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Combining fuzzy AHP and fuzzy Kano to optimize product varieties for smart cameras: A zero-one integer programming perspective

Chih-Hsuan Wang[a,*], Juite Wang[b]

[a] Department of Industrial Engineering & Management, National Chiao Tung University, 1001 University Road, Hsinchu 300, Taiwan
[b] Graduate Institute of Technology Management, National Chung Hsing University, 250 Kuo Kuang Road, Taichung 402, Taiwan

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ABSTRACT

In an era of global customization, dominating the majority market with a single product has become increasingly difficult and almost impossible for most companies. In contrast, they must provide various product varieties that attract diverse customers, particularly when acquiring distinct market segments. In practice, however, most companies cannot effectively reduce the gap between customer requirements and design characteristics, although this impacts the profitability and future growth of companies. Meanwhile, companies often get stuck in the trade-offs between enhancing product varieties and controlling manufacturing costs. Accordingly, this paper proposes a hybrid framework that combines fuzzy analytical hierarchy process (AHP), fuzzy Kano model with zero-one integer programming (ZOIP) to incorporate customer preferences and customer perceptions into the decision-making process of product configuration. Specifically, fuzzy AHP is used to extract customer preferences for core attributes while fuzzy Kano model is utilized to elicit customer perceptions of optional attributes. Finally, by virtue of ZOIP, the optimal product varieties (smart cameras) for distinct segments are determined by maximizing overall customer utility (OCU) and taking a firm's pricing policy into account.

1. Introduction

Today, owing to dynamically changing business uncertainties, achieving successful product development for multiple segments is becoming much more challenging than before. Traditionally, companies offered products with high quality, low cost, fast delivery and courteous after-sales service at most to satisfy market majorities. Nowadays, the concept of "mass customization" establishes a new paradigm for modern manufacturing industries since it treats each customer as an individual and provides "tailor-made" featured products that were only offered in the pre-industrial "craft" era [13]. In practice, balancing the trade-off between enhancing product varieties and controlling manufacturing cost, configuring attractive but limited product alternatives and launching them into niche segments has dominated the competition paradigm, particularly when a transition has been shifting from "mass" marketing to "target" marketing [5,13,15]. In particular, when the market becomes saturated (i.e. digital cameras, LCD TVs, and smart phones), brand companies must differentiate themselves from their main competitors.

Reuters News [34] reported one of the astounding news in Eastman Kodak's corporate bankruptcy in 2011 although it is one of the biggest brands in the U.S. Kodak has filed with the U.S. court in Manhattan for bankruptcy protection and plans to significantly shrink its business in the future. Unfortunately, several Taiwanese OEM/ODM camera manufacturers are now incurring huge losses for "*accounts receivable*" because of Kodak's bankruptcy. The digital camera, an ultimate cause of Kodak's decline, was also invented by this company. Most business consultants ascribe Kodak's bankruptcy to one primary driver- "*inability to adapt to the rise of digital photography and the end of film*". Although Kodak invented the digital camera in 1975, it had vacillated for a long time and failed to rapidly switch to digital cameras.

As a matter of fact, four crucial terms are frequently indicated to influence companies' market shares: product, price, place and promotion [17]. Among them, the first two "*P*"s (product and price) are more significant than the latter pair (place and promotion) because both are directly perceived by customers when making their purchase decisions. To significantly lower manufacturing cost (similar to a pricing weapon), brand companies have begun to outsource their manufacturing capacity and even their design capability to Asian partners. Despite the fact that

* Corresponding author. Tel.: +886 3 5712121 57310; fax: +886 3 5722392.
E-mail addresses: chihwang@mail.nctu.edu.tw, chihswang@gmail.com (C.-H. Wang), rdwang@dragon.nchu.edu.tw (J. Wang).

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Table 1
An overall comparison listed in a chronological order.

	Causalities between MRs and ECs	Customer preferences	Customer perceptions	Product configuration	Market segmentation
Askin and Dawson [1]	QFD	Utility theory	N/A	Mathematical programming	N/A
Liu and Hsiao [22]	ANP	N/A	N/A	Goal programming	Customer requirements
Sireli et al. [28]	QFD	N/A	N/A	Statistical testing	N/A
Chen and Chuang [7]	N/A	N/A	Kano model	Taguchi method + GRA	N/A
Lee et al. [19]	QFD	N/A	Fuzzy Kano	N/A	N/A
Lin et al. [21]	AHP	N/A	Not applicable	TOPSIS ranking	N/A
Delice and Güngör [11]	QFD	N/A	Kano model	Mixed integer programming	N/A
Chaudhuri and Bhattacharyya [6]	QFD	Conjoint analysis	N/A	Integer programming	N/A
Kwong et al. [18]	QFD	N/A	Kano model	Genetic algorithm	N/A
Chan et al. [5]	N/A	N/A	N/A	NPCA + genetic algorithm	Customer requirements
Wang and Chen [31]	QFD + fuzzy DEMATEL	N/A	N/A	Linear integer programming	Affordable prices
Wang and Hsueh [32]	DEMATEL	AHP	Kano model	AHP	Customer preferences
Wang and Shih [33]	QFD + DEMATEL	Conjoint analysis	N/A	TOPSIS ranking	Affordable prices
This paper	N/A	Fuzzy AHP	Fuzzy Kano	Zero-one integer programming	Affordable prices

N/A represents not applicable.

greater "product" variety significantly stimulates product sales, brand companies need to balance the trade-off between controlling manufacturing cost and enhancing product variety. In addition to higher manufacturing cost, product varieties also result in several adversities, such as larger inventory cost and longer cycle time [22].

To the best of our knowledge, numerous schemes have been proposed to balance the trade-offs, including product platform architecture [14], product family design [13,24], and data-mining based approaches [1,30]. Nevertheless, most of these merely support manufacturers without taking customer preferences or customer perceptions into account [3]. In a globally customized economy, as it was previously mentioned, this "*supplier-driven*" approach is too risky to achieve successful product development. Consequently, to assist companies in fulfilling multiple product design for distinct segments, this paper presents a framework that quantitatively captures customer preferences and perceptions and fuses them into the *overall customer utility* (OCU). For convenience, an overall comparison between the proposed framework and other previous publications is summarized in Table 1.

Customer preference for a product, by definition, is a reflection of an individual's inner perception [4], especially when a product's capability can be hierarchically decomposed in advance. Without loss of generality, this study partitions the entire market into several *ad-hoc* segments in which consumers' affordable prices and desires for products are jointly considered and quantitatively defined. In particular, this paper offers a systematic approach that allows a company to determine the optimal product varieties with respect to the recognized segments. The contribution of this work is summarized as follows:

- Without loss of generality, product attributes are functionally decomposed into multiple-level core attributes and dichotomous optional attributes for simplifying product complexity,
- A market-oriented approach is presented to quantitatively incorporate customer preferences and customer perceptions into the decision-making process of product development,
- The optimal product varieties for multi-segments are systematically determined with consideration of overall customer utility and a firm's pricing policies.

The remainder of this paper is organized as follows. Section 2 overviews several representative techniques including quality function deployment, conjoint analysis, and Kano model. Section 3 presents the details of the proposed framework. An industrial example for optimizing product varieties of smart cameras for multi-segments is illustrated in Section 4. Conclusions are drawn in Section 5.

2. Literature review

In an era of mass customization, companies must understand what customers need in order to avoid fatal mistakes before product strategies are implemented [10,21]. In practice, ensuring customer satisfaction by offering appropriate product varieties significantly stimulates product sales [29]. A new paradigm named mass customization tries to offer products or services that best fit customer requirements while maintaining near mass production efficiency [15]. In reality, incomplete marketing information or a poor understanding of customers usually result in worse product design, higher manufacturing costs, and longer cycle time. Several common techniques including quality function deployment (QFD), conjoint analysis (CA), and Kano model (KM) have been proposed to reduce the gaps between customer requirements and product varieties (also see Table 2).

Quality function deployment originally proposed by Akao [2] has been widely applied to various industries for translating marketing requirements (MRs) into engineering characteristics (ECs). By considering the inter-dependences between MRs and ECs

Table 2
An overall comparison among QFD, CA, AHP, and Kano model.

	QFD	Conjoint analysis	AHP	Kano model
Basic principle	Transforming MRs into ECs	Balancing the trade-offs among design alternatives	Conducting pair-wise comparisons among alternatives	Expressing two-dimensional perceptions
Handling a hierarchical tree structure	Difficult	Difficult	Good	Difficult
Handling numerous attributes on a hierarchy	Limited	Limited	Limited	Good
Handling multiple-level core attributes	Difficult	Good	Good	Limited
Handling dichotomous optional attributes	Difficult	Limited	Limited	Good

MRs stand for marketing requirements and ECs represent engineering characteristics.

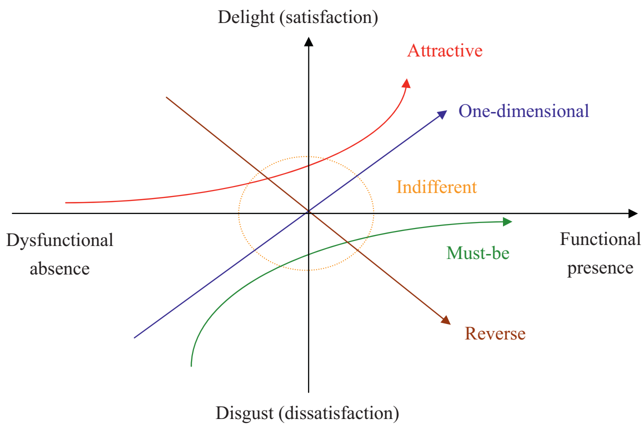

Fig. 1. An illustration of the Kano model.

and their inner-dependences, the conventional QFD generates the priorities of ECs in terms of the weights of MRs. Nevertheless, when a product is characterized by multiple-level core attributes associated with dichotomous optional attributes, the QFD is deficient in optimizing product configuration [31].

Conjoint analysis [23] is, by far, the most popular method used to measure customer preferences for multi-attributed products, brands, service plans. It assumes that the utility of an alternative perceived by a respondent is linearly additive and quantitatively decomposed into observable and random components as:

$$U_{hi} = \beta_0 + \sum_j \beta_j X_{hij} + \varepsilon_{hi} \quad (1)$$

where U_{hi} is respondent is utility of alternative h, ε_{hi} is a random component, X_{hij} denotes attribute js partial worth for alternative h for respondent i, β_0 and β_j are regression coefficients. In reality, CA requires a respondent to make trade-offs among various alternatives that are characterized by multiple attributes and a state-of-the-art review is referred to [12,33]. Obviously, when either product attributes or the associated levels are not limited, it is problematic for a respondent to rank numerous alternatives at the same time. Hopefully, the ranking process of CA can be simplified through fractional factorial design.

The Kano model [16], as shown in Fig. 1, provides a two-dimensional nonlinear approach that expresses customer perceptions: delight for functional presence and disgust for dysfunctional absence. Based on a so-called Kano questionnaire, an invited respondent needs to select one of the following five linguistic terms: "*like*", "*must-be*", "*neutral*", "*live-with*", and "*dislike*", for both the functional and the dysfunctional sides (see Table 3). According to Table 4, all possible combinations of these customer assessments are classified into one of the Kano categories, including attractive, one-dimensional, must-be, indifferent, reverse, and questionable. To understand more details, the readers are suggested to refer to a state-of-art review by Rashid [25]. The properties of Kano categories are briefly explained as follows:

- *Must-be (M)*: an attribute in this category causes extremely dissatisfaction if it is absent, but its presence does not increase the satisfaction level since customers take its presence for granted.
- *One-dimensional (O)*: the functional presence of an attribute in this category increases the satisfaction level and its absence proportionally decreases the satisfaction level.
- *Attractive (A)*: the functional presence of an attribute generates absolutely positive satisfaction while customers are not be dissatisfied when it is absent.
- *Reverse (R)*: an attribute in this category must be removed from a product since its presence is harmful to customer satisfaction.
- *Indifferent (I)*: an attribute in this category does not significantly contribute to customer satisfaction no matter they are present or absent in a product.
- *Questionable (Q)*: this outcome indicates that either the question is described incorrectly, or an illogical response is given by an evaluator.

Recently, several techniques were fused to solve different domain problems (see Table 1 again). For instance, Sireli et al. [28] integrated Kano model with the QFD for multiple product design. Lee et al. [19] suggested using QFD in conjunction with fuzzy Kano model for product lifecycle management. Chauduri and Bhattachayya [6] integrated QFD with integer programming to determine the attribute levels for conjoint study. To enhance customer satisfaction, Chen and Chuang [7] integrated Kano model with GRA (gray relational analysis) into a robust product design. Kwong et al. [18] combined Kano model with nonlinear programming to increase customer satisfaction. Delice and Güngör [11] combined MLIP (mixed integer linear programming) with Kano model to optimize the parameters of QFD in which design requirements are discrete values. As a result of these studies, this paper

Table 3
An illustrated questionnaire applied to the conventional Kano model.

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	√				
	Dysfunctional				√	
	Functional					
	Dysfunctional					
Attribute *n*	Functional		√			
	Dysfunctional					√

Table 4
An evaluation summary for classifying Kano categories.

Functional presence	Dysfunctional absence				
	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*

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

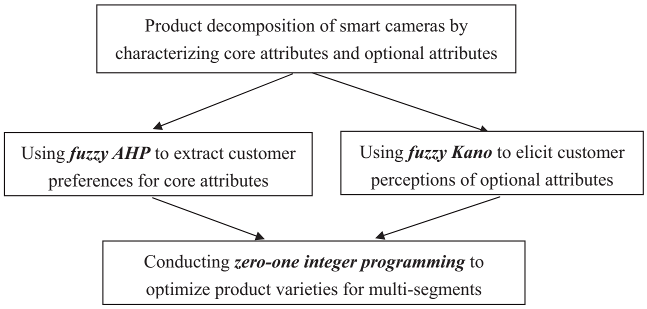

Fig. 2. The proposed approach to optimize product varieties.

proposes a hybrid fuzzy framework and the details are described in Section 3.

3. The proposed techniques

Fig. 2 shows various schemes including fuzzy AHP, fuzzy Kano model and ZOIP to accomplish market-oriented product design. For simplicity, the details are described as follows:

- Fuzzy AHP is used to efficiently extract customer preferences for core attributes that have multiple-level specifications.
- Fuzzy Kano model is utilized to effectively elicit customer perceptions (i.e. delight and disgust) of optional attributes that have dichotomous outcomes.
- Zero-one integer programming is conducted to optimize product varieties by maximizing overall customer utility as well as considering manufacturing costs.

3.1. Using fuzzy AHP to extract customer preferences for core attributes

AHP (analytic hierarchy process) was originally proposed by Saaty [26] back in the early 1970s to address the allocation of scarce resources for the military. In order to accommodate the linguistic nature of human judgments, fuzzy concept is incorporated into the AHP to measure the relative importance degrees (customer preferences) of core attributes and associated levels. Generally, fuzzy AHP [8,9] comprises the following steps:

- Firstly, pairwise comparisons between criteria (core attributes) and sub-criteria and (detail levels) are undertaken. A 5-point fuzzy scale (i.e. *E (equally)*, *S (slightly)*, *M (moderately)*, *T (strongly)*, and *X (extremely)*) expresses uncertain and imprecise preferences for core attributes.
- Secondly, different experts' judgments are aggregated. Suppose S evaluators assess m core attributes and expert k conducts pairwise comparisons by using a fuzzy scale. The relative importance of C_i over C_j is shown by the following fuzzy matrix:

$$S_k = \begin{bmatrix} \tilde{b}_{11k} & \tilde{b}_{12k} & \cdots & \tilde{b}_{1mk} \\ \tilde{b}_{21k} & \tilde{b}_{22k} & \cdots & \tilde{b}_{2mk} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{b}_{m1k} & \tilde{b}_{m2k} & \cdots & \tilde{b}_{mmk} \end{bmatrix} \quad i = 1, 2, \cdots m,$$

$$j = 1, 2, \cdots m, \quad k = 1, 2, \cdots S, \tag{2}$$

Table 5
A random index used by fuzzy AHP.

	Order of matrix (number of criteria)						
n	2	3	4	5	6	7	8
RI	0	0.58	0.90	1.12	1.24	1.32	1.41

where $\tilde{b}_{ijk}$ represents the fuzzy preference of C_i over C_j assessed by evaluator k. Then, experts' decisions are aggregated through Eqs. (3)–(5):

$$\tilde{b}_{ij} = (L_{ij}, M_{ij}, U_{ij})\, \tilde{b}_{ji} = \tilde{b}_{ij}^{-1} = \left(\frac{1}{U_{ij}}, \frac{1}{M_{ij}}, \frac{1}{L_{ij}} \right) \tag{3}$$

$$L_{ij} = \min_k(\tilde{b}_{ijk}),\ M_{ij} = \underset{k}{\mathrm{median}}(\tilde{b}_{ijk}),\ U_{ij} = \max_k(\tilde{b}_{ijk}) \tag{4}$$

$$b_{ij} = \left(\frac{L_{ij} + M_{ij} + U_{ij}}{3} \right), \tag{5}$$

where $\tilde{b}_{ij}$ denotes an aggregated fuzzy number and b_{ij} represents its defuzzified crisp value using the scheme of "center of area" [31].

- Thirdly, the maximum eigenvalue and its corresponding eigenvector are computed in order to estimate the weights of m criteria:

$$A = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1m} \\ b_{21} & b_{22} & \cdots & b_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mm} \end{bmatrix} \tag{6}$$

$$AW = \lambda_{\max} W \tag{7}$$

where A is an $m \times m$ crisp matrix among m attributes, $\lambda_{\max}$ is the largest eigenvalue of matrix A, and W denotes its corresponding eigenvector. In this study, the eigenvector is treated as customer preference (importance weights).

- Finally, the consistency of the matrix is verified. The property of transitivity implies that if $C1$ is preferred to $C2$, and $C2$ is preferred to $C3$, then $C1$ is preferred to $C3$. The consistency index (CI) and consistency ratio (CR) shown below are used to determine the consistency of the decision quality:

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \tag{8}$$

$$CR = \frac{CI}{RI}, \tag{9}$$

where CI represents the inconsistency index (a value closer to zero indicates greater consistency), and RI is a random index (see Table 5). If the value of CR exceeds 0.1, the decision process is deemed to be inconsistent and evaluators must revise their judgments.

3.2. Using fuzzy Kano model to elicit customer perceptions of optional attributes

The original Kano model forces an evaluator to select a single answer that reflects his/her feelings for an attribute, such as "like", "must-be", "neutral", "live-with", and "dislike", in a crisp manner. By contrast, fuzzy Kano model (see Table 6) is good at processing human vagueness and uncertainties, particularly when a respondent has multiple feelings for either functional presence or dysfunctional absence [19,20]. Here, human ambiguity or complex feelings (uncertainties) are expressed by the possibility degrees for deriving positive delight and negative disgust of optional attributes.

Table 6
An illustrated questionnaire applied to fuzzy Kano model.

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%

Let us use a five-element row vector to display an evaluator's feeling for both functional presence and dysfunctional absence. For the Kano model, a crisp scale is described by *fun* = (1, 0, 0, 0, 0) and *dys* = (0, 0, 0, 1, 0) while for the fuzzy Kano, a linguistic scale is depicted by *fun* = (0.75, 0, 0.25, 0, 0) and *dys* = (0, 0, 0.1, 0.8, 0.1). By virtue of matrix algebra, a 5 × 5 fuzzy relation matrix R is obtained via $(\text{fun})^t \times (\text{dys})$, where the superscript t denotes the transpose operation:

$$R = \begin{bmatrix} 0 & 0 & 0.075 & 0.6 & 0.075 \\ 0 & 0 & 0.025 & 0.2 & 0.025 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{10}$$

when the relation matrix R is obtained, a two-dimensional Kano classifier is represented by the following matrix form (see also Table 2):

$$\text{Kano} = \begin{bmatrix} Q & A & A & A & O \\ R & I & I & I & M \\ R & I & I & I & M \\ R & I & I & I & M \\ R & R & R & R & Q \end{bmatrix} \tag{11}$$

The possibility degrees for various Kano categories (i.e. *attractive*, *must-be*, *one-dimensional*, *indifferent*, *reverse*, and *questionable*) are derived as follows:

$$\text{possibility} = \left\{ \frac{0.675}{A}, \frac{0.025}{M}, \frac{0.075}{O}, \frac{0.225}{I}, \frac{0}{R}, \frac{0}{Q} \right\} \tag{12}$$

Notice that the possibility degrees are reserved rather than using the alpha-cut to immediately identify its crisp Kano category. Unfortunately, Kano model has been criticized to be difficult to quantify customer perceptions [27]. In this context, both positive delight (D_i^+) and negative disgust ($D_i{}^-$) are slightly modified and quantitatively derived as follows [11,32]:

$$D_i^+ = \frac{A_i + O_i - R_i}{A_i + O_i + M_i + R_i + I_i}, \tag{13}$$

$$D_i^- = -\frac{O_i + M_i - R_i}{A_i + O_i + M_i + R_i + I_i}, \tag{14}$$

where A_i, O_i, M_i, R_i, and I_i represent the corresponding percentages of responses for various Kano categories. It is noted that the quantitative degrees of delight or disgust are respectively applied to measure customer satisfaction/dissatisfaction with two scenarios: functional presence/dysfunctional absence.

3.3. Using ZOIP to conduct optimal product configuration for various segments

Two critical terms involving customer preferences for core attributes and customer perceptions of optional attributes are fused to maximize overall customer utility (*OCU*). For simplification, the objective *for a specific segment*, decision variables, and cost constraints are described as follows (see Eqs. (15)–(19)):

$$Max \quad \text{OCU} = \sum_i w_{ik} x_{ik} + \sum_j (d_j^+ y_j + d_j^- (1 - y_j)) \tag{15}$$

$$\text{subject to} \quad x_{ik} \in \{0, 1\} \sum_k x_{ik} = 1, i \in \{\text{core attributes}\} \tag{16}$$

$$y_j \in \{0, 1\}, j \in \{\text{optional attributes}\} \tag{17}$$

$$x_{lk} + x_{mk'} \le 1, l, m \in \{\text{core attributes}\} \tag{18}$$

$$\sum_i c_{ik} x_{ik} + \sum_j c_j y_j \le B_s, s \in \{\text{low, medium, high}\} \tag{19}$$

where w_{ik} is customer preference for level k of core attribute i (extracted via fuzzy AHP), and d_j^+/d_j^- represents positive delight/negative disgust with optional attribute j (elicited via fuzzy Kano model). Eq. (18) implies that level k of core attribute l cannot be compatible with level k' of core attribute m in a practical design (exclusive constraint). The manufacturing costs of core/optional attribute i/j are expressed by c_{ik}/c_j, respectively, and B_s represents the pricing policy for a specific segment (e.g. the low/medium/high end segment). Specifically, if $x_{ik} = 1$, level k is selected for core attribute i. Similarly, if $y_j = 1$, optional attribute j is included to fit the target segment.

4. An industrial example

In recent years, owing to the popularity of smart phones, growth in digital cameras has almost ceased or decreased. In the past, brand companies focused on enhancing image resolution or shrinking volume size to improve photo quality or portability. In order to further differentiate themselves from other competitors, companies now attempt to include more attractive features to acquire a greater market share. In the current business environments, it is found that several famous companies, such as Konica-Minolta (merged by Sony in 2006), Kodak (which announced bankruptcy in 2011) and Pentax have gradually withdrawn from this intensively competitive market.

However, Samsung has now become one of the top five camera suppliers by developing various smart cameras. Obviously, the speed with which new products are launched and the ability of controlling manufacturing costs still dominate the key competition rule for these brand companies. To exploit its ability in cost-controlling and manufacturing flexibility, a Taiwanese electronics company is now planning to develop various types of smart cameras to gain more OEM/ODM orders from Japanese or Korean brand companies.

4.1. Using fuzzy AHP and fuzzy Kano to capture customer preferences and perceptions

For simplification, it is assumed that a smart camera is functionally decomposed into multiple-level core attributes and

Table 7
Functional decomposition of a smart camera.

	Specifications	Costs ($TWD)
Core attributes	A1 Static pixels (1400 M/1600 M/1800 M)	550/750/1000
	A2 optical zoom (4–6×/7–10×/12–18×)	500/1000/1800
	A3 wide angle (28–35 mm/25–27 mm/22–24 mm)	400/800/1500
	A4 dynamic video (VGA/720P/1080P)	450/750/1250
	A5 screen size (2.7″/3″/3.3″ in.)	600/950/1300
Optional attributes	A6 high-speed shutter	1400
	A7 touch panel	1000
	A8 dust/water proof	1200
	A9 shock/freeze proof	1100
	A10 GPS tagging	950
	A11 Wi-Fi connectivity	700
	A12 digital compass	650
	A13 barometer	550

Table 8
The extracted customer preferences through fuzzy AHP.

	Specifications	Weights	Priorities
A1 static pixels (0.08)	A11 – 1400 M (0.17)	0.014	13
	A12 – 1600 M (0.387)	0.031	11
	A13 – 1800 M (0.443)	0.036	10
A2 optical zoom (0.365)	A21 – 3–5× (0.11)	0.040	9
	A22 – 7–10× (0.309)	0.113	4
	A23 – 12–18× (0.581)	0.212	1
A3 wide angle (0.304)	A31 – 28–35 mm (0.143)	0.043	8
	A32 – 25–27 mm (0.286)	0.087	5
	A33 – 22–24 mm (0.571)	0.174	2
A4 dynamic video (0.179)	A41 – VGA (0.106)	0.019	12
	A42 – 720P (0.26)	0.047	6
	A43 – 1080P (0.633)	0.114	3
A5 screen size (0.072)	A51 – 2.7 in. (0.175)	0.013	15
	A52 – 3 in. (0.192)	0.014	13
	A53 – 3.3 in. (0.633)	0.045	7

dichotomous optional attributes (see Table 7). During the process of product configuration, core attributes must be selected from the limited specifications but optional attributes are fully flexible to fit the target segment. Prior to demonstrating empirical results, the invited respondents need to be confirmed that they have sufficient knowledge to assess product attributes of smart cameras. To ensure the reliability and credibility of the questionnaires, they undergo a consistence test to filter out self-conflicting samples (using Eqs. (8)–(9)).

As indicated in Table 8, fuzzy AHP is used to extract customer preferences for core attributes and the priorities are in an order: $A2 \succ A3 \succ A4 \succ A1 \succ A5$ (see the values in parentheses). Apparently, customers are concerned more about "optical zoom", "wide angle", and "dynamic video" than "static pixels" and "screen size". Then, fuzzy Kano questionnaires (see Table 6 again) are sent to elicit asymmetric perceptions of optional attributes. Table 9 shows the percentages for Kano categories, which are used to derive the corresponding degrees of delight and disgust (see Eqs. (2)–(3)). Using the range that is defined by "*delight less disgust*" ($D_i^+ - D_i^-$), it is seen that the order: $A8 \succ A9 \succ A7 \succ A10$, shows the top four priorities. In other words, four optional attributes like "dust/water proof", "shock/freeze proof", "touch panel", and "GPS tagging", are more attractive to stimulate product sales.

Table 10
Optimizing product varieties for three market segments.

		M1: *Low-end* ($TWD 6000)	M2: *Medium-end* ($TWD 9900)	M3: *High-end* ($TWD 16,000)
Core attributes	A11	*	*	
	A12			
	A13			*
	A21	*		
	A22		*	
	A23			*
	A31	*		
	A32		*	
	A33			*
	A41	*		
	A42		*	
	A43			*
	A51	*	*	
	A52			
	A53			*
Optional attributes	A6			*
	A7		*	*
	A8	*	*	*
	A9	*	*	*
	A10		*	*
	A11		*	*
	A12	*	*	*
	A13	*	*	*

4.2. *Optimizing product varieties through conducting zero-one integer programming*

Depending on customers' affordable prices, the entire market is specifically divided into three segments: low-end, medium-end and high-end. In order to satisfy diverse requirements for multi-segments, manufacturing companies must provide different product varieties. Again, as shown in Eq. (15), "*overall customer utility*" consists of two components: customer preferences (obtained via fuzzy AHP) and customer perceptions (obtained via fuzzy Kano). By means of ZOIP (see Eqs. (16)–(19)), the optimal product varieties can be systematically determined with consideration of manufacturing cost constraints. The results for three market segments are summarized in Table 10.

For core attributes, all of the lowest and highest specifications are suggested in the low-end and high-end segments, respectively. However, the medium segment requires the lowest specifications for both "static pixels" (A1) and "screen size" (A5) and the medium specification for the other core attributes. Four optional attributes "dust/water proof" (A8), "shock/freeze proof" (A9), "digital

Table 9
The elicited customer perceptions through fuzzy Kano model.

	A	*O*	*M*	*I*	*R*	Delight	Disgust	Range	Priorities
A6	32%	28%	14%	26%		0.6	−0.42	1.02	7
A7	25%	47%	13%	15%		0.72	−0.6	1.32	3
A8	25%	40%	32%	3%		0.65	−0.72	1.37	1
A9	18%	45%	27%	10%		0.63	−0.72	1.35	2
A10	25%	33%	20%	22%		0.58	−0.53	1.11	4
A11	22%	34%	14%	30%		0.56	−0.48	1.04	5
A12	27%	30%	15%	28%		0.57	−0.45	1.02	7
A13	29%	31%	12%	28%		0.6	−0.43	1.03	6

compass" (A12), and "barometer" (A13) are concurrently required by three segments. However, three optional features including "touch panel" (A7), "GPS tagging" (A10) and "WiFi communication" (A11) are only required in the higher segments. Very interestingly, "high-speed shutter" (A6) is only configured in the high-end segment. In the future, more optional attributes can be appended and shifted from the high-end to the low-end when manufacturing costs are decreased.

5. Conclusions

In order to survive in a wide range of market segments, companies must offer sufficient product varieties to satisfy diverse customer needs while maintaining controllable manufacturing complexities. Consumers are usually scattered in the whole market in affordable prices, preference patterns, and their buying behaviors. Consequently, a cost-effective approach that incorporates customer preferences and customer perceptions into the decision-making process of product development has become much more difficult to achieve. Unlike most previous studies, this paper proposes a systematic, quantitative, yet, feasible framework that addresses the aforementioned issues. More importantly, it contributes to this domain by demonstrating the following merits:

- Fuzzy AHP is efficient to extract customer preferences for core attributes associated with multiple levels of specification when a product is functionally characterized.
- Fuzzy Kano model is effective to assist product designers in eliciting customer perceptions of optional attributes that correspond to dichotomous outcomes (i.e. functional presence and dysfunctional absence).
- For acquiring distinct segments, zero-one integer programming is capable to optimize product varieties by maximizing overall customer utility as well as considering a firm's pricing policies.

Depending on consumers' affordable prices, the entire market is partitioned into three distinct segments (low/medium/high). In future studies, market segmentation might be carried out according to customer demographic profiles (i.e. age, gender, occupation, and social status) or preferences for affective features (i.e. form style, body material, and color). Furthermore, other data-mining or soft-computing techniques such as association rule mining, decision tree and rough set could be fused to accomplish multiple product design for the recognized niche segments.

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