on the target customer's characteristics. Therefore, the adjusted membership is obtained, which can be used as a selection criterion of design elements that are highly relevant to individuals and facilitate the understanding of Kansei needs. The model's prediction results and participants' own evaluation have shown a high correlation ($r_{\text{Pair1}} = 0.985$,$r_{\text{Pair2}} = 0.994$,$r_{\text{Pair3}} = 0.892$) on randomly selected design elements and their mean, statistically, have no significant difference ($t_{\text{Pair1}} = 1.230$, $P_{\text{Pair1}}(\text{Sig.}(2-\text{tailed})) = 0.239$; $t_{\text{Pair2}} = -0.150$, $P_{\text{Pair2}}(\text{Sig.}(2-\text{tailed})) = 0.883$; $t_{\text{Pair3}} = -1.848$, $P_{\text{Pair3}}(\text{Sig.}(2-\text{tailed})) = 0.086$) in the case study. The paired-samples T test of experimental data also revealed that the customers in the same market segment ($r_{\text{Pair4}} = 0.871$, $r_{\text{Pair5}} = 0.633$, $r_{\text{Pair6}} = 0.925$) do exist individual differences ($t_{\text{Pair4}} = -2.184$, $P_{\text{Pair4}}(\text{Sig.}(2-\text{tailed})) = 0.046$; $t_{\text{Pair5}} = -2.210$, $P_{\text{Pair5}}(\text{Sig.}(2-\text{tailed})) = 0.044$; $t_{\text{Pair6}} = -2.153$, $P_{\text{Pair6}}(\text{Sig.}(2-\text{tailed})) = 0.049$) in Kansei terms and it appears that the proposed method is promising for handling individual Kansei variance in emotional design.

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References

Ben-Ze'ev A (2000) The subtlety of emotions. MIT Press, Cambridge

Camargo FR, Henson B (2015) Beyond usability: designing for consumers' product experience using the Rasch model. J Eng Des 26:121–139. https://doi.org/10.1080/09544828.2015.1034254

Chang YM, Chen CW (2016) Kansei assessment of the constituent elements and the overall interrelations in car steering wheel design. Int J Ind Ergon 56:97–105. https://doi.org/10.1016/j.ergon.2016.09.010

Childs T, Agouridas V, Barnes C, Henson B (2006) Controlled appeal product design: a life cycle role for affective (Kansei) engineering. In: Proceedings of LCE20060, pp 537–542

Gologlu C, Zurnaci E (2016) An approach for handling individual customer preferences and emotional needs—yielding 3D product assembly generation. Proc Inst Mech Eng Part C J Eng Mech Eng Sci 230:3706–3724. https://doi.org/10.1177/0954406215615910

Guo F, Qu Q-X, Nagamachi M, Duffy VG (2020) A proposal of the event-related potential method to effectively identify kansei words for assessing product design features in kansei engineering research. Int J Ind Ergon 76:102940

Guoyao F (1992) An algorithm for computing the transitive closure of a fuzzy similarity matrix. Fuzzy Sets Syst 51:189–194. https://doi.org/10.1016/0165-0114(92)90191-6

He L, Ming X, Li M, Zheng M, Xu Z (2017) Understanding customer requirements through quantitative analysis of an improved fuzzy Kano's model. Proc Inst Mech Eng Part B-J Eng Manuf 231:699–712. https://doi.org/10.1177/0954405415598894

Hong G, Dean P, Yang W, Tu Y, Xue D (2010) Optimal concurrent product design and process planning based on the requirements of individual customers in one-of-a-kind production. Int J Prod Res 48:6341–6366

Huang YX, Chen CH, Khoo LP (2012a) Kansei clustering for emotional design using a combined design structure matrix. Int J Ind Ergon 42:416–427. https://doi.org/10.1016/j.ergon.2012.05.003

Huang YX, Chen CH, Khoo LP (2012b) Products classification in emotional design using a basic-emotion based semantic differential method. Int J Ind Ergon 42:569–580. https://doi.org/10.1016/j.ergon.2012.09.002

Huang YX, Chen CH, Wang IHC, Khoo LP (2014) A product configuration analysis method for emotional design using a personal construct theory. Int J Ind Ergon 44:120–130. https://doi.org/10.1016/j.ergon.2013.11.005

Jiao JR, Zhang Y, Helander M (2006) A Kansei mining system for affective design. Expert Syst Appl 30:658–673

Kim W, Ko T, Rhiu I, Yun MH (2019) Mining affective experience for a kansei design study on a recliner. Appl Ergon 74:145–153

Lai H-H, Chang Y-M, Chang H-C (2005) A robust design approach for enhancing the feeling quality of a product: a car profile case study. Int J Ind Ergon 35:445–460

Li Z, Tian ZG, Wang JW, Wang WM, Huang GQ (2018) Dynamic mapping of design elements and affective responses: a machine learning based method for affective design. J Eng Des 29:358–380. https://doi.org/10.1080/09544828.2018.1471671

Li Y, Shieh M-D, Yang C-C (2019) A posterior preference articulation approach to Kansei engineering system for product form design. Res Eng Des 30:3–19

Mata MP, Ahmed-Kristensen S, Brockhoff PB, Yanagisawa H (2017) Investigating the influence of product perception and geometric features. Res Eng Des 28:357–379. https://doi.org/10.1007/s00163-016-0244-1

Meng-Dar S, Fang-Chen H (2013) Using FCM clustering for consumer segmentation in Kansei engineering system. Int J Digit Content Technol Appl 7:563–571. https://doi.org/10.4156/jdcta.vol7.issue1.65

Nagamachi M (1995) Kansei engineering: a new ergonomic consumer-oriented technology for product development. Int J Ind Ergon 15:3–11

Novak TP, MacEvoy B (1990) On comparing alternative segmentation schemes: the list of values (LOV) and values and life styles (VALS). J Consum Res 17:105–109

Ota M, Aoyama H (2002) Aesthetic design based on "Kansei Language." Initiatives of precision engineering at the beginning of a millennium. Springer, Boston, pp 917–921

Pine BJ, Pine J (1992) Mass customization. McGraw-Hill Companies, New York

Pine BJ, Pine J, Gilmore JH, Gilmore HW, Books I (1999) The experience economy: work is theatre & every business a stage. Harvard Business School Press, Brighton

Plutchik R (1991) The emotions. University Press of America, Lanham

Sakornsathien K, Sinthupinyo S, Anuntavoranich P (2019) Application of kansei engineering and data mining in developing an ingenious product Co-design system. Int J Mach Learn Comput 9:67–74https://doi.org/10.18178/ijmlc.2019.9.1.767

Shi FQ, Sun SQ, Xu J (2012) Employing rough sets and association rule mining in KANSEI knowledge extraction. Inf Sci 196:118–128. https://doi.org/10.1016/j.ins.2012.02.006

Shieh MD, Yeh YE, Huang CL (2016) Eliciting design knowledge from affective responses using rough sets and Kansei engineering system. J Ambient Intell Humaniz Comput 7:107–120. https://doi.org/10.1007/s12652-015-0307-6

Shimizu Y et al (2004) On-demand production system of apparel on the basis of Kansei engineering. Int J Cloth Sci Technol 16:32–42

Stappers PJ, Lee S, Harada A (2002) Design Based on Kansei. In: Pleasure with products: beyond usability. In: Green WS, Jordan PW, Taylor and Francis Inc, p 212–222

Takenouchi H, Tokumaru M (2017) Kansei retrieval agent model with fuzzy reasoning. Int J Fuzzy Syst 19:1803–1811. https://doi.org/10.1007/s40815-017-0360-8

Wang C-H, Chin H-T (2017) Integrating affective features with engineering features to seek the optimal product varieties with respect to the niche segments. Adv Eng Inform 33:350–359. https://doi.org/10.1016/j.aei.2016.10.002

Wang H, Yang Q (2012) Personalized customization in product design using customer attributes and artificial neural network. Proc Inst Mech Eng Part B J Eng Manuf 226:1416–1420

Wang WM, Wang J, Li Z, Tian Z, Tsui E (2019) Multiple affective attribute classification of online customer product reviews: a heuristic deep learning method for supporting Kansei engineering. Eng Appl Artif Intell 85:33–45

Yang CC (2011) Constructing a hybrid Kansei engineering system based on multiple affective responses: application to product form design. Comput Ind Eng 60:760–768. https://doi.org/10.1016/j.cie.2011.01.011

Yang C-C, Sun C-C, Lin P-J, Tsai C-C (2011) A general framework for Kansei engineering system. Int J Digit Content Technol Appl 5:173–180. https://doi.org/10.4156/jdcta.vol5.issue10.21

Zadeh LA (1988) Fuzzy logic. Computer 21:83–93. https://doi.org/10.1109/2.53

Zhai LY, Khoo LP, Zhong ZW (2009a) A dominance-based rough set approach to Kansei engineering in product development. Expert Syst Appl 36:393–402. https://doi.org/10.1016/j.eswa.2007.09.041

Zhai LY, Khoo LP, Zhong ZW (2009b) A rough set based decision support approach to improving consumer affective satisfaction in product design. Int J Ind Ergon 39:295–302. https://doi.org/10.1016/j.ergon.2008.11.003

Zhou X, Liang H, Dong Z (2017) A personalized recommendation model for online apparel shopping based on Kansei engineering. Int J Cloth Sci Technol 29:2–13. https://doi.org/10.1108/ijcst-12-2015-0137