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Fuzzy dual experience-based design evaluation model for integrating engineering design into customer responses

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Abstract Experience-based design is a recently emerging method used to capture the emotional content of customer experiences. Both the engineer's experiences and customer's experiences for dual experiences are important in delivering high quality user-centred product design. To assess dual experiential design optimization, fuzzy decision tree and fuzzy cognitive map are integrated in engineering design perspectives. This study aims at optimizing complex interactions and experiential design system with imprecise relationships while quantifying the performance impact of engineering design efficiency on customer satisfaction. The experiment is conducted by utilizing sensitivity analysis of the three degrees of fuzzy membership function using a product mix-experience problem. The evaluation results show that this dual experience-based design approach can help R&D design, deliver high quality product development experiences and co-create value with customers to yield a high performance engineering design.

Keywords Dual experiential design · Fuzzy decision tree ·
Fuzzy cognitive map · Engineering design ·
Interactive design

1 Introduction

Within the user-centered product exploration that typifies modern product development, engineering design faces a number of challenges. Confronted with these challenges, interaction and experience design has become a key issue.

Some previous studies have already purposed experience-centred design (ECD) to increase customer loyalty and thus maximize profits [5,36,47]. Experience-based design is a recently emerging method used to capture the emotional content of customer experiences [26]. When these customer experience methods assist designers to improve the customer satisfaction, they do not consider the consistence of customer's emotional experiential needs and product engineer's experiences. However, both the engineer's experiences and customer's experiences for dual experiences are important in delivering quality user-centered product design. Complementing ECD by considering both customer experience requirements and also engineer's experience factors is a complex and difficult issue, both from engineering design perspectives and from customer responses.

This paper adopts engineering design perspectives from [31], which consist of two perspectives: designer perspective (robust design, design optimisation, design cognition) and customer-centre design (requirements management, ergonomic design). From customer responses' perspectives, customer-centre design represents the front end of the customer requirements and is directly associated with the consumption behaviour. Luh et al. [33] proposed a systematic empathic design method (SEDM) based on participant observation, laddering interviews, implication matrix, hierarchical value maps and mind mapping, in order to develop customer-centered products. Chen et al. [13] explored the possibility and new procedure of applying environment-based design (EBD) to constructing evaluation criteria in AHP. In a product design environment, there is a lack of research considering both engineer's and customer's experience. In other words, the approach links experience and response design with customer satisfaction to ensure high quality product delivery via the design of appropriate interactive activities between engineer's experience and customer's

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experience. Both engineer's experience and customer's experience (dual experiences) stimulate customers with good expectation and enhance customer loyalty through consumption behaviour, then improve customer responses and increase product provider's profitability. Thus, this article adopts two measure metrics: product usability and consumption behavior. The product usability adopts usefulness of a product by [42]. The consumption behaviour adopts the RFM measure. The RFM incorporates three variable values: consumption recent interval (R), frequency (F), and money amount (M). Thus, the product design and customer–engineer interactions have evolved from usability and RFM method to optimize both from engineering design perspectives and customer responses.

The fuzzy decision tree (FDT) and fuzzy cognitive map (FCM) are integrated into dual experienced design optimization. Why FCM and FDT methods are adopted? Because dual experienced design needs structured data of historical cases to support experiential design optimization due to complex decision problems for the dual experience-based design approach. These experiences are representations of a historical decision case that includes the original consumption behaviour, usability attributes of product function from engineering design perspectives. The FDT decision is well suited to develop a forecasting model for generating decision rules in experiential design decisions due to the structure by which experience and new cases are represented. The engineering design perspectives integrate the customer and engineer factors such as designer perspective (robust design, design optimisation, design cognition) and customer-centre design (requirements management, ergonomic design), due to these factors related to experiential design. The uncertainty imposed on these factors to identify the causal relationships among them. For such uncertainty situations, fuzzy cognitive maps (FCM) can deal with complex system [45]. This article proposes the utilization of the fuzzy casual characteristics of FCM and inference mechanism as the underlying approach in order to generate engineering perspectives of design performance impact.

According to the above-mentioned integration between dual experiences and engineering design perspectives, this article proposes a novel approach combining FDT into FCM. This approach concludes that the dual experiences in experiential design create compelling customer responses and aid in the product design of high quality interactions. An increasing efficiency in enhancing customer and engineer interactions with product usability and consumption behaviour has prompted engineering design research that focuses on the importance of the experiential design optimization. In a word, this study accordingly presents a new dual experience-based design approach by using FDT with FCM based on engineering design perspectives and customer responses for optimization. It aims at optimizing complex interaction

and experiential design system with imprecise relationships while quantifying the performance impact of engineering design efficiency for customer satisfaction. To evaluate the proposed approach, this article addresses a linear programming model of the product mix-experience problem considering the proposed approach performance with total profit. The purpose of this evaluation is to help the proposed approach validate the total performance mode selection problem.

More recently, interactive design focuses on users' preferences for product features by product usability, experience and aesthetic quality that they let product influences consumers' attitudes. According to [34] literature, they indicate inactive design needs the "user experience" and aesthetic in interaction because of inconsistency. Thus, experience-based design has made it crucial to apply experience design in the interactive product design. The interactive product design process is developed for a user experience in product design. So that experiential design match the users' activities and needs. The experience-based design method appears to be crucially well suited to the design of products in which the experience of innovation and usability are critical to the product. The usability aims to easy to learn, effective to use according to user experience. Thus, this proposed paper adopts original consumption behaviour, usability attributes of product function from engineering design perspectives. These perspectives involve in the design of all the interactive concepts of a product. Accordingly, this paper approach is really interactive that is concerned with how to match product design quality based on user experiences.

Industrial 4.0 design is an integrated in engineering design perspectives. It applied to user-centered product exploration that is to be improved for the customer satisfaction through techniques of internet of things (IoT). Through emerging IoT, between consumer experiences and products design is close relationship interactions. The emerging IoT in user-centered design has stimulated a shift of focus from designer perspective's customer experience and customer- centered design perspective's engineer experience. According, industrial 4.0 design is an interactive process of design with aesthetics, human perception for customer and usability principles. In this proposed approach, the dual experiences in experiential design aid the product design of high quality interactions of industry 4.0 design and create a new focus in the research area of engineering design. This proposed evaluation solution comparing the present solution from usual publication of interactive product engineering is described as follows.

Schütte [43], applied Kansei engineering method to find relationships between product experience and product properties based on industrial design. The Institute of Ergonomics and Human Factors at TU Darmstadt explores future smart-based user centered design process (UCDP) to develop concepts for cyber physical system in industry 4.0 topic. The industry 4.0 is an ambient intelligence by detecting the con-

text of the user centered design process based on artificial intelligence [20].

Comparing with these previous works, the proposed approach has attracted the attention in various disciplines involved in interactive product design research such as product usability, customer behavioral human perception. Product usability is the dimension of the user-centered interactions that is affected by the customer's experience. RFM relies on three customer behavioral variables to find valuable customers and further develop customer experience. From industry 4.0 design perspective, this proposed approach also explores the above-mentioned five factors based on both customer experience and engineer experience consideration. The exploration can be improved industry 4.0 design performance because of its high interactive design. Furthermore, this proposed approach provides evaluation solution for product design performance. The purpose of this evaluation is to help this proposed approach validates the total performance mode selection problem using optimization problem in the product-mix of dual experiences.

This paper is organized as follows: Sect. 2 introduces related work such as FCM, FDT, and experience-based design. Section 3 presents the proposed approach, a new dual experience-based design approach by using FDT with FCM based on engineering design perspectives and customer responses for optimization. Section 4 presents the case study and numerical example for consumer electronic product such as notebook computer or smart phone. Section 5 presents evaluated experiments using product mix-experience problems that are conducted by utilizing sensitivity analysis of the three degrees of fuzzy membership function as low, medium and high among the influence of each perspective in the case study. Section 6 concludes the work and describes future research.

2 Related works

2.1 Experience-based design and user-centered design

User experience (UX) is a human-computer interaction (HCI) with important emotional significance from experiential aspects of usability. The HCI focused on UX aspects beyond the product usability [22]. Tesar [46] explored the ability of the discipline of mechanical engineering to satisfy a spectrum of human needs. Furthermore, it is crucial that UX combines product design to capture insights from which engineers can identify and co-design procedure for improvement by capturing the customer experience. Hudspith (1997) indicated that engineer experience supports how people interact with their products using a theoretical UX model to help product design.

Wright et al. [48] presented an interaction model using UX from a design perspective. Experience-based design (EBD) method is discussed in some industrial field. Experience-based design is a recently emerging method to construct cognitive models with a product. Russ et al. [39] proposed experience-based design questionnaire to identify and evaluate an experience-based design that can be used to incorporate patient and emotional experience into healthcare redesign. Thus, EBD can enhance product design quality to design better healthcare services using patient and staff experience in healthcare field. Hsieh et al. [25] proposed service experience design approach that explores quality service experiences and co-create value with customers in the service industry. Accordingly, this article uses EBD to evaluate design quality based on both engineering design and customer responses.

User-centered design (UCD) plays a critical role in the interactive design for product design process. The UCD may works effectively from an engineering perspective, it is often at the integration of both the customer experience and engineer experience. The goal of interaction design is to estimate this evaluation by bringing usability into the engineering perspective. Thus, this paper own definition for interactive design describes that the dual experiences in experiential design create compelling customer responses and aid in the product design of high quality interactions.

Some literatures discussion were described as follows from usual literature about interactive design. Fischer and Nadeau [49] present an in-depth study of new product design methods namely research in interactive design by demonstrations of real industrial problem-solving. An interactive motion planning framework drives the interaction between users and automatic path planners [51]. Poirson et al. [35] presented genetic algorithms for a user-centered design of products to solve the multi-objective optimization problem. Dilip et al. [16] proposed an overall sentiment rating algorithm for customer sentiment appraisal from user-generated product reviews using opinion mining techniques. User-centered design (UCD) plays a critical role in the interactive design process. The user-centred design (UCD) provides an excellent framework to foster brain-computer interface (BCI) development together [2]. Gregory and Shana [21] proposed a new conceptual UCD approach namely latent semantic engineering (LSE) to improve product quality, customer satisfaction, and product success.

Accordingly, I have a look on interactive design to position the proposed approach from these literatures. This position is a new field of study, namely, dual experience based design (DEBD). The DEBD explores a new experience-based interactive design by both the customer experience and engineer experience through emotional mapping and customer responses.

2.2 Fuzzy cognitive maps

Fuzzy cognitive maps (FCM) by Kosko [27] is a modelling methodology to formulate the adjacency matrix using casual chaining information for complex decision-making systems. FCM is a casual relationship links component to each other in a graphical illustration and seems to be a signed directed graph with multiple maps, loops, cycles, etc. The reachable adjacency matrices use vague degrees for causality degree. A FCM consists of nodes and weighted arcs (denoted Cij). Nodes represent concepts that are characterized by variables V_i and its weighted arcs represent causality between pairs of concepts. A FCM is composed of concept node (C) of a problem, signed directed arrows, and causality value (e_{ir} of Cij) among the other nodes. Meanwhile, the weighted arcs Cij are formed by the influence of causal concept V_i on concept V_j. The Cij take care value in the fuzzy interval $[-1, 1]$. Cij=0 indicates no relationship. Cij > 0 defines positive causality (increase). Cij < 0 indicates negative causality (decrease).

A good review of recent applications and advances in FCM modelling can be found in Glykas [18]. FCMs have been commonly used in the field of industry application but a few discussed in engineering design field. Salmeron and Gutierrez [41] proposed fuzzy grey cognitive map with a reliability analysis of a transformer active part in order to assist electric power system decision-making. Lee et al. [29] proposed feedback-based FCM for feedback design in product problem and also indicated "feedback" applied into FCM evaluation. Cheah et al. [12] proposed FCM constructor to verify product design decision making problems for modelling, representing, and reasoning about causal design knowledge [19]. According to the above-mentioned, the FCM was adopted to evaluating value of engineering design perspectives for product design process. However, they almost used expert's knowledge to collect factors' value. They rarely took into consideration fuzzy decision tree for collecting fuzzy data. It is crucial for decision-making based on decision tree induction with fuzzy data, because fuzzy decision tree can produce the inference that carried out the optimized efficiency by using fuzzy membership function. Lee et al. [30] proposed a method of constructing a web-based decision making system based on an expert's knowledge and experience for some patients by preference data using fuzzy cognitive map and fuzzy membership function.

2.3 Fuzzy decision tree (FDT)

Decision trees have been successful in classifications and prediction to classify data by sorting them with the tree from the root to the leaf nodes. Fuzzy sets defining the fuzzy terms used for building the tree are imposed on the algorithm. On the other hand, fuzzy decision trees are extensions of the classical decision tree algorithms and allow data to follow down

simultaneously multiple branches of a node with different satisfaction degrees at [0, 1]. A fuzzy decision tree is a generalization of the crisp case. For capability of representing vague and unclassified data, the fuzzy decision tree combines the fuzzy set with the decision tree. One of the main objectives of the fuzzy decision tree induction is to generate a tree with high accuracy of classification for unknown cases such as ID3 by Quinlan [37]. There are many studies trying to improve classifying efficiency. Chang and Liu [11] and Carvalho and Freitas [8] applied decision tree for other method such as K-mean, fuzzy C mean. Chandra and Varghese [10] proposed a binary decision tree algorithm using the Gini index as a split measure. Accordingly, given the theoretical developments presented fuzzy concept, the decision trees classification systems are referred to as fuzzy decision tree algorithm.

Experimental results show that the selection of attributes is an important factor to influence the accuracy of classification [7]. The construction method for the fuzzy decision tree is designed for a classification problem with attributes and classes represented in fuzzy linguistic terms [50]. According to the above literature, the fuzzy representation is becoming more and more popular in dealing with problems of uncertainty, noise, and inexact data [15]. It has been successfully applied to problems in many industrial areas. Horng et al. [24] proposed a hierarchical fuzzy clustering decision tree (HFCDT) for classifying recipes of the working wafers with the entropy-based C4.5 decision tree algorithm in an ion implanter. Liu et al. [32] proposed a method to construct the axiomatic fuzzy set (AFS) theory with a fuzzy rule-based classifier using coherence membership functions. Aydin et al. [4] proposed a boundary detection algorithm using fuzzy decision tree that has been designed to detect broken rotor bars and broken connector faults. Aurup and Akgunduz [3] proposed a unique methodology to capture user preferences from biological signals. Accordingly, the preference experience data is uncertain or fuzzy if the engineer explores product function with customer needs. Thus, this article applies FDT for experience data classification.

2.4 User-centered design with user preference

Several points can be made about this proposed approach and user preferences integration in the usual design process as follows.

From the user-centered design viewpoint, a user model with user preferences has been predicted using so-called interactive human-centered approach. The human-centered interaction design can produce a representation of the user preferences using adaptive concept. The adaptive concept can adjust user preferences to user requirement, but there is not yet sufficient experience data about the user's personal interests available. Thus, the user preferences need

involving user experience in interactive design. Interactive design applies artificial intelligence algorithm for preferences approaches with respect to reasoning among the user experiences. The user experiences hence may result in higher usability of the product through recommendations, because recommendations are based on the users' previous preferences with interactions. The recommendation has to rely on the past experiences of the users such as collaborative filtering and content based filtering system. Collaborative filtering focuses on make personalized predictions. The content-based filtering methods focuses on information retrieval systems using user-focused intelligent. For example, Netflix or Amazon.com includes recommender systems by eliciting preferences from the user model.

The user model with artificial intelligence predicts relevance more accurately when the user preferences consist of both new product design experience and new users experience. Accordingly, some literatures were discussed as follows Serena et al. [44] proposed interactive mechanical design that can be captured from the customers into new quantitative specifications by user's perceptual preferences. Kyriacos et al. [28] applied a data mining approach to the investigation of users' preferences in using interactive multimedia learning systems. The human-centered interaction can apply into product design in enhancing customer and engineer interactions with product usability. But it may be time-consuming and complex, so it needs integrate experience-based design that focuses on the importance of the experiential design optimization in order to enhance human-centered interaction. In this paper approach, dual experience-based design is based on both engineering design and customer responses. The general framework for dual experience-based design that applies to all customer responses that can be experienced in user-centred design through interaction.

Three elements of dual experience-based design are discussed: aesthetic experience, product usability experience, and emotional experience. It explores both the customer experience and engineer experience through emotional mapping and customer responses. The criteria of these experiences fall into relationship between designer perspective (S) and customer-centre design perspective (c) using the fuzzy accuracy probability of the classification using S(S, C) algorithm. Those in the classification make a direct contribution to the user and designer experiences. Each attribute has three values using RFM values in designer perspective (S). For example: was the product easy to satisfy customer requirement? The criteria also concerns the product usability used by the product's designers, which directly affect the user experience. Product usability is the dimension of the user-centered interactions that is affected by the customer's experience.

Furthermore, the user's preferences that are reasoned by a recommendation can be user-centred interaction. It is neces-

sary to think carefully about what a user preference is and how to involve user preferences in the interactive design process for product problem. To achieve the above-mentioned needs, user preference elicitation is available method that extracts preferences of a user experience in a product problem of interactive design. Chen and Pu [14] proposed an overview of existing systems that elicit user preferences. A user's preferences are user-centered design of preference elicitation which is needed to create customer responses that are adapted to dual experience-based design. Thus, this article proposes a novel approach combining FDT into FCM as preference elicitation in artificial intelligence method. The goal of proposed approach is to explore a user's preference in such a way as to optimize product design experience for solving the product problem. Our aim is intended to shed light on the product mix-experience optimization for firm performance using the relationship among engineering design perspective. Thus, this paper proposes a dual experience-based interaction for reasoning user preferences using product mix-experience problems in product design.

Afshari and Peng [1] proposed innovative application of big data analytics (BDA) to quantify the changes of customers' preferences during the life time of a product. Uncertainty is inevitable in product design process. However, dual experience-based design with the above-mentioned these factors is uncertainty to identify the causal relationships among them. Then, it aims at optimizing complex interaction and experiential design system with imprecise relationships while quantifying the performance impact of engineering design efficiency for customer satisfaction. Thus, it is crucial to enhance the accuracy of the user preference and dual experiences.

By comparing customer-centre design perspective's engineer experience and designer perspective's customer experience, this article explores two methods such as usability algorithm, the normalized RFM. By evaluating value of engineering design perspectives using AHP, we aim to evaluate the relative importance of the casual impact in the FCM-based system for engineering design perspectives. Then, by constructing the inference process for engineer experience and customer experience, we can predict new preferences for a user with imprecise relationships to develop good quality product design to both satisfy novelty design and customer needs. It is well-thought out and well-executed interactive design process

3 Fuzzy dual experience-based design approach

In this article, engineering design perspective is divided into five factors by Liu and Boyle [31]: robust design, design optimisation, design cognition factors (designer perspective) and requirements management, and ergonomic design fac-
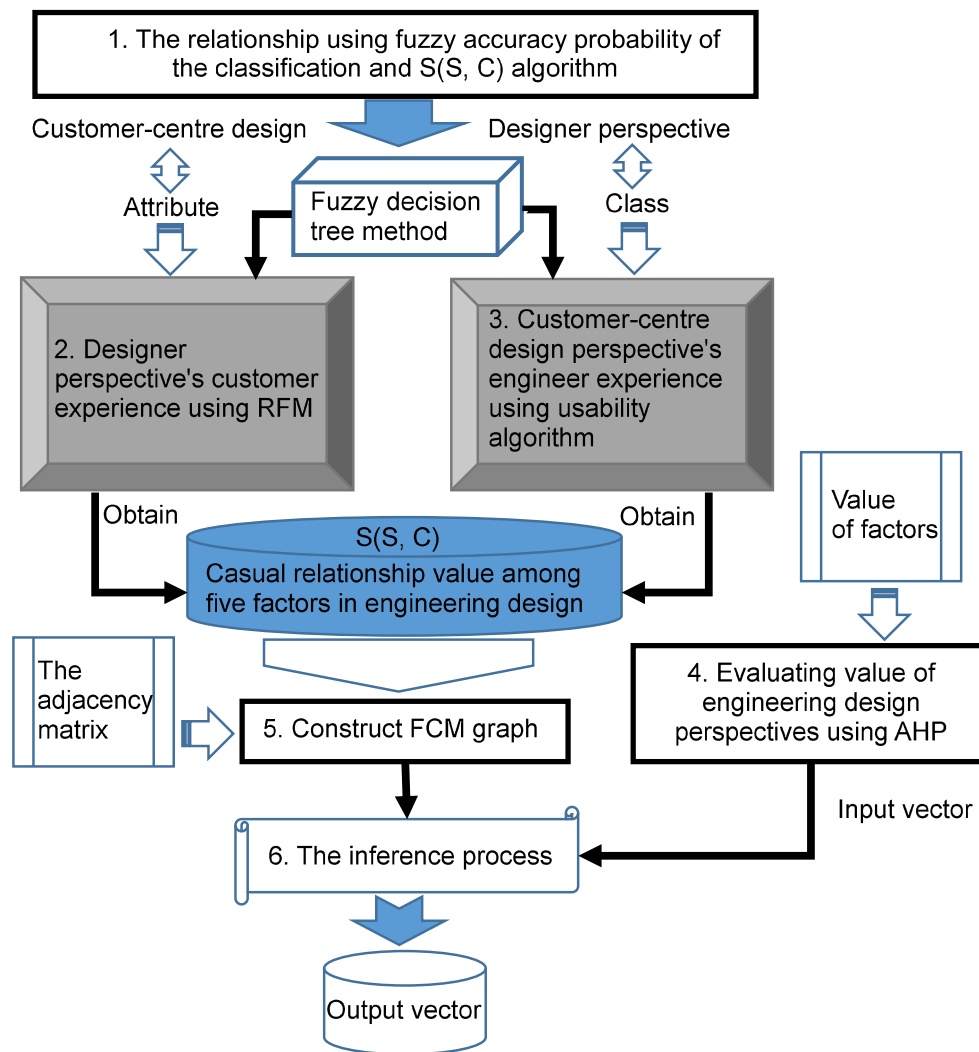
Fig. 1 The procedure of fuzzy dual experience-based design approach

tors (customer-centre design perspective). Dual experience based design (DEBD) is a new field of study. It explores both the customer experience and engineer experience through emotional mapping and customer responses. In such dual experiences thinking, this article proposes two key-points as follows. The first point aims at designer perspective's customer experience and customer-centre design perspective's engineer experience. The second point explores each value of five factors based on both customer experience and engineer experience consideration. The following paragraphs describe six steps from these two key-points in the fuzzy dual experience-based design process for integrating engineering design perspectives with customer responses as shown in Fig. 1. Furthermore, the case study and numerical example will be demonstrated in Sect. 4. Then, the sensitivity analysis will be proposed in Sect. 5.

The first step explores relationship between designer perspective and customer-centre design perspective using the fuzzy accuracy probability of the classification. It is used to form relationship among factors for constructing FCM graph. The next step is to formulate designer perspective's customer experience using RFM and then act on attributes' value from designer's perspective on fuzzy accuracy probability of the classification. The RFM represents customer behavior based on designer perspective. Furthermore, the RFM can be shown in the relationship with engineer experience. The third step is to formulate customer-centre design perspective's engineer experience using usability algorithm and then act on class value of customer-centre design perspective in fuzzy accuracy probability of the classification. The usability represents the user-centered interaction that is affected by the customer's experience. RFM and usability are composed into customer responses. According to step 2 and step 3 of the algorithm, this article obtains the casual relationship among five factors and shows on S(S, C) (see Eq. (1)). The forth step is to calculate values of five factors in engineering design

Fig. 2 The generalization of fuzzy sets

$$U_A(u)= \begin{cases} (u-a)/(b-a), & a<=u<=b \\ (u-c)/(b-c), & b<=u<=c, \ a<=b<=c \\ 0, & \text{other} \end{cases}$$
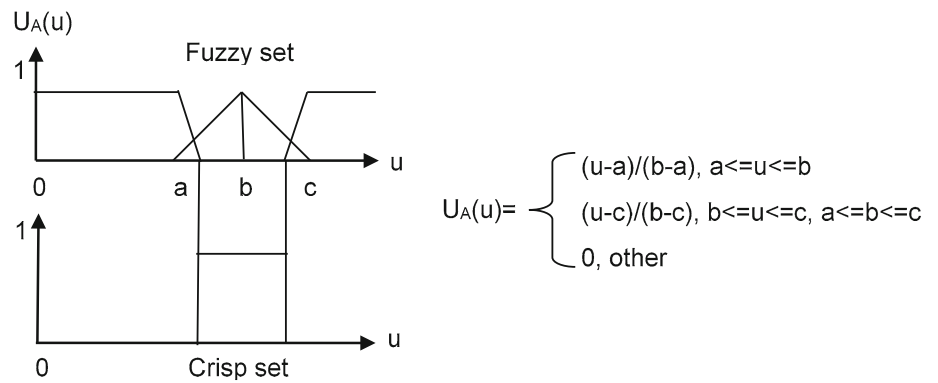
perspectives using AHP underlying two alternatives such as engineer experience and customer experience. These values act on input vector. Furthermore, the adjacency matrix of FCM will be constructed by S(S, C) and value of five factors in fifth step. After constructing of the FCM, the sixth step is used to simulate the inference process in order to improve the performance impact of decision-making efficiency for engineering design perspective using the numerical analysis of FCM. After calculating in the sixth step, the output vector will produce a change that affect these factors. These effects can assess engineering design perspectives and customer responses in dual experiential design optimization. The dual experiential design optimization result produces finally fuzzy inference using the fuzzy membership function.

A fuzzy membership function method is a generalization of the crisp values and fuzzy sets and is illustrated in Fig. 2. As shown in Fig. 2, they are fed to construct fuzzy decision trees.

The following steps describe six steps in detail:

Step 1. The relationship using fuzzy accuracy probability of the classification and S(S, C) algorithm

In this article, engineering design perspective is incorporated using a composite measure of design dimensions such as Designer perspective (robust design, design optimisation, design cognition) and customer-centre design perspective (requirements management, ergonomic design). More specifically, the designer perspective has not been fully addressed in customer-centre design perspective studies. Accordingly, the relationship between designer perspective and customer-centre design perspective is to address to what extent designer perspective impacts upon the various factors of customer-centre design perspective. In this article, I defined a fuzzy classification accuracy rate (S(S, C)) as the degree of relationship between designer perspective and customer-centre design perspective, which attributes to the relationship among factors for constructing FCM graph in the step 5. The engineering design perspective served as the dependent variables. The engineering design perspective perception was measured by fuzzy data. Zadeh [52] introduced

fuzzy set theory to illustrate the fuzzy phenomena occurring in cognitive process.

We define a fuzzy classification accuracy rate (S(S, C)) as the good degree of engineering perspective in Eq. (1), which is attributed to a composite measure of design dimensions [50].

Definition 1 Given the fuzzy data, the accuracy probability of the classification can be defined as

$$S(S, C) = \frac{M(S \cap C)}{M(S)} = \frac{\sum_{x \in U} \min(U_S(x), U_C(x))}{\sum_{x \in U}(U_S(x))} \tag{1}$$

The accuracy probability of the classification method is designed for classification problem with attributes and classes represented in fuzzy linguistic terms. It uses fuzzy linguistic method. The fuzzy subset hood S(S, C) measures the degree with the accuracy probability of the classification in which S (attribute) is a subset of C (class). Before giving the definition, we denote the following symbols:

$U(X)$ is the family of all fuzzy subsets defined on X, and the cardinality measure of a fuzzy subset. X is given finite data of $U(X)$.

S = Designer perspective, C = Customer-centre design perspective

S is defined by the membership of a fuzzy subset U_S which takes values in the interval [1, 0] in a universe of $U(X)$. For $x \in U$, $U_S(x) = 1$ means that x is definitely a member of S and $U_S(x) = 0$ means that x is definitely not a member of S, S is a crisp set.

$M(S) = \sum_{x \in U} S(x)$, probability summation for S

$$M(S \cap C) = \sum_{x \in U} \min(U_S(x), U_C(x)) \tag{2}$$

The intersection $S \cap C$ is defined by probability summation for S and C.

Step 2. Designer perspective's customer experience using RFM

The RFM values are defined as follows: R measures how long since customers use products. F measures how frequently they use products; and M measures how much money they spend. RFM relies on three customer behavioral variables to find valuable customers and further develop customer experience. The customer experience consists of how long since the last purchase by a customer, how often the customer purchases and how much the customer has bought. Thus, this research builds customer responses models using RFM variables integrated with the fuzzy decision tree model. Owing to consideration of both engineer experience and customer experience, RFM would be involved into designer perspective in fuzzy decision tree model. RFM also becomes values of the attribute for designer perspective and is described as follows.

The good degree of engineering design perspective (ED_j) is described by a collection of the attributes of designer perspective for product (s_q). This attribute gets one of the mutually exclusive values $V_q = \{V_{q1}, \ldots, V_{qz}\}$ from the product design experience, and each process node is classified into only one of the mutually exclusive data $C_j = \{C_{j1}, \ldots, C_{jm}\}$ from customer perspective data. The engineering design perspective formulation could be represented as follows:

ED_j: the good degree of engineering design perspective for product j

$S_q = \{S_{j1}, \ldots, S_{jq}\}$: attribute of the good degree of Designer perspective for product, where q is the attribute of the product j

$V_q = \{V_{q1}, \ldots, V_{qz}\}$: values of the attribute, where Z is the value of the attribute item q

$C_j = \{C_{j1}, \ldots, C_{jm}\}$: customer perspective class for engineering perspective, where m is the customer experience of the product j

The vague data expressions in the good degree of engineering perspective from Eq. (1) are illustrated in Table 1. For example, the probability ascertained for the attribute "Robust design" is between 0 and 1 of fuzzy values. It lists the Designer perspective (S) for customer perspective.

Designer perspective (S) has three attributes:

S = {Robust design, Design optimisation, Design cognition},

Each attribute has three values using RFM values. The RFM values were normalized as follows from profit-oriented viewpoint separately in Eq. (3). The RFM values of each cluster were normalized, and denoted as R', F', M'.

$$R' = (R - R^s)/(R^L - R^S), R' = (R - R^s)/(R^L - R^S),$$
$$R' = (R - R^s)/(R^L - R^S) \tag{3}$$

where R' and R represent the normalized and original values, R^L represents the largest value of all numbers, R^S represents the smallest value of all numbers.

Their superscripts of the F and M are the same as for the definitions of R.

They can be numbered as one Eq. (4).

(V_{q1}) Robust design $= \{recent\,(R'),\, frequency\,(F'),$
　　$money\,(M')\}$,
(V_{q2}) Design optimization $= \{recent\,(R'),$
　　$frequency\,(F'),\, money\,(M')\}$,
(V_{q3}) Design cognition $= \{recent\,(R'),$
　　$frequency\,(F'),\, money\,(M')\} \tag{4}$

The customer perspective has two classes including "Requirements management," and "Ergonomic design" as follows.

(C_{jm}) customer perspective
　$= \{$Requirements management,　Ergonomic design$\}$

Their values act as sources of data in attribute of the good degree of Designer perspective within Eq. (1).

Step 3. Customer-centre design perspective's engineer experience using usability algorithm

Some studies already discussed product usability as follows. The techniques of product usability did not aim to appeal to the user's emotional or experiential needs [6]. Chamorro-Koc et al. [9] proposed principles addressing differences between users' and designers' concepts of product usability. Product usability is the dimension of the user-centered interactions that is affected by the customer's experience. Thus, considering some parameters by Sarkar and Chakrabarti [42] in this article, the modified usefulness item assessment is shown in Eq. (5):

Usefulness (U) = Level of importance (Lu)
　　　　* Rate of popularity of use (Ru)
　　　　* Frequency of usage (F1)
　　　　* Duration of use per usage (Du)
　　　　* Benefit of use (Bu) (5)

In this Eq. (5), this article adds "Benefit of use" usefulness item assessment. Indications about the purpose of usability connected to user–product interaction are presented in Table 1.

These usefulness items assessments are described as follows:

Level of importance (Lu): The level of importance constructs a decision-making method with weight values to generate the relative importance of different priority

Table 1 Indications of usability

Indicator	Usefulness item	Formulation
The number of times used Useful times of use	Rate of popularity of use (Ru)	Ru = Useful times of use/the number of times used
Duration of use The number of times used	Frequency of usage (F1)	F1 = The number of times used/duration of use
Duration of use Large period of use	Duration of use per usage (Du)	Du = Duration of use/large period of use
Degree of ease of use Degree of efficiency of use	Benefit of use (Bu)	Bu = Degree of efficiency of use/degree of ease of use

mixes. This determines the weight of each decision element using eigenvalue computations to derive the weights of the level of importance using AHP (analytic hierarchy process). AHP could solve complex decision-making system problem involving multiple attributes by constructing hierarchy to the goal, attribute and alternatives [40]. These variables are expressed in the form of a pair-wise comparison matrix by expert choice software. The Expert Choice (http://www.expertchoice.com) is used to obtain the decision into criteria and alternatives by a computer software package for AHP method. By applying Romijn and Albaladejo [38] method, this article uses a five-point scale to represent the degree of novelty of product innovations as weight values for AHP procedure. They act as values of the level of importance and are described as follows:

I_5: Fundamentally new to the world (disruptive degree of novelty)

I_4: Similar innovations adopted in other industries (high degree of novelty)

I_3: Similar innovations adopted in firm's own industry (competitive degree of novelty)

I_2: Same or very similar innovations adopted by competitors (normal degree of novelty)

I_1: No major innovations at all (low degree of novelty)

The AHP method was used to determine the relative importance of the degree of novelty of product innovations variables, $I_1 \sim I_5$ in Fig. 3. The AHP data was gathered by interviewing the evaluators using a questionnaire with the scale importance such as 1 (equally), 3 (weak), 5 (strong) and 7 (extreme). This determines the weight of each decision element using eigenvalue computations to derive the weights of the $I_1 \sim I_5$. As to how important the use of a product depends on the impact of RFM for this article. Thus, three alternatives were invited to evaluate the relative importance of the R, F, and M variables.

Rate of popularity of use (Ru): It should be considered more useful than those that are used by less number of people.

Frequency of usage (Fu): Frequency of usage of a product is the number of times the product is used in duration.

Duration of use per usage (Du): Products that are used for a larger period should be considered more useful to the usability,

Benefit of use (Bu): Products that are used for degree of ease usability should be included degree of efficiency. Efficiency of use means that product uses less resource to provide the same service. The ease of use is the ability of usability to easily perform a function with a product. Its measurement degree value is assigned to 1–10. The higher value of degree is, the better the benefit of use is.

The above-mentioned usability should be considered integrated into customer-centre design perspective in fuzzy decision tree method. Their values act on source of data for requirements management and ergonomic design class within Eq. (1). Furthermore, after calculating values from steps 2 to 3, we can obtain S(S, C) using Eqs. (1) and (2). For example, it used Eqs. (1) and (2) with data of Table 2, S(Robust design $= R'$, Requirements management) $= P$(Robust design $= R' \cap$ Requirements management)/ P(Robust design $= R'$) $= \frac{0.3+0.2+0.3}{0.3+0.5+0.6} = 0.57$.

As result using average method for data no #1: $S (S_1, C_1)=$ S(Robust design, Requirements management)$=$ $(0.57 + 0.89 + 0.67)/3 = 0.71$.

Step 4. Evaluating value of engineering design perspectives using AHP

The engineering design perspective is particularly attentive to decision models that rely on the trade-off based on weighted criteria to determine a relative ranking. This determines the weight of each decision element using eigenvalue computations to derive the weights of these variables by AHP method. The AHP is relatively subjective-based important assessment among the alternative approaches. The relatively important assessment among the alternative creates the pair-wise comparison matrix.

This article constructs three levels for evaluating the best value of each perspective in engineering design perspec-
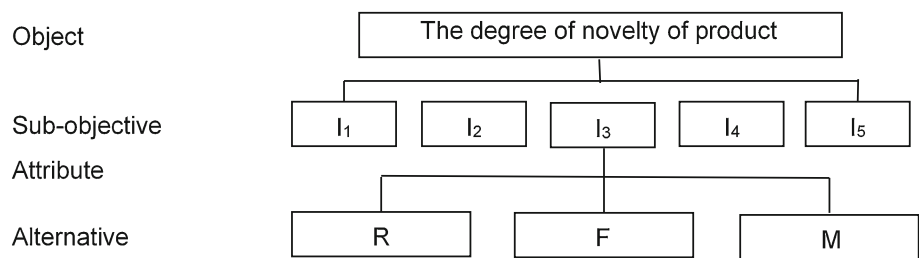
Fig. 3 The degree of novelty of product

Table 2 The fuzzy data for product #1 $(j = 1)$

Data no.	$S =$ Designer perspective (attributes)									$C =$ Customer-centre design perspective (classes)	
	Robust design			Design optimization			Design cognition			Requirements management	Ergonomic design
	R'	F'	M'	R'	F'	M'	R'	F'	M'		
1	0.3	0.4	0.6	0.7	0.6	0.5	0.5	0.4	0.6	0.5	0.3
2	0.5	0.3	0.5	0.5	0.5	0.5	0.5	0.5	0.7	0.2	0.4
3	0.6	0.2	0.4	0.7	0.4	0.5	0.5	0.7	0.6	0.3	0.3

Fig. 4 AHP for engineering design perspectives
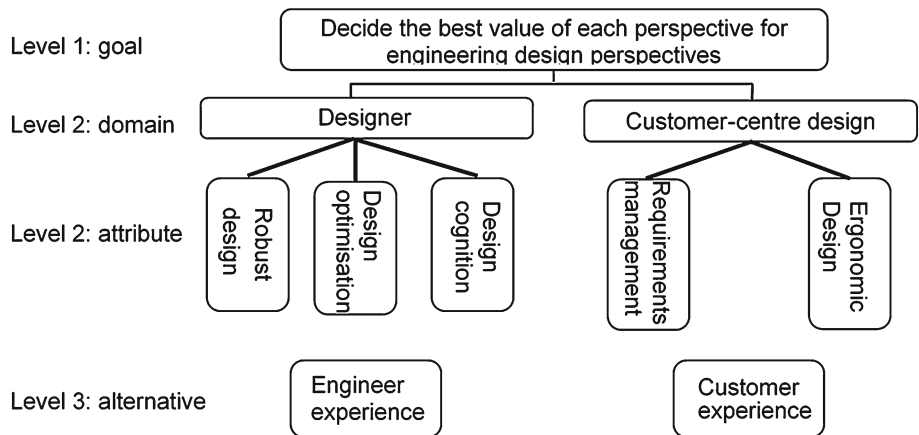
tives in the Fig. 4. Level 1 is the goal of engineering design perspectives to decide the best value of each perspective. Level 2 is divided into two domains (designer perspective and customer-centre design perspective) consisting of five attributes (factors) according to engineering design perspectives. Level 3 contains of two decision alternatives such as engineer experience and customer experience that affect the best selection of the goal. The five attributes were invited to evaluate the relative importance of the casual impact in the FCM-based system for engineering design perspectives.

According to calculated value of level 2 attributes using Expert Choice software, we obtain these values of factors that they were used to act on initial value for designer perspective and customer-centre design perspective in FCM. These values of factors also form input vector. In order to describe the fuzzy degree of these factors, it is possible to use fuzzy linguistic terms using fuzzy membership function. It is applied for measuring the value and categorizing the priority such as H (high), M (medium) and L (low) in the Fig. 5.

Step 5. Construct FCM graph

In this article, systematic approach for inference process using FCM is evaluated with casual relationship impact on decision making. The FCM illustrates inference process on how to construct dual experience-based design model and integrate design perspectives into customer responses with fuzzy casual relationship for the linkages among engineering perspective factors such as designer perspective (robust design, design optimisation, design cognition) and customer-centre design perspective (requirements management, ergonomic design). Fuzzy casual relationships link factors to each other and they formulate the adjacency matrix from S(S, C) according to steps 1, 2 and 3.

This step exploited the adjacency matrix representation of fuzzy cognitive maps. To identify the factors relevant to the dual experience-based design model, S(S, C) should be built and then analysed. Furthermore, a fuzzy casual model based on the factor data elicited from RFM and product usability algorithm includes dual experiences for engineer and cus-
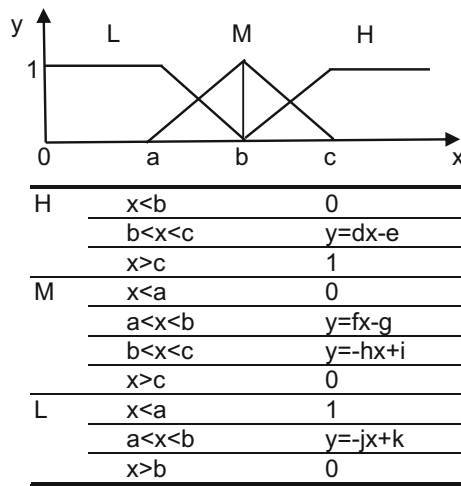
$$
\begin{array}{lll}
H & x<b & 0 \\
& b<x<c & y=dx-e \\
& x>c & 1 \\
M & x<a & 0 \\
& a<x<b & y=fx-g \\
& b<x<c & y=-hx+i \\
& x>c & 0 \\
L & x<a & 1 \\
& a<x<b & y=-jx+k \\
& x>b & 0
\end{array}
$$

Fig. 5 Fuzzy membership function

tomer using FCM, which describes the relationships between these factors. Based on this result of interrelationship matrix by this above-mentioned result from S(S, C), we can build the fuzzy causal relationship to gain initial version adjacency matrix of FCM. The initial version of adjacency matrix can be converted into following refined values between 0 and 1.

Step 6. The inference process for engineer experience and customer experience

After constructing the FCM, this step is used to simulate the inference process underlying two alternatives such as engineer experience and customer experience in order to improve the performance impact of decision-making efficiency for engineering design perspective using the numerical analysis of FCM. Based on the five factors of both designer perspective and customer-centre design perspective, it describes the input vectors separately from the two alternatives (see step 4). Based on the S(S, C), it describes the adjacency matrix of FCM (see step 5). In addition, the adjacency matrix can be used usefully for changes of multiple factors. Therefore multiplying this input vector with adjacency matrix, the inference process can obtain output vector. Once the factor values of the input vector are changed, the output vector may result in changes of perspective value. The factors affect each other. In a word, each value of perspective in engineering design perspective will affect other value of perspective through the relationships between these perspectives. This effect indicates how to explore dual experience-based design approach through understanding relationship among engineering design perspectives based on customer responses. It aims to develop good quality product design to both satisfy novelty design and customer needs through dual experiences such as engineer and customer experiences.

4 Case study and numerical example

Case study and numerical examples are presented to illustrate the proposed model and the sensitivity analysis with five perspectives in the optimal solutions with respect to parameters of the system is also carried out. A case study concerns product design using a consumer electronic product such as notebook computer or smart phone. Experience observations, interviews, and questionnaires were conducted to complete dual experience decision case that provides really valuable response to capturing consumer behavior and feelings. With a decision case solved, it is then captured as a training case and subsequently stored to the experience decision database. To validate the applicability for the proposed model, historical product design and customer responses cases were identified for each perspective to support the evaluation process, for simplicity the cases use ten datasets under five evaluated measure KPIs (key performance index). These KPIs includes robustness for robust design, repurchase for design optimization, RMA for design cognition, accepted function item for requirements management, customized function item for ergonomic design. The robustness is to represent the ability of product reliability under reducing performance variability based on the same environment. Thus, its measurement was defined as "used numbers successfully based on total used numbers" from customer experience. Design optimization is early considered trade-offs between product resources such as cost, function, manufacturability and quality for performance in the product design process. Thus, its measurement was defined as "re-purchase quantity based on product duration" from customer experience. Design cognition focuses on the cognitive behaviour of designers behind design problems and how they are solved. Thus, its measurement was defined as "RMA quantity based on produced order" from customer experience. Requirements management is the transformation that it transfers customer requirements into functional requirements to guide the development of the design solutions. Thus, its measurement was defined as "accepted function item based on all product function item" from engineer experience. Ergonomic design is recognized as human needs in order to optimize their well-being and overall system performance [17]. It aims to support effectively the customized design of products in higher customer satisfaction according to the design engineer's judgment. Thus, its measurement was defined as "customized function item based on all product function item" from engineer experience. According to the above-mentioned five evaluated measure groups with ten datasets, this section presents numerical analysis and application evaluation according to six steps in Fig. 1 as follows.
Step 1. Define relationship among perspectives using $S(S, C)$

According to Eq. (1), it measures the classification probability of the mapping attributes (design perspectives) which

belong to a certain class (customer-centred design perspective), and it replaces the traditional decision tree entropy with the accuracy probability of classification. The result is described as follows.

$S_q = \{S_{j1}, \ldots, S_{jq}\}$ = {Robust design $(q = 1)$, Design optimization $(q = 2)$, Design cognition $(q = 3)$}

$C_{jm} = \{C_{j1}, \ldots, C_{jm}\}$ = {Requirements management $(m = 1)$, Ergonomic design $(m = 2)$}

$S(S_1, C_1)$ = {S(Robust design = R', Requirements management) + S(Robust design = F', Requirements management) + S(Robust design = M', Requirements management)}/3

$S(S_1, C_2)$ = {S(Robust design = R', Ergonomic design) + S(Robust design = F', Ergonomic design) + S(Robust design = M', Ergonomic design)}/3

$S(S_2, C_1)$ = {S(Design optimization = R', Requirements management) + S(Design optimization = F', Requirements management) + S(Design optimization = M', Requirements management)}/3

$S(S_2, C_2)$ = {S(Design optimization = R', Ergonomic design) + S(Design optimization = F', Ergonomic design)+ S(Design optimization = M',, Ergonomic design)}/3

$S(S_3, C_1)$ = {S(Design cognition = R', Requirements management) + S(Design cognition = F', Requirements management)+ S(Design cognition = M',, Requirements management)}/3

$S(S_3, C_2)$ = {S(Design cognition = R', Ergonomic design) + S(Design cognition = F', Ergonomic design)+ S(Design cognition = M',, Ergonomic design)}/3

Step 2. Calculate values of designer perspective using normalized RFM

According to these results from step 1 of Sect. 4, this step 2 will calculate R', F', M'. Before calculating these results, this case study collected RFM data in Table 3 according to three evaluated measure groups [robustness for robust design, repurchase for design optimization, RMA (return materials authorization) for design cognition]. The Table 3 comes from simulated consumption of notebook computer product by referring to commerce transaction records. These raw data in Table 3 were divided into 10 sets. Each set has different sales number of product to represent different consumption groups. The case study adopts three different design roles according to the above-mentioned five KPIs. Thus, the three designers allocated the largest and smallest RFM values into three groups by expert experience method according to these KPIs. The three groups also decide largest and smallest RFM values according to design perspective, respectively. Table 3 presents the ten sets with the corresponding number of consumer electronic product usage for R, F and M values from customer responses. The last row also shows the overall average for all numbers.

Table 3 Consumer electronic product usage

Sets	Number of product sales (average)	Recency (days) (average)	Frequency (times) (average)	Monetary ($) (average)	Robust design		Design optimisation		Design cognition	
					Largest R/F/M	Smallest R/F/M	Largest R/F/M	Smallest R/F/M	Largest R/F/M	Smallest R/F/M
1	30	31	9	121	35/12/240	28/6/110	33/10/239	26/7/115	37/13/200	23/3/120
2	39	21	6	234	30/9/250	19/5/210	27/8/257	15/5/223	28/8/260	13/3/198
3	56	29	15	321	32/16/350	26/12/210	35/19/389	23/11/231	40/17/339	23/13/300
4	57	30	13	213	32/15/300	21/9/199	39/19/278	23/10/203	37/17/268	23/10/176
5	23	38	12	344	45/21/366	31/11/321	43/19/383	34/10/298	39/15/375	28/9/312
6	45	42	21	529	47/25/600	37/14/412	50/31/577	34/17/500	46/26/566	33/14/432
7	49	45	13	412	47/21/468	35/12/398	50/18/457	38/10/361	46/18/430	36/9/327
8	39	25	15	400	30/17/431	20/12/333	29/18/490	23/13/376	36/18/450	19/13/311
9	43	23	19	510	29/26/631	20/13/451	29/25/590	17/13/445	26/22/550	19/15/399
10	36	43	12	519	50/15/580	31/10/482	48/16/614	37/10/476	49/19/536	26/11/409
Overall average	33	13		360						

Table 4 The normalized RFM

| Sets	Robust design			Design optimisation			Design cognition		
	R'	F'	M'	R'	F'	M'	R'	F'	M'
1	0.43	0.50	0.08	0.71	0.67	0.05	0.57	0.60	0.01
2	0.18	0.25	0.60	0.50	0.33	0.32	0.53	0.60	0.58
3	0.50	0.75	0.79	0.50	0.50	0.57	0.35	0.50	0.54
4	0.82	0.67	0.14	0.44	0.33	0.13	0.50	0.43	0.40
5	0.50	0.10	0.51	0.44	0.22	0.54	0.91	0.50	0.51
6	0.50	0.64	0.62	0.50	0.29	0.38	0.69	0.58	0.72
7	0.83	0.11	0.20	0.58	0.38	0.53	0.90	0.44	0.83
8	0.50	0.60	0.68	0.33	0.40	0.21	0.35	0.40	0.64
9	0.33	0.46	0.33	0.50	0.50	0.45	0.57	0.57	0.74
10	0.63	0.40	0.38	0.55	0.33	0.31	−0.70	0.13	0.87
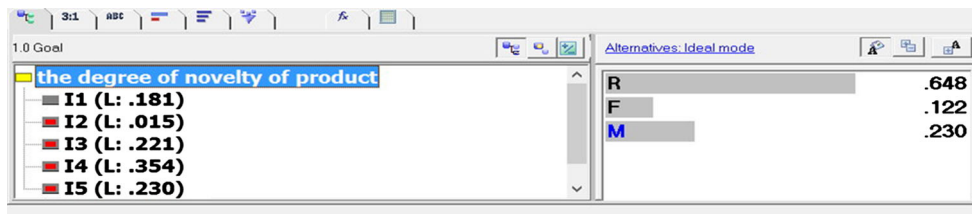
Fig. 6 Calculated ∼ result

Next, the normalized RFM values of each set are calculated and shown on Table 4 according to Eq. (3) and Table 3 for R', F', and M'.

Step 3. Calculated values of customer-centred design perspective using usability algorithm

According to step 3 of Sect. 3, this step will calculate values of customer-centred design perspective based on Eq. (5) and Table 4 from case study data. Firstly, Level of importance (Lu) is calculated by AHP in Fig. 3. The study distributed a total of 3 copies of the questionnaire according to this AHP for the degree of novelty of product with RFM alternatives. Figure 6 is the result calculated by performed Expert choice software.

Secondly, this step calculated values of customer-centre design perspective for requirements management and ergonomic design using usability algorithm according to case study data. The data of level of importance (Lu) in Table 5 was assumed by AHP calculated result in Fig. 6. Thus, the data of U in Table 5 was calculated by Eq. (3).

The $I_1 \sim I_5$ result are adopted by different level of importance (Lu). Their values in Table 5 act as source of data for requirements management and ergonomic design class within Eq. (1). Finally, after calculated values from step 2 and step 3 of this section, we can obtain S(S, C) in Table 6 using Eqs. (1) and (2).

Step 4. Evaluating own value of engineering design perspectives

According to step 4 of Sect. 3, this step calculated value of level 2 attributes for Fig. 4. These values are adopted by FCM graph and initial input vector. The study defined and distributed a total of 30 copies of the questionnaire according to Fig. 5. The 28 copies were valid because of the other 2 copies caused data missing. Figure 7 is the result calculated by level 2 attributes of AHP in Fig. 4. Then, Fig. 7 is the result calculated by performed Expert choice software. According to the result of the calculation in Fig. 7 using expert choice software, the AHP objective of the relative weights of the two alternatives in Fig. 4 is 0.833 (customer experience) and 0.167 (engineer experience), respectively.

Step 5. The adjacency matrix for FCM

According to the result of Table 6, Fig. 8 shows fuzzy casual relationships represented FCM graphic and forms initial version of adjacency matrix W.

Step 6. The inference for engineering design perspective

According to step 4 of Sect. 3, these values of factors also form input vector. I assume an inference vector which is defined as a vector showing a set of input or output values. By referring to Fig. 8, the adjacency matrix can be used for clearly measuring the effects resulting from change of multiple factors. Suppose that some factors are changed based on the value of level 2 attributes for Fig. 4, the input vector may be obtained as follows:

Input vector: [0.244, 0.121, 0.268, 0.146, 0.221]

Table 5 Values of customer-centre design perspective

Sets	Requirements management						Ergonomic design					
	(Lu)	(Ru)	(F1)	(Du)	(Bu)	(U)	(Lu)	(Ru)	(F1)	(Du)	(Bu)	(U)
1	0.015	0.86	0.65	0.67	9.00	0.05	0.181	0.71	0.68	0.73	8.00	0.51
2	0.181	0.87	0.82	0.73	7.00	0.66	0.221	0.89	0.80	0.73	5.00	0.57
3	0.221	0.93	0.83	0.80	6.00	0.81	0.221	0.90	0.77	0.67	4.00	0.41
4	0.181	0.62	0.88	0.73	5.00	0.36	0.354	0.72	0.81	0.80	5.00	0.83
5	0.181	0.74	0.61	0.83	7.00	0.47	0.23	0.42	0.72	0.80	6.00	0.33
6	0.181	0.61	0.52	0.73	9.00	0.38	0.23	0.84	0.64	0.80	8.00	0.80
7	0.221	0.60	0.45	0.87	9.00	0.46	0.221	0.85	0.88	0.67	5.00	0.55
8	0.354	0.49	0.57	0.77	8.00	0.60	0.23	0.73	0.74	0.77	3.00	0.44
9	0.181	0.85	0.67	0.80	7.00	0.58	0.181	0.78	0.76	0.87	6.00	0.56
10	0.230	0.91	0.79	0.80	5.00	0.66	0.221	0.59	0.85	0.87	6.00	0.60

Table 6 Values of S(S, C)

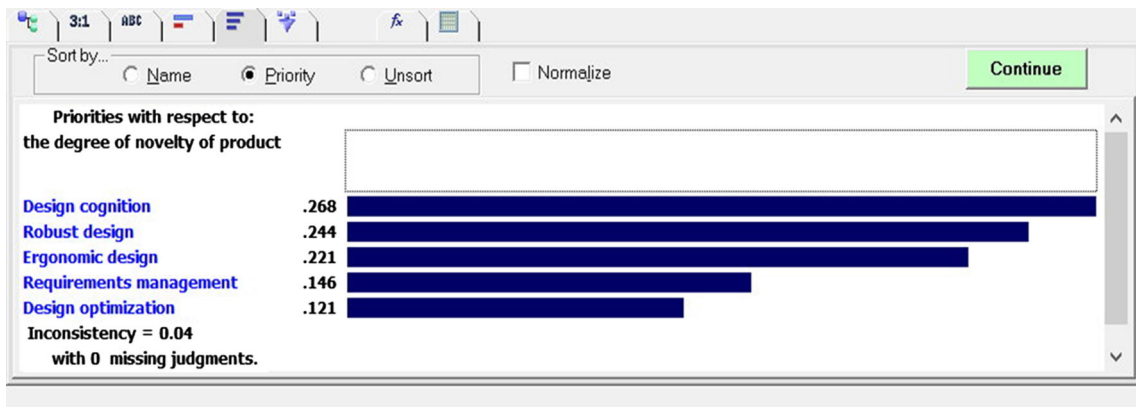| Values	Requirements management (m = 1)	Ergonomic design (m = 2)
Robust design (q = 1)	$S(S_1, C_1) = 0.808$	$S(S_1, C_2) = 0.858$
Design optimization (q = 2)	$S(S_2, C_1) = 0.871$	$S(S_2, C_2) = 0.915$
Design cognition (q = 3)	$S(S_3, C_1) = 0.768$	$S(S_3, C_2) = 0.840$

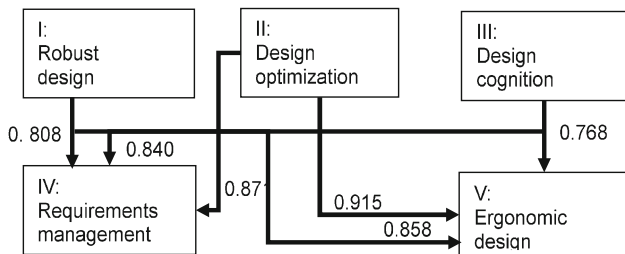**Fig. 7** Values of engineering design perspectives

Fig. 8 FCM for engineering design perspective

Therefore multiplying this input vector with adjacency matrix, we can obtain an output vector as follows:

Output vector: [0, 0, 0, 0.51, 0.55]

The values of output vector have no range. According to FCM algorithm, we define the values were favorable when they are larger than 0.5. In a word, the higher the values of output vector, the better the effectiveness. From the above calculated result, the output vector may be interpreted such that change in those factors including engineering design perspective affect requirements management by 0.51 and ergonomic design by 0.55. Therefore, we can conclude that changes of five factors may affect the requirements management and ergonomic design most favorably (> 0.5) for this case study. Furthermore, this result presents effectiveness of engineering design perspective both using customer experience and engineer experience by adjacency matrix. The adjacency matrix shows that the variation of some factors causes an effect on other factors with regarding to the effectiveness of engineering design perspective.

In order to describe the degree of these factors, it is possible to use fuzzy linguistic terms with fuzzy membership

function in Table 7. It is applied for measuring the value and categorizing the priority such as H (high), M (medium) and L (low) in the Fig. 5. It is possible to find the input vector that leads to the highest effectiveness of engineering design perspective in Table 7. As an example of the five KPIs, H (high), M (medium) and L (low) were generated as shown in Table 7. According to the selected KPIs in Table 7, we calculate H, M and L by formula in Fig. 5 using the survey data of this case study.

By referring to Table 7, the three input vector categories such as H, M and L may be obtained as follows:

Input vector (H): [0, 0.43, 0.16, 0, 0]
Input vector (M): [0.2, 0.56, 0.85, 0.5, 0.25]
Input vector (L): [0.2, 0, 0, 0.5, 0.75]

Therefore multiplying this input vector with adjacency matrix, we can obtain an output vector as follows:

Output vector (H): [0, 0, 0, 0.5, 0.53]
Output vector (M): [0, 0, 0, 1.3, 1.4]
Output vector (L): [0, 0, 0, 0.16, 0.17]

From the above calculated result, the output vector may be interpreted such that change in those factors including H degree, M degree, L degree affect requirements management by 0.5, 1.3, 0.16 and ergonomic design by 0.53, 1.4, 0.17. Therefore, we can conclude that changes of fuzzy linguistic terms may affect the requirements management and ergonomic design in M degree (1.3 and 1.4 > 0.5) most favorably. This result leads to the great effectiveness of engineering design perspective when it focuses on the priority of medium degree based on five evaluated measure KPIs for this case study.

5 Evaluation and sensitivity analysis

However, there are few models considering not only ambiguous situations but also customer experience and engineer experience, simultaneously. Therefore, in this section, we consider product mix problems to take several fuzzy logic and engineering design perspective into account. This evaluation addresses a linear programming model of the product mix-experience problem considering the proposed approach performance. The purpose of this evaluation is to help the proposed approach validate the total performance mode selection problem. Maximizing the total profit and fully utilizing the relationship among engineering design perspective are a key optimization problem in the product-mix of dual experiences. In the same time, another major difficulty is how to optimize the total revenue for selling product values and experience's values within the influence

Table 7 Input vector from fuzzy membership function

KPI	Robust design		Design optimization		Design cognition		Requirements management		Ergonomic design	
	Used numbers successfully = 18		Repurchase quantity = 10		RMA quantity=25		Accepted function item = 8		Customized function item = 4	
H	$y = 0.1x - 2$	0	$y = 0.11x - 0.67$	0.43	$y = 0.077x - 1.77$	0.155	$y = 0.167x - 1.67$	0	$y = 0.2x - 1.4$	0
M	$y = 0.1x - 1$	0.2	$y = 0.33x - 1$	0.56	$y = 0.1x - 1.3$	0.845	$y = 0.5x - 4$	0.499	$y = 0.25x - 0.75$	0.25
	$y = -0.1x + 3$		$y = -0.11x + 1.66$		$y = -0.077x + 2.77$		$y = -0.167x + 2.67$		$y = -0.2x + 2.4$	
L	$y = -0.1x + 2$	0.2	$y = -0.33x + 2$	0	$y = -0.1x + 2.3$	0	$y = -0.5x + 5$	0.5	$y = -0.25x + 1.75$	0.75

of each perspective for engineering design perspective. The experience's values by customer-centred design perspective indicate value-added product to add sale revenue. According to the above-mentioned two optimization results in the product mix optimization problem, fuzzy dual experience-based design involves the relative importance of the influence of each perspective and dual experiences to meet customer needs and the best total profit. This section discusses how R&D cost, design quality, and market capital should affect market share. The market share should affect profitability using measures of economic returns such as total profit. In design quality, this proposed approach adopts the influence value of designer perspective to evaluate its performance. The total profit is constructed using a methodology that maximizes the relationships among engineering design perspectives.

5.1 The formulation of product mix-experience problems considering engineering design perspective

Here, we describe the non-linear programming (non-LP) formulation for the product mix-experience problem.

Firstly, we introduce the following decision variables and parameters

x_j: amount of production to new product j

q_j: market price of new product j

r_j: experience's value of new product j with each perspective

a_{kj}: coefficient of product j in constraint k; i.e., capacity constraint,

b_k: maximum values of right hand side in constraint k

D_j: maximum demand of all new product j

Secondly, we mainly focus on maximizing the total revenue of market and value of experience under several constraints in production processes and new product development. This problem is equivalent to a non-linear programming problem in mathematical programming. The non-linear programming problem will be transferred into linear programming when r_j is constant. Therefore, we efficiently find an optimal solution by using linear programming approaches such as Simplex method. Generally, a basic model of product mix-experience problem maximizing total revenue (TR) and experience value is formulated as follows:

$$(TR) \, Maximize \sum_{j=1}^{n} (r_j + q_j) x_j \qquad (6)$$

subject to $\sum_{j=1}^{n} a_{kj} x_j \leq b_k, \, k = 1, 2, \ldots, m, \, j = 1, 2, \ldots, n, \, 0 \leq x_j \leq D_j$

where, $r_j = f(RM_i) = c_i + d_i \ln(RM_i)$, i=low, medium, high

RM_i is the influence value of requirement management perspective for different fuzzy membership function with low, medium, high from output vector.

Then, TR for all products will be obtained as:

$$(TR) \, Maximize \sum_{j=1}^{n} \left((c_i + d_i ln \, (RM_i)) + q_j \right) x_j \qquad (7)$$

where c_i and d_i are the constants

Thirdly, a significant void exists in current models of market share because of the market capital incorporates constructs related to product design. Total cost (TC) is by defining and discussing the links between R&D cost, market capital, and design quality for market share in Eq. (8). Market share can be gained by attracting customers with preferences more distant from the target market.

$$TC_t = R\&D \, cost + market \, capital + design \, quality \qquad (8)$$

By using the methods of Hayashi and Inoue [23], it is possible to show that the market and R&D value for capital aggregator can be written as follows in Eq. (9):

$$R\&D \, cost + market \, capital = \Phi \left(A_{jt}, K_{jt} \right)$$
$$= A_{jt} + \gamma_j K_{jt} \qquad (9)$$

where A_{jt} is the jth market capital on the time t,

where K_{jt} is the jth R&D capital on the time t,

where γ_j is a premium or discount for the R&D K_{jt}.

The capital aggregator is regarded as correlation with R&D cost and market price as shown in Eq. (10):

$$\gamma_j = f(ED) = g_i + h_i \ln(ED_i), \, i = low, medium, \, high \qquad (10)$$

where g_i and h_i are the constants.

ED_i is the influence value of engineering design perspective for different fuzzy membership function with low, medium, high from output vector.

Fourthly, after discussing above-mentioned R&D cost and market capital, we will further describe design quality as following. Of particular interest in this study is the extent to which various dimensions of the product mix may interact to produce differential impacts on design quality using design perspective. Design quality (DQ_{ij}) is defined as the extent to which quality is designed into the product mix. Design quality affects the competitiveness of a product mix to decrease design time and cost. Therefore, it is important to get new products to market faster for capturing larger market share.

In this section, design quality is incorporated using a composite measure of design perspective such as robust design, Design optimisation and Design cognition. After discussing above-mentioned design quality, we will gain total cost as in Eq. (11).

$$TC_t = \sum_{j=1}^{n} \Phi\left(A_{jt}, K_{jt}\right) \Big/ DQ_{ij}, \; i = low, \; medium, \; high \tag{11}$$

where, DQ_{ij} = the influence summary value of Robust design, Design optimisation and Design cognition from input vector for low, medium, high.

Finally, calculate total profit: TR-TC.

5.2 Numerical analysis

Numerical examples are presented to illustrate the proposed model and the sensitivity analysis for three cases with H, M and L mode in the optimal solutions with respect to parameters of the system is also carried out. We consider numerical examples adopted from the data in the study of consumer electronic product firms. The example of Tables 8 and 9 for three products attempts to show how results are brought for solving various cases in product mix-experience decision problems in multiple-critical case according to Eqs. (5)–(9). In this case study, we collect that three product types #1, #2 and #3 that are produced in seven different production capacity ($k = 1, 2, 3$) from b_1 to b_3, each resource of which has 180, 300 and 240 upper capacity. From Tables 8 and 9, the basic product mix-experience decision problem of linear programming model is given as the following.

Maximize $(2.93 + 3)x_1 + (1.45 + 3.5)x_2 + (1.98 + 2)x_3$
subject to $2 * x_1 + 1 * x_2 + 1 * x_3 \leq 180$
$1 * x_1 + 3 * x_2 + 2 * x_3 \leq 300$
$2 * x_1 + 1 * x_2 + 2 * x_3 \leq 240$

Once finished the above-mentioned ED_i, we can calculate TC_t ($461,970.51) from Eq. (10). Finally, we solve this product mix-experience problem and obtain its optimal solution and the maximum level of total profit ($246,029.49).

5.3 Sensitivity analysis

There are three alternatives feasible optimal solutions of the proposed model in product mix-experience based on different assumption of variables. Sensitive experiment analyses the results for three different cases based on fuzzy membership function for engineering design perspective. The results are analysed illustrating the most likely profit, design quality

Table 8 Relevant and calculated values

Product j	i	x_j (Calculated)	q_j ($1000 base)	r_j (Calculated) ($1000 base)	RM_i (Calculated)	ED_i (Calculated)	γ_j (Calculated)	DQ_{ij} (Calculated)	$\Phi\left(A_{jt}, K_{jt}\right)$ (Calculated)
1	H	48	$3	$2.93	0.5	0.53	4.49	0.59	$83,920.97
2	M	84	$3.5	$1.45	1.3	1.4	0.17	1.61	$45,890.00
3	L	0	$2	$1.98	0.16	0.23	0.12	0.2	$58,245.69

Table 9 Assumed production capacity

(k,j)	a_{kj}
(1,1)	2
(1,2)	1
(1,3)	1
(2,1)	1
(2,2)	3
(2,3)	2
(3,1)	2
(3,2)	1
(3,3)	2

Fig. 9 TP with respect to engineering design perspective for cases #1, 2, and 3

and the influence of engineering design perspective. Next, we study the sensitivity of the optimal solution by changing the values of the different parameters such as RM_i and ED_i associated with the proposed model on the optimal total profit. Applying the fuzzy product mix-experience with proposed approach yields the results in Table 10. The results obtained for illustrative three different cases provide certain insights about the product mix-experience problem studies. Some of them are described as in Table 10.

(a) Increasing the degree of fuzzy membership function will result in an increase in the optimal total profit for design quality. For example, total profit of case 2 is larger than case 1 and 3 because of the higher degree of fuzzy membership function such as both H (0.86) and M (1.33) degree. In case 3, the negative total profit is produced because that L value of design quality is too small (0.1). In this proposed approach, design quality is incorporated using a composite measure of designer perspective such as robust design, design optimisation and design cognition. Thus, we find that designer perspective affects total profit.

(b) Increasing the sum value of r_j will result in an increase in the optimal total profit. For example, case 3 has the larger total profit because of the larger sum value of r_j (7.56). In this articles, r_j is experience's value of new product j within the determined the influence of engineering design perspective. Thus, we find that dual experiences affect total profit. If the
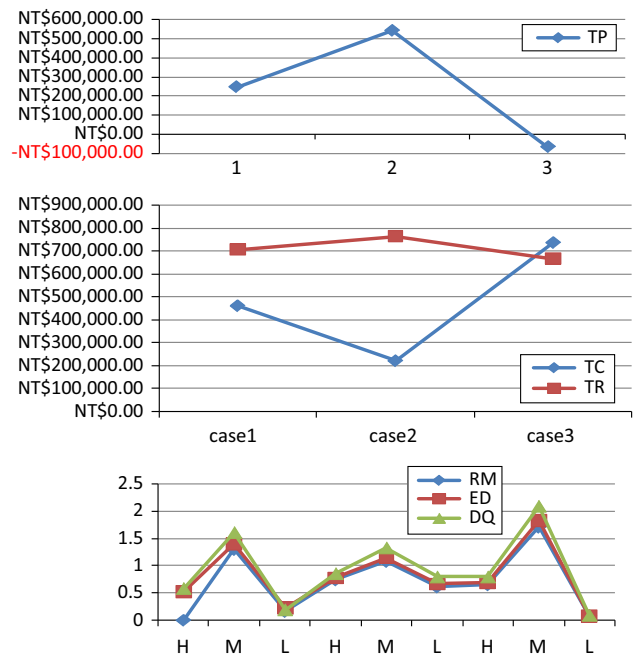
dual experiences have good design quality, then it obtains higher total profit.

(c) The influence of RM_i and ED_i are very sensitive to DQ_{ij} when the degree of fuzzy membership function fluctuates based on the optimal total profit.

The relevant values and relevant costs after considering different degree H, M, L and design quality are shown in Fig. 9. In summary, the rank of total profit will be case 2, case 1 and case 3, respectively. The design quality for the sum of degree H, M, and L for all case will be 2.25, 5.03, and 1.2, respectively. Thus, we find that degree M has larger effect for total profit in this numerical analysis. The product mix-experience for case #2 should be emphasized by expected producing total cost of $223,724 and resulting in the total profit of $541,035. The degree L for case #1, #2 and degree

Table 10 the sensitivity of the optimal solution

Case#(t) Degree i	#1 H	#1 M	#1 L	#2 H	#2 M	#2 L	#3 H	#3 M	#3 L
RM_i	0.5	1.3	0.16	0.74	1.08	0.61	0.65	1.71	0.08
ED_i	0.53	1.4	0.23	0.78	1.15	0.67	0.69	1.83	0.08
r_j	$2.93	$1.45	$1.98	$2.97	$1.13	$3.46	$2.96	$1.91	$1.22
DQ_{ij}	0.59	1.61	0.2	0.86	1.33	0.8	0.8	2.09	0.1
TC_t	$461,970.51			$223,724			$735,529.77		
TR_t	$708,000			$764,760			$667,440		
Total profit (TP)	$246,029.49 (sum of r_j=6.36)			$541,035.00(sum of r_j=7.56)			−$680, 89.77(sum of r_j = 6.09)		
Rank of total profit for all	2			1			3		

H for case #1 may not be beneficial for having the dual experiences design efficiency in product mix-experience solution.

6 Conclusion

Both the engineer's experience and customer's experience for dual experiences are important in delivering quality user-centred product design. This article proposes a new novelty method combining FDT into FCM. The sensitivity analysis concluded that the dual experiences in experiential design create a compelling customer responses and aid in the product design of a high quality interaction. This article proposes the utilization of the fuzzy causal characteristics of FCM and inference mechanism as the underlying approach in order to generate an engineering perspective of interaction performance impact. Furthermore, an evaluation for the design quality to help defining a product mix-experience was presented. This evaluation considers the degree of fuzzy membership function used for influence value of engineering design perspective. It was used to define a product mix-experience problem with dual experiences and each perspective. For practical purposes, this problem can find the optimal total profit of the design quality of product design considering the relationship between market price and experience's value of new product for production. Our findings also provide a preliminary indication of trade-offs between engineering design perspective and market share. We find that the degree of fuzzy membership function of each perspective actually may enhance as market share increases. Our aim is intended to shed light on the product mix-experience optimization for firm performance using the relationship among engineering design perspective. This evaluation result shows that dual experience-based design approach can help R&D design delivering quality product development experiences and creating value with customers for yielding a high performance engineering design.

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