Advanced Engineering Informatics 45 (2020) 101099

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

A new integrated approach for engineering characteristic prioritization in quality function deployment

Ye-Jia Ping[a], Ran Liu[a], Wanlong Lin[b,*], Hu-Chen Liu[c,d]

[a] School of Management, Shanghai University, Shanghai 200444, PR China
[b] Shanghai No.3 Rehabilitation Hospital, 100 JiaoCheng Road, Shanghai 200436, PR China
[c] College of Economics and Management, China Jiliang University, Hangzhou 310018, PR China
[d] School of Economics and Management, Tongji University, Shanghai 200092, PR China

ARTICLE INFO

Keywords:
Product development
Quality function deployment
Picture fuzzy linguistic set
EDAS method
Product-service system

ABSTRACT

As a customer-driven quality improvement tool, quality function deployment (QFD) can convert customer requirements (CRs) into appropriate engineering characteristics (ECs) in product design and development. However, the conventional QFD method has been criticized for a variety of drawbacks, which limit its efficiency and potential applications. In this study, a new QFD approach integrating picture fuzzy linguistic sets (PFLSs) and the evaluation based on distance from average solution (EDAS) method is proposed for the determination of ranking order of ECs. The PFLSs are utilized to express the judgements of experts on the relationships among CRs and ECs. Then, the EDAS method is extended under picture fuzzy linguistic environment for the prioritization of the ECs identified in QFD. Moreover, a combined weighing method based on technique for order of preference by similarity to ideal solution (TOPSIS) and maximum entropy theory is established to calculate the weights of experts objectively. Finally, a product-service system design is provided to illustrate the effectiveness of the proposed QFD approach. The result shows that the manufacturer should pay more attention to "Meantime before failure", "Warning feature" and "Quality of product manual". Feedback from domain experts indicates that the integrated approach being proposed in this paper is more suitable for assessing and prioritizing ECs in QFD.

1. Introduction

The quality function deployment (QFD), proposed by Akao [1], is a popular quality improvement tool used for the design and development of products, systems and services [2,3]. As a customer-driven technique, it is aimed at catching existing or potential customer requirements (CRs) and translate them into relevant engineering characteristics (ECs) to ensure that the output meets these requirements [4,5]. Through bridging the communication gap between customers and technicians, QFD can help product designers to determine the most important ECs to be focused during the process of product design or modification [6]. It can not only improve customer satisfaction, but also reduce cycle-time of product development and cut down production cost [7–9]. Because of its features and benefits, the QFD method has been applied for product design and quality improvement in various areas, which include manufacturing [10], construction [4,11], and service [3,12] industries.

A classical QFD model is consisted of four phases: scheme design, configuration of components, engineering and quality control as well as manufacturing work order [13–15]. Specifically, building house of quality (HOQ) is a core step in carrying out QFD. It is established to link the relationships between 'WHATs' and 'HOWs' for determining the priority of ECs. With the design-oriented characteristic of HOQ, CRs are easily converted into ECs to reduce the difference between customers and product designers. However, as reported in previous studies [5,16–19], there are many shortcomings of the traditional QFD method. For example, in the traditional QFD, crisp values are used to quantify the relationships between CRs and ECs. However, due to the inherent uncertainty and vagueness of human cognition, it is hard for experts to give their opinions using exact numbers. Besides, the traditional QFD uses the weighted average method to determine the prioritization of ECs, which is a fully compensatory method and may lead to biased ranking of ECs.

In a real QFD process, providing crisp judgments over the relationships between CRs and ECs is often difficult due to the uncertainty and vagueness of human perception. Instead, experts tend to use natural language to express their opinions [9,12,20], and they may even hesitate among several linguistic values because of time pressure and

* Corresponding author at: Shanghai No. 3, Rehabilitation Hospital, 100 JiaoCheng Road, Shanghai 200436, PR China.
E-mail addresses: wanlong.lin@yahoo.com (W. Lin), huchenliu@tongji.edu.cn (H.-C. Liu).

https://doi.org/10.1016/j.aei.2020.101099
Received 9 July 2019; Received in revised form 20 March 2020; Accepted 13 April 2020
Available online 24 April 2020
1474-0346/

lack of data. The concept of picture fuzzy linguistic sets (PFLSs) was presented by Liu and Zhang [21] to represent uncertain and complex decision making information more accurately. It not only provides three degrees (the positive membership degree, the neutral membership degree and the negative membership degree), but also uses linguistic terms to express the cognitive information of decision makers. Compared with other linguistic computing methods, the PFLSs have the following advantages [21,22]: First, PFLSs can capture decision makers' various judgements flexibly with more freedom degrees. Second, PFLSs take full advantage of linguistic variables to describe the subjective imprecision of human cognition. Because of its practicability in qualitative assessments, the PFLS theory has been used in enterprise resource planning system implementation [23], emerging technology enterprise assessment [24], service outsourcing supplier selection [25], etc. Therefore, it is expected to adopt the PFLSs to deal with experts' uncertain evaluation information on the relationships between CRs and ECs in QFD.

On the other hand, the determination of EC prioritization in QFD is often considered as a multi-criteria decision making (MCDM) problem involving conflicting CRs. Correspondingly, many MCDM methods have been used in previous studies for improving the performance of QFD [18,26,27]. The evaluation based on distance from average solution (EDAS) method is an efficient and relatively new MCDM approach proposed by Keshavarz Ghorabaee et al. [28]. It includes two measures for dealing with the desirability of alternatives, i.e., positive distance from average (PDA) and negative distance from average (NDA). The EDAS has simple logic and is especially useful for decision making problems with conflicting criteria. Since its introduction, this method has been a subject of great interest to researchers and applied in solving lots of MCDM problems, which include construction equipment evaluation [29], United Nations national sustainable development goal prioritization [30], hydrogen production pathway ranking [31], hydrogen mobility roll-up site selection [32], and third-party logistics provider selection [33]. Hence, it is of vital importance to utilize the EDAS method to determine a more precise ranking of ECs in the QFD analysis.

Against the above discussions, the objective of this paper is to develop a new product planning approach via integrating PFLSs and the EDAS method to improve the efficiency and effectiveness of QFD. More specifically, the PFLSs are applied to evaluate the relationships between CRs and ECs to manage the ambiguity and indeterminacy of judgments given by experts. An extended EDAS method in picture fuzzy linguistic environment is introduced to get the ranking orders of ECs. Besides, we present a combined weighing method based on technique for order of preference by similarity to ideal solution (TOPSIS) and maximum entropy theory to objectively calculate the weights of experts. Finally, an empirical case study regarding product-service system design is presented to verify the applicability and usefulness of our proposed new QFD approach.

The remainder of this paper is structured as follows: In Section 2, a literature review of previous works is performed. In Section 4, related basic concepts associated with the PFLSs are presented briefly. In Section 4, the new QFD model based on PFLSs and the EDAS method is put forward. In Section 3, an empirical example is given to demonstrate the proposed QFD approach. At last, conclusions and future research directions are provided in Section 5.

2. Literature review

2.1. Uncertainty theories for group decision making

Because of the complexity of group decision making problems, it is very difficult to express the cognitive information of decision makers precisely. Thus, a lot of researchers have paid their attention to the theories that can effectively deal with vagueness and impreciseness of decision making information in the past decades. Fuzzy set method was first introduced by Zadeh [34] for capturing the uncertainty in group decision making. Thereafter, the ordinary fuzzy sets have been extended to intuitionistic fuzzy sets [35], hesitant fuzzy sets [36], and Pythagorean fuzzy sets [37]. However, in the reality, there are some situations including three types of responses, i.e., yes, no and refusal. This cannot be exactly presented by the conventional uncertainty theories. To overcome this limitation, the picture fuzzy sets (PFSs) [38] were proposed as a new mathematical method for uncertain decision making. A PFS is characterized by three different functions representing positive, neutral and negative membership degrees, respectively. As a generalization of fuzzy sets and intuitionistic fuzzy sets, the PFS theory is more suitable to model the ambiguous and imprecise information given by decision makers. As a result, the PFSs have been employed in many researches for solving uncertain group decision making problems [39–41].

Although the PFS method has been applied in different fields, there are still real-life cases that cannot be represented by PFSs. Under many circumstances, it is easier and natural for decision makers to express their evaluations toward alternatives by using linguistic labels due to the shortage of knowledge and restricted attention. Consequently, several extensions of PFSs have been introduced in the literature, which include the picture uncertain linguistic sets [42], the picture 2-tuple linguistic sets [22], the hesitant picture 2-tuple linguistic variables [43], and the q-rung picture linguistic sets [25]. Among them, the PFLSs were proposed by Liu and Zhang [21], in which the three degrees of PFSs are denoted by linguistic terms. This theory is more in line with decision makers' cognitions and expressions, and can express their judgements more flexibly in the group decision making process.

2.2. Improved methods for QFD

To ameliorate the deficiencies of the traditional QFD, a variety of improved models have been proposed in previous studies, especially those based on MCDM methods. For example, Huang, You, Liu and Si [18] presented a QFD method by combining proportional hesitant fuzzy linguistic term sets with prospect theory, in which the best-worst method (BWM) was used to compute the weights of CRs based on pairwise comparisons. Wang, Fang and Song [19] suggested a hybrid model using cloud model theory and grey relational analysis (GRA) method for technical attribute prioritization in QFD. Wu and Liao [44] proposed an enhanced QFD approach which adopts probabilistic linguistic term sets and the ORESTE (organísation, rangement et Synthèse de données relarionnelles, in French) method to solve an innovation product design selection problem. Wu, Liu and Wang [26] developed an integrated hesitant fuzzy model for QFD, in which the decision making trial and evaluation laboratory (DEMATEL) was applied to compute the weights of CRs and the VIKOR (VIšekriterijumsko KOmpromisno Rangiranje) was used to determine the relative importance of ECs. Jia, Liu, Lin, Qiu and Tan [45] devised a multi-level hierarchical structure for QFD, in which fuzzy evidential reasoning method was employed to tackle the fuzziness and incompleteness of experts' evaluations and fuzzy Choquet integral was used to deal with the interactions among ECs in the aggregation process. In [46], an extended QUALIFLEX (qualitative flexible multiple criteria method) based on hesitant 2-tuple linguistic term sets was introduced to deal with the QFD problems with incomplete CR weight information. In [47], a method to calculate the exact expected values of fuzzy numbers was put forward and applied to derive the ranking of ECs in fuzzy QFD. In [16], a fuzzy QFD approach based on the TOPSIS method was proposed to support the market segment selection and evaluation process. In addition, various fuzzy QFD methods were reported and applied for dishwasher machine selection [17], job satisfaction improvement [10], supply chain performance measurement [48], and so on.

The above literature review shows that many uncertainty theories have been employed to deal with the imprecise assessment information in QFD processes. However, these theories are inefficient in expressing the uncertainty involved in decision makers' cognitive assessments. Moreover, no or little attention has been paid to the QFD problems under the context of PFLSs. On the other hand, plenty of MCDM methods have been adopted in prior researches to obtain the EC prioritization in QFD. To the best of our knowledge, no researchers have investigated QFD problems with the EDAS method yet. Therefore, in this paper, we fill the above gaps by developing a novel integrated approach based on PFLSs and an extended EDAS method to solve QFD problem with unknown expert weighing information. The developed QFD model can not only express the subjective cognitive evaluation information of experts more precisely, but also support engineers in effectively identifying critical ECs to optimize products or services.

3. The proposed QFD approach

In this section, an integrated framework based on PFLSs and an extended EDAS method is developed to determine the priority of ECs in QFD. The relationships between CRs and ECs are evaluated by utilizing PFLSs. The QFD approach presented in this paper is based on the use of a combined weighting method and the EDAS method in a picture fuzzy linguistic environment. The priority of ECs is determined with the picture fuzzy linguistic EDAS (PFL-EDAS) method. The detailed procedures of the new proposed QFD approach can be described in Fig. 1.

For the QFD analysis of a product planning problem, assume that there are n customer requirements $\mathrm{CR}_j (j = 1, 2, \ldots, n)$ and m related engineering characteristics $\mathrm{EC}_i (i = 1, 2, \ldots, m)$. Let $w = (w_1, w_2, \ldots, w_n)^T$ be the weight vector of the CRs, where $w_j \geqslant 0$, $j = 1, 2, \ldots, n$, and $\sum_{j=1}^{n} w_j = 1$. Suppose l experts $E_k (k = 1, 2, \ldots, l)$ are invited to provide their assessments for the relationships between ECs and CRs. Based on these assumptions, the proposed QFD approach to determine the ranking of ECs is introduced by three stages as follows.

Step 1: Formulate the picture fuzzy linguistic evaluation matrixes between ECs and CRs

Based on the judgements of experts on the correlations between ECs and CRs, the picture fuzzy linguistic evaluation matrixes $\tilde{P}^k (k = 1, 2, \ldots, l)$ can be constructed as given below:

$$\tilde{P}^k = (\tilde{p}_{ij}^k)_{m \times n}, \tag{1}$$

where $\tilde{p}_{ij}^k = \langle s_{\theta ij}^k, u_{ij}^k, \eta_{ij}^k, \nu_{ij}^k \rangle$ is the picture fuzzy linguistic number (PFLN) provided by E_k on the correlation between EC_i and CR_j; $s_{\theta ij}^k \in S$, $S = \{s_0, s_1, \ldots, s_t\}$, and u_{ij}^k, η_{ij}^k, ν_{ij}^k are the positive degree, neutral degree, and negative degree for $s_{\theta ij}^k$, respectively.

Step 2: Compute the collective picture fuzzy linguistic evaluation matrix

By the picture fuzzy linguistic weighted averaging (PFLWA) operator [21], the individual picture fuzzy linguistic evaluation matrixes $\tilde{P}^k (k = 1, 2, \ldots, l)$ are aggregated to obtain the collective picture fuzzy linguistic evaluation matrix $\tilde{P} = (\tilde{p}_{ij})_{m \times n}$, in which

$$\tilde{p}_{ij} = \mathrm{PFLWA}(\tilde{p}_{ij}^1, \tilde{p}_{ij}^2, \ldots, \tilde{p}_{ij}^l) = \lambda_1 \tilde{p}_{ij}^1 \oplus \lambda_2 \tilde{p}_{ij}^2 \oplus \cdots \oplus \lambda_n \tilde{p}_{ij}^l. \tag{2}$$

Note that the definition of the PFLWA operator is given as follows [21]: Assume that $\tilde{p}_i = \langle s_{\Theta i}, u_i, \eta_i, \nu_i \rangle (i = 1, 2, \ldots, n)$ is a set of PFLNs and $w = (w_1, w_2, \ldots, w_n)^T$ is the associated weight vector, which satisfies $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$. Then, the picture fuzzy linguistic weighted averaging (PFLWA) operator can be computed by

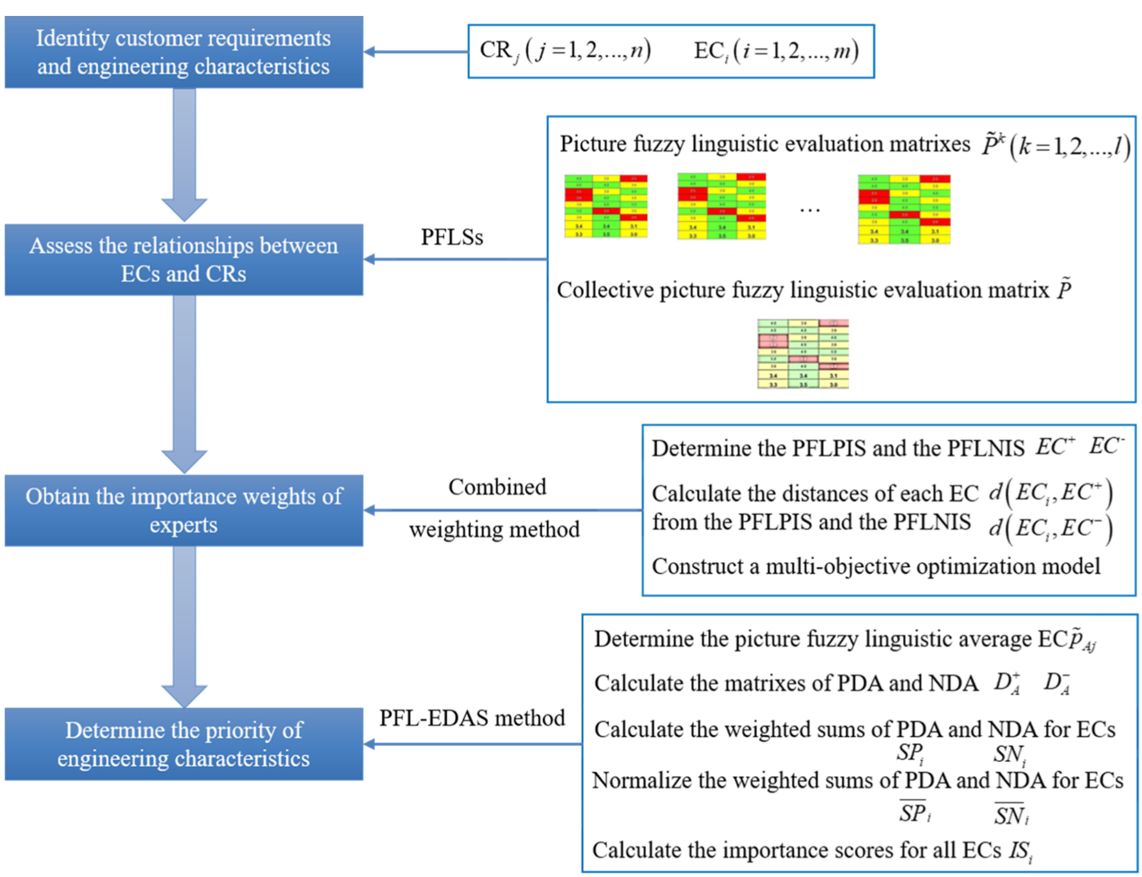

Fig. 1. Framework of the proposed QFD approach.

$$\begin{aligned}\mathrm{PFLWA}(\tilde{p}_1, \tilde{p}_2, \ldots, \tilde{p}_n) &= w_1\tilde{p}_1 \oplus w_2\tilde{p}_2 \oplus \cdots \oplus w_n\tilde{p}_n \\ &= \left\langle s_{\sum_{i=1}^{n} \frac{\theta_i w_i \ln((1-u_i)\eta_i\nu_i)}{\sum_{i=1}^{n} w_i \ln((1-u_i)\eta_i\nu_i)}}, 1 - \left(\prod_{i=1}^{n} (1-u_i)^{w_i}\right), \prod_{i=1}^{n} (\eta_i)^{w_i}, \prod_{i=1}^{n} (\nu_i)^{w_i} \right\rangle. \end{aligned} \tag{3}$$

The PFLWA operator becomes the picture fuzzy linguistic averaging (PFLA) operator if $w = (1/n, 1/n, \ldots,1/n)^T$.

Step 3: Determine the picture fuzzy linguistic positive ideal solution (PFLPIS) and the picture fuzzy linguistic negative ideal solution (PFLNIS)

When assessing the relations between CRs and ECs, the bigger the PFLN, the stronger their relationship. Thus, the PFLPIS and the PFLNIS can be determined as follows:

$$EC^{+} = (\tilde{p}_1^{+}, \tilde{p}_2^{+}, \ldots, \tilde{p}_n^{+}) = (\langle s_t, 1, 1, 1\rangle, \langle s_t, 1, 1, 1\rangle, \ldots, \langle s_t, 1, 1, 1\rangle), \tag{4}$$

$$EC^{-} = (\tilde{p}_1^{-}, \tilde{p}_2^{-}, \ldots, \tilde{p}_n^{-}) = (\langle s_0, 0, 0, 0\rangle, \langle s_0, 0, 0, 0\rangle, \ldots, \langle s_0, 0, 0, 0\rangle). \tag{5}$$

Step 4: Calculate the distances of each EC from the PFLPIS and the PFLNIS

A comparative series with n CRs can be represented as $EC_i = (\tilde{p}_{i1}, \tilde{p}_{i2}, \ldots, \tilde{p}_{in})$, where $\tilde{p}_{ij} (j = 1, 2, \ldots, n)$ are obtained from the collective picture fuzzy linguistic evaluation matrix $\tilde{P}$. Then, the distances of each EC from the PFLPIS and the PFLNIS are calculated by

$$d(EC_i, EC^{+}) = \frac{1}{n} \sum_{j=1}^{n} d(\tilde{p}_{ij}, \tilde{p}_j^{+}), \tag{6}$$

$$d(EC_i, EC^{-}) = \frac{1}{n} \sum_{j=1}^{n} d(\tilde{p}_{ij}, \tilde{p}_j^{-}). \tag{7}$$

Note that for two PFLNs $\tilde{p}_1 = \langle s_{\theta_1}, u_1, \eta_1, \nu_1\rangle$ and $\tilde{p}_2 = \langle s_{\theta_2}, u_2, \eta_2, \nu_2\rangle$, the distance between $\tilde{p}_1$ and $\tilde{p}_2$ is defined as:

$$d(\tilde{p}_1, \tilde{p}_2) = \frac{1}{2}(|\theta_1 u_1 - \theta_2 u_2| + |\theta_1 \eta_1 - \theta_2 \eta_2| + |\theta_1 \nu_1 - \theta_2 \nu_2| + |\theta_1 \pi_1 - \theta_2 \pi_2|). \tag{8}$$

Step 5: Construct a multi-objective optimization model to calculate expert weights

Based on the basic idea of TOPSIS, the selected EC should be closer with the PFLPIS and far away from the PFLNIS. Besides, according to the maximum entropy theory, the entropy of the expert weight vector should be maximized. Thus, for determining the weights of experts, the following multiple non-linear optimization model can be established:

$$(\mathrm{M}-1)\begin{cases} \min z_1(\lambda_1, \lambda_2, \ldots, \lambda_l) = d(EC_i, EC^{+}), \quad i = 1, 2, \ldots, m \\ \max z_2(\lambda_1, \lambda_2, \ldots, \lambda_l) = d(EC_i, EC^{-}), \quad i = 1, 2, \ldots, m \\ \max z_3(\lambda_1, \lambda_2, \ldots, \lambda_l) = -\sum_{k=1}^{l} \lambda_k \ln(\lambda_k) \\ \text{subject to: } \sum_{k=1}^{l} \lambda_k = 1, \lambda_k \geqslant 0, \ k = 1, 2, \ldots, l. \end{cases} \tag{9}$$

To solve the above optimization model, we transform it into a single objective optimization model as below:

$$(\mathrm{M}-2)\begin{cases} \min z(\lambda_1, \lambda_2, \ldots, \lambda_l) = \beta \frac{1}{n} \sum_{i=1}^{m} \frac{d(EC_i, EC^{-})}{d(EC_i, EC^{+}) + d(EC_i, EC^{-})} \\ \quad - (1-\beta) \sum_{k=1}^{l} \lambda_k \ln(\lambda_k) \\ \text{subject to: } \sum_{k=1}^{l} \lambda_k = 1, \lambda_k \geqslant 0, \ k = 1, 2, \ldots, l, \end{cases} \tag{10}$$

where β is a parameter denoting the attitude of a decision maker toward different objectives. Model (M-2) can be easily solved by a mathematical software and the optimal solution is used as the weighting vector of experts $\lambda = (\lambda_1, \lambda_2, \ldots,\lambda_l)^T$.

Step 6: Determine the picture fuzzy linguistic average EC

Based on the weighting vector of experts λ, the collective picture fuzzy linguistic evaluation matrix $\tilde{P} = (\tilde{p}_{ij})_{m\times n}$ can be computed by Eq. (2). In this step, the picture fuzzy linguistic average EC (EC_A) is defined as $\tilde{P}_A = (\tilde{p}_{Aj})_{1\times n}$ by the PFLA operator. That is,

$$\tilde{p}_{Aj} = \frac{1}{m} \bigoplus_{i=1}^{m} \tilde{p}_{ij}. \tag{11}$$

Step 7: Calculate the matrixes of the PDA and the NDA

In this step, the PDA matrix $D_A^{+} = (d_{ij}^{+})_{m\times n}$ and the NDA matrix $D_A^{-} = (d_{ij}^{-})_{m\times n}$ are, respectively, computed by

$$d_{ij}^{+} = \begin{cases} \frac{\max\{0, d(\tilde{p}_{ij}, \tilde{p}_{Aj})\}}{E_A(\tilde{p}_{Aj})} & if\ \tilde{p}_{ij} > \tilde{p}_{Aj}, \\ 0 & if\ \tilde{p}_{ij} \leqslant \tilde{p}_{Aj}, \end{cases} \tag{12}$$

$$d_{ij}^{-} = \begin{cases} \frac{\max\{0, d(\tilde{p}_{ij}, \tilde{p}_{Aj})\}}{E_A(\tilde{p}_{Aj})} & if\ \tilde{p}_{ij} < \tilde{p}_{Aj}, \\ 0 & if\ \tilde{p}_{ij} \geqslant \tilde{p}_{Aj}. \end{cases} \tag{13}$$

Step 8: Calculate the weighted sums of PDA and NDA for all ECs

Considering the weight of each CR, the weighted sums of PDA and NDA for all ECs are calculated as follows:

$$SP_i = \sum_{j=1}^{n} (w_j d_{ij}^{+}), \quad i = 1, 2, \ldots, m, \tag{14}$$

$$SN_i = \sum_{j=1}^{n} (w_j d_{ij}^{-}), \quad i = 1, 2, \ldots, m. \tag{15}$$

Step 9: Normalize the weighted sums of PDA and NDA for all ECs

The normalized values of SP_i and SN_i for all ECs can be computed by

$$\bar{SP}_i = \frac{SP_i}{\max_i(1, SP_i)}, \quad i = 1, 2, \ldots, m, \tag{16}$$

$$\bar{SN}_i = 1 - \frac{SN_i}{\max_i(1, SN_i)}, \quad i = 1, 2, \ldots, m. \tag{17}$$

Step 10: Calculate the importance scores for all ECs

The EC which has more positive distances and less negative distance from the picture fuzzy linguistic average EC is more important in the QFD process. Thus, the importance scores for the m ECs can be obtained by

$$IS_i = \frac{1}{2}(\bar{SP}_i + \bar{SN}_i), \quad i = 1, 2, \ldots, m. \tag{18}$$

Finally, the priority of all the ECs is determined by ranking their importance scores $IS_i (i = 1, 2, \ldots, m)$ in descending order. The EC with the highest importance score is the most important one among the m ECs.

4. Illustrative example

In this section, a product-service system design at a manufacturer [49] is provided to illustrative the applicability and effectiveness of our proposed QFD approach.

4.1. Background

In recent years, the use of product service systems has become more and more popular. By integrating products and services, a product-service system can achieve functional results that augment the offering's value. On the one hand, a product-service system allows manufacturers to improve their environmental performance; on the other

Table 1
ECs and CRs considered for the case study.

CRs	Customer requirements	ECs	Engineering characteristics
CR_1	Ease of use of the device (ergonomics)	EC_1	Product size: adequate dimensions and weight for easy use and transport
CR_2	Real-time process information	EC_2	Monitor: high-resolution display
CR_3	Short replacement time (if the device is unrepairable or requires off-site maintenance)	EC_3	Meantime before failure: the device must be functional for extended periods of time prior to breaking down
CR_4	Short intervention time	EC_4	Warning feature: availability of an auto-testing system and an alarm system for a malfunctioning notification
CR_5	Availability and readiness for use	EC_5	Environmentally friendly consumables
CR_6	Environmental friendliness	EC_6	Quality of product manual: providing all necessary descriptions for the correct use and functioning of the device
CR_7	Availability of remote technical support		

hand, they increase the value of their products throughout the lifecycle [50]. As a result, a manufacturer can increase its market share to gain competitive advantages through the product-service system design. However, compared with the requirements for an actual product, it is more challenging to study the requirements of customers for services, because they are intangible and different customers have different perceptions [51]. Hence, the design of product-service systems has attracted considerable attention from both researchers and practitioners. In this case study, it is necessary to determine important ECs of a product-service system in the medical sector with the proposed QFD framework, in order to help manufacturers to reduce costs and create value beyond products themselves.

Through market survey and expert interview, seven CRs (CR_j, $j = 1, 2, ..., 7$) and six ECs (EC_i, $i = 1, 2, ..., 6$) are considered for the product-service system in medical sector, which are described in Table 1. For the QFD problem, the weight vector of CRs is assumed to be $w = (0.12, 0.11, 0.21, 0.17, 0.27, 0.05, 0.07)^T$. Four experts $E_k (k = 1, 2, 3, 4)$ from the manufacturer have been invited to give their evaluations on the interrelations between the ECs and CRs. The evaluations are conducted by using the linguistic term set S:

$$S = \left\{ \begin{array}{c} s_0 = none,\ s_1 = extremely\ weak,\ s_2 = weak,\ s_3 = medium,\ s_4 \\ = strong, \\ s_5 = extremely\ \text{strong},\ s_6 = perfect \end{array} \right\}$$

4.2. Implementation

According to the three phases of our proposed QFD approach, the implementation results are elaborated as follows.

Step 1: Based on the assessment results of experts toward the relationships between ECs and CRs, the picture fuzzy linguistic evaluation matrixes $\widetilde{P}^k = (\widetilde{p}_{ij}^k)_{6\times 7} (k = 1, 2, ..., 4)$ can be obtained. For example, the assessment matrix of the first expert $\widetilde{P}^1$ is shown in Table 2.

Step 2: By Eq. (2), the four individual evaluation matrixes $\widetilde{P}^k (k = 1, 2, ..., 4)$ are aggregated to get the collective picture fuzzy linguistic evaluation matrix $\widetilde{P} = (\widetilde{p}_{ij})_{6\times 7}$.

Step 3: According to Eqs. (4) and (5), the PFLPIS and the PFLNIS are derived as: $EC^+ = (\langle s_t, 1, 1, 1\rangle, \langle s_t, 1, 1, 1\rangle, ..., \langle s_t, 1, 1, 1\rangle)$,

$EC^- = (\langle s_0, 0, 0, 0\rangle, \langle s_0, 0, 0, 0\rangle, ..., \langle s_0, 0, 0, 0\rangle)$.

Steps 4–5: Via Eqs. (6) and (7), the distances of each EC from the PFLPIS and the PFLNIS can be calculated. Then, based on Eq. (10), the following non-linear optimization model is built:

$$\left\{ \begin{array}{l} \min z(\lambda_1, \lambda_2, ..., \lambda_4) = 0.37 \times \frac{1}{6} \sum\limits_{i=1}^{6} \frac{d(EC_i, EC^-)}{d(EC_i, EC^+) + d(EC_i, EC^-)} \\ \quad - 0.63 \times \sum\limits_{k=1}^{4} \lambda_k \ln(\lambda_k) \\ \quad \text{subject to: } \sum\limits_{k=1}^{4} \lambda_k = 1, \lambda_k \geqslant 0,\ k = 1, 2, ..., 4. \end{array} \right.$$

By solving the above model, the weight vector of the four experts is acquired as: $\lambda = (0.152, 0.279, 0.319, 0.250)^T$.

Step 6: Based on the expert weight vector λ and by using Eq. (2), the collective picture fuzzy linguistic evaluation matrix $\widetilde{P} = (\widetilde{p}_{ij})_{6\times 7}$ is determined as shown in Table 3. Then, using Eq. (11), the picture fuzzy linguistic average EC (EC_A) is defined as:

$$\widetilde{P}_A = \left(\begin{array}{c} \langle s_{3.12}, 0.66, 0.22, 0.06\rangle, \langle s_{2.92}, 0.72, 0.18, 0.06\rangle, \\ \langle s_{1.60}, 0.58, 0.27, 0.09\rangle, \\ \langle s_{2.09}, 0.64, 0.22, 0.08\rangle, \langle s_{2.50}, 0.69, 0.17, 0.09\rangle, \\ \langle s_{1.69}, 0.66, 0.22, 0.08\rangle, \\ \langle s_{1.25}, 0.66, 0.20, 0.10\rangle \end{array} \right).$$

Step 7: By utilizing Eqs. (12) and (13), the PDA matrix $D_A^+ = (d_{ij}^+)_{6\times 7}$ and the NDA matrix $D_A^- = (d_{ij}^-)_{6\times 7}$ are calculated as shown in Tables 4 and 5, respectively

Step 8: Considering the weights of CRs w, the weighted sum of PDA and NDA for all ECs, $SP_i (i = 1, 2, ..., 6)$ and $NP_i (i = 1, 2, ..., 6)$, are calculated by Eqs. (14) and (15). The computation results are displayed in Table 6.

Step 9: Via Eqs. (16) and (17), the normalized values of SP_i and SN_i for all ECs, $\bar{SP}_i (i = 1, 2, ..., 6)$ and $\bar{NP}_i (i = 1, 2, ..., 6)$, are calculated as shown in Table 6.

Step 10: By Eq. (18), we can calculate the importance scores for the six ECs $IS_i (i = 1, 2, ..., 6)$ as listed in Table 6.

By ranking the values of $IS_i (i = 1, 2, ..., 6)$ in decreasing order, the

Table 2
The picture fuzzy linguistic evaluation matrix $\widetilde{P}^1$.

ECs	CRs						
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
EC_1	$\langle s_6, 0.91, 0.03, 0.05\rangle$	$\langle s_0, 0.63, 0.20, 0.08\rangle$	$\langle s_1, 0.41, 0.31, 0.19\rangle$	$\langle s_2, 0.88, 0.07, 0.02\rangle$	$\langle s_1, 0.60, 0.22, 0.18\rangle$	$\langle s_1, 0.62, 0.23, 0.12\rangle$	$\langle s_0, 0.63, 0.22, 0.08\rangle$
EC_2	$\langle s_1, 0.75, 0.16, 0.07\rangle$	$\langle s_6, 0.81, 0.12, 0.06\rangle$	$\langle s_0, 0.67, 0.09, 0.21\rangle$	$\langle s_0, 0.65, 0.11, 0.23\rangle$	$\langle s_2, 0.52, 0.23, 0.20\rangle$	$\langle s_0, 0.50, 0.38, 0.11\rangle$	$\langle s_2, 0.77, 0.12, 0.08\rangle$
EC_3	$\langle s_0, 0.40, 0.36, 0.19\rangle$	$\langle s_0, 0.64, 0.21, 0.12\rangle$	$\langle s_5, 0.64, 0.16, 0.15\rangle$	$\langle s_5, 0.88, 0.08, 0.04\rangle$	$\langle s_6, 0.83, 0.08, 0.05\rangle$	$\langle s_0, 0.58, 0.37, 0.02\rangle$	$\langle s_5, 0.73, 0.17, 0.06\rangle$
EC_4	$\langle s_3, 0.88, 0.08, 0.02\rangle$	$\langle s_5, 0.72, 0.13, 0.08\rangle$	$\langle s_2, 0.54, 0.31, 0.15\rangle$	$\langle s_5, 0.68, 0.26, 0.06\rangle$	$\langle s_5, 0.78, 0.13, 0.08\rangle$	$\langle s_0, 0.40, 0.35, 0.19\rangle$	$\langle s_2, 0.68, 0.19, 0.10\rangle$
EC_5	$\langle s_1, 0.67, 0.22, 0.08\rangle$	$\langle s_0, 0.51, 0.37, 0.09\rangle$	$\langle s_0, 0.48, 0.32, 0.19\rangle$	$\langle s_0, 0.63, 0.22, 0.08\rangle$	$\langle s_2, 0.74, 0.13, 0.09\rangle$	$\langle s_6, 0.89, 0.02, 0.05\rangle$	$\langle s_0, 0.42, 0.35, 0.18\rangle$
EC_6	$\langle s_5, 0.64, 0.16, 0.15\rangle$	$\langle s_5, 0.73, 0.13, 0.07\rangle$	$\langle s_1, 0.68, 0.25, 0.06\rangle$	$\langle s_1, 0.70, 0.15, 0.12\rangle$	$\langle s_2, 0.62, 0.23, 0.10\rangle$	$\langle s_1, 0.76, 0.14, 0.06\rangle$	$\langle s_2, 0.69, 0.21, 0.07\rangle$

Table 3
The collective picture fuzzy linguistic evaluation matrix $\tilde{P}$.

ECs	CRs						
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
EC_1	$\langle s_6, 0.86, 0.07, 0.04\rangle$	$\langle s_0, 0.67, 0.21, 0.09\rangle$	$\langle s_{0.76}, 0.49, 0.33, 0.11\rangle$	$\langle s_{0.77}, 0.58, 0.29, 0.06\rangle$	$\langle s_{0.59}, 0.66, 0.17, 0.11\rangle$	$\langle s_{0.14}, 0.59, 0.28, 0.10\rangle$	$\langle s_0, 0.66, 0.19, 0.11\rangle$
EC_2	$\langle s_{1.86}, 0.74, 0.18, 0.07\rangle$	$\langle s_6, 0.78, 0.12, 0.05\rangle$	$\langle s_0, 0.42, 0.35, 0.15\rangle$	$\langle s_0, 0.55, 0.23, 0.17\rangle$	$\langle s_{0.58}, 0.66, 0.17, 0.15\rangle$	$\langle s_0, 0.61, 0.27, 0.09\rangle$	$\langle s_{1.02}, 0.71, 0.17, 0.09\rangle$
EC_3	$\langle s_{0.25}, 0.27, 0.59, 0.05\rangle$	$\langle s_{0.3}, 0.53, 0.33, 0.09\rangle$	$\langle s_{4.75}, 0.80, 0.11, 0.06\rangle$	$\langle s_{4.86}, 0.67, 0.21, 0.08\rangle$	$\langle s_6, 0.75, 0.13, 0.09\rangle$	$\langle s_0, 0.61, 0.24, 0.09\rangle$	$\langle s_{4.4}, 0.70, 0.21, 0.05\rangle$
EC_4	$\langle s_3, 0.64, 0.26, 0.04\rangle$	$\langle s_{4.71}, 0.75, 0.17, 0.06\rangle$	$\langle s_{1.05}, 0.62, 0.26, 0.09\rangle$	$\langle s_{4.5}, 0.72, 0.20, 0.05\rangle$	$\langle s_5, 0.71, 0.16, 0.09\rangle$	$\langle s_0, 0.47, 0.37, 0.10\rangle$	$\langle s_{0.52}, 0.63, 0.18, 0.14\rangle$
EC_5	$\langle s_{0.78}, 0.58, 0.29, 0.10\rangle$	$\langle s_0, 0.67, 0.23, 0.05\rangle$	$\langle s_0, 0.52, 0.32, 0.09\rangle$	$\langle s_0, 0.52, 0.29, 0.10\rangle$	$\langle s_{0.68}, 0.70, 0.20, 0.05\rangle$	$\langle s_6, 0.87, 0.06, 0.04\rangle$	$\langle s_0, 0.64, 0.22, 0.10\rangle$
EC_6	$\langle s_{4.48}, 0.66, 0.20, 0.10\rangle$	$\langle s_{4.52}, 0.82, 0.11, 0.04\rangle$	$\langle s_{1.12}, 0.51, 0.35, 0.07\rangle$	$\langle s_{1.28}, 0.74, 0.14, 0.08\rangle$	$\langle s_{1.56}, 0.66, 0.18, 0.10\rangle$	$\langle s_{0.62}, 0.61, 0.27, 0.06\rangle$	$\langle s_{1.05}, 0.62, 0.23, 0.10\rangle$

Table 4
The PDA matrix D_A^+.

ECs	CRs						
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
EC_1	0.78	0	0	0	0	0	0
EC_2	0	0.71	0	0	0	0	0
EC_3	0	0	1.59	0.97	0.96	0	1.82
EC_4	0	0.43	0	0.84	0.69	0	0
EC_5	0	0	0	0	0	1.86	0
EC_6	0.31	0.39	0	0	0	0	0

Table 5
The NDA matrix D_A^-.

ECs	CRs						
	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7
EC_1	0	0.67	0.43	0.47	0.53	0.66	0.72
EC_2	0.29	0	0.81	0.74	0.53	0.72	0.13
EC_3	0.65	0.60	0	0	0	0.72	0
EC_4	0.07	0	0.28	0	0	0.72	0.42
EC_5	0.53	0.67	0.81	0.74	0.50	0	0.72
EC_6	0	0	0.25	0.29	0.26	0.46	0.11

Table 6
Computation results via the PFL-EDAS method.

ECs	SP_i	SN_i	$\bar{SP}_i$	$\bar{SN}_i$	IS_i
EC_1	0.094	0.470	0.094	0.530	0.312
EC_2	0.078	0.519	0.078	0.481	0.280
EC_3	0.885	0.180	0.885	0.820	0.853
EC_4	0.376	0.133	0.376	0.867	0.622
EC_5	0.093	0.619	0.093	0.381	0.237
EC_6	0.080	0.203	0.080	0.797	0.439

priority of the considered six ECs is obtained as: $EC_3 \succ EC_4 \succ EC_6 \succ EC_1 \succ EC_2 \succ EC_5$. Therefore, the product-service system manufacturer should pay more attention to EC_3 which is the most important EC for reducing costs and improving customer satisfaction.

4.3. Comparative analysis

To demonstrate the effectiveness and preponderance of the proposed QFD approach, a comparative analysis with relevant QFD methods is made in this section. The compared methods include the traditional QFD [50], the fuzzy QFD [10], the cloud model GRA [19], and the hesitant fuzzy VIKOR [26]. In the fuzzy QFD method, the interrelationships between CRs and ECs are evaluated by using triangular fuzzy numbers. Additionally, the ranking orders of ECs are determined by calculating their fuzzy weights and defuzzifying them into crisp values. For the cloud model GRA method, the relationship assessments among CRs and ECs are expressed as cloud droplet, and the priorities of ECs are obtained by computing their grey relational coefficients and grey degrees. In the hesitant fuzzy VIKOR method, hesitant fuzzy sets are employed to analyze the correlations between CRs and ECs and an extended VIKOR is used to determine the ranking of ECs. Fig. 2 shows the ranking results of all the six ECs as determined with these five methods.

From Fig. 2, it can be observed that the top two ECs and the last EC according to the listed methods are exactly the same. Moreover, the ranking result by the proposed approach is consistent with that obtained by the hesitant fuzzy VIKOR method. Therefore, the proposed integrated approach for practical applications is validated. However, there is a slight difference in the ranking orders obtained by the proposed QFD and the other three compared methods. In the traditional QFD method, the priority orders of EC_1, EC_2 and EC_6 are $EC_1 \succ EC_2 \succ EC_6$. But the result provided by the proposed approach shows that $EC_6 \succ EC_1 \succ EC_2$. Additionally, the priorities of EC_1 and EC_6 in the cloud model GRA are different from those in the proposed QFD, and the ranking orders of EC_1 and EC_6 are the same by the fuzzy QFD method.

The main reasons for the different ranking results of ECs yielded by the proposed QFD and the compared methods mainly lie in the following aspects. First, the weights of experts are not taken into account in the compared methods. Second, the traditional QFD uses numerical values to evaluate the relationships between CR_S and EC_S and the fuzzy QFD can only capture the fuzziness of experts' relationship evaluations. Furthermore, the cloud model GRA can reflect the uncertainty and randomness of judgments provided by experts but cannot express the hesitancy in human mind. Third, the weighted average method used in the traditional QFD and the fuzzy QFD methods has been extensively criticized for the occurrence of non-robust ranking orders of ECs. Moreover, the cloud model GAR method is too subjective and decision makers' psychological behavior is not considered in the GRA analysis.

The comparative analysis indicates superior results can be obtained by the proposed QFD approach, which performs distinctively better than other methods. The underlying driver of this high performance relies on more precise incorporation of experts' judgments on the relationships between ECs and CRs, so that the results reflect experts' actual thoughts and assessments. Besides, the proposed approach yields critical ECs more effectively via combining the TOPSIS method and the maximum entropy theory to determine the importance weights of experts and adopting the PFL-EDAS method to derive the priority ranking of ECs. To further assess the effectiveness of our proposed QFD approach, specialists and managers of the manufacturer are asked to check the result determined in this case study. According to the experts, the proposed QFD is more suitable for the considered product-service system design problem and can find the most significant ECs effectively. Compared with the traditional QFD and its variants, the product planning approach presented in this paper has the following advantages and distinguishing characteristics:

(1) By applying PFLSs to depict the relationships between CRs and ECs, the proposed approach enables decision makers to express their opinions more flexibly and accurately in uncertain linguistic environment.

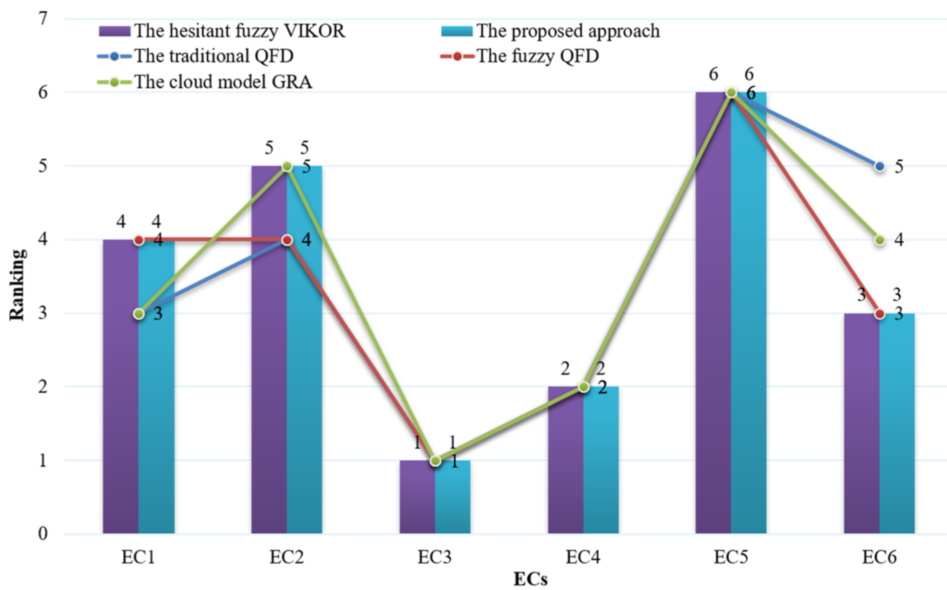

Fig. 2. The EC ranking results of comparative analysis.

(2) A combined weighting method is constructed to compute the weights of experts objectively. This makes the proposed QFD to deal with the situations where expert weight information is unknown and mitigates the influence of experts' subjective judgments.
(3) An extended EDAS method is adopted to determine the priority ranking of ECs in QFD. Hence, the proposed approach can derive a more credible and reasonable ranking of ECs and help product engineers get a final solution efficiently.

5. Conclusions

As a customer-driven product development technique, QFD has been widely used in various fields to define CRs and translate them into ECs for maximizing customer satisfaction. In this paper, an improved approach that combines PFLSs and an extended EDAS method was put forward to enhance the analysis capability of QFD. The main contributions of the paper can be summarized as follows: First, the PFLSs were applied to QFD for evaluating the relationships between CRs and ECs. Second, a PFL-EDAS method was proposed to determine the ranking orders of ECs. Moreover, a combined weighing method based on the TOPSIS and maximum entropy theory was designed to determine the weights of experts objectively. Finally, the practicability and effectiveness of the presented integrated approach was illustrated by a product-service system design case. The results show that the QFD model proposed in this study is effective, which can capture the uncertainty and hesitancy of experts' assessment information as well as acquire a more precise and robust prioritization of ECs in product planning.

Future studies can focus on the following directions. First, CRs and ECs may not independent between each other in the real-life product development. Therefore, in future research, effort can be devoted to incorporate the correlations among CRs and the correlations among DRs into the proposed QFD. Second, there are many situations in which the CR weight information is completely unknown. Thus, it is suggested to further extend the proposed approach for solving the QFD problems with unknown CR weights in the future. Last but not least, the QFD approach being developed can be applied to other industry sectors to further verify its effectiveness and efficiency.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors are very grateful to the respected editor and the anonymous referees for their insightful and constructive comments, which helped to improve the overall quality of the paper. This work was partially supported by the National Natural Science Foundation of China (Nos. 61773250 and 71671125) and the Open Research Fund Project of Key Laboratory of Quality Infrastructure Efficacy Research (No. KF20180303).

References

[1] Y. Akao, New product development and quality assurancequality deployment system, Stand. Qual. Control 25 (1972) 7–14.
[2] J. Fan, S. Yu, J. Chu, D. Chen, M. Yu, T. Wu, J. Chen, F. Cheng, C. Zhao, Research on multi-objective decision-making under cloud platform based on quality function deployment and uncertain linguistic variables, Adv. Eng. Inf. 42 (2019) 100932.
[3] M.A. Beheshtinia, M. Farzaneh Azad, A fuzzy QFD approach using SERVQUAL and Kano models under budget constraint for hotel services, Total Qual. Manage. Bus. Excell. 30 (2019) 808–830.
[4] S. Eleftheriadis, P. Duffour, D. Mumovic, Participatory decision-support model in the context of building structural design embedding BIM with QFD, Adv. Eng. Inf. 38 (2018) 695–711.
[5] S.M. Wu, X.Y. You, H.C. Liu, L.E. Wang, Improving quality function deployment analysis with the cloud MULTIMOORA method, Int. Trans. Operat. Res. 27 (2020) 1600–1621.
[6] L.K. Chan, M.L. Wu, Quality function deployment: a literature review, Eur. J. Oper. Res. 143 (2002) 463–497.
[7] J.A. Carnevalli, P.C. Miguel, Review, analysis and classification of the literature on QFD-Types of research, difficulties and benefits, Int. J. Prod. Econ. 114 (2008) 737–754.
[8] A.J.C. Trappey, C.V. Trappey, C.Y. Fan, I.J.Y. Lee, Consumer driven product technology function deployment using social media and patent mining, Adv. Eng. Inf. 36 (2018) 120–129.
[9] H.C. Liu, S.M. Wu, Z.L. Wang, X.Y. Li, A new method for quality function deployment with extended prospect theory under hesitant linguistic environment, IEEE Trans. Eng. Manage. (2019), https://doi.org/10.1109/tem.2018. 2864103.
[10] S. Filketu, A. Dvivedi, B.B. Abebe, Decision-making on job satisfaction improvement programmes using fuzzy QFD model: a case study in Ethiopia, Total Qual. Manage. Bus. Excell. 30 (2019) 1068–1091.
[11] N. Azam Haron, H. Abdul-Rahman, C. Wang, L.C. Wood, Quality function deployment modelling to enhance industrialised building system adoption in housing projects, Total Qual. Manage. Bus., Excell. 26 (2015) 703–718.
[12] Z.P. Tian, R.X. Nie, J.Q. Wang, L. Li, Group multigranular linguistic QFD for prioritizing service designs with combined weighting method, Expert Syst. 36 (2019) e12419.
[13] L.K. Chan, M.L. Wu, Quality function deployment: a comprehensive review of its

concepts and methods, Qual. Eng. 15 (2002) 23–35.
[14] M. Fargnoli, T. Sakao, Uncovering differences and similarities among quality function deployment-based methods in design for X: benchmarking in different domains, Qual. Eng. 29 (2017) 690–712.
[15] A.H.I. Lee, H.Y. Kang, C.Y. Lin, J.S. Chen, A novel fuzzy quality function deployment framework, Qual. Technol. Quant. Manage. 14 (2017) 44–73.
[16] L.Q. Dat, T.T. Phuong, H.P. Kao, S.Y. Chou, P.V. Nghia, A new integrated fuzzy QFD approach for market segments evaluation and selection, Appl. Math. Model. 39 (2015) 3653–3665.
[17] B. Efe, Fuzzy cognitive map based quality function deployment approach for dishwasher machine selection, Appl. Soft Comput. 83 (2019) 105660.
[18] J. Huang, X.Y. You, H.C. Liu, S.L. Si, New approach for quality function deployment based on proportional hesitant fuzzy linguistic term sets and prospect theory, Int. J. Prod. Res. 57 (2019) 1283–1299.
[19] X. Wang, H. Fang, W. Song, Technical attribute prioritisation in QFD based on cloud model and grey relational analysis, Int. J. Prod. Res. (2019), https://doi.org/10.1080/00207543.2019.1657246.
[20] Z. Wang, R.Y.K. Fung, Y.L. Li, Y. Pu, A group multi-granularity linguistic-based methodology for prioritizing engineering characteristics under uncertainties, Comput. Ind. Eng. 91 (2016) 178–187.
[21] P. Liu, X. Zhang, A novel picture fuzzy linguistic aggregation operator and its application to group decision-making, Cogn. Comput. 10 (2018) 242–259.
[22] G. Wei, F.E. Alsaadi, T. Hayat, A. Alsaedi, Picture 2-tuple linguistic aggregation operators in multiple attribute decision making, Soft. Comput. 22 (2018) 989–1002.
[23] S. Zeng, M. Qiyas, M. Arif, T. Mahmood, Extended version of linguistic picture fuzzy TOPSIS method and its applications in enterprise resource planning systems, Math. Probl. Eng. 2019 (2019) 8594938.
[24] M. Qiyas, S. Abdullah, S. Ashraf, M. Aslam, Utilizing linguistic picture fuzzy aggregation operators for multiple-attribute decision-making problems, Int. J. Fuzzy Syst. 22 (2020) 310–320.
[25] L. Li, R. Zhang, J. Wang, X. Shang, K. Bai, A novel approach to multi-attribute group decision-making with q-rung picture linguistic information, Symmetry 10 (2018) 172.
[26] S.M. Wu, H.C. Liu, L.N. Wang, Hesitant fuzzy integrated MCDM approach for quality function deployment: a case study in electric vehicle, Int. J. Prod. Res. 55 (2017) 4436–4449.
[27] S. Hosseini Motlagh, M. Behzadian, J. Ignatius, M. Goh, M. Sepehri, T. Hua, Fuzzy PROMETHEE GDSS for technical requirements ranking in HOQ, Int. J. Adv. Manuf. Technol. 76 (2015) 1993–2002.
[28] M.K. Ghorabaee, E.K. Zavadskas, L. Olfat, Z. Turskis, Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS), Informatica 26 (2015) 435–451.
[29] M. Keshavarz Ghorabaee, M. Amiri, E.K. Zavadskas, J. Antucheviciene, A new hybrid fuzzy MCDM approach for evaluation of construction equipment with sustainability considerations, Arch. Civil Mech. Eng. 18 (2018) 32–49.
[30] A. Karaşan, C. Kahraman, A novel interval-valued neutrosophic EDAS method: prioritization of the United Nations national sustainable development goals, Soft. Comput. 22 (2018) 4891–4906.
[31] J. Ren, S. Toniolo, Life cycle sustainability decision-support framework for ranking of hydrogen production pathways under uncertainties: an interval multi-criteria decision making approach, J. Cleaner Prod. 175 (2018) 222–236.
[32] D. Schitea, M. Deveci, M. Iordache, K. Bilgili, İ.Z. Akyurt, I. Iordache, Hydrogen mobility roll-up site selection using intuitionistic fuzzy sets based WASPAS, COPRAS and EDAS, Int. J. Hydrogen Energy 44 (2019) 8585–8600.
[33] F. Ecer, Third-party logistics (3PLs) provider selection via fuzzy AHP and EDAS integrated model, Technol Econ. Dev. Econ. 24 (2018) 615–634.
[34] L.A. Zadeh, The concept of a linguistic variable and its application to approximate reasoning—I, Inf. Sci. 8 (1975) 199–249.
[35] K. Atanassov, Intuitionistic fuzzy sets, Fuzzy Sets Syst. 20 (1986) 87–96.
[36] V. Torra, Hesitant fuzzy sets, Int. J. Intell. Syst. 25 (2010) 529–539.
[37] R.R. Yager, A.M. Abbasov, Pythagorean membership grades, complex numbers, and decision making, Int. J. Intell. Syst. 28 (2013) 436–452.
[38] B.C. Cuong, Picture fuzzy sets, J. Comput. Sci. Cyber. 30 (2014) 409–420.
[39] C. Jana, T. Senapati, M. Pal, R.R. Yager, Picture fuzzy Dombi aggregation operators: application to MADM process, Appl. Soft Comput. 74 (2019) 99–109.
[40] Y. Ju, D. Ju, E.D.R. Santibanez Gonzalez, M. Giannakis, A. Wang, Study of site selection of electric vehicle charging station based on extended GRP method under picture fuzzy environment, Comput. Ind. Eng. 135 (2018) 1271–1285.
[41] L. Wang, H.Y. Zhang, J.Q. Wang, L. Li, Picture fuzzy normalized projection-based VIKOR method for the risk evaluation of construction project, Appl. Soft Comput. 64 (2018) 216–226.
[42] S.J. Wu, G.W. Wei, Picture uncertain linguistic aggregation operators and their application to multiple attribute decision making, Int. J. Knowl.-Based Intell. Eng. Syst. 21 (2017) 243–256.
[43] Y. Wang, L. Wang, H. Wang, X. Feng, Hesitant Picture 2-tuple linguistic aggregation operators based on archimedean T-Norm and T-Conorm and their use in decision-making, Symmetry 10 (2018) 629.
[44] X. Wu, H. Liao, An approach to quality function deployment based on probabilistic linguistic term sets and ORESTE method for multi-expert multi-criteria decision making, Inform. Fus. 43 (2018) 13–26.
[45] W. Jia, Z. Liu, Z. Lin, C. Qiu, J. Tan, Quantification for the importance degree of engineering characteristics with a multi-level hierarchical structure in QFD, Int. J. Prod. Res. 54 (2016) 1627–1649.
[46] Z.L. Wang, J.X. You, H.C. Liu, Uncertain quality function deployment using a hybrid group decision making model, Symmetry 8 (2016) 119.
[47] J. Liu, Y. Chen, J. Zhou, X. Yi, An exact expected value-based method to prioritize engineering characteristics in fuzzy quality function deployment, Int. J. Fuzzy Syst. 18 (2016) 630–646.
[48] P. Akkawuttiwanich, P. Yenradee, Fuzzy QFD approach for managing SCOR performance indicators, Comput. Ind. Eng. 122 (2018) 189–201.
[49] N. Haber, Prioritizing customer requirements in a product-service system (PSS) context, TQM J. 31 (2019) 257–273.
[50] T.T. Sousa-Zomer, P.A. Cauchick-Miguel, Exploring business model innovation for sustainability: an investigation of two product-service systems, Total Qual. Manage. Bus. Excell. 30 (2019) 594–612.
[51] W. Song, T. Sakao, Service conflict identification and resolution for design of product-service offerings, Comput. Ind. Eng. 98 (2016) 91–101.