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New Approach for Quality Function Deployment Based on Linguistic Distribution Assessments and CRITIC Method

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Abstract: Quality function deployment (QFD) is a customer-oriented quality management tool used to maximize customer satisfaction by considering the correlations between customer requirements and engineering characteristics. However, the conventional QFD method exhibits some shortcomings when used in real situations, especially in terms of correlation evaluation and engineering characteristic ranking. Therefore, the objective of this study is to propose a new QFD approach based on linguistic distribution assessments and the CRiteria Importance Through Inter-Criteria Correlation (CRITIC) method to improve the effectiveness of the traditional QFD. Specifically, linguistic distribution assessments are utilized to describe the relationships between customer requirements and engineering characteristics. The CRITIC method is extended and used to determine the ranking orders of the engineering characteristics identified in QFD. To demonstrate the feasibility and practicality of the proposed QFD, a case example regarding the performance management system's development is presented. It is shown that the QFD approach proposed in this paper can not only represent experts' uncertain linguistic relationship evaluations flexibly but also determine more reliable importance rankings of engineering characteristics in production planning.

Keywords: quality function deployment (QFD); linguistic distribution assessment; CRITIC method; product development

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1. Introduction

Quality function deployment (QFD) is a well-known product planning approach utilized for examining the interrelationships between customer needs and design requirements [1,2]. The core of this approach is the house of quality (HOQ), which comprises both customer needs and design requirements. The objective of QFD is to support research and design teams for transforming customer requirements (CRs) into related engineering characteristics (ECs) during different stages of new product development [3,4]. By employing QFD, the translation process is enhanced, leading to improved product development efficiency and accuracy. QFD holds significant potential for advancing the field of research and design in the context of customer-centric product development [5,6]. Implementing QFD in an organization can shorten cycle times, reduce costs, and improve quality [7–9]. Inspired by these attractive properties, QFD has recently been used in various industries to improve the competitiveness of organizations and increase customer satisfaction [10–12].

Although QFD is an effective quality management tool, the traditional method has some shortcomings when used in the real world [13–15]. The main drawback is the use of exact numbers such as 1, 3, 5, to describe the relationships between CRs and ECs. However, it is often difficult for QFD team members to provide precise numerical values when evaluating the relationships between CRs and ECs due to the limitations in knowledge, the problem complexity, and time pressure. They prefer to use linguistic terms rather than numerical values to express the CR–EC relationship evaluation information [15–17]. To represent the linguistic decision information accurately, Zhang et al. [18] proposed the linguistic distribution assessment (LDA) method, in which symbolic proportions are assigned to the linguistic terms in a linguistic term set. The LDA method is a generalization of the two-tuple linguistic method and probabilistic linguistic term sets, and defined as a set of binary relationships between linguistic variables and their symbolic probabilities [19,20]. Compared with other linguistic computing methods, the LDA method can efficiently represent uncertain information and reflect the real experience of decision makers [21,22]. Over the past couple of years, the LDA method has been applied to depict the subjective vagueness and differing evaluations of decision makers in various decision making problems [21,23,24].

On the other hand, determining the priority of ECs in QFD can be considered a multi-criteria decision making (MCDM) problem [13,14,25]. Thus, a lot of MCDM methods have been used to solve QFD problems in previous studies [15,26]. The criteria importance through inter-criteria correlation (CRITIC) method proposed by Diakoulaki et al. [27] is an improved method of the technique for order of preference by similarity to ideal solution (TOPSIS). It is an objective mathematical procedure used to derive the level of significance of the criteria involved in a decision making process. The main advantage of CRITIC is that it can standardize the decision matrix by dealing with the ideal values of cost and benefit criteria at the same time [28,29]. It can measure the similarity of standards by calculating the correlation coefficient between standards according to the values in the decision matrix. By calculating the standard deviation of normalized values, the CRITIC captures the interrelationship among criteria and variability in the preference distribution [30,31]. Recently, the CRITIC method has been used for the analysis and evaluation of criteria weights in MCDM [29,32,33]. In addition, different extensions of the CRITIC method [34–36] have been proposed to deal with real-world decision making problems more efficiently.

Based on the aforementioned discussions, the research questions to be addressed in this study are as follows: How do we handle experts' distributed linguistic relational assessment information between CRs and ECs, and how do we obtain a reliable importance ranking of the identified ECs in QFD? Therefore, the objective of this paper is to propose a new QFD approach based on LDAs and the CRITIC method to improve the effectiveness of the traditional QFD. First, the LDA method is adopted to quantify the linguistic opinions of experts on the relationships between CRs and ECs. Second, the CRITIC method is modified and utilized to derive the importance priorities of ECs by analyzing their correlations. Finally, a real case study of performance management system design is provided to illustrate the feasibility and practicality of the proposed new QFD approach.

The rest of the paper is structured as follows: In Section 2, a brief review of current improved methods for QFD is presented. In Section 3, the basic concepts and operational rules related to LDAs are introduced and the QFD approach using linguistic distribution evaluations and the CRITIC method is developed. Section 4 illustrates the application of the proposed QFD methodology through a practical case study and a comparative analysis. Finally, Section 5 provides the conclusions of this study and points out future research directions.

2. Literature Review

QFD is a systematic framework employed in the design of products and services, aiming to bridge the gap between customer preferences and engineering considerations by effectively translating the voice of the customer into design characteristics [2]. The classical QFD method focuses on customer-driven product development, aiming at converting CRs into ECs to enhance the satisfaction level of customers [3,5]. However, the traditional QFD method shows some deficiencies when used in real situations [15,26]. Therefore, many improved QFD methods have been proposed in previous studies to surmount the limitations of the conventional method. In this section, we reviewed studies which improved the QFD model based on MCDM methods. For example, Fu et al. [37] proposed an interval-valued spherical fuzzy QFD method to identify human-centered ECs to guide the conceptual design process a of metaverse collaborative system. Liu et al. [38] constructed a QFD model based on the spherical fuzzy bipartite graph to consider the dependency relationships between CRs and DRs during assistive product design. Kumar Gangadhari et al. [12] utilized a spherical-fuzzy-based QFD method to assess manufacturing capabilities in alignment with consumer requirements. Du et al. [39] enhanced QFD through the integration of rough sets and ordinal priority approach and applied it to the electric vehicle manufacturing development. Seker and Aydin [6] improved QFD with Fermatean fuzzy sets and employed it for designing a sustainable mobility hub center. Ayyildiz et al. [40] applied the Pythagorean fuzzy analytic hierarchy process (AHP)-integrated QFD method to analyze the cultivation process of grown hazelnuts. In addition, the hesitant fuzzy–QFD (HF-QFD) [41], the linguistic Z-number QFD (LZ-QFD) [42], and the double hierarchy hesitant linguistic QFD [43] have been suggested for improving the prioritization of ECs in QFD.

Recently, it has been a trend to employ consensus-driven methods to handle the diversity and complex linguistic ratings in QFD. For instance, Xiao and Wang [44] introduced an optimization-based consensus-reaching process into QFD for handling incomplete and conflicting customer opinions, where customer opinions were modeled with incomplete linguistic distribution assessments. Wang et al. [13] presented a QFD model using the cooperative game consensus-reaching process and three-way decision theory in which the cooperative game-based consensus mechanism was used to help experts reach a consensus on the CR-EC correlation assessments. Gai et al. [14] developed a QFD model from the perspective of group decision making and social network analysis, and applied it to product design in the Chinese e-commerce scene. In [16], an integrated QFD approach based on the interval two-tuple Pythagorean fuzzy linguistic sets (I2PFLSs), the social network consensus-reaching (SNCR) model, and an extended combined compromise solution (CoCoSo) method was provided. In [25], a hybrid QFD approach based on multi-granular unbalanced linguistic information and a consensus-reaching process was proposed. Other consensus-based QFD methods proposed in the literature include those in [45,46]. A summary of the reviewed QFD methods is shown in Table 1.

Table 1. Summary of QFD studies related to the topic covered in this paper.

Authors	Years	Correlation Assessment Methods	EC Ranking Methods	Research Aims	Main Results
Fu et al. [37]	2024	Interval-valued spherical fuzzy sets	VIKOR method	To develop an interval-valued spherical fuzzy QFD method for metaverse collaborative system design	The proposed QFD approach for metaverse collaborative systems is able to handle uncertainty and vagueness in design processes
Liu et al. [38]	2024	Spherical fuzzy sets	Bipartite graph prioritization	To introduce a spherical fuzzy bipartite graph-based QFD method for assistive product design	The proposed QFD method can enhance product design efficiency in assistive technologies
Kumar Gangadhari et al. [12]	2024	Spherical fuzzy sets	Weighted average method	To redefine N95 respirator design using QFD-based optimization model	The presented optimized design method can improving functionality and compliance with new standards for N95 respirators
Du et al. [39]	2024	Rough sets	Ordinal priority mehtod	To enhancing QFD through the integration of rough sets and ordinal priority method	The proposed QFD can effectively prioritize engineering characteristics in the electric vehicle manufacturing
Seker and Aydin [6]	2023	Fermatean fuzzy sets	Weighted average method	To apply fermatean fuzzy QFD method to sustainable mobility hub center design	The proposed method is helpful for the related authorities while designing mobility hubs to meet passenger needs and requirements
Ayyildiz et al. [40]	2023	Interval-valued Pythagorean fuzzy sets	Weighted average method	To integrate interval-valued Pythagorean fuzzy AHP with QFD for hazelnut production optimization	The proposd method is practical for farmers and companies to improve the quality of hazelnut production
Wang et al. [41]	2021	Double hierarchy hesitant fuzzy linguistic term sets	Axiomatic design method	To develop a QFD methodology using double hierarchy hesitant fuzzy linguistic term sets and axiomatic design	The new method can capture the ambiguity and hesitancy in experts' evaluation information and obtain a accurate prioritization of ECs
Mao et al. [42]	2021	Linguistic Z-numbers	Evaluation based on distance from average solution (EDAS) method	To propose a linguistic Z-numbers-based QFD approach integrated with EDAS	The method can represent experts' evaluation information flexibly and produce a reasonable prioritization of ECs
Shi et al. [43]	2022	Double hierarchy hesitant linguistic term sets	Improved ORESTE method	To prioritize ECs in QFD using improved ORESTE with hesitant linguistic information	The proposed method is flexibility in handling experts' hesitant evaluations and effective in ranking ECs
Xiao and Wang [44]	2024	Incomplete linguistic distribution assessments	Multi-criteria optimization	To handle incomplete and conflicting opinions in QFD through consistency and consensus-reaching processes	Improved the robustness of QFD methodologies in scenarios with incomplete and conflicting stakeholder inputs
Wang et al. [13]	2024	Probabilistic linguistic term sets	Three-way decision method	To develop a new QFD approach combining cooperative game-based consensus and three-way decision making	The proposed method can help domain experts acquire more consensual correlation evaluations between CRs and ECs

Table 1. *Cont.*

Authors	Years	Correlation Assessment Methods	EC Ranking Methods	Research Aims	Main Results
Gai et al. [14]	2024	Hesitant fuzzy linguistic term sets	Prospect theory	To enhance QFD using social network and group decision-making techniques	The proposed method can generate effective and stable results for QFD implementation
Wang et al. [16]	2023	Interval 2-tuple Pythagorean fuzzy linguistic sets	Extended CoCoSo method	To propose a new QFD approach based on social network analysis and interval 2-tuple Pythagorean fuzzy linguistic information	The new QFD can express experts' uncertain linguistic assessments and deal with experts' consensus in correlation assessment process
Han et al. [25]	2023	Multi-granular unbalanced linguistic term sets	Extended CoCoSo method	To develop a QFD method based on multi-granular unbalanced linguistic information and consensus reaching process	The proposed approach can represent complex linguistic relationship assessments and determine accurate priority orders of ECs
Xiao et al. [45]	2022	Two-tuple linguistic method	Weighted average method	To propose a QFD using a consensus-based approach with minimum-maximum adjustments	The propsoed method can manage diversity and complex linguistic ratings in QFD
Xiao et al. [46]	2022	Two-tuple linguistic method; Comparative linguistic expressions	Extended TOPSIS method	To propose a consensus-based QFD to derive the consensual prioritization of ECs	The proposed method is able to deal with diverse and conflicting ratings in QFD prioritization tasks
The current study	2025	Linguistic distribution assessments	Extended CRITIC method	To develop a QFD based on linguistic distribution assessments and CRITIC method	The proposed approach can represent experts' uncertain linguistic relationship evaluations and determine reliable importance ranking of ECs

The review of the relevant literature shows that various fuzzy and linguistic methods have been used to facilitate relationship assessments between CRs and ECs in aforementioned studies. However, the current methods are incapable of describing complex linguistic expressions related to linguistic distributional expressions in a comprehensible manner. On the other hand, despite the widespread application of MCDM methods to determine the ranking orders of ECs, little research attention has been paid to QFD problems based on the CRITIC method, especially in the LDA environment. To fill these research gaps, this paper introduces a new QFD approach that integrates LDAs with an extended CRITIC method to improve the performance of conventional QFD. The proposed QFD can accurately capture the subjective evaluation information provided by experts, and provide a practical and reliable solution for identifying critical ECs, thereby facilitating quality improvement in product design and planning.

3. Method

This section introduces an improved QFD approach for determining the high importance of ECs in the product development process. The first subsection recalls some fundamental concepts of LDAs. The second subsection explains the two-stage QFD approach based on an integrated LDA-CRITIC method.

3.1. Preliminaries

LDAs were proposed by Zhang et al. [18] for computing with words, in which the linguistic terms are assigned with symbolic proportions in a linguistic term set.

Definition 1 ([18]). *Let $S = \{S_0, S_1, \ldots, S_g\}$ be a linguistic term set, where $g + 1$ is a granularity of S and s_t represents a possible linguistic value. Then, an LDA of S is defined as*

$$L = \{ \langle s_t, \beta_t \rangle | t = 0, 1, \ldots, g \}, \tag{1}$$

where $s_t \in S$, $\beta_t \geq 0$, $\sum_{t=0}^{g} \beta_t = 1$, and β_t is the symbolic proportion of s_t.

Definition 2 ([18]). *Let $L = \{ \langle s_t, \beta_t \rangle | t = 0, 1, \ldots, g \}$ be an LDA of S; the expectation of L is computed by*

$$E(L) = \sum_{t=0}^{g} \beta_t s_t. \tag{2}$$

Definition 3 ([18]). *Let L_1 and L_2 be any two linguistic distribution assessments of S:*

(1) If $E(L_1) > E(L_2)$, then L_1 is bigger than L_2;
(2) If $E(L_1) = E(L_2)$, then L_1 is equal to L_2.

Definition 4 ([18]). *Considering a set of LDAs $\{L_1, L_2, \ldots, L_n\}$ of S with an associated weighting vector $w = (w_1, w_2, \ldots, w_n)^{\mathrm{T}}$ satisfying $w_i \geq 0$ and $\sum_{i=1}^{n} w_i = 1$, the linguistic distributional weighted averaging (LDWA) operator is defined as*

$$\mathrm{LDWA}_w(L_1, L_2, \ldots, L_n) = \{ \langle s_t, \beta_t \rangle | t = 0, 1, \ldots, g \}, \tag{3}$$

where $\beta_t = \sum_{i=1}^{n} w_i \beta_t^i, t = 0, 1, \ldots, g$.

3.2. The Proposed QFD Approach

In this section, a new integrated QFD approach based on LDAs and the CRITIC method is introduced to acquire the importance priority of ECs. The proposed QFD is divided into two stages: (1) an assessment of the intricate relationships between CRs and ECs by using the LDA method; (2) the determination of the prioritization of ECs with an extended CRITIC method. Details of the procedure of the proposed QFD approach are depicted in Figure 1.

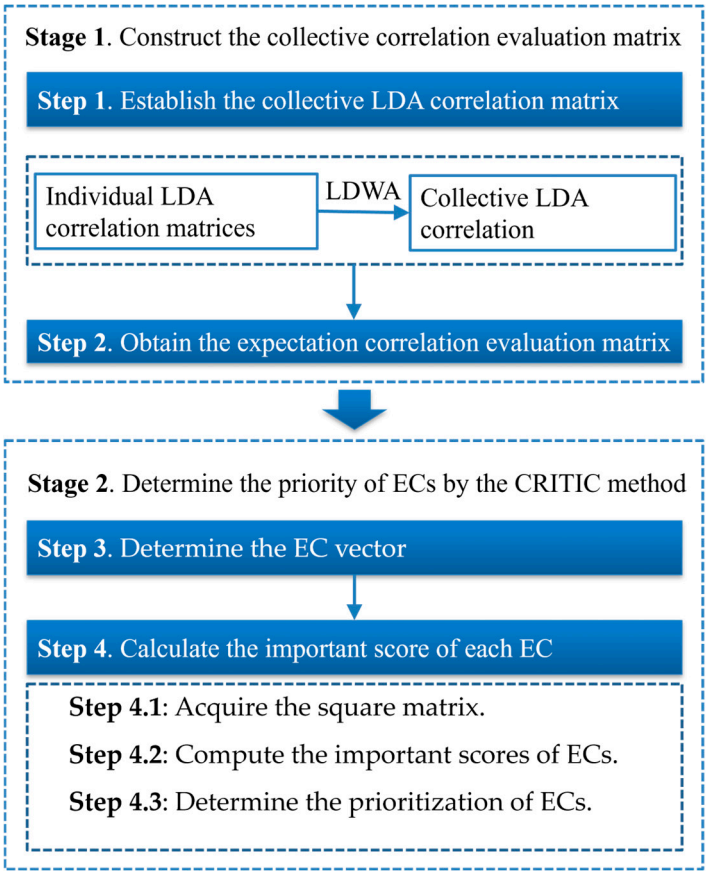


Figure 1. Framework of the proposed QFD model.

For a QFD analysis problem, suppose that there are m engineering characteristics $EC_i (i = 1, 2, \ldots, m)$ and n customer requirements $CR_j (j = 1, 2, \ldots, n)$. In addition, l experts $E_k (k = 1, 2, \ldots, l)$ are invited to provide their assessments for the relationships between CRs and ECs, and each expert is assigned a weight λ_k satisfying $\lambda_k > 0$ and $\sum_{k=1}^{l} \lambda_k = 1$ to describe their relative importance in QFD analysis. Let $L_k = \left(p_{ij}^k\right)_{m \times n}$ be the LDA correlation matrix provided by E_k, where $p_{ij}^k = \left\{ \left\langle s_{t(ijk)}, \beta_{t(ijk)} \right\rangle \middle| t = 0, 1, \ldots, g \right\}$ is the linguistic distribution evaluation of EC_i with respect to CR_j based on the linguistic term set $S = \{S_0, S_1, \ldots, S_g\}$. According to these assumptions, the proposed QFD approach is described as follows:

Stage 1. Construct the collective correlation evaluation matrix.

Step 1. Establish the collective LDA correlation matrix.

By using the LDWA operator, the individual LDA correlation matrices $L_k (k = 1, 2, \ldots, l)$ can be aggregated to obtain the collective LDA correlation matrix $L = \left(p_{ij}\right)_{m \times n}$, in which

$$p_{ij} = \mathrm{LDWA}_{\lambda}\left(p_{ij}^1, p_{ij}^2, \ldots, p_{ij}^l\right) = \left\{ \left\langle s_{t(ij)}, \beta_{t(ij)} \right\rangle | t = 0, 1, \ldots, g \right\}, \quad (4)$$

where $\beta_{t(ij)} = \sum_{k=1}^{l} \lambda_k \beta_{t(ij)}^k, t = 0, 1, \ldots, g$ and $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_l)^T$.

Step 2. Obtain the expectation correlation evaluation matrix.

The expectation correlation evaluation matrix $R = (r_{ij})_{m \times n}$ is calculated by the following equation:

$$r_{ij} = E(p_{ij}),\ i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n. \tag{5}$$

Stage 2. Determine the importance priority of ECs by the CRITIC method.

The CRITIC method is a highly effective approach for solving MCDM problems as it objectively determines the weights of criteria [31]. It is distinguished by its ability to assign weights that encapsulate both the contrast intensity inherent in each criterion and the degree of conflict among various criteria [33,35]. In this stage, the CRITIC method is employed to determine the importance priority of ECs within the LDA environment.

Step 3. Determine the EC vector.

Let $R_i = (r_{1i}, r_{2i}, \ldots, r_{ni})$ denote the vector of the ith EC; the transformations of performance values can be derived according to the following rules:

(1) If r_{ji} is a beneficial criterion, then

$$r_{ji} = \frac{r_{ji} - r_i^-}{r_i^* - r_i^-}, \tag{6}$$

(2) If r_{ji} is a non-beneficial criterion, then

$$r_{ji} = \frac{r_i^- - r_{ji}}{r_i^- - r_i^*}. \tag{7}$$

Note that r_i^* and r_i^- are the ideal and the anti-ideal values with respect to EC_i.

Step 4. Calculate the importance score of each EC.

Step 4.1. Acquire the square matrix.

The square matrix $\widetilde{R} = (\widetilde{r}_{ik})_{m \times m}$ is composed of elements which are the linear correlation coefficients between the vectors R_i and R_k.

Step 4.2. Compute the importance scores of ECs.

The importance score H_i of each EC can be determined by

$$H_i = \sigma_i \sum_{k=1}^{m} (1 - \widetilde{r}_{ik}),\ i = 1, 2, \ldots, m, \tag{8}$$

where σ_i is the standard deviation of each criterion vector r_i.

Step 4.3. Determine the prioritization of ECs.

The bigger the value of the importance score H_i, the more important the engineering characteristics EC_i. Therefore, the priority of the m ECs can be determined according to the descending order of their importance degrees H_i (i = 1,2,. . .,m).

4. Findings and Discussion

In this section, we present an empirical case study on the design of a performance management system [47] to illustrate the applicability and efficacy of our proposed QFD methodology.

4.1. Application

In the environment of uncertainty, complexity and ambiguity, employee performance management is important for organizations in order to adapt the accelerating shift in socio-eco-techno activities. In such conditions, performance management is considered a pivotal

tool in aiding strategic decisions pertaining to training, career advancement, compensation, employee transfers, promotions, retention strategies, and termination [47]. Performance management helps employees to align their goals with the strategic plan and objectives of a company. An effective performance management system is widely recognized as an instrument for performance management which can realize employers' performance expectations. Nevertheless, it is difficult to describe the performance expectations of management in a given language, and there are complex relationships between design features. Thus, the QFD method is introduced into the performance management system's design to determine which points are potentially needed to enhance corporate performance. In this case study, the proposed QFD approach is used for performance management system design to examine the relationship between employers' expectations and the conditions necessary to fulfill them.

Through a literature analysis and interviews of experts [47], 10 CRs $(CR_j, j = 1, 2, \ldots, 10)$ and 10 ECs $(EC_i, i = 1, 2, \ldots, 10)$ were determined for the priority of the design targets of the performance management system, which are presented in Table 2. Five experts from different domains $E_k (k = 1, 2, \ldots, 5)$ were invited to assess the correlations between CRs and ECs based on the following linguistic term set:

$$S = \{s_0 = \text{Very low}, s_1 = \text{Low}, s_2 = \text{Medium}, s_3 = \text{High}, s_4 = \text{Very high}\}$$

As a result, the linguistic correlation assessments obtained from the five experts could be represented through the utilization of LDAs, so LDA correlation matrixes $L_k = \left(p_{ij}^k\right)_{10\times10} (k = 1, 2, \ldots, 5)$ were obtained. For instance, the LDA correlation matrix L_1 given by the first expert is shown in Table 3.

Table 2. CRs and ECs identified in the case.

CRs	Customer Requirements	ECs	Engineering Characteristics	Units
CR_1	Budget adherence	EC_1	Realistic budget	Deviation from budget allocated
CR_2	Right compensation for responsibility level	EC_2	Appropriate compensation for the role and responsibility	Comparing with industry average
CR_3	Contribution in increase in overall profit	EC_3	Clear objectives derived from company's vision	Extent to which goals are assigned to the employees
CR_4	Successful internal customer relationships	EC_4	Clearly defined policies and organizational hierarchy	Number of deviations when the policy documents could not be linked to decisions made
CR_5	Successful external customer relationships	EC_5	Improved post-sale service/supplier relationships	Number of customer/supplier complaints
CR_6	Task completed on schedule	EC_6	Improved departmental communication and coordination system	Number of events of miscommunication/delays due to lack of coordination
CR_7	Task success rate	EC_7	Quality of production/service process	Number of deviations
CR_8	Resource efficiency	EC_8	Clarity in product/service specifications	Quantity of rejected products
CR_9	Trainings undertaken	EC_9	Access to training and growth opportunities inside or outside the company	Number of relevant training opportunities provided by company
CR_{10}	Number of improvement suggestions made	EC_{10}	Employee empowerment	Number of employee suggestions applied/executed

Next, the introduced QFD approach was employed to determine critical ECs in the performance management system's design.

Step 1: By using the LDWA operator, the collective LDA correlation matrix L is derived as presented in Table 4, in which the importance of each expert is assumed to be equal, i.e., $\lambda_k = 0.2 (k = 1, 2, \ldots, 5)$.

Table 3. The linguistic distribution assessments given by the first expert.

	EC_1	EC_2	EC_3	EC_4	EC_5	EC_6	EC_7	EC_8	EC_9	EC_{10}
CR_1	$\{\langle s_1, 0.5\rangle, \langle s_2, 0.5\rangle\}$	$\{\langle s_2, 0.5\rangle, \langle s_3, 0.5\rangle\}$	$\{\langle s_2, 0.5\rangle, \langle s_3, 0.5\rangle\}$			$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_2, 0.2\rangle, \langle s_3, 0.3\rangle, \langle s_4, 0.5\rangle\}$		
CR_2		$\{\langle s_3, 0.2\rangle, \langle s_4, 0.8\rangle\}$								$\{\langle s_1, 0.3\rangle, \langle s_2, 0.7\rangle\}$
CR_3			$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$		$\{\langle s_0, 0.5\rangle, \langle s_1, 0.5\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_4, 1\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_4, 1\rangle\}$	$\{\langle s_1, 0.3\rangle, \langle s_2, 0.7\rangle\}$
CR_4			$\{\langle s_2, 0.1\rangle, \langle s_3, 0.3\rangle, \langle s_4, 0.6\rangle\}$	$\{\langle s_2, 1\rangle\}$	$\{\langle s_2, 1\rangle\}$	$\{\langle s_2, 1\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_2, 0.5\rangle, \langle s_3, 0.5\rangle\}$		$\{\langle s_0, 1\rangle\}$
CR_5			$\{\langle s_0, 0.5\rangle, \langle s_1, 0.5\rangle\}$	$\{\langle s_2, 1\rangle\}$	$\{\langle s_1, 0.5\rangle, \langle s_2, 0.5\rangle\}$	$\{\langle s_4, 1\rangle\}$				
CR_6				$\{\langle s_0, 0.4\rangle, \langle s_1, 0.6\rangle\}$		$\{\langle s_1, 0.3\rangle, \langle s_2, 0.4\rangle, \langle s_3, 0.3\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$		$\{\langle s_2, 1\rangle\}$	$\{\langle s_2, 1\rangle\}$
CR_7						$\{\langle s_2, 0.9\rangle, \langle s_3, 0.1\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_2, 1\rangle\}$	$\{\langle s_0, 1\rangle\}$
CR_8				$\{\langle s_0, 0.2\rangle, \langle s_1, 0.8\rangle\}$		$\{\langle s_2, 1\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_4, 1\rangle\}$	$\{\langle s_4, 1\rangle\}$	
CR_9				$\{\langle s_1, 0.5\rangle, \langle s_2, 0.5\rangle\}$			$\{\langle s_0, 0.3\rangle, \langle s_1, 0.7\rangle\}$	$\{\langle s_2, 0.6\rangle, \langle s_3, 0.4\rangle\}$	$\{\langle s_4, 1\rangle\}$	$\{\langle s_1, 0.2\rangle, \langle s_2, 0.8\rangle\}$
CR_{10}		$\{\langle s_2, 1\rangle\}$	$\{\langle s_1, 0.5\rangle, \langle s_2, 0.5\rangle\}$				$\{\langle s_0, 0.3\rangle, \langle s_1, 0.7\rangle\}$	$\{\langle s_0, 0.6\rangle, \langle s_1, 0.4\rangle\}$		$\{\langle s_4, 1\rangle\}$

Table 4. The collective LDA correlation matrix L.

	EC_1	EC_2	EC_3	EC_4	EC_5	EC_6	EC_7	EC_8	EC_9	EC_{10}
CR_1	$\{\langle s_1, 0.32\rangle, \langle s_2, 0.68\rangle\}$	$\{\langle s_2, 0.48\rangle, \langle s_3, 0.52\rangle\}$	$\{\langle s_2, 0.62\rangle, \langle s_3, 0.38\rangle\}$			$\{\langle s_3, 0.34\rangle, \langle s_4, 0.64\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_2, 0.2\rangle, \langle s_3, 0.3\rangle, \langle s_4, 0.5\rangle\}$		
CR_2		$\{\langle s_3, 0.44\rangle, \langle s_4, 0.56\rangle\}$								$\{\langle s_1, 0.06\rangle, \langle s_2, 0.94\rangle\}$
CR_3			$\{\langle s_3, 0.42\rangle, \langle s_4, 0.58\rangle\}$		$\{\langle s_0, 0.64\rangle, \langle s_1, 0.36\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_4, 1\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_4, 1\rangle\}$	$\{\langle s_1, 0.06\rangle, \langle s_2, 0.94\rangle\}$
CR_4			$\{\langle s_2, 0.1\rangle, \langle s_3, 0.3\rangle, \langle s_4, 0.6\rangle\}$	$\{\langle s_1, 0.2\rangle, \langle s_2, 0.8\rangle\}$	$\{\langle s_1, 0.04\rangle, \langle s_2, 0.92\rangle, \langle s_3, 0.04\rangle\}$	$\{\langle s_2, 1\rangle\}$	$\{\langle s_3, 0.38\rangle, \langle s_4, 0.62\rangle\}$	$\{\langle s_2, 0.58\rangle, \langle s_3, 0.42\rangle\}$		$\{\langle s_0, 1\rangle\}$
CR_5			$\{\langle s_0, 0.38\rangle, \langle s_1, 0.62\rangle\}$	$\{\langle s_2, 1\rangle\}$	$\{\langle s_1, 0.5\rangle, \langle s_2, 0.5\rangle\}$	$\{\langle s_4, 1\rangle\}$				
CR_6				$\{\langle s_0, 0.4\rangle, \langle s_1, 0.6\rangle\}$		$\{\langle s_1, 0.3\rangle, \langle s_2, 0.4\rangle, \langle s_3, 0.3\rangle\}$	$\{\langle s_3, 0.42\rangle, \langle s_4, 0.58\rangle\}$		$\{\langle s_2, 1\rangle\}$	$\{\langle s_2, 0.96\rangle, \langle s_3, 0.04\rangle\}$
CR_7						$\{\langle s_2, 0.9\rangle, \langle s_3, 0.1\rangle\}$	$\{\langle s_3, 0.42\rangle, \langle s_4, 0.58\rangle\}$	$\{\langle s_3, 0.42\rangle, \langle s_4, 0.58\rangle\}$	$\{\langle s_2, 1\rangle\}$	$\{\langle s_0, 0.96\rangle, \langle s_2, 0.04\rangle\}$
CR_8				$\{\langle s_0, 0.2\rangle, \langle s_1, 0.8\rangle\}$		$\{\langle s_2, 0.92\rangle, \langle s_3, 0.08\rangle\}$	$\{\langle s_3, 0.5\rangle, \langle s_4, 0.5\rangle\}$	$\{\langle s_4, 1\rangle\}$	$\{\langle s_3, 0.08\rangle, \langle s_4, 0.92\rangle\}$	
CR_9				$\{\langle s_1, 0.1\rangle, \langle s_2, 0.9\rangle\}$			$\{\langle s_0, 0.3\rangle, \langle s_1, 0.7\rangle\}$	$\{\langle s_2, 0.6\rangle, \langle s_3, 0.4\rangle\}$	$\{\langle s_3, 0.08\rangle, \langle s_4, 0.92\rangle\}$	$\{\langle s_1, 0.2\rangle, \langle s_2, 0.8\rangle\}$
CR_{10}		$\{\langle s_2, 1\rangle\}$	$\{\langle s_1, 0.1\rangle, \langle s_2, 0.9\rangle\}$				$\{\langle s_0, 0.3\rangle, \langle s_1, 0.7\rangle\}$	$\{\langle s_0, 0.7\rangle, \langle s_1, 0.3\rangle\}$		$\{\langle s_4, 1\rangle\}$

Step 2: By Equation (5), the expectation correlation evaluation matrix is computed to be as follows:

$$R = \begin{bmatrix} 1.68 & 2.52 & 2.38 & 0 & 0 & 3.58 & 3.5 & 3.3 & 0 & 0 \\ 0 & 3.56 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1.94 \\ 0 & 0 & 3.58 & 0 & 0.36 & 3.5 & 4 & 3.5 & 4 & 1.94 \\ 0 & 0 & 3.5 & 1.8 & 2 & 2 & 3.62 & 2.42 & 0 & 0 \\ 0 & 0 & 0.62 & 2 & 1.5 & 4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.6 & 0 & 2 & 3.58 & 0 & 2 & 2.04 \\ 0 & 0 & 0 & 0 & 0 & 2.1 & 3.58 & 3.58 & 2 & 0.08 \\ 0 & 0 & 0 & 0.8 & 0 & 2.08 & 3.5 & 4 & 3.92 & 0 \\ 0 & 0 & 0 & 1.9 & 0 & 0 & 0.7 & 2.4 & 3.92 & 1.8 \\ 0 & 2 & 1.9 & 0 & 0 & 0 & 0.7 & 0.3 & 0 & 4 \end{bmatrix}.$$

Step 3: According to Equations (6) and (7), the EC vectors $R_i (i = 1, 2, \ldots, 10)$ are calculated as listed below:

$$\begin{aligned} R_1 &= [1, 0, 0, 0, 0, 0, 0, 0, 0, 0], \\ R_2 &= [1.5, 2.12, 0, 0, 0, 0, 0, 0, 0, 1.19], \\ R_3 &= [1.42, 0, 2.13, 2.08, 0.37, 0, 0, 0, 0, 1.13], \\ R_4 &= [0, 0, 0, 1.07, 1.19, 0.36, 0, 0.48, 1.13, 0], \\ R_5 &= [0, 0, 0.21, 1.19, 0.89, 0, 0, 0, 0, 0], \\ R_6 &= [2.13, 0, 2.08, 1.19, 2.38, 1.19, 1.25, 1.24, 0, 0], \\ R_7 &= [2.08, 0, 2.38, 2.15, 0, 2.13, 2.13, 2.08, 0.42, 0.42], \\ R_8 &= [1.96, 0, 2.08, 1.44, 0, 0, 2.13, 2.38, 1.43, 0.18], \\ R_9 &= [0, 0, 2.38, 0, 0, 1.19, 1.19, 2.33, 2.33, 0], \\ R_{10} &= [0, 1.15, 1.15, 0, 0, 1.21, 0.05, 0, 1.07, 2.38]. \end{aligned}$$

Step 4.1: The square matrix $\widetilde{R} = (\widetilde{r}_{ik})_{m \times m}$ is determined as presented in Table 5.

Step 4.2: Via Equation (8), the importance scores of the 10 ECs H_i (i = 1,2,. . .,10) are obtained as shown in Table 6.

Step 4.3: Based on the descending order of the importance degrees H_i (i = 1,2,. . .,10), the prioritization of ECs is determined as follows: $EC_9 > EC_{10} > EC_2 > EC_7 > EC_8 > EC_6 > EC_3 > EC_4 > EC_5 > EC_1$.

Table 5. The square matrix $\widetilde{R}$.

	0.44	0.28	−0.29	−0.18	0.38	0.24	0.28	−0.31	−0.30
0.44	1.00	0.01	−0.54	−0.35	−0.35	−0.41	−0.33	−0.58	0.32
0.28	0.01	1.00	−0.08	0.46	0.36	0.38	0.27	−0.19	0.02
−0.29	−0.54	−0.08	1.00	0.67	0.07	−0.27	−0.13	0.04	−0.35
−0.18	−0.35	0.46	0.67	1.00	0.38	−0.02	−0.13	−0.39	−0.42
0.38	−0.35	0.36	0.07	0.38	1.00	0.47	0.31	−0.01	−0.62
0.24	−0.41	0.38	−0.27	−0.02	0.47	1.00	0.68	0.36	−0.37
0.28	−0.33	0.27	−0.13	−0.13	0.31	0.68	1.00	0.56	−0.50
−0.31	−0.58	−0.19	0.04	−0.39	−0.01	0.36	0.56	1.00	0.02
−0.30	0.32	0.02	−0.35	−0.42	−0.62	−0.37	−0.50	0.02	1.00

Table 6. The importance scores of ECs.

H_1	H_2	H_3	H_4	H_5	H_6	H_7	H_8	H_9	H_{10}
2.54	8.25	6.37	4.86	3.74	6.86	7.69	7.62	9.73	8.70

4.2. Comparative Analysis

To further show the effectiveness and benefits of our proposed QFD approach, we conduct a comparative analysis with several existing methods, which include the classical QFD, the HF-QFD [41], and the LZ-QFD [42]. The ranking results of the importance of ECs generated by the listed QFD methods are exhibited in Figure 2.

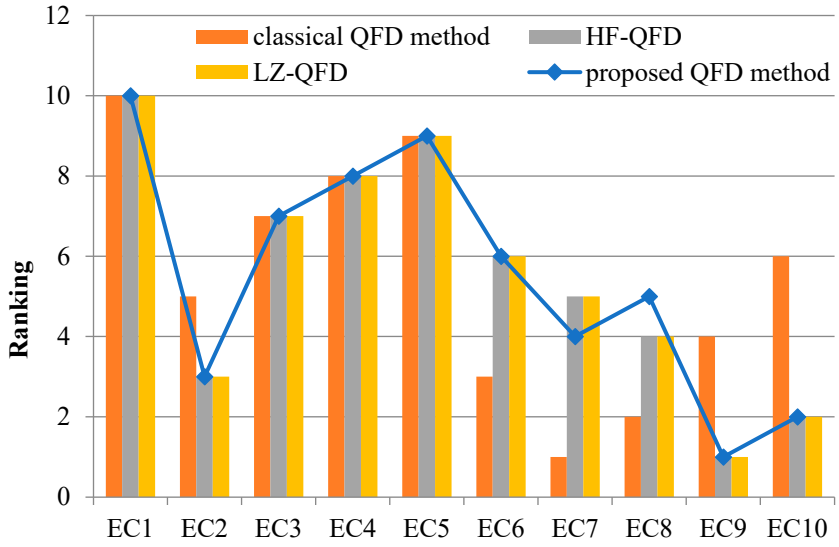


Figure 2. EC ranking results obtained by different methods.

As can be seen from Figure 2, the top three ECs obtained by HF-QFD, LZ-QFD, and the proposed method of QFD are the same, i.e., EC_9, EC_{10}, and EC_2. In addition, the ranking orders of four ECs (EC_1, EC_3, EC_4, and EC_5) derived by the proposed QFD are consistent with the ones determined by the three compared methods. These outcomes demonstrate the effectiveness of the proposed QFD approach. Furthermore, the results determined by the proposed QFD approach is line with real situations. By analyzing the identified performance expectations with respect to its importance degree in goal achievement, the current status of employee performance and the planned target performance level illustrate reasonable outcomes [48]. For example, EC_9 (access to training and growth opportunities inside or outside the company) is an enduring technical requirement for employees to perform well on the given parameters [47]. Human resource policy formulation should include this technical design feature, which has a strong positive relationship with the performance indicator [49].

On the other hand, there are still some differences between the EC importance rankings obtained by the proposed QFD approach and those obtained by the other three methods. First, there is a large difference between the two sets of EC priority rankings produced by the proposed approach and the classical QFD method. The explanations for the inconsistent ranking results may be as follows: (1) Crisp numbers are used in classical QFD to describe the correlations between CRs and ECs, which are unable to handle the uncertainty in experts' judgments [8,50]. (2) A compensatory method was used to determine the importance rankings of ECs in classical QFD, which may have resulted in biased rankings [6,43].

Second, the proposed QFD approach gives different rankings for EC_7 and EC_8 in comparison with the HF-QFD and the LZ-QFD methods. This could be attributed to the fact that different evaluation and prioritization mechanisms are used by the compared methods. Specifically, HF-QFD adopts double-hierarchy hesitant linguistic term sets to evaluate the CR-EC relationships and the axiomatic design method to determine the importance priority of ECs [41]. LZ-QFD uses linguistic Z-numbers to deal with the vague relationship evaluation information and the evaluation based on distance from average

solution (EDAS) method to rank ECs [42]. The two compared methods cannot describe complex linguistic expressions related to linguistic distributional expressions in QFD.

From the aforementioned analyses, it can be concluded that a rational and robust result for the ranking of ECs can be obtained by using the proposed QFD approach. This not only offers engineers a more practical solution but also contributes significantly to the design of performance management systems.

4.3. Managerial Implications

Considering the findings of this study, the proposed QFD approach has some practical implications for mangers and designers to improve performance management systems for reducing costs and enhancing customer satisfaction. They should focus on the critical ECs, such as "Access to training and growth opportunities inside or outside the company", "Employee empowerment", and "Appropriate compensation for the role and responsibility", to achieve planned performance. In addition, the proposed QFD approach exhibits the following benefits in real-world applications: Frist, the utilization of LDAs allows for a more precise representation of the uncertain linguistic evaluation data provided by experts. Consequently, the proposed QFD offers a convenient and flexible way to obtain comprehensive and reliable correlation evaluations. Second, the proposed QFD incorporates an expanded CRITIC methodology for determining the order of importance of ECs. Because it quantifies informational content to differentiate between ECs, the ranking outcomes generated by the proposed approach are more rational and reliable.

5. Conclusions

In this study, we proposed a new QFD approach by integrating LDAs with the CRITIC method to improve the efficiency of QFD implementation. First, the LDA method is introduced to manage evaluations of the intricate relationships between CRs and ECs provided by experts. Subsequently, the standard CRITIC method is modified and utilized to determine the rankings of the importance of ECs in performing QFD. Finally, a case study regarding performance management system design is conducted to illustrate the proposed QFD approach and to compare it with previously existing methods. The results show that the proposed QFD approach not only captures the uncertainty and diversity of assessment information provided by domain experts, but also acquires more precise and dependable importance rankings of ECs, ultimately contributing to performance management system improvement.

The proposed QFD approach has some limitations worth addressing in future studies. First, the proposed approach fails to consider the correlations among ECs, which may exist in some practical situations. Thus, incorporating the correlations between ECs into the proposed QFD approach is a promising direction to take in future research. Second, inconsistent and conflicting relationship assessments between CRs and ECs are not discussed in this study. Sometimes, experts may provide conflicting opinions due to their differing professional knowledge and experience backgrounds. Therefore, using a consensus-reaching process to ensure that experts reach a consensus viewpoint in QFD is a recommendable research direction. In addition, the proposed approach can be applied to address QFD problems in other industries in the future to further verify this approach's feasibility and practicality.

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