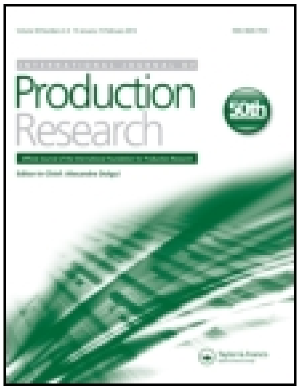

International Journal of Production Research
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tprs20

Incorporating customer satisfaction into the decision-making process of product configuration: a fuzzy Kano perspective

Chih-Hsuan Wang[a]
[a] Department of Industrial Engineering & Management, National Chiao Tung University, Hsinchu, Taiwan.
Published online: 08 Aug 2013.

International Journal of Production Research, 2013
Vol. 51, No. 22, 6651–6662, http://dx.doi.org/10.1080/00207543.2013.825742

Incorporating customer satisfaction into the decision-making process of product configuration: a fuzzy Kano perspective

Chih-Hsuan Wang*

Department of Industrial Engineering & Management, National Chiao Tung University, Hsinchu, Taiwan

(*Received 29 October 2012; final version received 26 June 2013*)

In an era of global customisation, buyers continuously benefit from the flexibility of selecting their desired options when making decisions on purchasing. Most manufacturing companies, however, need to balance the trade-offs between enhancing product variety and controlling manufacturing cost. In order to fulfil the goal of market-oriented product development, customer satisfaction needs to be well incorporated into the decision-making process of product configuration. Therefore, a hybrid framework is presented to address two critical issues in new product development: customer satisfaction and product configuration. In the beginning, fuzzy Kano model is employed to elicit customer perception of product attributes and extract customer satisfaction. Consecutively, information entropy is used for deriving the important weights of product attributes. Lastly, by means of *Technique for Order Preference by Similarity to Ideal Solution*, competing design alternatives are efficiently prioritised and configured. In particular, a case study on configuring varieties of smart pads is demonstrated to justify the validity of the proposed framework. With consideration of and the pricing policies of multi-segments, a systematic framework to effectively bridge customer satisfaction and product configuration is offered for the academics and industrial practitioners.

Keywords: fuzzy Kano model; information entropy; TOPSIS; customer satisfaction; product configuration; smart pads

1. Introduction

Today, remarkable advances in manufacturing technologies coupled with dynamically changing customer desires have urged an enterprise to reconsider their product strategies. Traditionally, companies considered offering products with high quality, low cost, acceptable performance and courteous after-sales service at most, to satisfy market majorities. Nowadays, for acquiring different groups and even for 'customized' individuals, companies think and create different ways to conceive attractive products or services (Kumar, Chen, and Simpson 2009). Although the concept of 'mass customization' embarks a new paradigm for modern manufacturing industries, however, heterogeneous customers are widely scattered in their preferences, buying behaviours, and even social or psychological demographics (Hsiao and Liu 2005). As a result, it is quite challenging for companies to compromise the trade-offs between satisfying diverse customer needs and controlling reasonable manufacturing complexities (Liu and Hsiao 2006).

In reality, an industry paradigm has been recently shifting from 'mass' marketing to 'target' marketing to tackle the aforementioned dilemma (Wang and Chen 2012). Based on the concept of strategic marketing, a so-called segmentation-targeting-positioning approach has been frequently adopted in practice. Based on customer profiles (i.e. affordable prices, gender, demographics and preferences), diverse customers should be previously segmented into *ad hoc* groups. In order to avoid fatal mistakes in product configuration, doubtlessly, customer perception or satisfaction should be tightly incorporated into the entire decision-making process (Askin and Dawson 2000; Krishnan and Ulrich 2001; Kwong, Chen, and Chan 2011). In terms of a market-oriented manner, companies could screen out potential design alternatives, transform alternatives into prototypes and finally launch products to niche segments.

Nevertheless, product configuration is not an easy task because it requires close collaboration across functional departments (Alisantoso et al. 2005). In particular, two activities, such as concept generation and concept evaluation, are recognised to critically influence the eventual success of new product development (Ayağ 2005; Ayağ and Özdemir 2009). Specifically, product configuration which is practically considered as selecting/arranging combinations of components that satisfy given customer needs or design specifications could help an enterprise implement product customisation, particularly with respect to distinct market segments (Sabin and Weigel 1998; Jiao and Tseng 1999).

*Email: chihwang@mail.nctu.edu.tw

Recently, more and more companies start to focus their core competencies on configuring potential product varieties to acquire target segments rather than scattering their limited resources on the whole market (Zhu et al. 2008; Wang and Hsueh, 2013).

To our best knowledge, several schemes including product architecture, product family, product platform and modular design (Kreng and Lee 2004; Hsiao and Liu 2005; Jiao et al. 2007; Kazemzadeh et al. 2009; Kumar, Chen, and Simpson 2009) have been employed to realise cost-effective product configuration (i.e. *developing highly related but differentiated product varieties*). In addition, numerous quantitative techniques, including mathematical programming, multi-criteria decision making and data-mining algorithms, are sorely or conjointly adopted to resolve different domain problems (Agard and Kusiak 2004; Ayağ 2005; Lin et al. 2008; Zhu et al. 2008; Ayağ and Özdemir 2009; Song and Kusiak 2009).

Although numerous methods and studies have been presented to fulfil product configuration, several shortcomings are found and listed as follows:

- The issue of incorporating customer satisfaction into the entire decision-making process of product configuration deserves to be well explored.
- Customer perceived importance weights of product features usually vary a lot from individual to individual and thus, a customer-driven way is necessary to generate these weights.
- Rather than depending on experts' subjective assessments, a market-oriented approach for conducting concept generation and concept evaluation is particularly imperative to capture newly emerging market opportunities.

As indicated by Figure 1, this study attempts to focus on a common business scenario in which customer satisfaction and product configuration are fused together. Without a loss of generality, the entire market is separated into three segments, namely, the low, the medium and the high segment. Apparently, with the consideration of suppliers' manufacturing costs (or customers' affordable prices) and the overall customer satisfaction (OCS), product varieties can be efficiently prioritised and effectively configured with respect to multi-segments. The remaining of this paper is organised as follows. Section 2 briefly overviews Kano model (KM) and it also discusses how customer perception and satisfaction are derived. Section 3 presents the proposed framework through integrating fuzzy Kano model (FKM), information entropy theory with *Technique for Order Preference by Similarity to Ideal Solution* (TOPSIS) ranking. An industrial case study on configuring varieties of smart pads for multi-segments is illustrated in Section 4. Concluding remarks are drawn in Section 5.

2. Overview of KM for capturing customer perception

As indicated by Figure 2, KM originated in 1984 provides a two-dimensional way to characterise the concept of non-symmetric customer perceptions of two scenarios: functional presence (positive delight) and dysfunctional absence (negative disgust). Based on the Kano questionnaire (see Table 1), an invited respondent needs to select one statement among the linguistic terms, such as 'like', 'must-be', 'neutral', 'live-with' and 'dislike', separately for both functional and dysfunctional scenarios. Thereafter, based on Table 2, 25 possible combinations of assessments could be classified into one of the following Kano categories, including attractive (A), one-dimensional (O), must-be (M), indifferent (I), reverse (R) and questionable (Q). For reference, more details of Kano categories are briefly explained below:

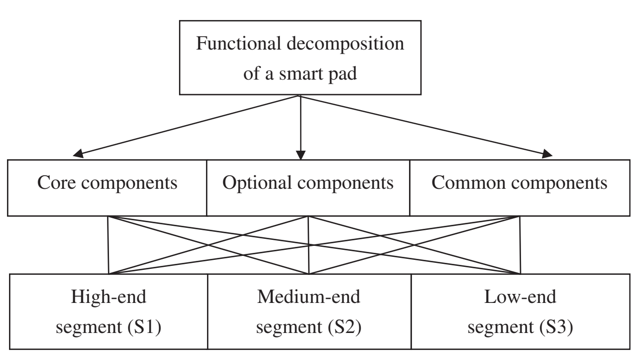

Figure 1. An illustration of product configuration with respect to multi-segments.

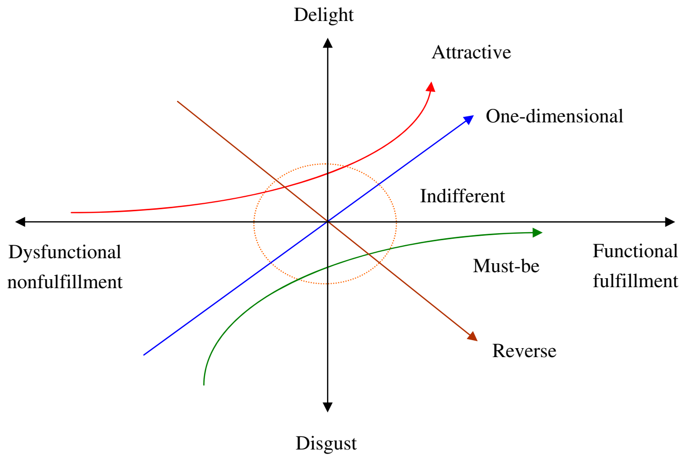

Figure 2. The conventional KM for capturing customer perception.

Table 1. An illustrated Kano questionnaire.

How do you feel about this attribute?		I *like* it that way	It *must be* that way	I am *neutral*	I can *live with* it	I *dislike* it that way
Attribute 1	Functional	√ (100%)				
	Dysfunctional				√ (100%)	
⋮	Functional					
	Dysfunctional					
Attribute *n*	Functional		√ (100%)			
	Dysfunctional					√ (100%)

Table 2. An evaluation summary for Kano classification.

	Dysfunctional absence				
Functional presence	Like (L)	Must-be (M)	Neutral (N)	Live-with (W)	Dislike (D)
Like (L)	*Q*	*A*	*A*	*A*	*O*
Must-be (M)	*R*	*I*	*I*	*I*	*M*
Neutral (N)	*R*	*I*	*I*	*I*	*M*
Live-with (W)	*R*	*I*	*I*	*I*	*M*
Dislike (D)	*R*	*R*	*R*	*R*	*Q*

Notes: *A* = attractive, *I* = indifferent, *M* = must-be, *O* = one-dimensional, *R* = reverse and *Q* = questionable.

- *Must-be* (*M*): The attributes fallen in this category consist of basic criteria of a product since customers will be extremely dissatisfied if attributes are not fulfilled. On the other hand, their fulfilment does not significantly influence satisfaction level since customers take them for granted.
- *One-dimensional* (*O*): This category means that an attribute's functional presence will proportionally increase customer satisfaction while its dysfunctional absence will reversely decrease satisfaction level, concurrently. Obviously, this type of attributes consolidates customer loyalty for companies.
- *Attractive* (*A*): The attributes are acted as a weapon to differentiate companies from their competitors since their fulfilment generates absolute satisfaction. By contrast, customers do not feel dissatisfied when they are not fulfilled.

- *Reverse* (R): The attributes fallen in this category should be removed from a product because its functional presence will decrease customer satisfaction and vice versa.
- *Indifferent* (I): This category means that attributes do not contribute to customer satisfaction at all no matter when they are present or absent in a product.
- *Questionable* (Q): This category implies that either the questionnaire is sent incorrectly or an illogical response is given by a respondent.

Recently, KM has been widely applied to solve different problems. Lee, Sheu and Tsou (2008) integrated quality function deployment (QFD) (Akao 1990) with FKM to carry out product lifecycle management. Delice and Güngör (2011) combined mixed integer goal programming with KM to optimise the parameters of the QFD in which the values of design requirements are discrete. To understand more details for tracking the research trend of KM, interested reads can refer to a state-of-art review offered by Rashid (2010). Moreover, Ullah and Tamaki (2011) presented an approach to fuse information contents of customer answers, especially in dealing with the imprecision and uncertainty in customer response. Despite the KM has been widely applied to various domains, it is difficult to be equipped with quantitative assessments in practice (Wang and Ji 2010). Intuitively, better performance ought to lead to greater customer satisfaction. Based on this concept, Tan and Shen (2000) measured the relationship between product performance and customer satisfaction by using Equation (1):

$$\Delta S/S = k\ (\Delta P/P), \tag{1}$$

where S stands for customer satisfaction; P means product performance; and k is a proportional constant. Here, for 'must-be' features, $0 < k < 1$; for 'one-dimensional' features, $k = 1$; and for 'attractive' attributes, $k > 1$.

Furthermore, Kwong, Chen and Chan (2011) suggested using a non-linear function to characterise the OCS:

$$\text{OCS} = \left(\sum_i \omega_i y_i^s\right)^s + \sum_j \omega_j y_j + \left(\sum_k \omega_k y_k^{1/t}\right)^t, \tag{2}$$

where i, j and k represents the category of 'attractive', 'one-dimensional' and 'must-be'; $y_i/y_j/y_k$, respectively, stands for associated satisfaction degrees of above-mentioned categories; and $\omega_i/\omega_j/\omega_k$, respectively, means the weights of product features of above-mentioned categories. Followed by Berger et al. (1993), Matzler and Hinterhuber (1998), Wang and Ji (2010) and Delice and Güngör (2011), positive delight (d_j^+) and negative disgust (d_j^-) are slightly modified and derived as:

$$d_j^+ = \frac{A_j + O_j - R_j}{A_j + O_j + M_j + R_j + I_j}, \tag{3}$$

$$d_j^- = -\frac{O_j + M_j - R_j}{A_j + O_j + M_j + R_j + I_j}, \tag{4}$$

where A_j, O_j, M_j, R_j and I_j represent attribute j's corresponding percentages of Kano categories. Originally, both Equations (3) and (4) are used to tackle a dichotomous scenario: an optional component is either functional (present) or dysfunctional (absent). For processing multi-levelled core components (i.e. CPU characterised by atom, dual or quad cores), the aforementioned concepts need to be further generalised. Referring to Figure 3, attribute j's satisfaction degree (S_j) is derived as:

$$S_j = p_j d_j^+ + (1 - p_j) d_j^-, \tag{5}$$

where attribute j's functional performance (p_j) is normalised as a value greater than zero but less than or equal to unity. Then, attribute j's satisfaction degree (S_j) is generated through interpolating the two end points, namely, full performance associated with positive delight ($(1, d_j^+)$) and zero performance associated with negative disgust ($(0, d_j^-)$). Obviously, S_j is obtained by using a weighted average between positive delight (d_j^+) and negative disgust (d_j^-).

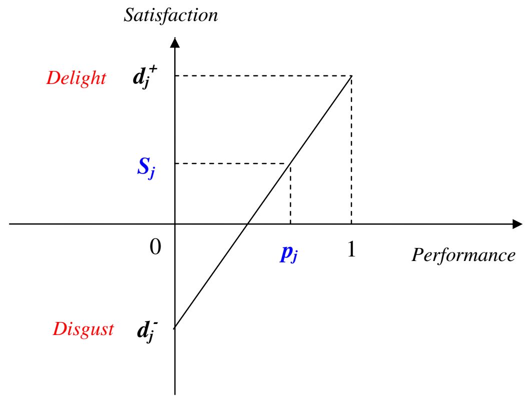

Figure 3. A plot to convert an attribute's performance into its satisfaction degree.

3. The proposed techniques for product configuration

A hybrid framework which combines fuzzy Kano model (FKM), information entropy, with TOPSIS ranking, as shown in Figure 4, is proposed and its operation procedures are briefly described below:

- In the beginning, FKM is employed to gather customers' perceptions of product attributes and then transform an attribute's performance rating into its associated satisfaction degree (see Section 3.1).
- Secondly, when attributes' percentages among Kano categories are obtained, information entropy is applied to their discrete distribution for deriving the importance weights of product attributes (see Section 3.2).
- Lastly, by the virtue of the TOPSIS, a market-oriented process is offered to efficiently prioritise design alternatives for multi-segments (see Section 3.3).

3.1 *Use of FKM to elicit customer perception of product attributes*

Since traditional Kano model (TKM) is deficient in processing human vagueness and uncertainties, the concept of fuzzy set theory is incorporated into KM to accommodate linguistic properties of subjective and vague human perception (Lee, Sheu, and Tsou 2008; Lee and Huang 2009; Wu and Wang 2012). In practice, FKM has been found that it is more capable to mimic a realistic cognition process since an evaluator's multi-feelings could be expressed by the possibility degrees among multiple items. For instance, in terms of five linguistic items (e.g. 'like', 'must-be', 'neutral', 'live-with' and 'dislike'), an evaluator is consulted and required to express his/her multi-feelings for two scenarios of product attributes: functional presence and dysfunctional absence. Then, the normalisation process will be applied to confirm that the sum of possibility degree among multiple answers equals unity. Apparently, human ambiguity or multi-feelings (uncertainties) are reserved during the process of assessment. For convenience, let us use a five-element row vector to display an evaluator's multi-feelings.

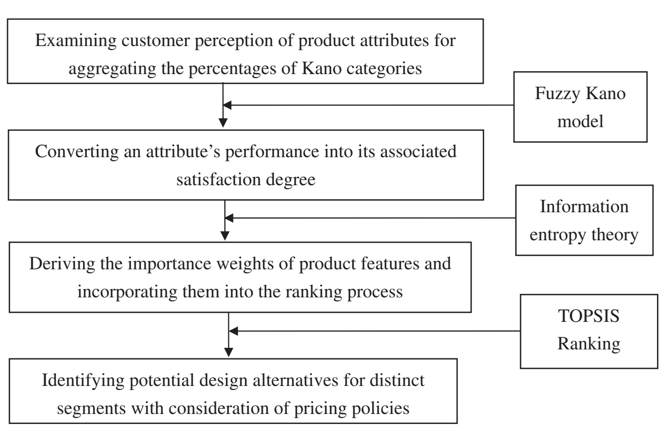

Figure 4. The proposed research framework.

For the TKM (see Table 1 again), a crisp scale is described by *fun* = (1, 0, 0, 0, 0) and *dys* = (0, 0, 0, 1, 0). While for the FKM (see Table 3), a fuzzy scale is depicted by *fun* = (0.75, 0, 0.25, 0, 0) and *dys* = (0, 0, 0.1, 0.8, 0.1). By the use of matrix algebra, a 5 × 5 fuzzy relation matrix R is obtained via $(fun)^t \times (dys)$, where a superscript t denotes the transpose operation:

$$R = \begin{bmatrix} 0 & 0 & 0.075 & 0.6 & 0.075 \\ 0 & 0 & 0.025 & 0.2 & 0.025 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{6}$$

After a relation matrix R is obtained, the identification of Kano category for each attribute is based on Table 2. For convenience, a two-dimensional Kano classifier is represented by using a matrix form:

$$\text{Kano} = \begin{bmatrix} Q & A & A & A & O \\ R & I & I & I & M \\ R & I & I & I & M \\ R & I & I & I & M \\ R & R & R & R & Q \end{bmatrix} \tag{7}$$

And the possibility degree among various Kano categories (i.e. attractive, must-be, one-dimensional, indifferent, reverse and questionable) is extracted as follows:

$$\text{possibility} = \left\{ \frac{0.675}{A}, \frac{0.025}{M}, \frac{0.075}{O}, \frac{0.225}{I}, \frac{0}{R}, \frac{0}{Q} \right\} \tag{8}$$

Once the possibility degree of each attribute is gathered from all respondents, its mean value is aggregated and extracted for deriving their importance weights.

3.2 *Use of information entropy to derive the importance weights of product attributes*

Entropy, originated from information theory, has become a powerful index to measure the information content of uncertain message. Suppose the uncertainty of the information is represented by a discrete probability distribution composed of k categories like $(p_1, p_2, \cdots p_k)$, a distribution with larger variations among all p_i's $(1 \le i \le k)$ contains more uncertainties than a distribution with small variation (Hwang and Yoon 1981). Theoretically, information entropy was measured as:

$$E(p_1, p_2, \ldots p_k) = -\phi_k \sum_{i=1}^{k} p_i \ln p_i, \tag{9}$$

where $\phi_k = 1/\ln(k)$ is a positive constant to guarantee that the entropy will be confined to the interval of [0,1]. Apparently, the larger the entropy is, the less information it contains. One extreme shows that 'zero' entropy means maximum information whereas 'unit' entropy implies minimum information. In this study, to form a discrete

Table 3. An illustrated questionnaire applied to FKM.

How much possibility do you feel about this attribute?		I *like* it that way	It *must be* that way	I am *neutral*	I can *live with* it	I *dislike* it that way
Attribute 1	Functional	75%	25%			
	Dysfunctional			10%	80%	10%
⋮	Functional					
	Dysfunctional					
Attribute *n*	Functional	30%	55%	15%		
	Dysfunctional				35%	65%

distribution, 'information entropy' is applied to each attribute to obtain the percentages among various Kano categories (see Table 3 again). And the importance weights of an attribute could be derived as (Chan et al. 1999):

$$w_j = \frac{1 - E(x_j)}{\sum_j (1 - E(x_j))}, \tag{10}$$

where $E(x_j)$ denotes the entropy of attribute j. Again, when an attribute possesses small variation (i.e. balanced distribution) among Kano categories, it gives rise to more information entropy (lower importance weight) and vice versa.

3.3 *Use of TOPSIS to determine priorities of design alternatives*

TOPSIS was originally proposed by Hwang and Yoon (1981). It was originally devised to seek an optimal solution closest to the positive ideal solution ('PIS') while farthest from the negative ideal solution ('NIS'). Suppose there are m alternatives and n features (attributes), the TOPSIS is operated by the following procedures (Lin et al. 2008):

- Generating a decision matrix: A $m \times n$ decision matrix (i.e. m represents the number of alternatives and n denotes the number of attributes) X comprising the elements of x_{ij} represents the performance rating of the ith alternative with respect to the jth attribute.
- Construing a normalised decision matrix: To reduce the scale effect among multiple dimensions, the normalised matrix Y is obtained as:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad i = 1, \ldots m; \; j = 1 \ldots n, \tag{11}$$

- Searching for the elements of 'PIS' (S^+) and 'NIS' (S^-) by using:

$$S_j^+ = \left\{ \underset{i}{Max} \quad y_{ij} \,|\, j = 1, 2, \ldots, n \right\}, \tag{12}$$

$$S_j^- = \left\{ \underset{i}{Min} \quad y_{ij} \,|\, j = 1, 2, \ldots n \right\}, \tag{13}$$

  where S_j^+/S_j^- denote the jth element of S^+/S^-, respectively. Here, the 'benefit' attributes have the property of 'the-larger-the-better' while the 'cost' attributes own the characteristic of 'the-smaller-the-better'.

- Measuring a weighted distance from alternative i to the 'PIS' and the 'NIS':

$$dis_i^+ = \sqrt{\sum_{j=1}^{n} w_j \times (y_{ij} - S_j^+)^2}, \quad i = 1, 2, \ldots m \tag{14}$$

$$dis_i^- = \sqrt{\sum_{j=1}^{n} w_j \times (y_{ij} - S_j^-)^2}, \quad i = 1, 2, \ldots m, \tag{15}$$

  where w_j represents the importance weight of attribute j.

- Conducting a priority index (PI) for competing design alternatives:

$$PI_i = \frac{dis_i^-}{dis_i^+ + dis_i^-}, \quad i = 1, 2, \ldots m \tag{16}$$

In this study, competing design alternatives are assessed with respect to multidimensional 'satisfaction degree' of product attributes. Intuitively, the 'PIS' and 'NIS' could be obtained by the following:

$$S^{+} = \{d_1^{+}, d_2^{+}, \cdots d_n^{+}\}, \quad S^{-} = \{d_1^{-}, d_2^{-}, \cdots d_n^{-}\}, \tag{17}$$

where d_j^{+}/d_j^{-} $(1 \leq j \leq n)$ means positive delight/negative disgust of attribute j, respectively. Again, recall that the weights of product attributes (w_j) are extracted through information entropy (see Equation (10)) and incorporated into the TOPSIS ranking.

4. An illustrative example

In recent years, the market shares of smart-phone vendors have dramatically fluctuated, especially when wireless technology has shifted from the second generation to the third generation (Işıklar and Büyüközkan 2007). Meanwhile, the boundary between smart phones, smart cameras and smart pads is now becoming much more blurred than before and this implies that these products are functionally replaceable to some degree. For instance, the popularity of smart phones results in decreasing sales of digital cameras, significantly. On the contrary, smart pads also give rise to increasing sales of large-screen-sized smart phones (Wang and Hsueh, forthcoming). In order to capture customer perception more precisely, a large-scale Taiwanese OEM/ODM company plans to implement a thorough marketing survey prior to launching its next-generation smart pads. After consulting experienced focus groups, a smart pad is functionally characterised by three types of components, namely, core components (A1–A5), optional components (A6–A10) and common components (A11–A12), and their specifications are briefly shown in Table 4.

Generally, core components consist of multi-levelled specifications (limited flexibility) while optional components are fully adaptive (e.g. presence or absence). It is noted that common components are necessarily configured from segment to segment (unified specification). With consideration of specific levels and flexible options of product features, there are up to 2304 design alternatives ($3^2 \times 2^4 \times 2^4$) to be possibly generated. Obviously, determining the priorities of competing alternatives with respect to multi-segments is critically important for this company to select potential prototypes. After considering the manufacturing costs of product components as well as pricing policies of multi-segments, this company can assess competing alternatives for acquiring distinct groups (i.e. low/medium/high segment).

Suppose there are m design alternatives and n product attributes, a multi-attributed 'overall customer satisfaction' is defined as:

Table 4. Representative product attributes for characterising a smart pad.

	Description	Specification	Cost (in $TWD)
Core components	A1 CPU type	Atom (A11)	990
		Dual (A12)	1980
		Quad (A13)	4550
	A2 Memory capacity	4 GB (A21)	550
		8 GB (A22)	1050
	A3 Panel size	8 inch (A31)	890
		10 inch (A32)	1150
	A4 Battery capacity	3000 mAH (A41)	780
		5500 mAH (A42)	2040
	A5 Camera pixels	200 M (A51)	650
		300 M (A52)	800
		500 M (A53)	1150
Optional components	A6 Keyboard docking	Present/absent	1980
	A7 GPS chip	Present/absent	840
	A8 DVB chip	Present/absent	1250
	A9 Scratch proof	Present/absent	1020
	A10 Digital compass	Present/absent	650
Common components	A11 WiFy chip	Required	480
	A12 Gravity sensor	Required	280

$$\mathrm{OCS}_i = \{w_1 S_1, \cdots, w_j S_j, \cdots w_n S_n\}, \quad i = 1 \ldots m,\ j = 1 \ldots n, \tag{18}$$

$$p_j = \sum_k x_{jk}\, p_{jk}, \quad x_{jk} \in \{0, 1\},\ \sum_k x_{jk} = 1,\ j \in \{\text{core components}\}, \tag{19}$$

$$p_{jk} = \frac{p_{jk}}{\max_k p_{jk}}, \text{ belonging to the ‘benefit’ attributes (the-larger-the-better)}, \tag{20}$$

$$p_{jk} = \frac{\min_k p_{jk}}{p_{jk}}, \quad \text{belonging to the ‘cost’ attributes (the-smaller-the-better)}, \tag{21}$$

$$p_j = y_j, \quad y_j \in \{0, 1\}, \quad j \in \{\text{optional components}\}, \tag{22}$$

$$p_j = z_j, \quad z_j = 1, \quad j \in \{\text{common components}\}, \tag{23}$$

$$\sum_j \left(a_{jk} x_{jk} + b_j y_j + c_j z_j\right) \leq B_s, \tag{24}$$

where w_j means attribute j’s weight; p_j denotes its normalised performance; and S_j stands for an associated satisfaction degree (see Equation (5) again). Moreover, the symbols of $a_{jk}/b_j/c_j$ represent manufacturing costs of core/optional/common components, respectively, and B_s is the budget constraint for a target segment. Apparently, common components are not involved in the OCS (because of no option) although they do contribute to the manufacturing costs of a product alternative. In brief, design alternatives are assessed through compromising the trade-offs between maximising OCS and minimising total manufacturing costs.

4.1 *Marketing planning through employing FKM*

Initially, a couple of two-dimensional Kano questionnaires (see Table 3 again) were sent to invited respondents to examine their perceptions of product features for characterising an ideal smart pad. Actually, the invited respondents were acted as experienced users (similar to a focus group) to carry out marketing surveys. Instead of using a crisp rating scale in the conventional KM, this study adopts FKM to express respondents’ multi-feelings in terms of the possibility degrees among the multiple items (i.e. ‘like’, ‘must-be’, ‘neutral’, ‘live-with’ and ‘dislike’). Once all evaluators completed their surveys on product attributes, the results are aggregated and displayed in Table 5. For instance, attribute A1 (CPU type) is concluded as 26% ‘attractive’, 63% ‘one-dimensional’ and 11% ‘must-be’, and similar explanations could be applied to the other product attributes.

Subsequently, based on the percentages among discrete Kano categories, the importance weights of product attributes are derived using information entropy (see Equations (9) and (10)). Specifically, the top six priorities present an order of

Table 5. Experimental results through employing FKM.

	A (%)	O (%)	M (%)	I	R	Q	Delight	Disgust	Entropy	Weights	Rank
A1	26	63	11				0.890	−0.740	0.805	0.119	4
A2	12	64	24				0.760	−0.880	0.803	0.120	3
A3	13	62	25				0.750	−0.870	0.827	0.106	5
A4	8	43	49				0.510	−0.920	0.832	0.102	6
A5	10	52	38				0.620	−0.900	0.854	0.089	7
A6	58	36	6				0.940	−0.420	0.776	0.137	2
A7	8	28	64				0.360	−0.920	0.768	0.142	1
A8	52	33	15				0.850	−0.480	0.902	0.060	9
A9	18	54	28				0.720	−0.820	0.908	0.056	10
A10	46	42	12				0.880	−0.540	0.888	0.068	8

Table 6. The top three priorities of product varieties for three segments (in $TWD).

	S1 (Low < $5000)			S2 (Medium < $10,000)			S3 (High < $15,000)		
	#1	#2	#3	#1	#2	#3	#1	#2	#3
A1	A11	A11	A11	A11	A11	A11	A12	A13	A13
A2	A21	A21	A21	A22	A22	A22	A22	A22	A22
A3	A32	A31	A31	A32	A31	A32	A32	A31	A31
A4	A41	A41	A41	A41	A41	A41	A42	A41	A42
A5	A51	A52	A51	A51	A52	A53	A53	A53	A53
A6				√	√	√	√	√	√
A7					√	√	√	√	√
A8				√			√	√	
A9				√	√		√	√	√
A10				√	√	√	√	√	√
A11	√	√	√	√	√	√	√	√	√
A12	√	√	√	√	√	√	√	√	√

$A7 \succ A6 \succ A2 \succ A1 \succ A3 \succ A4$ and this indicates that significant core or optional attributes for configuring a smart pad include CPU type, memory storage, panel size, battery capacity, GPS navigation and keyboard docking. In reality, a smart pad has been perceived as a multifunctional product which supports multimedia entertainment, social media and wireless transmission, concurrently. For an attribute, both positive delight for functional presence and negative disgust for dysfunctional absence are derived through its discrete percentages of Kano categories (Equations (3) and (4)).

4.2 *Product configuration through prioritising OCS*

After an attribute's performance is converted into associated satisfaction degree (see Equation (5)), competing design alternatives comprising various combinations of product attributes can be systematically assessed after considering different pricing policies of multi-segments. As it is mentioned earlier, the entire market is divided into three segments (i.e. low end, medium end and high end), based on customers' affordable prices. With the aid of the TOPSIS, the top three priorities of design alternatives for distinct market segments are derived and shown in Table 6.

After looking at the details of Table 6, let us take a glance at the current business scenario for justifying the validity of our experimental results. For the core components (A1–A5), memory capacity (A2) can distinguish the low end from the other segments. Besides, either 'Dual CPU' or 'Quad CPU' is merely accepted by the high-end segment because of its larger component cost. In the future, high-performed CPUs will be gradually popular once their component costs have been significantly reduced. For simplicity, similar explanations can be generalised to other core components.

For the optional components (A6–A10), no attributes are suggested to be configured in the low-end segment. On the contrary, owing to their maximal budget constraint, all attributes are almost recommended to be configured in the high-end segment. In particular, both keyboard docking (A6) and digital compass (A10) are favoured by the medium-end and the high-end segments, simultaneously. Apparently, through making the trade-offs among product attributes, customer satisfaction has been effectively incorporated into the entire decision-making process of product configuration; no matter it is used for extracting the importance weights of product attributes or determining the priorities of design alternatives. More importantly, in terms of a customer-driven manner, the presented approach is capable to help smart-pad companies visualise the relative strengths of competing design alternatives.

5. Concluding remarks

In order to survive in a wide spectrum of 'buyer-dominated' market, most brand companies need to tackle a dilemma between increasing product varieties (enhancing customer satisfaction) and controlling manufacturing costs. Despite many schemes (i.e. product family architecture, platform-based development and multiple product design) have been proposed, the front-end issues like customer preference and customer satisfaction are rarely addressed and incorporated into the decision-making process of product configuration. In addition, the weights of product features and the priorities of design alternatives are usually reliant on experts' subjective assessments rather than conducting themselves in a customer-driven way. One of the main reasons might be owing to the difficulties in extracting inherent customer attitude, particularly when human perception is psychologically subjective, uncertain and diverse among individuals. Consequently, this study presents an integrated framework combining FKM, information entropy theory with TOPSIS ranking, to fulfil the goal of 'market-oriented' product configuration.

In particular, an industrial case study on configuring varieties of smart pads has been justified to validate the applicability of the proposed framework. Based on the experimental results, this paper attempts to contribute to this field through demonstrating the following merits:

- FKM is effectively employed to capture vague customer perceptions of product attributes and convert an attribute's performance into its associated satisfaction level.
- In terms of a data-driven manner, information entropy is applied to attributes' discrete percentages among Kano categories to derive their importance weights.
- By virtue of TOPSIS, competing design alternatives with respect to multi-segments are efficiently prioritised through maximising OCS as well as considering an enterprise's distinct pricing policies.

In this study, it is noted that two limitations are listed below. First, based on customers' affordable prices, the entire market is simply divided into three segments. Second, a target product (smart pad) is characterised by 'functional' components without taking 'aesthetic' factors (i.e. form, style, colour, etc.) into account. In future studies, customer preferences may be considered as segmentation variables to group diverse customers. Furthermore, in addition to KM, other schemes like QFD (Akao 1990) and Kansei engineering (Nagamachi 1995) can be applied to incorporate customer-affective needs into the process of customer requirement management.

Acknowledgements

The author particularly thanks two anonymous referees' constructive comments. This paper is financially supported by Taiwan National Science Council under Grant NSC-101-2410-H-009-002.

References

Agard, B., and A. Kusiak. 2004. "Data-mining Based Methodology for the Design of Product Families." *International Journal of Production Research* 42 (15): 2955–2969.

Akao, Y. 1990. *Quality Function Deployment: Integrating Customer Requirements into Product Design*. Cambridge, MA: Springer.

Alisantoso, D., L. P. Khoo, B. H. Lee, and S. C. Fok. 2005. "A Rough Set Approach to Design Concept Analysis in a Design Chain." *International Journal of Advanced Manufacturing Technology* 26 (5–6): 427–435.

Askin, R. G., and D. W. Dawson. 2000. "Maximizing Customer Satisfaction by Optimal Specification of Engineering Characteristics." *IIE Transactions* 32 (1): 9–20.

Ayağ, Z. 2005. "A Fuzzy AHP-based Simulation Approach to Concept Evaluation in a NPD Environment." *IIE Transactions* 37 (4): 827–842.

Ayağ, Z., and R. G. Özdemir. 2009. "A Hybrid Approach to Concept Selection through Fuzzy Analytic Network Process." *Computers & Industrial Engineering* 56 (1): 368–379.

Berger, C., R. Blauth, D. Boger, C. Bolster, G. Burchill, W. DuMouchel, F. Pouliot, et al. 1993. "Kano's Method for Understanding Customer-defined Quality." *Center for Quality of Management Journal* 2 (4): 3–35.

Chan, L. K., H. P. Kao, A. Ng, and M. L. Wu. 1999. "Rating the Importance of Customer Needs in Quality Function Deployment by Fuzzy and Entropy Methods." *International Journal of Production Research* 37 (11): 2499–2518.

Delice, E. K., and Z. Güngör. 2011. "A Mixed Integer Goal Programming Model for Discrete Values of Design Requirements in QFD." *International Journal of Production Research* 49 (10): 2941–2957.

Hsiao, S. W., and E. Liu. 2005. "A Structural Component-based Approach for Designing Product Family." *Computers in Industry* 56 (1): 13–28.

Hwang, C. L., and K. Yoon. 1981. *Multiple Criteria Decision Making: Methods and Applications*. New York: Springer-Verlag.

Işıklar, G., and G. Büyüközkan. 2007. "Using a Multi-criteria Decision Making Approach to Evaluate Mobile Phone Alternatives." *Computers Standards & Interfaces* 29 (2): 265–274.

Jiao, J., and M. M. Tseng. 1999. "A Methodology of Developing Product Family Architecture for Mass Customization." *Journal of Intelligent Manufacturing* 10 (1): 3–20.

Jiao, J., L. Zhang, T. W. Simpson, and Z. Siddique. 2007. "Product Family Design and Platform-based Product Development: A State-of-the-art Review." *Journal of Intelligent Manufacturing* 18 (1): 5–29.

Kano, N. 1984. "Attractive Quality and Must-be Quality." *The Journal of Japanese Society for Quality Control* 14 (2): 39–48.

Kazemzadeh, R. B., M. Behzadian, M. Aghdasi, and A. Albadvi. 2009. "Integration of Marketing Research Techniques into House of Quality and Product Family Design." *International Journal of Advanced Manufacturing Technology* 41 (9–10): 1019–1033.

Kreng, V. B., and T. P. Lee. 2004. "QFD-based Modular Product Design with Linear Integer Programming – a Case Study." *Journal of Engineering Design* 15 (3): 261–284.

Krishnan, V., and K. T. Ulrich. 2001. "Product Development Decisions: A Review of the Literature." *Management Science* 47 (1): 1–21.

Kumar, D., W. Chen, and T. W. Simpson. 2009. “A Market-driven Approach to Product Family Design.” *International Journal of Production Research* 47 (1): 71–104.

Kwong, C. K., Y. Chen, and K. Y. Chan. 2011. “A Methodology of Investigating Marketing with Engineering for Defining Specifications of New Products.” *Journal of Engineering Design* 22 (3): 201–213.

Lee, Y. C., and S. Y. Huang. 2009. “A New Fuzzy Concept Approach for Kano’s Model.” *Expert Systems with Applications* 36 (3): 4479–4484.

Lee, Y. C., L. C. Sheu, and Y. C. Tsou. 2008. “Quality Function Deployment Implementation Based on Fuzzy Kano Model: An Application in PLM System.” *Computers & Industrial Engineering* 55 (1): 48–63.

Lin, M. C., C. C. Wang, M. S. Chen, and C. A. Chang. 2008. “Using AHP and TOPSIS Approaches in Customer-driven Product Design Process.” *Computers in Industry* 59 (1): 17–31.

Liu, E., and S. W. Hsiao. 2006. “ANP-GP Approach for Product Variety Design.” *International Journal of Advanced Manufacturing Technology* 29 (3–4): 216–225.

Matzler, K., and H. H. Hinterhuber. 1998. “How to Make Product Development Projects More Successful by Integrating Kano’s Model of Customer Satisfaction into Quality Function Deployment.” *Technovation* 18 (1): 25–38.

Nagamachi, M. 1995. “Kansei Engineering: A New Ergonomic Consumer Oriented Technology for Product Development.” *International Journal of Industrial Ergonomics* 15: 3–11.

Rashid, M. M. 2010. “A Review of State-of-art on Kano Model for Research Direction.” *International Journal of Engineering Science and Technology* 2 (12): 7481–7490.

Sabin, D., and R. Weigel. 1998. “Product Configuration Frameworks – a Survey.” *IEEE Intelligent Systems and Their Applications* 13 (4): 42–49.

Song, Z., and A. Kusiak. 2009. “Optimising Product Configuration with a Data-mining Approach.” *International Journal of Production Research* 47 (1): 1733–1751.

Tan, K. C., and X. X. Shen. 2000. “Integrating Kano’s Model in the Planning Matrix of Quality Function Deployment.” *Total Quality Management* 11 (8): 1141–1151.

Ullah, A. M. M. S., and J. Tamaki. 2011. “Analysis of Kano-model-based Customer Needs for Product Development.” *System Engineering* 14 (2): 154–171.

Wang, C. H., and J. N. Chen. 2012. “Using Quality Function Deployment for Collaborative Product Design and Optimal Selection of Module Mix.” *Computers & Industrial Engineering* 63 (4): 1030–1037.

Wang, C. H., and O. Z. Hsueh. 2013. “A Novel Approach to Incorporate Customer Preference and Perception into Product Configuration: A Case Study on Smart Pads.” *Computer Standards & Interfaces* 35 (5): 549–556.

Wang, T., and P. Ji. 2010. “Understanding Customer Needs through Quantitative Analysis of Kano’s Model.” *International Journal of Quality and Reliability Management* 27 (2): 173–184.

Wu, M., and L. Wang. 2012. “A Continuous Fuzzy Kano’s Model for Customer Requirements Analysis in Product Development.” *Proceedings of the Institution of Mechanical Engineers, Journal of Engineering Manufacture* 226 (3): 535–546.

Zhu, B., Z. Wang, H. Yang, R. Mo, and Y. Zhao. 2008. “Applying Fuzzy Multiple Attributes Decision Making for Product Configuration.” *Journal of Intelligent Manufacturing* 19 (5): 591–598.