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ORIGINAL ARTICLE

New rating methods to prioritize customer requirements in QFD with incomplete customer preferences

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Abstract Customer satisfaction is one of the critical success factors to many leading companies over the world. Quality function deployment (QFD) has gained extensive international support as one of the powerful techniques to increase the customer satisfaction. In the QFD, correctly rating the final importance of customer requirements (CRs) is a crucial and essential process since it largely affects the target value setting of design requirements. The final importance ratings of CRs are generally determined by combining relative importance ratings and competitive priority ratings. However, determining the final importance ratings is very difficult due to the typical uncertainty or imprecision of customer's judgment (or perceptions). This paper proposes a novel approach to prioritize CRs in QFD process by developing two sets of new rating methods, called customer preference rating (CPR) method and customer satisfaction rating (CSR) method, for relative importance ratings and competitive priority ratings, respectively. The CPR method provides a simple and intuitive technique to capture the customers' incomplete or uncertain perceptions on the relative importance of CRs based on their own preferences, allowing them to give a partial ordering of CRs. The CSR method constructs the customer satisfaction model based on the competitive benchmarking analysis and then evaluates the performance quality of company product using our satisfaction and uncertainty measure. Furthermore, the CSR method is integrated with the Kano's model to capture the different impacts of CRs on customer satisfaction. Finally, the proposed approach is illustrated with a numerical example of car door design problem.

Keywords Quality function deployment · Customer needs or requirements · Customer preference · Customer satisfaction · Importance ratings or priorities

1 Introduction

The current global marketplace can be characterized by intense international competition, fragmented markets of discriminating customers, and rapid technological change [1]. In this highly competitive marketplace, customer satisfaction is one of the critical success factors to many leading companies throughout the world [1–4]. Since the customer satisfaction is the best indicator for the company's future [2], the company should be able to efficiently design, develop, and manufacture products that will be preferred by customers over those offered by competitors [1].

Quality function deployment (QFD) has gained extensive international support as one of the powerful techniques to increase the customer satisfaction [2, 4–9]. In addition to the high level of customer satisfaction, the implementation of QFD results in many significant improvements in the product development process, including fewer and earlier design changes, fewer startup problems, improved multifunctional/cross-functional communications, improved product quality, reduced prouct development time and cost, etc. [1, 10–12].

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Typically, QFD utilizes four sets of matrices called house of quality (HOQ) to translate customer requirements (CRs; also called customer needs, customer demands, customer attributes) into design requirements (DRs; also called engineering characteristics), and subseqeuntly into parts characteristics, process plans, and production requirements [6, 13–16]. The customer input is the key starting point for QFD process, and if it does not accurately reflect what the customer expects from a product, the process may lead to inaccurate forecasts [17]. Therefore, the first set of matrices called product planning house of quality (PPHOQ) is of fundamental and strategic importance in QFD system [12–15, 18–20]. The subsequent HOQs can be also built in a similar way to the PPHOQ. Thus, we describe in detail the development of PPHOQ.

The PPHOQ process can be divided into nine steps as shown in Fig. 1 [13]. Among these steps, correctly rating the final importance of CRs is a crucial and essential process of PPHOQ as it could largely affect the target value setting of DRs to be determined in the later stage [13–15, 21–24]. Based on these ratings, a company can purposefully design and develop a product to achieve higher customer satisfaction and thus more competitive advantages [13–15]. Since the final importance ratings of CRs are finally transformed into the final technical ratings of DRs, consideratble efforts must be committed to properly acquire the final importance ratigns of CRs, thus enabling the customer-oriented product development.

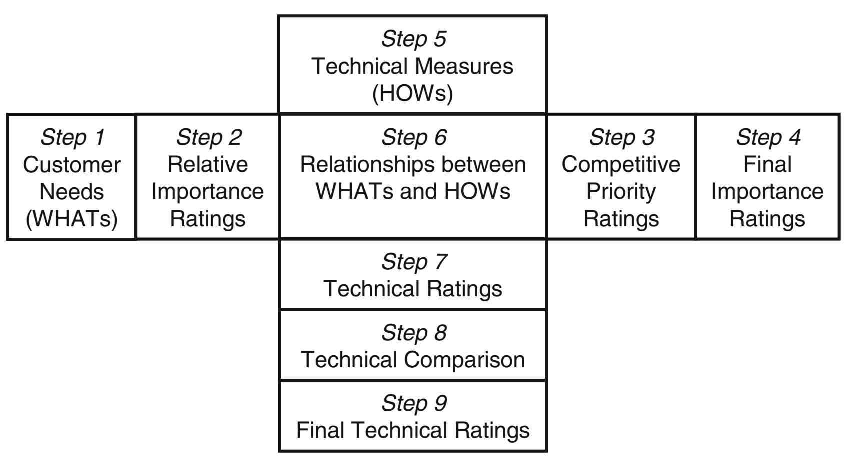
Therefore, we restrict our discussion to the first four steps of PPHOQ [13–15], and particularly focus on the rating methods of CRs for the scope of this paper. Although QFD offers a systematic methodology for mapping CRs to subsequent design and process parameters, the procedures in QFD do not provide details about how to obtain the final importance ratings of CRs [25].

The PPHOQ process begins by collecting customer needs and organizing them as a set of CRs (step 1). Once a set of CRs is obtained, the CRs should be prioritized from the customer's perspective to determine the relative importance ratings (sometimes called fundamental or basic importance ratings; step 2). After prioritizing CRs in terms of the relative importance, CRs should be also prioritized from the customer's perspective using the competitive analysis [6, 13, 15, 22, 23]. The competitive analysis (e.g., benchmarking) compares the company and its competitors in terms of quality performance regarding each CR. Then, company performance ratings can be otained through the competitive benchmarking analysis, and analyzing the company performance ratings results in the competitive priority ratings of CRs (step 3). Finally, the final importance ratings of CRs are determined by combining the relative importance ratings and competitive priority ratings (step 4).

A lot of researches have formed a rich body of literature related to the relative importance ratings of CRs, including point direct scoring metod [10, 11], analytic hierarchy process (AHP) [14, 15, 26–29], analytic network process (ANP) [16, 28, 30, 31], outranking method [5, 32], and so on. Conventional approaches usually use crisp numbers when rating or comparing CRs to determine the importance ratings of CRs. However, customer's judgment (or perception) on the relative importance of CRs is often imprecise and uncertain in nature [13, 23, 24, 33]. Using precise crisp numbers to represent the customers' assessments of CRs is not very reasonable [13]. Therefore, their fuzzy variants have also been proposed in order to model this kind of uncertainty in human preference [13, 21, 23, 24, 33–36]. The basic concept of these fuzzy approaches is to convert the linguistic or vague assessment into fuzzy numbers (e.g., triangular fuzzy numbers [13, 21, 24]) in order to take into account the uncertainty associated with the mapping of customer's perception to a number. However, the selection of the membership function in fuzzy sets is difficult and affected by the subjective experience [14].

In addition, various methods have been used to determine the competitive priority ratings of CRs, such as improvement ratio [14, 15, 22], sales point [9, 14], entropy method [13], fuzzy mean method [23], maximal deviation method

Fig. 1 House of Quality



[15], etc. Most of them have assumed that the relationship between product quality criteria (i.e., CRs) and customer satisfaction is 1D or linear—the higher the perceived quality, the higher the customer's satisfaction, and vice versa [2, 3, 37]. However, this assumption may not adequately represent the complexity of customer preferences, since fulfilling the individual CRs to a great extent does not necessarily imply a high level of customer satisfaction [2, 37]. To improve its ability to recognize customer's expectations, a lot of researches have associated Kano's model [38] with QFD over the past several years [2, 17–19, 39, 40]. However, even though these methods can capture different aspects of CRs, all of them are still integrated with conventional relative importance rating methods (e.g., point scoring method) and conventional competitive priority rating methods (e.g., improvement ratio, sales point).

More detailed descriptions on the related works and their limitations are given in the following section. From the literature review, it is concluded that there is no uniform framework to determine the final importance ratings of CRs in PPHOQ process because of the lack of individual methods suitable for the determination of relative importance ratings and competitive priority ratings with incomplete information. Therefore, it is clear that new rating methods should be developed to determine the relative important ratings and competitive priority ratings in more accurate and consistent manner.

This paper proposes two sets of new rating methods, called customer preference rating (CPR) method and customer satisfaction rating (CSR) method to determine the relative importance ratings and the competitive priority ratings of CRs, respectively. In our previous research, we have proposed the graph theory-based representation technique to model the human's incomplete or uncertain preference structure, so called 'preference graph' (PG) [41, 42]. First, the CPR method utilizes the PG representation to capture the customers' incomplete or uncertain perceptions on the relative importance of CRs. While the existing methods, such as AHP, ANP, fuzzy AHP, and fuzzy ANP, require the customers to make pair-wise complete comparisons of all pairs of CRs, the CPR method enables each customer to make incomplete comparisons of CRs, thus allowing the partial ordering of CRs. Then, a method for analyzing customers' preference structures (i.e., PGs) on CRs is developed for the determination of relative importance ratings. Second, the CSR method models the customers' expectations on the CRs using the concept of satisfaction function [6]. The satisfaction functions of CRs can be constructed through the competitive benchamarking analysis. Then, two measures are developed to estimate the satisfaction level and uncertainty level, respectively, of customers' perceptions with respect to the performances of the company's product under study. Using these two measures, initial competitive priority ratings of CRs are obtained, and further integrated with an adjustment factor obtained from the Kano's analysis. Third, the final importance ratings of CRs are determined by combining the CPR and CSR.

The rest of the paper is organized as follows. Section 2 gives a short review of the prior researches related to the ranking or prioritization methods of CRs and their limitations. Section 3 proposes a novel approach for prioritizing CRs in PPHOQ process, including CPR and CSR methods. A numerical illustrative example is shown in Section 4. Section 5 concludes the paper.

2 Related works and their limitations

2.1 Relative importance rating methods

Many papers have been published in this field, and various methods have been applied to determine the relative importance ratings (or degree of importance) of CRs. The simplest and easist method in prioritizing CRs is based on the point scoring scale, such as 1–5 and 1–10 [10, 11]. However, the use of pre-defined arbitrary numerical scale leads to some drawbacks. Since it is easy to produce different results by choosing different scales, the priority rank can change depending on the type of scales used [5]. Thus, there is low robustness in the variation of the values of the cardinal scale elements [43]. Even though the discrete scale has the advantage of simplicity and easiness for use, it does not take into account the uncertainty associated with the mapping of customers' vague and incomplete perception (or judgment) to a number [13, 21]. Hence, it cannot effectively capture customer perceptions [24] and is unable sufficiently to reflect the importance structure of customers' needs [13]. This point scoring method uses absolute importance to identify the degree of importance for each CR. This assumes that accurate and representative data in an absolute scale is available [27]. However, it cannot always work effectively because many customers tend to rate almost every requirement as being important [23, 27]. If the absolute weighing data tend to be bunched near the highest possible scores, it does not contribute much to helping develpers to prioritize technical responses [9].

Therefore, the AHP method [26] has been widely used to measure the relative degree of importance between criteria or the intensity of the relationships between the row and column variables during the QFD implementation process [14, 15, 27, 28]. Besides the QFD, various analytical methods have been integrated with the AHP, including mathematical programming, metaheuristics, SWOT analysis, and data envelopment analysis [29]. In addition, the conjoint analysis [44] is used to determine the relative importance of CRs. Since the conjoint analysis employs pair-wise comparison of CRs [21], this procedure is similar to the method of assessment used in the AHP [1]. Basically, the AHP is based on the independence assumption, but each individual criterion is not always completely independent [31]. In order to solve the limitation of AHP with its independence assumptions on upper levels from lower levels and the independence of the elements within a level, the ANP method [30] has also been used to determine the relative importance weights [16, 28, 31]. However, in the ANP, the relative importance values are determined in a similar manner to AHP using pair-wise comparisons [16].

Thus, for all these methods, each customer is required to compare the relative importance of each pair of CRs. However, since customers should provide a lot of comparisons (even for small-scale problems), these methods require too much elaborate information from each customer, and may become very tedious and lead to inconsistencies in judgment. It is thus unrealistic to expect customers to provide so much elaborate and repetitious information timely and seriously [13]. More importantly, these pair-wise comparison methods usually use a point scale (e.g., five-, seven-, or nine-point scale). However, CRs are often described usually using linguistic terms, and always contain ambiguity and multiple meanings. Many of CRs are intangible or nonmonetary because they reflect customers' preferences [43]. Furthermore, customer's judgment (or perception) on the relative importance of CRs is often imprecise and uncertain in nature [13, 23, 24, 33]. Therefore, using precise crisp numbers to represent the customers' assessments of CRs is, although widely adopted, not very reasonable [13, 24], and thus these conventional methods seem inadequate to capture CRs explicitly and determine the relative importance ratings of CRs accurately [13, 21, 33]. The outranking method [32] has also been used to derive the DRs' importance ratings from quantified CRs' importance ratings and ordinal relationships between CRs and DRs [5]. However, like other methods, it cannot also explicitly capture various inputs from customers, e.g., customer perception, judgment, and evaluation on importance of CRs, which usually are subjective and incomplete [43].

In order to model this kind of uncertainty in human preference, fuzzy set-based applications to the conventional methods have been presented to determine the relative importance ratings, including fuzzy arithmetic [13, 23], fuzzy AHP [21, 33, 34], fuzzy ANP [24], and fuzzy out-ranking method [35, 36]. All these methods are incremental methods to more precisely define CRs or deal with the fact that QFD uses simple qualitative inputs and judgment in interpreting the results matrices [1]. The basic concept of these fuzzy approaches is to convert the linguistic assessment into fuzzy numbers (e.g., triangular fuzzy numbers [13, 21, 24]) in order to take into account the uncertainty associated with the mapping of customer's perception to a number. Thus, when using these methods, one of the issues to be addressed is the selection of the membership functions. However, the selection of the membership function in fuzzy set is difficult and affected by the subjective experience [14].

More recently, a linear partial ordering approach is suggested to assess the incomplete inputs of customers and prioritize the DRs [43]. Here, the linear partial information represented by four types of dominance relation is used as a quantified form that captures the importance of CRs from pairwise comparison of customer's perspective. However, since it is unrealistic to expect the customers to provide the four types of dominance relation among CRs, this approach is more appropriate for decision makers than customers in specifying the relative importance of CRs. Also, the set of linear partial ordering information from decision maker is integrated with a linear programming model as a constraint set. Therefore, this approach does not provide any quantitative method to determine the relative importance weights of CRs.

2.2 Competitive priority rating methods

After prioritizing CRs in terms of the relative importance as described above, the competitive priority ratings of CRs should also be determined to prioritize the CRs. The competitive priority ratings indicate the degree of importance of CRs that companies should focus on in order to be competitive [23]. Then, the company would work on the most important CRs and disregard the unimportant CRs to make best use of its resources [13].

Using the competitive analysis such as benchmarking, the performance score of the company's product and that of competitors' products with respect to each CR is listed usually on a scale (i.e., company performance ratings). Then, the competitive priority ratings can be obtained by analyzing the company's relative positions based on the company performance ratings.

In the current literature, there are various methods that incorporate the performance quality of the company's product perceived by customers in comparison with that of its competitors' products, including the use of improvement ratio [14, 15, 22], sales point method [9, 14], entropy method [13], and some other methods [14, 23].

On the basis of the competitive benchmarking analysis and strategic considerations, a target performance for customer satisfaction is set for each CR, and then an improvement ratio is obtained by dividing the target performance by the current performance [14, 15]. Next, sales points are set for CRs that are expected to influence sales more than average. A sales point contains information characterizing the ability to sell the product or service, based on how well each customer need is met [9]. In other worlds, a sales point is something you want to cherish because of the possibility it will give the company a unique selling proposition [13], and hence it usually indicates a unique selling position to separate one's own product from competitors' products [23]. The most common values assigned to sales point are: 1 for no sales point, 1.25 for moderate sales point, and 1.5 for strong sales point [13]. Then, the priority of CRs is then determined by multiplying the relative degree of importance by improvement ratio and/or the sales point [22].

However, the improvement ratio and sales point methods, although commonly used, are very subjective [13] because their settings are left up to the developers. In addition, the sales point method may cause a different type of problem, so-called 'double counting' because it also takes the relative importance rating into account when setting a sales point [9]. More importantly, the sales point method cannot help designers to find the CR that can be a strong sales point. It can only help to highlight the CR that developers have decided to be a strong sales point [23].

To analyze company performance ratings more objectively and convincingly, the traditional sales point concept should be modified or other methods should be applied. However, the modification of the conventional sales point is not easy to make and, even made, cannot avoid the subjectivity and arbitrariness. Therefore, the entropy method [13] is used to obtain competitive priority ratings of CRs using the Shannon's entropy measure [45]. According to the entropy concept, a CR is paid more (less) attention if the performance ratings of the companies on this CR are less (more) diverse, thus giving the highest value to the CR in which all the companies perform the same. It assumes that when all companies perform the same, it means there is a good opportunity to be outstanding. However, these assumptions may not be correct in many situations [15, 23]. For example, suppose that a company perform badly in a specific CR, and according to the entropy method, this CR is assigned a lower priority. However, the company cannot simply overlook its disadvantage. It may be a good opportunity for its competitors to attack one's own product [23].

More recently, the fuzzy mean method [23] and maximal deviation method [15] are presented to resolve the problem of the entropy method in prioritizing CRs. The common idea of these methods is to assign a higher priority to CRs that the deviations (or gaps) of the companies' performances are larger. However, the fuzzy mean method is based on the (triangular) fuzzy number, and thus has the same difficulties as most of fuzzy set-based approaches. In addition, the maximal deviation method is based on the conventional rating methods (e.g., point scoring method, AHP), and thus cannot accurately capture the customers' perceptions of CRs with incomplete information.

So far, it has mostly been assumed that the relationship between product quality criteria (i.e., CRs) and customer satisfaction is 1D or linear—the higher the perceived product quality, the higher the customer's satisfaction, and vice versa [2, 3, 37]. However, this assumption may not adequately represent the complexity of customer preferences, because some CRs may make the customer disproportionately satisfied while others may not affect customer satisfaction to a large extent even though their performance level is high [2, 17]. Therefore, existing competitive priority rating methods may not be able to completely illustrate the relationship between quality criteria and customer satisfaction levels [3]. Since the impact on customer satisfaction is different for each CR, it is very important to determine which CRs of a product bring more satisfaction than others [18]. The Kano's model of customer satisfaction [38] has a unique way of identifying CRs in more detail by assigning different categories of quality (i.e., must-be, 1D, attractive, indifferent, reverse, and questionable qualities [3, 17, 40]) to different requirements as shown in Fig. 2, and can provide more accurate the voice of customer as an input to QFD analysis [17].

To improve its ability to recognize customer's expectations, a lot of researches have proposed combining the Kano's model with QFD over the past several years [2, 17–19, 39, 40]. An approximate transformation function of assigning the different values into CRs (e.g., 0.5, 1, and 2 for must-be, 1D and attractive requirement, respectively) is employed to adjust the improvement ratio of each CR [19]. However, the selection of those values (i.e., weights) is quite subjective [17]. Therefore, the customer satisfaction (CS) coefficient [39] and the modified CS coefficients [18] are suggested to provide a more quantitative method for the prioritization of CRs. More recently, a quantitative method based on more elaborate CS coefficient is provided to adjust the improvement ratio of CRs accurately [40]. More detailed descriptions on these approaches can be found in [18, 40]. These methods can capture different aspects of CRs. However, all of them still use the improvement ratio and the conventional relative importance rating methods to determine the final priority of CRs.

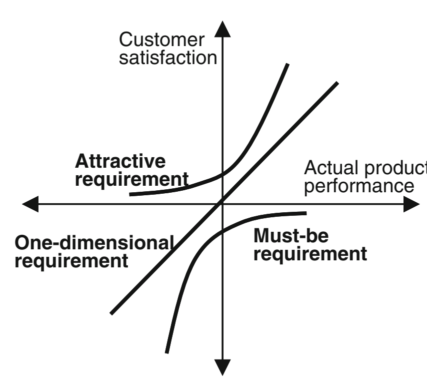


Fig. 2 Kano's model of customer satisfaction

From above discussions, it is clear that new different methods should be developed to determine the relative importance ratings and competitive priority ratings of CRs in more accurate and consistent manner.

3 Proposed approach

3.1 CPR method for relative importance ratings

A lot of CR candidates may be collected by the widely used marketing methods (e.g., focus group or individual interviews, mail or telephone surveys using questionnaires, etc. [11]) or the use of existing information. CR candidates are usually expressed in customers' words that are too general or too detailed to be directly used as CRs [13]. In addition, a large number of CR candidates would be often obtained from the marketing surveys. However, it is not possible nor understandable to include all of them as CRs [20]. For this purpose, the affinity diagram [9], cluster analysis [11], factor analysis [20], rough set theory [14], etc., can be used to reduce or condense the amount of CR candidates and organize them as a smaller set of CRs with a tree-like structure [15, 23].

As mentioned earlier, customer's judgment (or perception) on the importance of CRs is usually imprecise and uncertain in nature. The proposed CPR method focuses on the uncertainty associated with customer's perception of determining the relative importance of CRs. The CPR method enables customers to make incomplete or partial comparisons of CRs. Therefore, the customer's preference structure on the relative importance of CRs is represented by a partial ordering of CRs. In our previous research, we have proposed a qualitative and simple technique for representing human's preference structure with incomplete information by using graph theory, the so-called PG [41, 42]. It is assumed that a discrete set can be represented as a directed acyclic graph with an arrowhead.

For the CPR method, the PG representation is employed to represent customer's preference structure on the relative importance of CRs (see Fig. 3). The main advantage of this representation technique is that customers do not need to establish a preference between every possible pair of CRs, but can begin by specifying only the preferences that they clearly know initially. That is, it allows customers to specify partial orderings of CRs. Finally, the CPR method is a new rating approach that can intuitively capture and simply quantify incomplete customer perceptions of relative importace among CRs to determine the relative importance ratings of CRs.

Suppose that, through appropriate way, K customers have been selected and M CRs have been identified based on a marketing survey for K customers. These K customers are denoted as $\mathrm{CT}_1, \mathrm{CT}_2, \cdots, \mathrm{CT}_k, \cdots, \mathrm{CT}_K$, and M CRs denoted

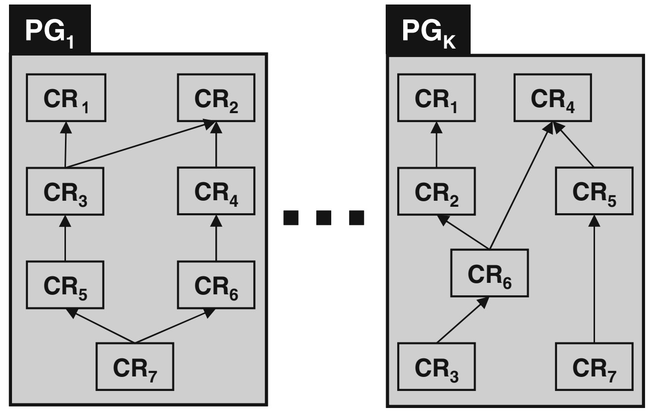


Fig. 3 Representation of relative importance of CRs using preference graph (PG)

as $CR_1, CR_2, \cdots, CR_m, \cdots, CR_M$, respectively. Then, PGs represented by K customers can be denoted as $\mathrm{PG}_1, \mathrm{PG}_2, \cdots, \mathrm{PG}_k, \cdots, \mathrm{PG}_K$. For example, as shown in Fig. 3, a preference graph (PG_1) over seven CRs may be made by customer 1. That is, customer 1 (CT_1) may prefer CR_2 to either CR_3 or CR_4, and both CR_5 and CR_6 to CR_7, but has not determined its relative preference between CR_3 and CR_4. Similarly, PG_K is given by CT_K. In this manner, customers can intuitively generate PGs that represent partial orderings of CRs with respect to the relative importance based on their own preferences.

Suppose a PG to be represented by k customer, CT_k. Then, let PG_k be an adjacency matrix for the PG and let M be a positive integer. Then, the entry pg_{ij} ($i, j=1, 2,\cdots, m, \cdots ., M$) of PG_k^M gives the number of M stage dominances of i over j. That is, the dominance matrix D^k is:

$$D^k = \mathrm{PG}_k^1 + \mathrm{PG}_k^2 + \ldots \mathrm{PG}_k^m \ldots + \mathrm{PG}_k^M \tag{1}$$

The sum of the entries $\left(d_m^k\right)$ in row m of the dominance matrix means the total number of ways that m is dominant one, two, …, M stages [46]. In this paper, ($M-1$)-stage dominances are considered for the PG. For the example of Fig. 3, the adjacency matrix of PG_1 can be represented by:

$$\mathrm{PG}_1 = \begin{bmatrix} 0&0&1&0&0&0&0 \\ 0&0&1&1&0&0&0 \\ 0&0&0&0&1&0&0 \\ 0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&0 \end{bmatrix} \tag{2}$$

In this case with M=7, the dominance matrix (D^1) of PG_1 can be computed by:

$$D^1 = \mathrm{PG}_1^1 + \mathrm{PG}_1^2 + \mathrm{PG}_1^3 + \mathrm{PG}_1^4 + \mathrm{PG}_1^5 + \mathrm{PG}_1^6 \tag{3}$$

Using Eq. 3, the D^1 of PG_1 is then obtained as:

$$D^1 = \begin{bmatrix} 0&0&1&0&1&0&1 \\ 0&0&1&1&1&1&2 \\ 0&0&0&0&1&0&1 \\ 0&0&0&0&0&1&1 \\ 0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&0 \end{bmatrix} \begin{matrix} \rightarrow 3 \\ \rightarrow 6 \\ \rightarrow 2 \\ \rightarrow 2 \\ \rightarrow 1 \\ \rightarrow 1 \\ \rightarrow 0 \end{matrix} \qquad (4)$$

From Eq. 4, $d_1^1 = 3,\ d_2^1 = 6,\ d_3^1 = 2,\ d_4^1 = 2,\ d_5^1 = 1,\ d_6^1 = 1$, and $d_7^1 = 0$. In other words, CR_1 is dominated in 0+0+1+0+1+0+1=3 ways, while CR_2 is dominated in six ways, CR_3 in two ways, CR_4 in two ways, CR_5 in one way, and CR_6 in one way. Following the above computation procedure for PK_K of Fig. 3 results in $d_1^K = 3,\ d_2^K = 2,\ d_3^K = 0,\ d_4^K = 4,\ d_5^K = 1,\ d_6^K = 1$, and $d_7^K = 0$. In our context, each d_m^k implies which CRs are preferred to which other ones either directly or indirectly. If a specific CR (CR_m) of a customer (CT_k) is not dominated over any CRs, then d_m^k is equal to 0. However, since it is considered as a CR of product under consideration, the importance of 0 is not reasonable. For this purpose, 1 is added to d_m^k for the computation of relative dominances (i.e., preferences). Considering this compensation, the relative degree of preference (RDP) of each customer (k) can be obtained by the following expression to be the maximum of 1:

$$\mathrm{rdp}_m^k = \frac{\left(1 + d_m^k\right)}{\max\limits_{m=1,\ldots,M}\left(1 + d_m^k\right)},\ k = 1, \ldots, K \qquad (5)$$

For the illustrative convenience, let us denote the RDP of each customer (k) as a vector:

$$\mathrm{RDP}_k = \left(\mathrm{rdp}_1^k, \mathrm{rdp}_2^k, \ldots, \mathrm{rdp}_m^k, \ldots \mathrm{rdp}_M^k\right) \qquad (6)$$

Based on the RDP of each customer, we can obtain the relative importance ratings of CRs. Since K customers are taken into account, the relative importance rating (RIR) of each CR is determined by the following normalization to be the maximum of 1, and its vector expression can be also denoted as:

$$\mathrm{rir}_m = \frac{\sum_{k=1}^K \mathrm{rdp}_m^k}{\max_{m=1,\ldots M}\left(\sum_{k=1}^K \mathrm{rdp}_m^k\right)} \qquad (7)$$

$$\mathrm{RIR} = (\mathrm{rir}_1, \mathrm{rir}_2, \ldots, \mathrm{rir}_m, \ldots, \mathrm{rir}_M) \qquad (8)$$

In the example of Fig. 3, $\max_{m=1,\ldots M}\left(1 + d_m^1\right) = 7$ and $\max\limits_{m=1,\ldots M}\left(1 + d_m^K\right) = 5$ for PG_1 and PG_K, respectively, and thus $\mathrm{RDP}_1 = \left(\frac{4}{7}, \frac{7}{7}, \frac{3}{7}, \frac{3}{7}, \frac{2}{7}, \frac{2}{7}, \frac{1}{7}\right)$ and $\mathrm{RDP}_K = \left(\frac{4}{5}, \frac{3}{5}, \frac{1}{5}, \frac{5}{5}, \frac{2}{5}, \frac{2}{5}, \frac{1}{5}\right)$. Then, RIR=(0.857, 1, 000, 0.393, 0.893, 0.429, 0.429, 0.214) because $\max_{m=1,\cdots,M}\left(\sum_{k=1}^K rdp_m^k\right) = 1.6$. Finally, we can obtain the importance ranking order of 7 CRs as follows:

$$CR_2 > CR_4 > CR_1 > CR_5, CR_6 > CR_3 > CR_7 \qquad (9)$$

, where > means 'more important than'.

3.2 CSR method for competitive priority ratings

After determining the relative importance ratings of CRs, it should be also viewed from the customer's perspective to determine the competitive priority ratings. The competitive priority ratings indicate which CRs the company should more highly focus on to be competitive in comparison with its competitors. In the QFD process, the competitive benchmarking analysis compares the company and its competitors in terms of performance quality regarding each CR [6, 13–15, 23]. To understand customer perceptions on product quality, we should know the degree of customer satisfaction of the current product but also the customer satisfaction of the competitors' products.

First, based on the benchmarking results about the competitors' products, the proposed CSR method models the customer's preference structure (called 'satisfaction function') that represents the quality criteria or goals required to satisfy customers, utilizing the concepts of acceptability function [47] and satisfaction function [6].

Second, the degree of satisfaction of the company's product under consideration is evaluated with respect to the satisfaction function of each CR. However, customer perceptions on product quality are commonly obtained with a distribution of its score for each CR. In other words, obtaining the degree of satisfaction includes the probabilistic uncertainty of customer perceptions. Thus, the degree of uncertainty of customer perceptions is obtained using our new uncertainty measure [41].

Third, as mentioned before, the relationship between product quality criteria (i.e., CRs) and customer satisfaction is not always 1D or linear. Since the impact on customer satisfaction is different for each CR, it is very important to determine which CRs bring more satisfaction than others. Therefore, the Kano's analysis is conducted and its result is combined, as an adjustment factor (called Kano's factor), with the degrees of satisfaction and uncertainty.

3.2.1 Satisfaction and uncertainty analysis for competitive priority ratings

– Measuring degree of satisfaction of company performance ratings

  Again, suppose that K customers and M CRs denoted by CT_k (k=1,2,…,K) and CR_m (m=1,2,…,M). Also, let us denote the company under study and N competitors as company's product under study as CP_0 and CP_n (n=1, 2, ⋯, N), respectively. The competitive benchmarking analysis can be usually conducted by respectively asking K customers to rate the relative performance estimation of the company and its competitors on each CR in a same scale (e.g., nine-point scale), thereby the companies' performance ratings obtained.

Suppose that, in total, K customers are surveyed and CT_k customers give performance ratings for competitors CP_n's products. And, let us denote the customer perception of the fulfillment degree of CR_m in CP_n as y_{mn}. If nine-point scale is used, each y_{mn} is rated from 1 to 9. Then, averaging the K sets of performance ratings on the M CRs, the performance ratings for all competitors (CP_n) are obtained and denoted as a column vector $y_n=(y_{1n}, y_{2n},\ldots,y_{mn},\ldots,y_{Mn})^T$ [13]. The performance ratings of all competitors regarding each CR can be also denoted as a row vector $y_m=(y_{m1}, y_{m2},\ldots,y_{mn},\ldots,y_{mN})$. Here, y_{mn} of each competitor (n) indicates the mean value of performance ratings from all customers (K) with respect to each CR (m). Then, we can have the performance rating matrix of all competitors (CP_n) as follows:

$$\begin{array}{c} \\ \begin{array}{c} CR_1 \\ CR_2 \\ \vdots \\ CR_m \\ \vdots \\ CR_M \end{array} \end{array} \begin{array}{c} \begin{array}{ccccccc} CP_0 & CP_1 & CP_2 & \cdots & CP_n & \cdots & CP_N \end{array} \\ \left[\begin{array}{ccccccc} y_{10} & y_{11} & y_{12} & \cdots & y_{1n} & \cdots & y_{1N} \\ y_{20} & y_{21} & y_{22} & \cdots & y_{2n} & \cdots & y_{2N} \\ \vdots & \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ y_{m0} & y_{m1} & y_{m2} & \cdots & y_{mn} & \cdots & y_{mN} \\ \vdots & \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ y_{M0} & y_{M1} & y_{M2} & \cdots & y_{Mn} & \cdots & y_{MN} \end{array}\right] \end{array} \quad (10)$$

Similarly, the performance ratings of the CP_0 can be obtained, but the difference is that the numbers (y_{m0}) of CP_0 are not crisp numbers (i.e., mean values), but distributions of customer perceptions. For example, suppose that 40 customers were surveyed for a CR_1 of CP_0, and one rated 4, eight rated 5, seventeen rated 6, twelve rated 7, and two rated 8. The distribution looks as shown in Fig. 4. Then, we can obtain its probability density of CR_1 with 1/40, 8/40, 17/40, 12/40, 2/40, respectively. In the CSR method, this probability distribution of each CR for the CP_0 is taken into consideration for the subsequent uncertainty analysis.

Customer satisfaction is one of the critical success factors that are candidates for benchmarking. Since the performance quality of product is ultimately judged in terms of customer satisfaction, understanding customer perceptions is essential to remain competitive.

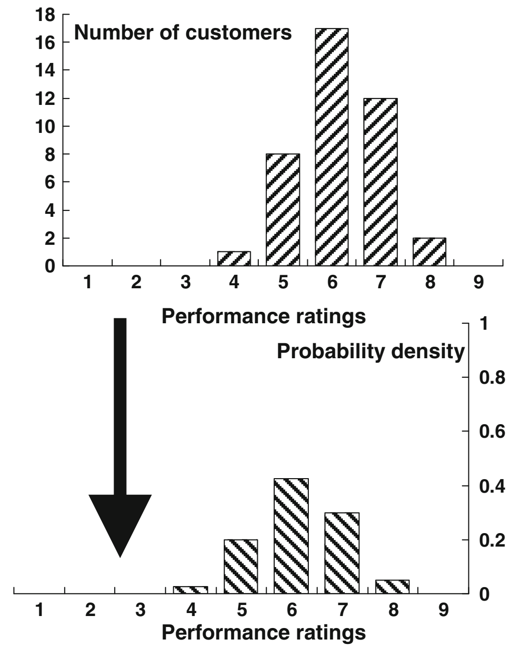


Fig. 4 Probabilistic distribution of company performance ratings from customers

Based on the performance rating matrix of competitors, the satisfaction function [6] of each CR can be constructed as shown in Fig. 5. According to the satisfaction function ($p(y_m)$), customer satisfaction is measured in terms of satisfaction with the maximum levels of fulfillment of CRs. y_m^L and y_m^U indicate the lower and upper bounds of satisfaction levels with respect to y_m, respectively. For example, if the nine-point scale is used, $y_m^L = 1$ and $y_m^U = 9$. In addition, y_m^B and y_m^W indicate the customer perceptions of the fulfilment degree of CR_m, with respect to y_m of the best and

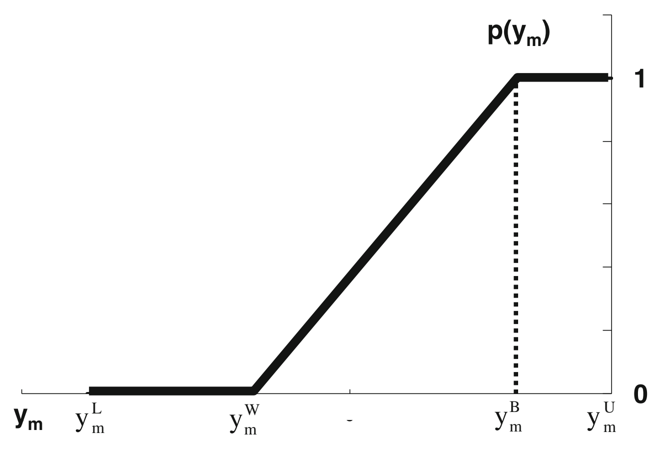


Fig. 5 Construction of satisfaction function based on competitive benchmarking analysis

worst competitors. These values can be obtained by taking a maximum or minimum value from all competitors' performance ratings for each CR.

$$y_m^B = \max_{n=1,\ldots,N}(y_{mn}) \text{ and } y_m^W = \min_{n=1,\ldots,N}(y_{mn}), m = 1, \ldots, M \tag{11}$$

Then, the customer satisfaction will monotonously decrease when y_m tends towards y_m^L and it will increase when y_m tends towards y_m^U. Therefore, the satisfaction function ($p(y_m)$) measures how satisfactory it is when y_m takes on a particular value. According to Fig. 5, the customer is completely dissatisfied with a fulfillment degree of CR$_m$ between y_m^L and y_m^W (i.e., $y_m^L \le y_m \le y_m^W$). The customer satisfaction is increasing when y_m belongs to the interval: $y_m^W < y_m < y_m^B$. The customer is completely satisfied with a design (his degree of satisfaction will be at its maximal value of 1) when y_m are within the interval, $y_m^B \le y_m \le y_m^U$. The satisfaction function $p(y_m)$ can be expressed as follows:

$$p(y_m) = \begin{cases} 0 & \text{if } y_m^L \le y_m \le y_m^W \\ \left(y_m - y_m^W\right)/\left(y_m^B - y_m^W\right) & \text{if } y_m^W < y_m < y_m^B \\ 1 & \text{if } y_m^B \le y_m \le y_m^U \end{cases} \tag{12}$$

As shown in Fig. 4, y_m of CP$_0$ is described in the form of probability distribution. Our method to reflect the uncertainty of customer perceptions on product quality when computing the degree of satisfaction is the two-staged approach in that the degree of satisfaction ($p(y_m)$) is first obtained simply by taking the mean value of y_m and then adjusted by the degree of uncertainty of y_m. Therefore, the degree of satisfaction (DS) for the CP$_0$ for each CR can be obtained by assigning the mean value $\left(y_m^a\right)$ as probability distribution (y_m) in Eq. 12, and its vector expression can be also denoted as:

$$\mathrm{ds}_m = P(y_m^a) \tag{13}$$

$$\mathrm{DS} = (\mathrm{ds}_1, \mathrm{ds}_2, \ldots, \mathrm{ds}_m, \ldots, \mathrm{ds}_M) \tag{14}$$

– Measuring degree of uncertainty of company performance ratings

Although the DS is a good measure to evaluate the quality performance (y_m) with respect to the satisfaction function ($p(y_m)$), its single use is not sufficient because it does not consider the uncertainty of y_m. For example, as shown in Fig. 6, suppose a satisfaction function ($p(y_1)$) and two probabilistic distributions of y_m ($q(y_1)'$, $q(y_1)''$), respectively. Then, the DS measure provides similar results between the two distributions, $q(y_1)'$ and $q(y_1)''$, because the distributions have similar mean values. However, from the viewpoint of robustness, $q(y_1)'$ is better than $q(y_1)''$ because $q(y_1)'$ contains the smaller variation. Therefore, in addition to the DS measure, a different measure is needed to evaluate the degree of uncertainty (DU) of quality performance (y_m).

In our previous research, we have developed a new measure of uncertainty, called 'preference and stability (PS) measure' [41, 42]. In the CSR method, the PS measure is used to the uncertainty analysis of y_m. To date, a number of measures of uncertainty have been proposed, including Shannon's entropy measure [45], γ-level measure [48], and so on. However, it is found that those measures of uncertainty often fail to make correct measures according to the shape and height of distribution. On the contrary, our PS measure consistently produces reasonable measures, regardless of the height and shape of distribution. The complete comparison between our PS measure and other measures is given in [41].

Letting the probability distribution of quality performance (y_m) be $q(y_m)$, the DU of $q(y_m)$ for the CP$_0$ can be obtained using the following PS measure:

$$\mathrm{du}_m = \mathrm{PS}(q(y_m)) = \alpha \sum_{y_m}^{|q|} E(q(y_m)) \tag{15}$$

, where

$$\alpha = \frac{|q|}{\mathrm{area}(q(y_m))} \tag{16}$$

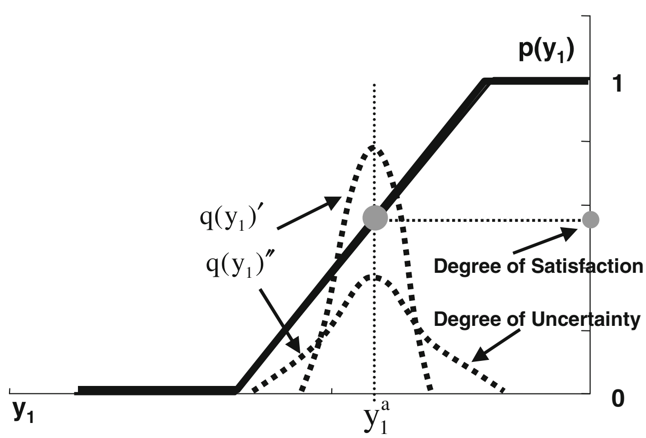


Fig. 6 Comparison of two different distributions of customers' assessments of CR

$$E(q(y_m)) = \begin{cases} q(y_m)\ln(q(y_m)) + (1-q(y_m)) \times \ln(1-q(y_m)) - \ln(0.5) & \textit{if } 0 < q(y_m) < 0.5 \text{ or } 0.5 < q(y_m) < 1 \\ -\ln(0.5) & \textit{if } q(y_m) = 0 \text{ or } q(y_m) = 1 \\ 0 & \textit{if } q(y_m) = 0.5 \end{cases} \quad (17)$$

Here, α is correction factor to make correct measures about the subnormal $q(y_m)$ [49]. $|q|$ is the width of interval at $q(y_m)$=0 and area($q(y_m)$) is the area of $q(y_m)$. Thus, the PS measure can be regarded as an inverse type of Shannon's entropy function with the correction factor. For the illustrative convenience, the DU can be also denoted as a vector:

$$\mathrm{DU} = (\mathrm{du}_1, \mathrm{du}_2, \ldots, \mathrm{du}_m, \ldots, \mathrm{du}_M) \quad (18)$$

Before adjusting the original degree of satisfaction with the help of the degree of uncertainty, let us first describe the characteristics of both of them. Note that the larger the DS value, the better the satisfaction. On the contrary, the smaller the DU value, the less the uncertainty. In addition, it is noted that if the customer is completely dissatisfied with a CR, the degree of satisfaction is equal to 0. In this case, we should put maximum efforts to improve it. Also, it should be noted that if all customers' perceptions of quality performance are nested with a single number (i.e., the number of y_m is 1), the degree of uncertainty is 0. Therefore, the relative degree of satisfaction (RDS) of CRs, which is adjusted with the help of the relative degree of uncertainty, can be obtained by the following equation, and its vector expression is also denoted as follows:

$$\mathrm{rds}_m = \left(\frac{(1+\mathrm{ds}_m)}{\left(\max\limits_{m=1,\ldots,M} (1+\mathrm{ds}_m) \right)} \right) \times \left(\frac{\min\limits_{m=1,\ldots,M} (1+\mathrm{du}_m)}{(1+\mathrm{du}_m)} \right), \quad m = 1, \ldots, M \quad (19)$$

$$\mathrm{RDS} = (\mathrm{rds}_1, \mathrm{rds}_2, \ldots, \mathrm{rds}_m, \ldots, \mathrm{rds}_M) \quad (20)$$

In the CSR method, the RDS measures how well it meets the CR with uncertain information. In other words, the larger the RDS value, the better the quality performance. The more important CRs that company should focus on are the ones that the company performs worse than competitors, thus resulting in lower customer satisfaction. If the company does not improve this CR, it can very likely be others' strong sales point and make the company in an adverse situation. Therefore, we should give a higher priority to those CRs that the company performs worse than competitors do, namely CRs with lower RDS values.

Finally, in order to determine the competitive priority ratings of CRs, the normalized RDS (NRDS) is obtained by making CRs with lower RDS values be more highly prioritized, and its vector expression is also denoted as follows:

$$\mathrm{nrds}_m = \frac{\min\limits_{m=1,\ldots,M} (\mathrm{rds}_m)}{\mathrm{rds}_m} \quad (21)$$

$$\mathrm{NRDS} = (\mathrm{nrds}_1, \mathrm{nrds}_2, \ldots, \mathrm{nrds}_m, \ldots, \mathrm{nrds}_M) \quad (22)$$

3.2.2 Competitive priority ratings combined with Kano's factor

It should be noted that the proposed CSR method resolves the shortcomings of existing competitive priority rating methods. However, it is not sufficient to capture all aspects of CRs. For some CRs, customer satisfaction is dramatically increased with only a small improvement in performance, while for other CRs, customer satisfaction is increased only a small amount even when the product performance is greatly improved [19]. For example, better gas mileage in a car provides proportional customer satisfaction, and worse gas mileage causes proportional customer dissatisfaction. On the other hand, having poor brakes in a car causes high customer dissatisfaction, but having good brakes does not increase customer satisfaction [2, 17].

Since the impact on customer satisfaction is different for each CR, it is very important to determine which CRs of a product bring more satisfaction than others [18]. The Kano's model distinguishes CRs into different types of categories which influence customer satisfaction (see Fig. 2) [2, 37, 38]:

- Must-be (or basic) CR (M): If these CRs are not fulfilled, the customer will be extremely dissatisfied. On the other hand, as the customer takes these CRs for granted, their fulfillment will not increase his satisfaction. Fulfilling these CRs will only lead to a state of 'not dissatisfied'.
- One dimensional CR (O): Customer satisfaction is proportional to the level of fulfillment—the higher the level of fulfillment, the higher the customer satisfaction and vice versa.
- Attractive CR (A): These CRs are the product criteria which have the greatest influence on how satisfied a customer will be with a given product. Fulfilling these CRs brings more than proportional satisfaction, but there is no feeling of dissatisfaction even if they are not met.

- Indifferent CR (I): This category means that the customer is indifferent to this CR and is not very interested in whether it is present or not.

To capture CRs more correctly, the Kano's model has been combined with the QFD over the past several years [2, 18, 19, 39, 40]. Most of Kano's model-based approaches to quantitatively incorporate the Kano's factor into the QFD process are based on the customer satisfaction (CS) coefficient [39] and its variants [18, 19]. More recently, a quantitative method based on more elaborate CS coefficient is provided to adjust the improvement ratio of CRs, expressed as the following [40]:

$$\mathrm{IR}_{\mathrm{adj}} = \mathrm{IR}_0 \times (1+\lambda)^r,$$

where

$$\lambda = \max(|SI|, |DI|) \tag{23}$$

Here, $\mathrm{IR}_{\mathrm{adj}}$ is the adjusted improvement ratio and IR_0 is the traditional improvement ratio. Also, SI and DI are the satisfaction and dissatisfaction indexes [39], and value of r is decided according to the different Kano category (i.e., M, O, A, or I) and can be taken as 0, 0.5, 1, and 1.5 for indifferent (I), must-be (M), 1D (O) and attractive (A) requirements, respectively. Kano's analysis uses a specific questionnaire format since the type of CR cannot be detected via traditional customer surveys. Kano questionnaire contains a pair of questions for each CR, including one functional and dysfunctional form of the same question. The functional form captures the customer's reaction if the product has a certain CR. On the other hand, the dysfunctional form describes the customer's reaction if the product does not have that CR. After the customer survey using the Kano questionnaire, the Kano's category of each CR is identified according to a Kano evaluation table. Based on the Kano's categories of CRs, SI and DI are calculated using [2, 37]:

$$\mathrm{SI} = \frac{(A+O)}{(A+O+M+I)}, \mathrm{DI} = \frac{-(M+O)}{(A+O+M+I)} \tag{24}$$

SI indicates how much the influence on customer satisfaction is increased by providing a particular CR, and DI shows how much the influence on customer satisfaction is decreased by not providing that CR. More detailed descriptions on the Kano's analysis can be found in [37, 39].

In the existing Kano model-based approaches, the improvement ratio or sales point has been mainly combined with the Kano's factor in order to determine the competitve priority ratings of CRs. However, as mentioned earlier, the improvement ratio (target performance/current performance) and sales point are determiend in a subjective or ad hoc manner because their settings are left up to the developers. Our approach is to combine the Kano's factor with our competitive priority ratings (i.e., NRDS) in replacement of improvement ratio or sales point. The competitive priority ratings (i.e., NRDS) is adapted with the help of Kano's factor, thus improving its ability to reflect the satisfaction levels of CRs.

Hence, the competitive priority rating of each CR, denoted as cpr_m, can be adjusted by integrating the NRDS with the Kano's factor (i.e., $(1+\lambda)^r$) of Eq. 23, and also its vector expression is obtained as follows:

$$\mathrm{cpr}_m = \mathrm{nrds}_m \times (1+\lambda_m)^{r_m}, m = 1, \ldots, M \tag{25}$$

$$\mathrm{CPR} = (\mathrm{cpr}_1, \mathrm{cpr}_2, \ldots, \mathrm{cpr}_m, \ldots, \mathrm{cpr}_M) \tag{26}$$

, where λ_m and r_m are coefficients of Kano's factor for each CR, respectively.

Then, the normalized competitive priority ratings (NCPR) of each CR can be obtained by the following normalization to be the maximum of 1:

$$\mathrm{ncpr}_m = \frac{\mathrm{cpr}_m}{\max\limits_{m=1,\ldots,M}(\mathrm{cpr}_m)} \tag{27}$$

For the illustrative convenience, we also denote the NCPR of CRs as a vector:

$$\mathrm{NCPR} = (\mathrm{ncpr}_1, \mathrm{ncpr}_2, \ldots, \mathrm{ncpr}_m, \ldots, \mathrm{ncpr}_M) \tag{28}$$

The proposed CSR method determines the competitive priority ratings of CRs in terms of customer satisfaction. The product should satisfy the customer, and the product quality is ultimately perceived by the customer in terms of satisfaction. The CSR method gives a higher priority to those requirements that have a lower satisfaction due to a bigger gap with customer expectations (i.e., using NRDS), and are more attractive to the customer (i.e., using Kano's factor). Therefore, the CSR method provides a clear semantics in determining CRs that company should focus on to improve its competitiveness.

3.3 Final importance ratings with a combined CPR and CSR

The CRs with larger relative importance rating and larger competitive priority rating should receive higher attention. Therefore, the final importance ratings (FIR) of CRs are determined by the integration of the relative importance rating (i.e., RIR) and the competitive priority rating (i.e., NCPR) which are obtained using the proposed CPR and CSR methods, respectively:

$$\mathrm{fir}_m = \frac{(\omega_1 \mathrm{rir}_m + \omega_2 \mathrm{ncpr}_m)}{\left(\sum_{m=1}^{M}(\omega_1 \mathrm{rir}_m + \omega_2 \mathrm{ncpr}_m)\right)}, m = 1, \ldots, M \tag{29}$$

where $\omega_1+\omega_2=1$, ω_1 is the relative weight of RIR and ω_2 is the relative weight of NCPR. These relative weights can be determined by decision makers using pair-wise comparison method (e.g., AHP) according to the specific competitive environment. If the competition is very keen, ω_2 can be larger than ω_1. If the market is fast gworing, customers' views are more important and ω_2 can be lower than ω_1 [23]. For the illustrative convenience, we also denote the final importance ratings of CRs as a vector:

$$\mathrm{FIR} = (\mathrm{fir}_1, \mathrm{fir}_2, \ldots, \mathrm{fir}_m, \ldots, \mathrm{fir}_M) \tag{30}$$

In summary, our approach to determine the final importance ratings of CRs gives more priority to those CRs that have a lower satisfaction and more attractive, and that customers think more importanct.

4 An illustrative example

To demonstrate the performance of the proposed approach for rating the final importance of CRs in QFD process, a case study of product improvement of a car door design problem [13] is illustrated in this section. The available data are limited, and thus some are given as the hypothetical data.

4.1 Determining relative importance ratings of CRs

A company is improving an old type of car door. According to the company's sales network and through market survey, the company's five customers, denoted as CT_k (k=1, …, 5), are selected to help identify CRs for the company's product. By focus group, individual interviews, and using existing information, 90 initial CR candidates are collected, and then affinity diagram or cluster method is successfully used to organize those candidates. Finally, suppose that 10 major CRs are identified to represent the biggest concerns of the customers. They are: 'easy to close from outside' (CR_1), 'easy to open from outside' (CR_2), 'easy to close from inside' (CR_3), 'easy to open from inside' (CR_4), 'stays open on a hill' (CR_5), 'does not leak in rain' (CR_6), 'does not leak in car wash' (CR_7), 'no road noise' (CR_8), 'no wind noise' (CR_9), and 'does not rattle' (CR_{10}).

The proposed CPR method enables customers to reveal their preference structures over CRs with the simple graph representation (i.e., preference graph (PG)). The 5 PGs from customers are provided as shown in Fig. 7. Then, the RDP over 10 CRs of five customers can be computed using Eq. 1–5. For example, the adjacency matrix of PG_1 from customer 1 is obtained as:

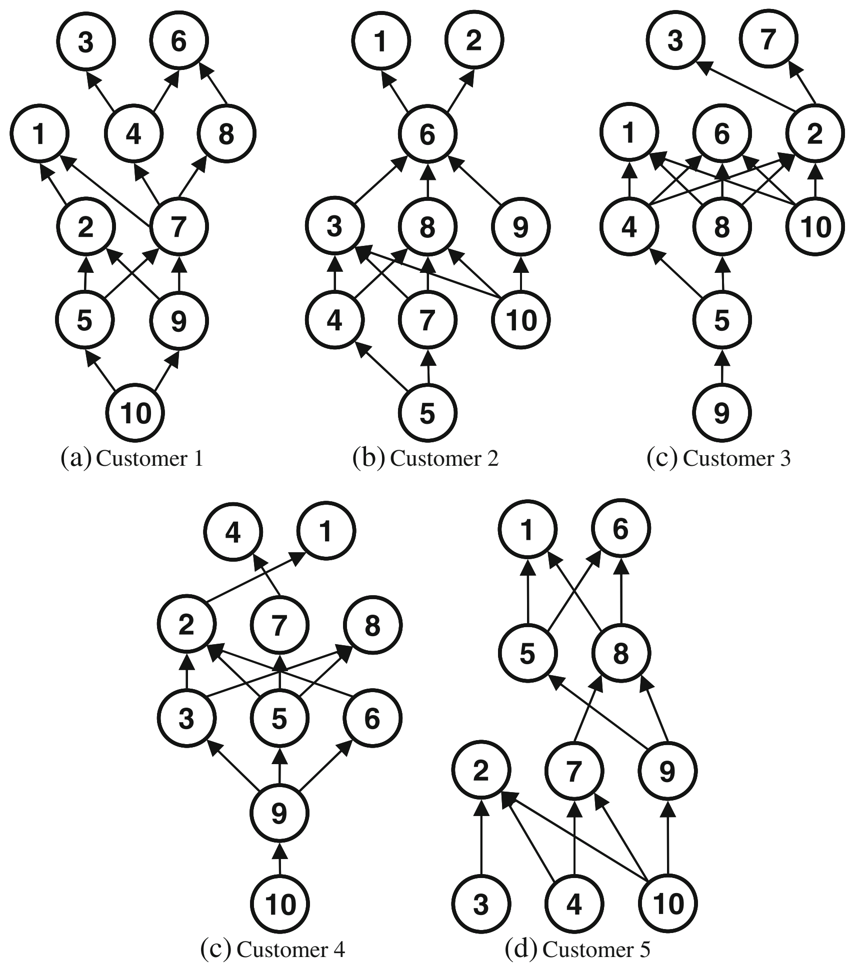


Fig. 7 Preference graphs for representing relative importance of CRs

$$\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Then, since 10 CRs are taken into consideration for this example, the dominance matrix of PG_1 is computed by taking the nine-stage dominances as follows:

$$\begin{array}{c} \begin{bmatrix} 0 & 1 & 0 & 0 & 2 & 0 & 1 & 0 & 2 & 4 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 2 \\ 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 2 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 2 & 0 & 2 & 1 & 2 & 4 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 2 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \begin{array}{l} \rightarrow 10 \\ \rightarrow 4 \\ \rightarrow 6 \\ \rightarrow 5 \\ \rightarrow 1 \\ \rightarrow 12 \\ \rightarrow 4 \\ \rightarrow 5 \\ \rightarrow 1 \\ \rightarrow 0 \end{array}$$

Here, the CR_6 is dominated in 12 ways, and thus $\max_{m=1,\ldots,10}\left(1+d_m^1\right)=13$. Then, the RDP values of customer 1 can be computed using Eq. 5 as:

$$\begin{aligned} RDP_1 &= \left(rdp_1^1, \ldots, rdp_{10}^1\right) \\ &= (11/13, 5/13, 7/13, 6/13, 2/13, 13/13, 5/13, 6/13, 2/13, 1/13) \\ &= (0.846, 0.385, 0.538, 0.462, 0.154, 1.000, 0.385, 0.462, 0.154, 0.077). \end{aligned}$$

In the same manner, the RDP values of other customers are obtained as:

$$\begin{aligned} RDP_2 &= \left(rdp_1^2, \ldots, rdp_{10}^2\right) \\ &= (1.000, 1.000, 0.375, 0.125, 0.063, 0.938, 0.125, 0.375, 0.125, 0.063), \\ RDP_3 &= \left(rdp_1^3, \ldots, rdp_{10}^3\right) \\ &= (0.889, 0.889, 1.000, 0.333, 0.222, 0.889, 1.000, 0.333, 0.111, 0.111), \\ RDP_4 &= \left(rdp_1^4, \ldots, rdp_{10}^4\right) \\ &= (1.000, 0.909, 0.273, 0.455, 0.273, 0.273, 0.364, 0.637, 0.182, 0.091), \text{and} \\ RDP_5 &= \left(rdp_1^5, \ldots, rdp_{10}^5\right) \\ &= (1.000, 0.444, 0.111, 0.111, 0.333, 1.000, 0.222, 0.556, 0.222, 0.111). \end{aligned}$$

Then, based on the RDP values of 5 customers, the RIR of 10 CRs are determined using Eq. 7 as:

$$\begin{aligned} RIR &= (rir_1, \ldots, rir_{10}) \\ &= (1.000, 0.766, 0.485, 0.314, 0.221, 0.866, 0.443, 0.499, 0.167, 0.096). \end{aligned}$$

Therefore, we can see that the 10 CRs have the following ranking order from the viewpoint of importance of CRs:

$$CR_1 > CR_6 > CR_2 > CR_8 > CR_3 > CR_7 > CR_4 > CR_5 > CR_9 > CR_{10}.$$

4.2 Determining competitive priority ratings of CRs

According to the five customers' assessments of the relative performance of the five companies' similar products in terms of the 10 CRs, a company performance rating matrix can be obtained as shown in Table 1. The competitors' performance assessments are listed by averaging for each competitor its customers' assessments. On the other hand, the company's performance assessments are given with all scores rated by the five customers. Based the competitors' performance rating matrix, satisfaction functions of the 10 CRs are constructed as shown in Fig. 8. For example, for the CR_1, the worst $\left(y_1^W\right)$ and best $\left(y_1^B\right)$ competitors are the competitor 1 (i.e., y_{11}=1.80)

Table 1 Company performance ratings assessed by customers

CRs	Company's product under study					Competitors' products			
	CP_0					CP_1	CP_2	CP_3	CP_4
	CT_1	CT_2	CT_3	CT_4	CT_5				
CR_1	3	3	1	2	2	1.80	2.00	2.75	4.00
CR_2	3	4	5	4	8	5.20	5.75	5.00	5.75
CR_3	7	9	8	7	9	8.20	8.00	7.75	8.25
CR_4	9	5	7	8	7	3.20	3.75	4.25	2.25
CR_5	4	3	2	1	2	8.20	7.75	7.70	5.50
CR_6	7	5	3	5	4	7.40	7.00	7.75	6.00
CR_7	9	7	9	9	6	5.80	3.25	5.00	7.75
CR_8	3	5	5	4	6	6.20	3.50	5.00	5.50
CR_9	5	6	5	7	3	3.20	4.25	2.75	3.00
CR_{10}	3	2	3	5	2	5.20	5.75	5.00	6.50

and competitor 4 (i.e., y_{14}=4.00), respectively. In addition, since these ratings are here made using nine-point scale, $y_1^L = 1$ and $y_1^U = 9$. In the same manner, the satisfaction functions of other CRs can be obtained as shown in Fig. 8.

First, the DS of the company's product for each CR is computed by inserting the mean value of customers' assessments into y_m in Eq. 12. For example, the mean value $\left(y_1^a\right)$ of the CR_1 is 2.20. The DS values of the 10 CRs are obtained as:

$$\begin{aligned}\mathrm{DS} &= (\mathrm{ds}_1, \ldots, \mathrm{ds}_{10})\\ &= (0.182, 0.000, 0.500, 1.000, 0.000, 0.000, 1.000, 0.407, 1.000, 0.000).\end{aligned}$$

Second, the DU of the company's product for each CR is computed using Eq. 15. Here, the distribution ($q(y_m)$) of customers' assessments could be simply expressed in a discrete form [13]. For example, the distribution of CR_1 on the company's product is composed of the five customers' performance ratings on CR_1. That is, one rated 1, two rated 2, and two rated 3. Then, the probability density of $q(y_1)$ can be computed as 1/5, 2/5, and 3/5 as shown in Fig. 4. In this case, the area (area($q(y_1)$)) of $q(y_1)$ is equal to 1, and the width ($|q|$) of $q(y_1)$ is 2 because the best assessment is 3 and the worst one is 1. Thus, the correction factor (α) of Eq. 16 is computed as $\alpha = \frac{|q|}{\mathrm{area}(q(y_1))} = \frac{2}{1} = 2$, and the degree of uncertainty (du_1) is obtained using Eqs. 15 and 17 as:

$$\begin{aligned}\mathrm{du}_1 &= 2\left\{\begin{array}{l}\left(\frac{1}{5}\ln\left(\frac{1}{5}\right) + \left(1-\frac{1}{5}\right)\ln\left(1-\frac{1}{5}\right) - \ln(0.5)\right)\\ +\left(\frac{2}{5}\ln\left(\frac{2}{5}\right) + \left(1-\frac{2}{5}\right)\ln\left(1-\frac{2}{5}\right) - \ln(0.5)\right)\\ +\left(\frac{3}{5}\ln\left(\frac{3}{5}\right) + \left(1-\frac{3}{5}\right)\ln\left(1-\frac{3}{5}\right) - \ln(0.5)\right)\end{array}\right\}\\ &= 2\{0.1928 + 0.0201 + 0.0201\} = 0.466\end{aligned}$$

In this manner, the DU values of 10 CRs are obtained as:

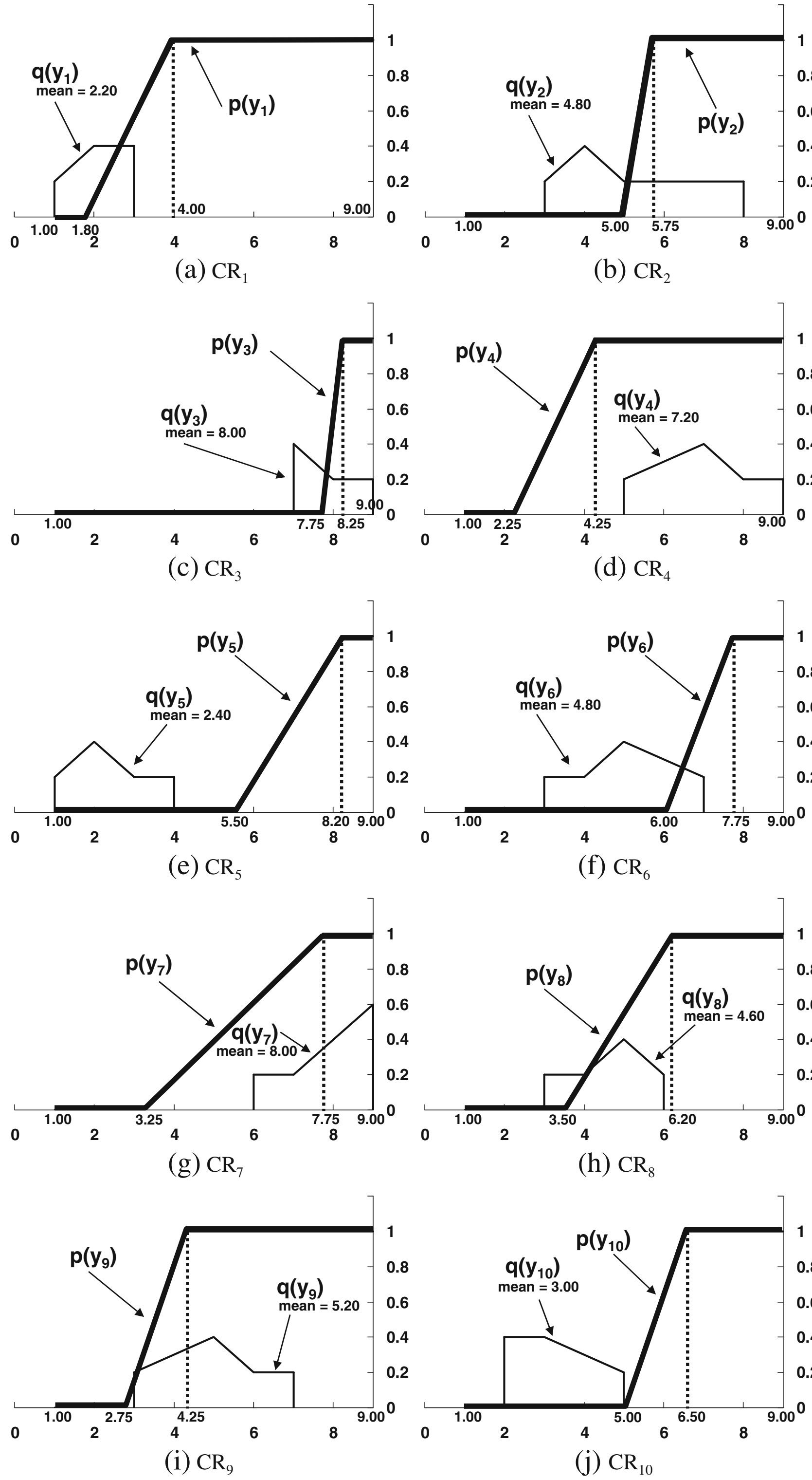
$$\begin{aligned}\mathrm{DU} &= (\mathrm{du}_1, \ldots, \mathrm{du}_{10})\\ &= (0.466, 2.992, 0.466, 2.393, 1.795, 2.393, 1.217, 1.795, 2.393, 0.699).\end{aligned}$$

Based on these DS and DU values, the relative degree of satisfaction (RDS) of CRs can be obtained using Eq. 19 as:

$$\begin{aligned}\mathrm{RDS} &= (\mathrm{rds}_1, \ldots, \mathrm{rds}_{10})\\ &= (0.591, 0.184, 0.750, 0.432, 0.262, 0.216, 0.662, 0.369, 0.432, 0.431).\end{aligned}$$

From the DS values, we can see that CR_4, CR_7, and CR_9 are completely satisfied because they have the values of 1. But the DU value of CR_4 (or CR_9) is the larger than that of CR_7. This means that customers'

Fig. 8 Satisfaction functions and probability distributions of customers' assessments



assessment of CR_7 has the less uncertainty than that of CR_4 (or CR_9). Even though the three CRs have the same DS values, the CR_7 is the better than CR_4 (or CR_9). Our method produces reasonable results by adjusting the degree of satisfaction to reflect its degree of uncertainty. As we can see from the RDS values, the relative degree of satisfaction of CR_7, 0.662, is the larger than that of CR_4 (or CR_9), 0.432.

Based on the RDS values, the competitive priority ratings (NRDS) of CRs are determined using Eq. 21 as:

$$\begin{aligned}\mathrm{NRDS} &= (\mathrm{nrds}_1, \ldots, \mathrm{nrds}_{10})\\ &= (0.310, 1.000, 0.245, 0.425, 0.700, 0.850, 0.278, 0.498, 0.425, 0.426).\end{aligned}$$

The NRDS values indicate which CRs the company should focus on to improve its competitiveness. It is clear that more important CRs are the ones that the company does not satisfy the customers well. As seen in the NRDS values, the CR_2, CR_6, and CR_5 are more highly prioritized than other CRs, because they are completely dissatisfied (i.e., the DS value of 0). Thus, the NRDS value can be used as a good measure to make the company achieve its competitiveness, since it gives a higher priority to those CRs that the company performs worse than competitors do, thus resulting in lower customer satisfaction.

In our method, the NRDS is further combined with the Kano's factor as described in Section 3.2.2, in order to correctly capture the different impacts of CRs on customer satisfaction. As shown in Table 2, it is assumed that the values of SI, DI, and category of the 10 CRs are obtained according to the Kano's analysis. Then, the CPR of CRs adjusted by the Kano's factor and their NCPR can be obtained using Eqs. 25 and 27, respectively, as:

$$\begin{aligned}\mathrm{CPR} &= (\mathrm{cpr}_1, \ldots, \mathrm{cpr}_{10})\\ &= (0.404, 1.590, 0.377, 0.556, 0.700, 1.131, 0.361, 0.951, 0.901, 0.878).\\ \mathrm{NCPR} &= (\mathrm{ncpr}_1, \ldots, \mathrm{ncpr}_{10})\\ &= (0.254, 1.000, 0.237, 0.350, 0.440, 0.711, 0.227, 0.598, 0.567, 0.552).\end{aligned}$$

Note that CR_8, CR_9, and CR_{10} are regarded as the attractive (A) CRs. Then, we can see that the priorities of attractive CRs increased with higher NCPR values. On the contrary, the priority of CR_5 assigned as the indifferent (I) CR greatly decreased. In this manner, our method gives a higher priority to those requirements that have lower satisfaction and are more attractive to the customer.

Finally, we can see that the 10 CRs have the following ranking order from the viewpoint of company's competitiveness:

$$\mathrm{CR}_2 > \mathrm{CR}_6 > \mathrm{CR}_8 > \mathrm{CR}_9 > \mathrm{CR}_{10} > \mathrm{CR}_5 > \mathrm{CR}_4 > \mathrm{CR}_1 > \mathrm{CR}_3 > \mathrm{CR}_7.$$

4.3 Determining final importance ratings of CRs

Based on a combination of the relative importance ratings and the competitive priority ratings of CRs, the FIR of CRs can be determined using Eq. 29. Considering the same weights (i.e., 0.5) of RIR and NCPR, the FIR is obtained as:

$$\begin{aligned}\mathrm{FIR} &= (\mathrm{fir}_1, \ldots, \mathrm{fir}_{10})\\ &= (0.128, 0.180, 0.074, 0.068, 0.068, 0.161, 0.068, 0.112, 0.075, 0.066).\end{aligned}$$

Finally, the 10 CRs have the following ranking order from the viewpoint of importance and competitiveness of CRs:

$$CR_2 > CR_6 > CR_1 > CR_8 > CR_9 > CR_3 > CR_7 > CR_4 > CR_5 > CR_{10}.$$

5 Conclusions

This paper proposes two sets of new rating methods, called CPR and CSR methods to determine the relative importance ratings and the competitive priority ratings of CRs, respectively,

Table 2 SI, DI, and category of CRs

Customer requirements		SI	DI	Category
CR_1	Easy to close from outside	0.44	0.69	M
CR_2	Easy to open from outside	0.53	0.59	O
CR_3	Easy to close from inside	0.51	0.54	O
CR_4	Easy to open from inside	0.41	0.71	M
CR_5	Stays open on a hill	0.38	0.28	I
CR_6	Does not leak in rain	0.36	0.77	M
CR_7	Does not leak in car wash	0.30	0.69	M
CR_8	No road noise	0.54	0.37	A
CR_9	No wind noise	0.65	0.29	A
CR_{10}	Does not rattle	0.62	0.21	A

in the QFD process. Then, the final importance ratings of CRs are determined by combining the CPR and CSR methods.

Compared with most of exising methods for prioritizing the CRs, the main advantages of proposed approach can be summarized as follows:

- First, the CPR method provides a simple and intuitive method to capture the customers' incomplete or uncertain perceptions on the relative importance of CRs, allowing them to give a partial ordering of CRs;
- Second, while existing conventional methods for the competitive priority ratings is mainly combined with the improvement ratio or sales point which is set in a subjective or ad hoc manner, the CSR method provides an objective and quantitative method based on the satisfaction and uncertainty analysis of company's quality performance with respect to an expectation model (i.e., satisfaction function) constructed by the competitive benchmarking analysis;
- Third, the uncertainty analysis using our new uncertainty measure is more reliable than the conventional entropy method;
- Fourth, the CSR method includes an objective and quantitative Kano's factor by which subjective sales point method can be replaced; and
- Last, more importantly, the CPR and CSR methods provide a clear and consistent semantics of capturing, understanding and prioritizing the CRs in terms of customer preference and satisfaction.

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