Taylor & Francis
Taylor & Francis Group

Quality Engineering

ISSN: 0898-2112 (Print) 1532-4222 (Online) Journal homepage: http://www.tandfonline.com/loi/lqen20

Prioritization of QFD Customer Requirements Based on the Law of Comparative Judgments

Fiorenzo Franceschini & Domenico Maisano

Quality Engineering, 27:437–449, 2015

ISSN: 0898-2112 print / 1532-4222 online
DOI: 10.1080/08982112.2015.1036292

Taylor & Francis
Taylor & Francis Group

Prioritization of QFD Customer Requirements Based on the Law of Comparative Judgments

Fiorenzo Franceschini, Domenico Maisano
Politecnico di Torino, Department of Management and Production Engineering, Torino, Italy

ABSTRACT Quality function deployment (QFD) is a useful tool to improve the design/development process of products and services. The initial phases of the QFD process—that is, those concerning the collection and analysis of the so-called voice of the customer—are probably the most critical, because any distortion can propagate to the whole process results, making it ineffective or even misleading. The focus of this article is on the phase of prioritization of customer requirements (CRs). There are numerous techniques for this task; however, (1) the simplest often introduce questionable or unrealistic assumptions, whereas (2) the most sophisticated often require too much elaborate and repetitious information from customers, which may lead to inconsistencies. This article introduces a new prioritization technique based on the Thurstone's law of comparative judgment. This technique makes it possible to aggregate the evaluations by multiple respondents and transform them into an interval scale, which depicts the relative importance of CRs. The greatest strength of this technique is combining a refined theoretical model with a simple and user-friendly data collection process. The description is supported by a realistic application example concerning the prioritization of QFD's CRs in the design of an aircraft seat.

KEYWORDS customer requirements, interval scale, law of comparative judgment, prioritization, QFD, relative importance ratings, Thurstone scaling

INTRODUCTION AND LITERATURE REVIEW

Quality function deployment (QFD) is a powerful technique to increase the customer satisfaction of product and services. The implementation of QFD may generate significant improvements in the design/development process, such as fewer and earlier design changes, improved cross-functional communications, improved product/service quality, and reduced development time and cost (Franceschini 2002; Griffin and Hauser 1993; Hauser and Clausing 1988; Tran and Sherif 1995). These improvements are critical success factors to companies in a global marketplace characterized by intense international competition.

Address correspondence to Fiorenzo Franceschini, Politecnico di Torino, Department of Management and Production Engineering, Corso Duca degli Abruzzi 24, 10129, Torino, Italy. E-mail: fiorenzo.franceschini@polito.it

The great diffusion of QFD is demonstrated by the literally thousands of scientific publications illustrating a variety of industrial applications, methodological improvements, new variants, and possible integration with other tools.

Typically, QFD utilizes four sets of matrices—the so-called Houses of Quality (HoQs). The four HoQs respectively translate (1) customer requirements (CRs) into engineering characteristics and, in turn, into (2) parts characteristics, (3) process plans, and (4) production requirements (Franceschini 2002). For detailed information, we refer the reader to the vast literature and extensive reviews (e.g., Chan and Wua 2002; Sharma, Rawani, and Barahate 2008).

The customer input, also defined as voice of the customer (VoC), is the key starting point for the QFD process; if it does not accurately reflect what the customer expects from the product/service of interest, the process may lead to incorrect conclusions (Sireli, Kauffmann, and Ozan 2007). Therefore, the first HoQ, also defined as product planning HoQ, is of fundamental and strategic importance (Gonzalez, Quesada, and Bahill 2003). The product planning HoQ construction process can be summarized into ten phases, as shown in Figure 1.

Among these phases—described in detail in the literature (see, e.g., Chan and Wua 2002; Franceschini 2002; Franceschini and Rossetto 2002)—particularly significant are those related to the VoC collection and analysis. The initial phase (i.e., phase 1, "customer requirements," in the scheme in Figure 1) concerns the VoC collection—through interviews and questionnaires—and analysis, in order to determine an exhaustive list of CRs. For this task, it is necessary to select a representative sample of (potential) customers, with reasonable knowledge of the product/service to be designed. It was found empirically that samples consisting of twenty to thirty respondents are sufficient to cover most CRs; in addition, for data collected to be reasonable and applicable, respondents have to gain a full understanding of the task required (Urban and Hauser 1993).

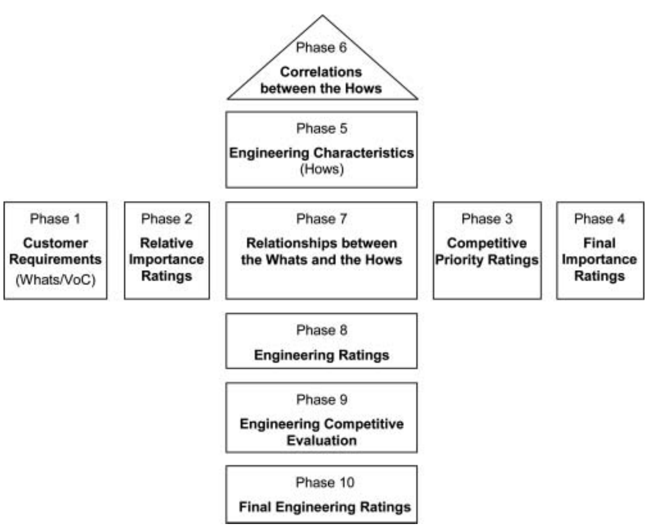

FIGURE 1 **Main phases of the product planning HoQ construction process.**

In the second part of this phase, a cross-functional team of experts—composed of members from marketing, design, quality, finance, and production—have to review, reorganize, and insert the CRs into the product planning HoQ.

The next stage, which is the focus of this article, is that of the prioritization of CRs (i.e., phase 2, "relative importance ratings," in the scheme in Figure 1), presuming that the main CRs related to the product/service to be designed have already been identified in phase 1. The expression "relative importance ratings" indicates that this prioritization is aimed at discriminating a CR based on its importance over the others. On the other hand, phase 4, "final importance ratings" (see Figure 1), denotes a prioritization that also takes into account the comparison of quality performance of the products/services of the company and those of its competitors.

In phase 2, a sample of customers—generally the same involved in phase 1—have to prioritize the QFD's CRs using several possible approaches. Some of them are point direct scoring method (Griffin and Hauser 1993; Hauser and Clausing 1988), analytic hierarchy process (AHP; Chuang 2001; Li et al. 2009), analytic network process (ANP; Karsak, Sozer, and Alptekin 2002; Lee, Wu, and Tzeng 2008), outranking methods (Figueira, Greco, and Ehrgott 2005; Franceschini and Rossetto 1995), fuzzy variants (Buyukozkan et al. 2004; Chan, Kao, and Wu 1999; Kwong and Bai 2002), and techniques derived from the Kano model (Chaudha et al. 2011; Matzler and Hinterhuber 1998; Sireli, Kauffmann, and Ozan 2007). Without going into these techniques in detail, we remark that they may use different kinds of response data and elaborations from respondents. Even though all of these techniques are supposed to reflect the VoC, sometimes they may lead to misleading results, especially when the data collection approach is too complex and elaborate. Here are some examples:

- Techniques based on the AHP and ANP method require CR judgments in the form of paired comparison data, defined on a *ratio* scale; for example, CR_1 is twice as important as CR_2 (Chuang 2001; Franceschini 2002; Kwong and Bai 2002; Lee, Wu, and Tzeng 2008, Li et al. 2009). These evaluations are inevitably arbitrary and subjective because respondents may find it difficult to express their judgments on this scale. Techniques that integrate the Kano model in the QFD environment require relatively complex questionnaires (Nahm, Ishikawa, and Inoue 2013) and the definition of arbitrary weights for the (qualitative) Kano categories (i.e., *basic* or *must-be* (B), *one dimensional* (O), *attractive* (A), *indifferent* (I), *reverse* (R), and *questionable* (Q); Tan and Shen 2000).
- Other sophisticated techniques for the CR prioritization, such as that proposed by Nahm, Ishikawa, and Inoue (2013), model the uncertainty in customer requirements, taking into account the uncertainty of customer's judgment. Unfortunately, they generally include complex and structured questionnaires and, sometimes, introduce questionable assumptions in the response data processing.
- In the classical questionnaires for prioritizing QFD's CRs, respondent judgements are defined on a five-level rating response scale (1 = *not at all important*, 2 = *low importance*, 3 = *medium importance*, 4 = *high importance*, and 5 = *very high importance*). This response scale has two inherent limitations:
  1. Because it is an ordinal scale, it only allows comparisons like "CR_1 is more important than CR_2." Unfortunately, a typical abuse is "promoting" this scale to an interval or even ratio scale, in order to make incorrect comparisons like "the distance, in terms of importance, between CR_1 and CR_2 is greater than that between CR_3 and CR_4" or "CR_1 is three times more important than CR_2" (Burke, Kloeber, and Deckro 2002; Franceschini,Galetto, and Maisano 2007; Stevens 1946).
  2. These scales are used subjectively, because there is no absolute reference shared by all respondents. In general, "indulgent" respondents will tend to assign higher levels of importance, wheras "severe" respondents will tend to assign lower ones. For example, let us consider the ratings about three CRs (i.e., CR_1, CR_2, and CR_3) by two fictitious respondents (A and B). These ratings on a five-level scale are respectively A: 3, 2, 1, and B: 5, 4, 2. Although the relative rankings are identical (i.e., $CR_1 > CR_2 > CR_3$), judgments by A (severe respondent) are concentrated in the lowest levels of the scale, whereas those of B (indulgent respondent) are concentrated in the highest. For this reason, it is questionable to aggregate judgments by different respondents through indicators of central tendency, such as the median or the mean value.

The objective of this article is to introduce a simple technique for the CR prioritization, based on the so-called Thurstone's law of comparative judgement, for aggregating the judgments by multiple respondents and transforming them into a numerical interval scale (Thurstone 1927).

An important benefit of this technique is combining a simple and user-friendly data collection process—based on the definition of respondent judgements on a five-level ordinal scale—with a refined theoretical model.

The remainder of this article is structured into three sections. The following section provides some background information, which is helpful to grasp the logic of the novel prioritization technique: (1) basic concepts concerning the Thurstone model and (2) description of a process for deriving response data suitable to this model, keeping data collection as simple and user-friendly as possible. The following section shows a realistic application example concerning the prioritization of the QFD's CRs in the design of an aircraft seat for passengers. The concluding section summarizes the original contributions of the article, focusing on the benefits and limitations of the proposed technique and possible future research.

BACKGROUND INFORMATION

Basics of Thurstone's Law of Comparative Judgment

In 1927, Thurstone presented his law of comparative judgement (LCJ); that is, a mathematical model to estimate scale values based on binary choices between stimuli. The explanation of this model will refer to the problem of the relative importance prioritization of QFD's CRs on the basis of the VoC.

Thurstone postulated that each stimulus (CR in this case) will possess some attribute (importance level in this case) in varying but unknown degrees. For each of the CRs and among all subjects, it is assumed that a preference will exist. These two conditions imply the assumption of unidimensionality of the scale representing the importance of CRs (McIver and Carmines 1981). It is also assumed that, for each *i*th CR, the preference will be distributed normally; that is, $\mathrm{CR}_i \sim N(\mu_i, \sigma_i^2)$, where μ_i and σ_i^2 are the unknown mean value and variance of that CR. A person's preference for each CR versus every other CR is thereby obtained. The more persons who select one CR of a pair over the other CR, the greater the importance for that CR and thus the greater its scale weight (Edwards 1957).

Thurstone's LCJ is an indirect form of measurement based on a transformation of individual preferences (input data) into scale values on a psychological continuum. Such indirect approaches are referred to as "scaling" processes. There are many scaling models; the most well known are the Rasch model (Jansen 1984; Rasch 1966) and conjoint analysis (Luce and Tukey 1964). In addition, the LCJ model is based on deriving group scale values from dispersed individual choice data. Therefore, it can be also considered as a statistic choice model.

In Thurstone's terminology, choices are mediated by a *discriminal process*. He defines this as the process by which an individual identifies, distinguishes, or reacts to stimuli. Let us consider the theoretical distributions of the discriminal process for any two CRs, CR_i and CR_j (see Figure 2a). In the LCJ model, the distribution associated with a given CR is characterized by a dispersion (or variance) of that CR, which reflects the subject-to-subject variability. Dispersions may be different for different CRs. Let μ_i and μ_j correspond to the (unknown) scale values of the two CRs and σ_i^2 and σ_j^2 the (unknown) variances.

The difference ($\mathrm{CR}_{ij} = \mathrm{CR}_i - \mathrm{CR}_j$) will follow a normal distribution with parameters

$$\mu_{ij} = \mu_i - \mu_j \text{ and } \sigma_{ij} = \sqrt{\sigma_i^2 + \sigma_j^2 - 2 \cdot \rho_{ij} \cdot \sigma_i \cdot \sigma_j}, \quad [1]$$

where μ_i and μ_j denote the (unknown) mean values of CR_i and CR_j; σ_i^2 and σ_j^2 denote the (unknown) variances of CR_i and CR_j; and ρ_{ij} denotes the (unknown) correlation between the pairs of discriminal processes CR_i and CR_j.

Considering the area subtended by the distribution of CR_{ij}, let us draw a vertical line passing through the point with $\mathrm{CR}_{ij} = \mathrm{CR}_i - \mathrm{CR}_j = 0$ (see Figure 2b). The area to the right of the line depicts the observed proportion of times (p_{ij}) that $\mathrm{CR}_{ij} \geq 0$. Of course, the area to the left depicts the complementary proportion $(1 - p_{ij})$.

In the standard method of Thurstone scaling, the paired comparison approach is used to collect response data. Under the protocol, respondents are forced to express a preference for one CR over another (i.e., by asking them to rank order CRs two at a time rather than all at once). All possible $\binom{n}{2} = \frac{n \cdot (n-2)}{2}$ pairs are assessed, where *n* is the number of CRs of interest.

Paired comparison data of each respondent are reported into a "binary" matrix (B). For the purpose of example, Figure 3a shows three matrices (B_1, B_2, and B_3) related to three fictitious respondents. The element of the single respondent's matrix is 1 when the CR in

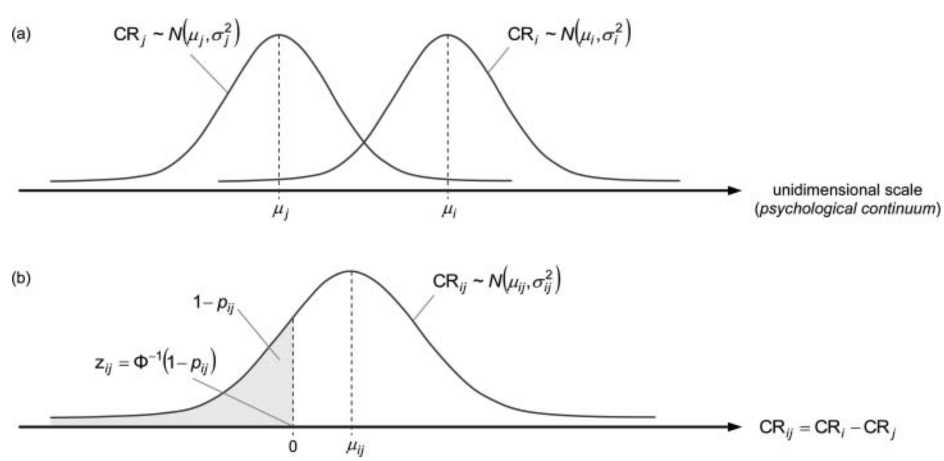

FIGURE 2 **(a) Theoretical distributions of the discriminal process for two CRs (i.e., CR_i and CR_j). (b) Link between $\mathrm{CR}_{ij} = \mathrm{CR}_i - \mathrm{CR}_j$, and z_{ij}; that is, the unit normal deviate corresponding to the probability $1 - p_{ij}$, where $p_{ij} = \Pr(\mathrm{CR}_{ij} \geq 0)$.**

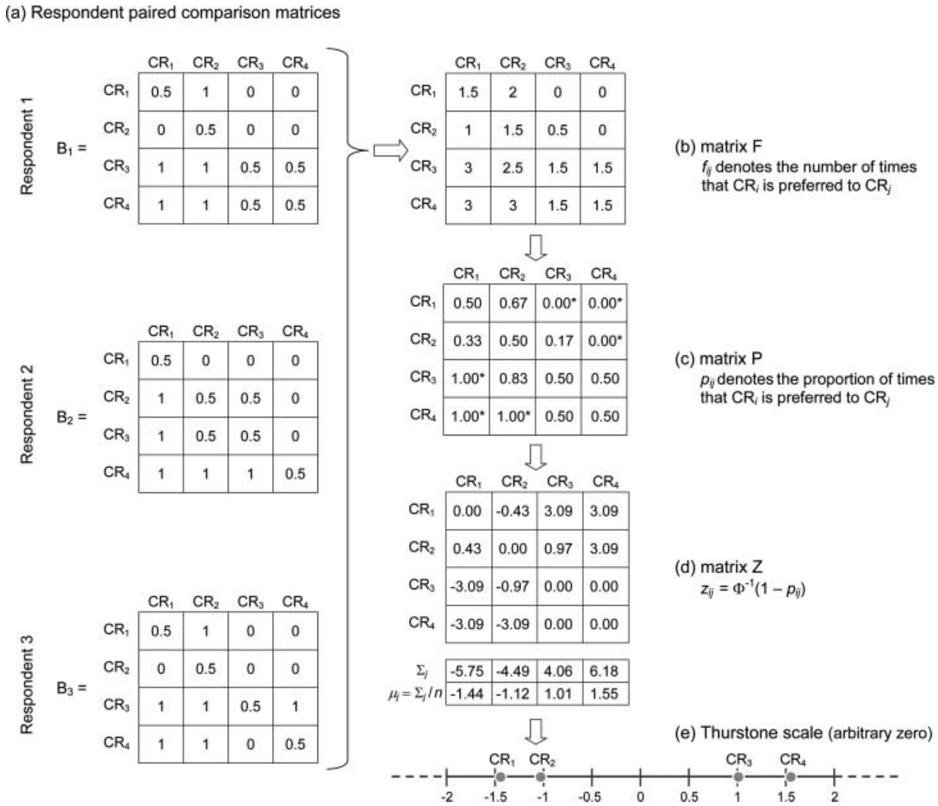

FIGURE 3 Main steps of Thurstone scaling.

the ith row is preferred to that in the jth column. If two CRs have identical level of importance (e.g., CR_3 and CR_4 in matrix B_1), their mutual paired comparisons are conventionally 0.5.

After the total pairs of CRs have been determined for a large number of respondents (N), respondents' matrices can be summed into a single frequency matrix (F), whose general element f_{ij} represents the number of times that CR_i was preferred to CR_j. Figure 3b reports the matrix F aggregating the judgment matrices B_1, B_2, and B_3. The general element f_{ij}, which appears in the ith row and jth column, denotes the observed number of times that CR_i was judged better or worse than CR_j.

Matrix P (Figure 3c) is constructed from matrix F ($p_{ij} = \frac{f_{ij}}{N}$). The element p_{ij} is the observed proportion of times that CR_i was chosen over CR_j. Symmetric cells now sum to unity.

Interpreting p_{ij} in probabilistic terms, it can be stated that $p_{ij} = \Pr(CR_{ij} \geq 0)$. Since CR_{ij} follows a normal distribution, a standardized variable can be defined:

$$z_{ij} = \frac{CR_{ij} - \mu_{ij}}{\sigma_{ij}}, \qquad [2]$$

where the element z_{ij} is the unit normal deviate. For $CR_{ij} = 0$, the unit normal deviate is determined by the theoretical proportion $(1 - p_{ij})$; that is, $z_{ij} = \Phi^{-1}(1 - p_{ij})$, where Φ is the cumulative distribution function of the standard normal distribution (see Figure 2b). The element z_{ij} will be positive for all values of $(1 - p_{ij})$ over 0.50 and negative for all values of $(1 - p_{ij})$ under 0.50.

In detail, for $CR_{ij} = 0$, Eq. [2] becomes

$$z_{ij} = \frac{0 - \mu_{ij}}{\sigma_{ij}} = -\frac{\mu_{ij}}{\sigma_{ij}} \quad \rightarrow \quad \mu_{ij} = -z_{ij} \cdot \sigma_{ij}, \text{ with } z_{ij} = \Phi^{-1}(1 - p_{ij}). \qquad [3]$$

Combining the second formula in Eq. [3] with the expression of σ_{ij} in Eq. [1], we obtain.

$$\mu_{ij} = \mu_i - \mu_j = -z_{ij} \cdot \sqrt{\sigma_i^2 + \sigma_j^2 - 2 \cdot \rho_{ij} \cdot \sigma_i \cdot \sigma_j}, \qquad [4]$$

Matrix P is used to construct matrix Z (see Figure 3d), the basic transformation matrix. Zeros are entered in the diagonal cells in matrix Z because we can ordinarily assume that here $\mu_i - \mu_i = 0$.

Apart from the aforementioned assumptions, the Thurstone model considered here is based on the following further hypotheses:

- CRs are judged differently by subjects; if all subjects would express the same preference for each outcome, the model would not be viable (proportions of 1.00 and 0.00 in the matrix P cannot be used because the z values corresponding to these proportions are $\pm\infty$). This is the case for the pair-wise comparisons CR_1 and CR_3, CR_1 and CR_4, and CR_2 and CR_4 in the matrix P in Figure 3c: in every comparison the second CR is unanimously preferred to the first. A simplified approach for tackling this problem is associating values of $p_{ij} \leq 0.001$ with $z_{ij} = \Phi^{-1}(1 - 0.001) = 3.09$ and values of $p_{ij} \geq 0.999$ with $z_{ij} = \Phi^{-1}(1 - 0.999) = -3.09$ (see the items marked with "*" in the matrix P in Figure 3c). More sophisticated solutions to deal with this issue have been proposed (Edwards 1957; Krus and Kennedy 1977).
- As a further practical assumption, it is assumed that the CRs' standard deviations are all equal ($\sigma_i = \sigma_j = \ldots = \sigma$). Therefore Eq. [4] turns into

$$\mu_{ij} = -z_{ij} \cdot \sqrt{2 \cdot \sigma^2 \cdot \left(1 - \rho_{ij}\right)}, \qquad [5]$$

- It is further assumed that the intercorrelations are all equal to one another ($\rho_{ij} = \rho, \ \forall i,j$), so that Eq. [5] turns into

$$\mu_{ij} = -z_{ij} \cdot \sqrt{2 \cdot \sigma^2 \cdot (1 - \rho)},. \qquad [6]$$

More precisely, Thurstone (1927) stated that in a paired judgment in which the evaluation of one of the stimuli has no influence on the evaluation of the other stimulus, the correlation ρ_{ij} is likely to be very low and possibly even zero. In addition, the assumption that the intercorrelations are all equal to zero is relatively safe when (1) the set of stimuli is rather variegated[1] and (2) the group of respondents is not too small. Since, in the case of the QFD's CR prioritization, both these conditions are generally satisfied, it does not seem unreasonable to assume that $\rho_{ij} = \rho = 0, \ \forall i,j$.

[1]The adjective "variegated" indicates that the stimuli of interest represent different basic concepts, not the same one, just stated in different ways.

Then, under the assumptions we have made, $\sqrt{2 \cdot \sigma^2 \cdot (1 - \rho)}$ (or $\sqrt{2 \cdot \sigma^2}$ in the case ρ is assumed to be zero) will be a constant and is the common scale factor of the various arithmetic mean pairs of CRs. Without any loss of generality, this common scale factor is set to 1, so that

$$\mu_{ij} = \mu_i - \mu_j = -z_{ij}. \qquad [7]$$

Equation [7], with the assumptions involved in its derivation, is commonly referred to as Case V of the LCJ (Thurstone 1927).

Now we can show that Thurstone scale values for each CR can be obtained from the elements of the matrix Z. Actually, if we sum the entries in the jth column of the matrix Z, we obtain

$$\sum_{i=1}^{n} z_{ij} = \sum_{i=1}^{n} \left(\mu_j - \mu_i\right) = n \cdot \mu_j - \sum_{i=1}^{n} \mu_i, \qquad [8]$$

where $\sum_{i=1}^{n} z_{ij}$ means that the jth column is held constant and the summation is over the n rows of the table. The first term on the right is the sum of the scale value of the jth CR and the second term is the sum of the scale values of all n CRs on the psychological continuum. Dividing both sides of Eq. [8] by n, we have

$$\bar{z}_{\cdot j} = \frac{\sum_{i=1}^{n} z_{ij}}{n} = \mu_j - \frac{\sum_{i=1}^{n} \mu_j}{n} = \mu_j - \mu, \qquad [9]$$

where $\bar{z}_{\cdot j}$ is the arithmetic mean of the entries in the jth column of the matrix Z; μ is the arithmetic mean of the (n) μ_i values; and μ_j is the mean value of the jth CR.

Thus, we see that the mean of the z values in the jth column of the matrix Z expresses the mean value of the jth CR in terms of its deviation from the mean of all of the μ_i values (i.e., μ). This procedure can be applied to every column of matrix Z, in order to obtain the scale values of every CR. These values are shown in the second row at the bottom of matrix Z (Figure 3d) and graphically represented in Figure 3e.

As a check upon calculations, we observe that the sum of the scale values in deviation form is equal to zero $\left(\sum_{j=1}^{n} \bar{z}_{\cdot j} = \sum_{j=1}^{n} \mu_j - \sum_{j=1}^{n} \mu = n\mu - n\mu = 0\right)$. CRs with negative scale values are thus judged to be less favorable than the average of the scale values of all CRs and those with positive scale values are judged to be more favorable than the average. Because the scale origin—taken as the mean of the scale values of the CRs on the psychological continuum—is arbitrary, we can apply a permissible scale transformation (i.e., monotonically increasing linear function; Stevens 1946) to obtain numerical values that are easier to handle. This will not change the relative position of the scale values on the psychological continuum.

Practical Response Mode

As shown in the previous subsection, in the standard method of Thurstone scaling, the paired comparison approach is used to collect response data. A drawback of this approach is that it can be tedious and complex to manage for *n* greater than 4 or 5, because it requires so much repetitious information from respondents. An alternative response mode, which also yields data suitable for Thurstone scaling, is based on two steps:

1. Turning each respondent's judgments, typically expressed on a five-level rating scale (see Figure 4a), into rank order data (see Figure 4b).
2. For each respondent, rank order data can be transformed into paired comparison data and reported into a matrix (see Figure 4c). The element of the single respondent's matrix is 1 when the CR in the *i*th row is preferred to that in the *j*th column. If two CRs have identical level of importance, their mutual paired comparisons are conventionally 0.5.

The response mode based on a five-level rating scale—as well as being less tedious and time consuming than the paired comparison approach—forces the respondent to be transitive (e.g., if $CR_1 > CR_2$ and $CR_2 > CR_3$, then $CR_1 > CR_3$). In addition, it is

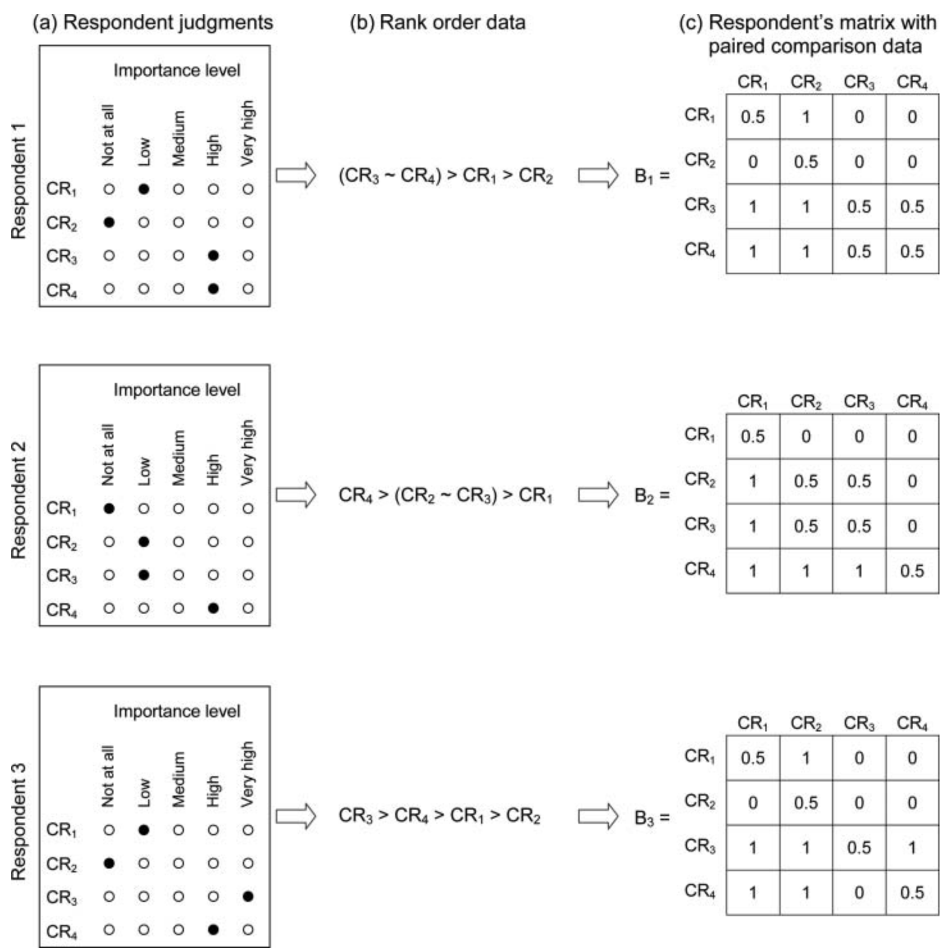

FIGURE 4 **Process for deriving paired comparison data based on respondents' judgments, defined on a five-level rating scale. The binary matrices (B_1, B_2, and B_3) in (c) are derived from the results of the questionnaires in (a). The same three fictitious respondents introduced in Figure 3 are considered. In (b), symbols "$\sim$" and "$>$", respectively, mean "indifferent to" and "preferred to."**

generally familiar to respondents and therefore less subject to misinterpretation.

APPLICATION EXAMPLE

To exemplify the performance of the proposed approach, this section illustrates an example about the CR prioritization for a civilian aircraft seat, from the perspective of passengers.

Through market survey, a sample of thirty respondents—that is, regular air passengers—are selected to identify the CRs by individual interview, focus groups and existing information. Finally, twelve major CRs (reported in Table 1) are identified to represent the major concerns of customers.

Then, a questionnaire for assessing the level of importance of each of the twelve CRs is submitted to each of the respondents. Results, defined on a five-level rating scale, are reported in Table A1 (see Appendix).

For each respondent, judgments are then transformed into rank-order data and, in turn, into paired comparison data, according to the procedure described in the previous subsection. For example, as regards respondent 1, rank-order data are ($CR_5 \sim CR_7$) > ($CR_1 \sim CR_3 \sim CR_6$) > ($CR_2 \sim CR_8 \sim CR_9$) > CR_{10} > ($CR_4 \sim CR_{11} \sim CR_{12}$), which are transformed into the matrix in Figure A1 (see Appendix).

We remark that, consistently with the convention introduced in the previous subsection, the mutual paired comparisons of two CRs with identical importance are both 0.5 (e.g., see CR_1 and CR_8 or CR_1 and CR_{12} in the matrix in Figure A1).

TABLE 1 **List of the Major CRs Related to an Aircraft Seat, from the Perspective of Passengers**

Abbreviation	Description
CR_1	Comfortable (does not give you backache)
CR_2	Enough leg room
CR_3	Comfortable when you recline
CR_4	Does not hit person behind when you recline
CR_5	Comfortable seat belt
CR_6	Seat belt feels safe
CR_7	Arm rests not too narrow
CR_8	Arm rest folds right away
CR_9	Does not make you sweat
CR_{10}	Does not soak up a spilled drink
CR_{11}	Hole in tray for coffee cup
CR_{12}	Magazines can be easily removed from rack

Next, the paired comparison data matrices relating to the thirty respondents are summed into a single frequency matrix (F), in Figure A2 (see Appendix).

The matrix F is transformed into the matrix P (in Figure A3; see Appendix) and subsequently into the matrix Z (in Figure A4; see appendix).

According to the convention illustrated in the previous section, for $p_{ij} \leq 0.001$ and $p_{ij} \geq 0.999$, z_{ij} values have been set to 3.090 and −3.090, respectively (see the p_{ij} values marked with "*", in the matrix P, Figure A3).

Thurstone scale values for each CR are finally calculated through the mean value of the column elements of the matrix Z (see the second row at the bottom of matrix Z, Figure A4). Because the unit and the origin of the resulting interval scale are both arbitrary, we can transform the scale values so that they are included in the interval [1; 5], according to the transformation

$$\frac{\mu_j' - 1}{5 - 1} = \frac{\mu_j - \min(\mu_j)}{\max(\mu_j) - \min(\mu_j)}, \qquad [10]$$

where μ_j is the scale value related to the jth CR, resulting from Thurstone scaling and μ_j' is the transformed scale value related to the jth CR in the interval scale [1, 5].

Figure 5 provides a graphical representation of the Thurstone scale values, before and after the transformation in Eq. [10]. This transformation is nothing else than a monotonically increasing linear function of the type

$$\mu_j' = a + b \cdot \mu_j, \qquad [11]$$

where

$$a = \frac{\max(\mu_j) - 5 \cdot \min(\mu_j)}{\max(\mu_j) - \min(\mu_j)} \text{ and}$$
$$b = \frac{4}{\max(\mu_j) - \min(\mu_j)} > 0.$$

This transformation eases phases 4 and 8 of the product planning HoQ construction process (see Figure 1), because they are traditionally based on CR importance levels defined on a one to five scale.

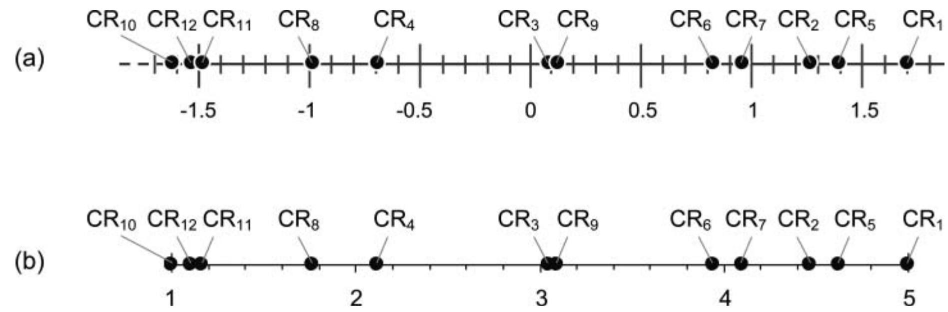

FIGURE 5 Resulting Thurstone scale values (a) before and (b) after the scale transformation in Eq. [10].

CONCLUDING REMARKS

The following three subsections respectively discuss (1) the benefits of the proposed procedure, (2) its limitations, and (3) some ideas for future research.

Benefits

- The proposed procedure allows aggregation of the typical CR judgments—generally expressed on ordinal response scales—into a continuous interval scale, avoiding the typical abuses (e.g., arbitrary promotion of the scale properties) of the classical approaches (Franceschini, Galetto, and Maisano 2007).
- Unlike other methods, such as the AHP, ANP, or Kano model, the proposed procedure does not require complicated elaborations by respondents. Particularly in populations in which educational attainment and numeracy are limited, a simple measurement strategy may have considerable practical advantages over more complex techniques, such as ease of comprehension and greater reliability due to reduced measurement error. However, the fact remains that the Thurstone model can be extended to more complex response modes, such as questionnaires in which CRs are ordered or compared in pairs by each respondent.
- The Thurstone model is relatively robust to incomplete data, like the omission of a portion of judgments by respondents. When the incidence of incomplete data is high, the model presented can be replaced by more refined ones, and it is also possible to check the internal consistency of the results obtained (Edwards 1957; Thurstone 1927). However, if CRs were identified correctly, the number of omitted judgments should not be too large. The opposite could mean that the CRs in use do not reflect the real needs of the customer.

Limitations

- Like any model, that of Thurstone is based on several assumptions, such as (1) the phenomena to be scaled must lie on a latent unidimensional scale, (2) the model is based on the normal distribution of *stimuli*, and (3) dispersion and correlation of the stimuli are assumed to be equal. Some of these assumptions can be relaxed when using more sophisticated but also complex variants of the proposed model (Maydeu-Olivares and Böckenholt 2008).
- The five-level rating scale for CR judgments is simple and intuitive for the respondent but has a relatively limited resolution. In some cases, this can make the analysis uncertain, because it may generate a significant number of "ties" (i.e., CRs with identical levels of importance) when judgments are transformed into paired comparison data. The problem can be solved by using alternative response scales with a larger number of levels or questionnaires in which the CRs are ranked or compared in pairs by each respondent.
- As for most of the statistical models, the larger the sample of respondents, the more reasonable and robust the results will be. Thurstone (1927) recommended that there be at least a few tens of respondents. This seems to be in line with the typical amount of customers involved in the initial phases of QFD process.

Ideas for Future Research

Further research should investigate the relationship between results acquired from different techniques for CR prioritization. Moreover, the use of the Thurstone LCJ could be extended to other prioritization processes within QFD, such as phases 3 and 9 in Figure 1.

ABOUT THE AUTHORS

Fiorenzo Franceschini is Professor of Quality Engineering at Politecnico di Torino (Italy), Department of Management and Production Engineering. He is author or coauthor of seven books and many published papers in prestigious scientific journals and international conference proceedings. His current research interests are in the areas of quality engineering, industrial metrology, and scientometrics. He serves as a member of the Editorial Boards of *Journal of Engineering Manufacture* (Part B of the *Proceedings of the Institution of Mechanical Engineers*), *International Journal of Services and Operations Management*, and *International Journal of Quality & Reliability Management*. He is a member of the ASQ. Franceschini may be contacted at fiorenzo.franceschini@polito.it

Domenico Maisano (Ph.D.) is currently Associate Professor of Quality Engineering and Quality Management Systems at Politecnico di Torino (Italy). His research interests are quality engineering/management, industrial metrology, performance indicators, and scientometrics. Maisano may be contacted at domenico.maisano@polito.it

REFERENCES

Buyukozkan, G., T. Ertay, C. Kahraman, and D. Ruan. 2004. Determining the importance weights for the design requirements in the house of quality using the fuzzy analytic network approach. *International Journal of Intelligent Systems* 19(5): 443–61.

Burke, E., J. M. Kloeber, Jr., and R. F. Deckro. 2002. Using and abusing QFD scores. *Quality Engineering* 15(1): 9–21.

Chan, L. K., and M. L. Wua. 2002. Quality function deployment: A comprehensive review of its concepts and methods. *Quality Engineering* 15(1): 23–35.

Chan, L. K., H. P. Kao, and M. L. Wu. 1999. Rating the importance of customer needs in quality function deployment by fuzzy and entropy methods. *International Journal of Production Research* 37(11): 2499–518.

Chaudha, A., R. Jain, A. R. Singh, and P. K. Mishra. 2011. Integration of Kano's model into quality function deployment (QFD). *International Journal of Advanced Manufacturing Technology* 53(5–8): 689–98.

Chuang, P. T. 2001. Combining the analytic hierarchy process and quality function deployment for a location decision from a requirement perspective. *International Journal of Advanced Manufacturing Technology* 18(11): 842–49.

Edwards, A. L. 1957. *Techniques of attitude scale construction*. New York: Irvington Publishers.

Figueira, J., S. Greco, and M. Ehrgott. 2005. *Multiple criteria decision analysis: State of the art surveys*. New York: Springer.

Franceschini, F. 2002. *Advanced quality function deployment*. Boca Raton, FL: St. Lucie Press/CRC Press LLC

Franceschini, F., and S. Rossetto. 1995. QFD: The problem of comparing technical/engineering design requirements. *Research in Engineering Design* 7(4): 270–78.

Franceschini, F., and S. Rossetto. 2002. QFD: An interactive algorithm for the prioritization of product's technical design characteristics. *Integrated Manufacturing Systems* 13(1): 69–75.

Franceschini, F., M. Galetto, and D. Maisano. 2007. *Management by measurement: Designing key indicators and performance measurement systems*. Berlin: Springer.

Gonzalez, M. E., G. Quesada, and A. T. Bahill. 2003. Improving product design using quality function deployment: The school furniture case in developing countries. *Quality Engineering* 16(1): 47–58.

Griffin, A., and J. R. Hauser. 1993. The voice of customer. *Marketing Science* 12(1): 1–27.

Hauser, J. R., and D. Clausing. 1988. The house of quality. *Harvard Business Review* 66(3): 63–73.

Karsak, E. E., S. Sozer, and S. E. Alptekin. 2002. Product planning in quality function deployment using a combined analytic network process and goal programming approach. *Computers & Industrial Engineering* 44: 171–90.

Krus, D. J., and P. H. Kennedy. 1977. Normal scaling of dominance matrices: The domain-referenced model. *Educational and Psychological Measurement* 37: 189–93.

Kwong, C. K., and H. Bai. 2002. A fuzzy AHP approach to the determination of importance weights of customer requirements in quality function deployment. *Journal of Intelligent Manufacturing* 13(5): 367–77.

Jansen, P. G. W. 1984. Relationships between the Thurstone, Coombs, and Rasch approaches to item scaling. *Applied Psychological Measurement* 8: 373–83.

Lee, Y. T., W. W. Wu, and G. H. Tzeng. 2008. An effective decision-making method using a combined QFD and ANP approach. *WSEAS Transactions on Business and Economics* 12(5): 541–51.

Li, Y., J. Tang, X. Luo, and J. Xu. 2009. An integrated method of rough set, Kano's model and AHP for rating customer requirements' final importance. *Expert Systems with Applications* 36(3): 7045–53.

Luce, R. D., and J. W. Tukey. 1964. Simultaneous conjoint measurement: A new type of fundamental measurement. *Journal of Mathematical Psychology* 1(1): 1–27.

Maydeu-Olivares, A., and U. Böckenholt. 2008. Modeling subject health outcomes. Top 10 reasons to use Thurstone's method. *Medical Care* 46(4): 346–48.

Matzler, K., and H. H. Hinterhuber. 1998. How to make product development projects more successful by integrating Kano's model of customer satisfaction into quality function deployment. *Technovation* 18(1): 25–38.

McIver, J. P., and E. G. Carmines. 1981. *Unidimensional scaling*. Beverly Hills, CA: Sage Publications; 1981.

Nahm, Y. E., H. Ishikawa, and M. Inoue. 2013. New rating methods to prioritize customer requirements in QFD with incomplete customer preferences. *International Journal of Advanced Manufacturing Technology* 65(9–12): 1587–604.

Rasch, G. 1966. An item analysis which takes individual differences into account. *British Journal of Mathematical and Statistical Psychology* 19(1): 49–57.

Sireli, Y., P. Kauffmann, and E. Ozan. 2007. Integration of Kano's model into QFD for multiple product design. *IEEE Transactions on Engineering Management* 54(2): 380–90.

Sharma, J. R., A. M. Rawani, and M. Barahate. 2008. Quality function deployment: A comprehensive literature review. *International Journal of Data Analysis Techniques and Strategies* 1(1): 78–103.

Stevens, S. S. 1946. On the theory of scales of measurement. *Science* 103 (2684): 677–80.

Tan, K. C., and X. X. Shen. 2000. Integrating Kano's model in the planning matrix of quality function deployment. *Total Quality Management* 11(8): 1141–51.

Thurstone, L. L. 1927. A law of comparative judgments. *Psychological Review* 34: 273–86.

Tran, T. L., and J. S. Sherif. 1995. Quality function deployment (QFD): An effective technique for requirements acquisition and reuse. Paper presented at the 2nd IEEE Software Engineering Standards Symposium, Montreal, Canada, August 21–25, 1995.

Urban, G. L., and J. R. Hauser. 1993. *Design and marketing of new products*. Vol. 2. Englewood Cliffs, NJ: Prentice Hall.

APPENDIX

TABLE A1 **Levels of Importance Assigned by 30 Respondents to the CRs, through a Five-Level Rating Scale (1 = *not at all important*, 5 = *very high importance*)**

Respondent no.	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	CR_8	CR_9	CR_{10}	CR_{11}	CR_{12}
1	4	3	4	1	5	4	5	3	3	2	1	1
2	4	3	3	2	4	3	5	1	4	1	1	2
3	5	5	4	3	5	5	4	3	4	1	1	1
4	5	5	4	2	5	5	4	1	3	1	1	2
5	5	4	2	1	4	4	5	2	3	2	2	2
6	5	5	4	3	5	3	3	2	3	1	2	1
7	5	3	3	1	5	4	5	3	4	2	1	2
8	4	3	1	3	5	3	2	1	3	1	1	1
9	5	5	4	4	4	5	2	3	3	1	1	1
10	3	5	2	1	5	2	3	1	2	1	1	2
11	5	3	5	3	3	4	3	1	3	1	2	2
12	5	4	3	1	5	3	3	2	3	1	1	2
13	5	4	3	2	5	3	5	1	1	1	2	1
14	4	5	1	1	3	3	3	2	3	1	1	1
15	4	5	4	3	4	4	5	3	4	1	1	2
16	5	4	3	3	5	5	5	3	3	2	3	1
17	4	4	4	2	5	5	5	3	2	2	2	1
18	5	5	4	2	3	3	2	2	4	1	1	1
19	5	4	4	2	3	4	3	2	3	1	1	2
20	4	5	3	3	5	3	5	2	4	2	1	1
21	5	4	4	2	3	3	3	1	1	1	1	1
22	5	5	4	4	5	4	3	2	3	1	2	1
23	5	4	3	2	4	4	5	2	4	2	3	1
24	5	5	3	3	3	5	3	2	2	2	2	1
25	5	4	2	1	4	3	2	2	4	1	1	1
26	4	4	1	2	5	3	4	2	2	1	1	2
27	4	5	2	2	4	3	3	3	3	1	1	1
28	4	4	2	3	5	3	4	2	4	2	3	1
29	5	5	2	1	4	5	3	1	3	2	1	1
30	5	4	4	1	5	3	5	1	3	2	1	1

$B_1 =$

	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	CR_8	CR_9	CR_{10}	CR_{11}	CR_{12}
CR_1	0.5	1	0.5	1	0	0.5	0	1	1	1	1	1
CR_2	0	0.5	0	1	0	0	0	0.5	0.5	1	1	1
CR_3	0.5	1	0.5	1	0	0.5	0	1	1	1	1	1
CR_4	0	0	0	0.5	0	0	0	0	0	0	0.5	0.5
CR_5	1	1	1	1	0.5	1	0.5	1	1	1	1	1
CR_6	0.5	1	0.5	1	0	0.5	0	1	1	1	1	1
CR_7	1	1	1	1	0.5	1	0.5	1	1	1	1	1
CR_8	0	0.5	0	1	0	0	0	0.5	0.5	1	1	1
CR_9	0	0.5	0	1	0	0	0	0.5	0.5	1	1	1
CR_{10}	0	0	0	1	0	0	0	0	0	0.5	1	1
CR_{11}	0	0	0	0.5	0	0	0	0	0	0	0.5	0.5
CR_{12}	0	0	0	0.5	0	0	0	0	0	0	0.5	0.5

FIGURE A1 **Paired comparison data relating to the judgments by respondent 1 in Table A1.**

$F =$

	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	CR_8	CR_9	CR_{10}	CR_{11}	CR_{12}
CR_1	15.0	19.5	28.0	30.0	17.0	25.0	20.5	30.0	28.0	30.0	30.0	30.0
CR_2	10.5	15.0	25.0	29.0	14.0	20.0	18.5	29.0	25.0	30.0	30.0	30.0
CR_3	2.0	5.0	15.0	23.5	5.5	9.5	9.5	24.0	15.0	27.0	26.0	27.0
CR_4	0.0	1.0	6.5	15.0	1.5	2.5	5.0	17.0	8.0	22.0	22.0	21.5
CR_5	13.0	16.0	24.5	28.5	15.0	20.0	20.0	30.0	25.5	30.0	30.0	30.0
CR_6	5.0	10.0	20.5	27.5	10.0	15.0	14.5	29.5	20.0	30.0	29.5	29.5
CR_7	9.5	11.5	20.5	25.0	10.0	15.5	15.0	27.5	21.0	30.0	30.0	30.0
CR_8	0.0	1.0	6.0	13.0	0.0	0.5	2.5	15.0	5.0	22.0	20.0	21.5
CR_9	2.0	5.0	15.0	22.0	4.5	10.0	9.0	25.0	15.0	28.0	27.0	28.0
CR_{10}	0.0	0.0	3.0	8.0	0.0	0.0	0.0	8.0	2.0	15.0	14.0	15.5
CR_{11}	0.0	0.0	4.0	8.0	0.0	0.5	0.0	10.0	3.0	16.0	15.0	15.0
CR_{12}	0.0	0.0	3.0	8.5	0.0	0.5	0.0	8.5	2.0	14.5	15.0	15.0

FIGURE A2 **Matrix F, obtained from the paired comparison data originated from the respondents' judgments in Table A1.**

P =

	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	CR_8	CR_9	CR_{10}	CR_{11}	CR_{12}
CR_1	0.500	0.650	0.933	1.000*	0.567	0.833	0.683	1.000*	0.933	1.000*	1.000*	1.000*
CR_2	0.350	0.500	0.833	0.967	0.467	0.667	0.617	0.967	0.833	1.000*	1.000*	1.000*
CR_3	0.067	0.167	0.500	0.783	0.183	0.317	0.317	0.800	0.500	0.900	0.867	0.900
CR_4	0.000*	0.033	0.217	0.500	0.050	0.083	0.167	0.567	0.267	0.733	0.733	0.717
CR_5	0.433	0.533	0.817	0.950	0.500	0.667	0.667	1.000*	0.850	1.000*	1.000*	1.000*
CR_6	0.167	0.333	0.683	0.917	0.333	0.500	0.483	0.983	0.667	1.000*	0.983	0.983
CR_7	0.317	0.383	0.683	0.833	0.333	0.517	0.500	0.917	0.700	1.000*	1.000*	1.000*
CR_8	0.000*	0.033	0.200	0.433	0.000*	0.017	0.083	0.500	0.167	0.733	0.667	0.717
CR_9	0.067	0.167	0.500	0.733	0.150	0.333	0.300	0.833	0.500	0.933	0.900	0.933
CR_{10}	0.000*	0.000*	0.100	0.267	0.000*	0.000*	0.000*	0.267	0.067	0.500	0.467	0.517
CR_{11}	0.000*	0.000*	0.133	0.267	0.000*	0.017	0.000*	0.333	0.100	0.533	0.500	0.500
CR_{12}	0.000*	0.000*	0.100	0.283	0.000*	0.017	0.000*	0.283	0.067	0.483	0.500	0.500

FIGURE A3 **Matrix P, obtained from the matrix F in Figure A2.**

Z =

	CR_1	CR_2	CR_3	CR_4	CR_5	CR_6	CR_7	CR_8	CR_9	CR_{10}	CR_{11}	CR_{12}
CR_1	0.000	-0.385	-1.501	-3.090	-0.168	-0.967	-0.477	-3.090	-1.501	-3.090	-3.090	-3.090
CR_2	0.385	0.000	-0.967	-1.834	0.084	-0.431	-0.297	-1.834	-0.967	-3.090	-3.090	-3.090
CR_3	1.501	0.967	0.000	-0.784	0.903	0.477	0.477	-0.842	0.000	-1.282	-1.111	-1.282
CR_4	3.090	1.834	0.784	0.000	1.645	1.383	0.967	-0.168	0.623	-0.623	-0.623	-0.573
CR_5	0.168	-0.084	-0.903	-1.645	0.000	-0.431	-0.431	-3.090	-1.036	-3.090	-3.090	-3.090
CR_6	0.967	0.431	-0.477	-1.383	0.431	0.000	0.042	-2.128	-0.431	-3.090	-2.128	-2.128
CR_7	0.477	0.297	-0.477	-0.967	0.431	-0.042	0.000	-1.383	-0.524	-3.090	-3.090	-3.090
CR_8	3.090	1.834	0.842	0.168	3.090	2.128	1.383	0.000	0.967	-0.623	-0.431	-0.573
CR_9	1.501	0.967	0.000	-0.623	1.036	0.431	0.524	-0.967	0.000	-1.501	-1.282	-1.501
CR_{10}	3.090	3.090	1.282	0.623	3.090	3.090	3.090	0.623	1.501	0.000	0.084	-0.042
CR_{11}	3.090	3.090	1.111	0.623	3.090	2.128	3.090	0.431	1.282	-0.084	0.000	0.000
CR_{12}	3.090	3.090	1.282	0.573	3.090	2.128	3.090	0.573	1.501	0.042	0.000	0.000
Σ_j	20.451	15.132	0.974	-8.339	16.722	9.894	11.460	-11.876	1.414	-19.522	-17.851	-18.459
$\mu_j = \Sigma_j / n$	1.704	1.261	0.081	-0.695	1.394	0.825	0.955	-0.990	0.118	-1.627	-1.488	-1.538
μ'	5.000	4.468	3.051	2.119	4.627	3.944	4.100	1.765	3.095	1.000	1.167	1.106

FIGURE A4 **Matrix Z containing the unit normal deviates (z_{ij}) corresponding to the complementary probabilities ($1 - p_{ij}$) to those in matrix P (p_{ij}). Values of $p_{ij} \leq 0.001$ and ≥ 0.999 (marked with "*" in Figure A3) have been conventionally associated with $z_{ij} = 3.090$ and -3.090, respectively.**