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An Integrated Approach for Failure Mode and Effects Analysis Based on Weight of Risk Factors and Fuzzy PROMETHEE II

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Abstract: Design experts need to fully understand the failure risk of a product to improve its quality and reliability. However, design experts have different understandings of and concepts in the risk evaluation process, which will lead to cognitive asymmetry in the product's redesign. This phenomenon of cognitive asymmetry prevents experts from improving the reliability of a product, increasing the risk of product development failure. Traditionally, failure mode and effects analysis (FMEA) has been widely used to identify the failure risk in redesigning products and a system's process. The risk priority number (RPN), which is determined by the risk factors (RF), namely, the occurrence (O), severity (S), and detection (D), is the index used to determine the priority ranking of the failure modes (FM). However, the uncertainty about the evaluation information for the RF and the coupling relationship within the FM have not been taken into account jointly. This paper presents an integrated approach for FMEA based on an interval-valued intuitionistic fuzzy set (IVIFS), a fuzzy information entropy, a non-linear programming model, and fuzzy PROMETHEE II to solve the problem of cognitive asymmetry between experts in the risk evaluation process. The conclusions are as follows: Firstly, an IVIFS is used to present the experts' evaluation information of the RF with uncertainty, and the fuzzy information entropy is utilized to obtain the weight of the experts to integrate the collective decision matrix. Secondly, a simplified non-linear programming model is utilized to obtain the weight of the RF to derive the weighted preference index of the FM. Subsequently, the coupling relationship within the FM is estimated by fuzzy PROMETHEE II, where the net flow is given to estimate the priority ranking of the FM. Finally, the proposed approach is elaborated on using a real-world case of a liquid crystal display. Methods comparison and sensitivity analyses are conducted to demonstrate the validity and feasibility of the proposed approach.

Keywords: failure mode and effects analysis; interval-valued intuitionistic fuzzy set; cognitive asymmetry; fuzzy PROMETHEE II; liquid crystal display

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1. Introduction

Design experts need to fully understand the failure risk of a product to improve its quality and reliability [1]. However, design experts have different understandings of and concepts in the risk evaluation process, which will lead to cognitive asymmetry in the product's redesign. This phenomenon of cognitive asymmetry prevents experts from improving the reliability of a product, increasing the risk of product development failure [2]. As a systematic method, failure mode and effects analysis (FMEA) has been widely used to identify the potential failure risk in the redesign process of products and systems [3]. Of late, FMEA has been implemented in product redesign, risk evaluation, and mechanical manufacturing [4–6]. Traditionally, the risk priority number (RPN), the multiplication value of the risk factors (RF), namely, the occurrence (O), severity (S), and detection (D), was used to identify the priority ranking of the failure modes (*FM*) [7], and an *FM* with a higher RPN is given considerable attention. However, the shortcomings of this method have been criticized for a variety of reasons such as: (1) At times RPN failed to address the risk evaluation in an uncertain environment. (2) Singular values of a *RF* may be sensitive to the priority ranking of the *FM* due to the multiplication formula for the RPN. (3) In cases of an extreme value of a *RF*, the multiplication of the *RF* was unsuitable for addressing various problems, where the importance weight of the *RF* was assigned equal values in the FMEA procedure. For example, for an *FM* whose multiplication values of the *RF* are $RNP_1 = O_1 * S_1 * D_1 = 3 * 4 * 5 = 60$ and $RNP_2 = O_2 * S_2 * D_2 = 5 * 3 * 4 = 60$, in this case, it is impossible to determine the priority ranking of the *FM*.

To overcome the above defects and improve the robustness of FMEA, numerous methods have been put forward. Among these methods, the artificial intelligence method is well known in dealing with fuzzy rules. In the case of the different rules requirements of applied fields, rule-based methods require considerable if–then rules and fail to rank the *FM* if the rules are given equal consequence but different preconditions [5–7]. Another popular method for FMEA consists of multi-attributes decision making [8], such as fuzzy set theory [9], FAHP [10], ANP [11], TOPSIS [12], and VIKOR [3]. These methods give a sort of *FM* based on some kinds of rules [13], for example, an approach to determine the weight of the *RF* or team experts [14]. As an efficient decision-making method, PROMETHEE was proposed by Brans, Vincke, and Mareschal [15]. Then, PROMETHEE II was applied in decision making based on pairwise comparisons of alternatives [16,17]. The method takes the rank-no-lower relationship as the core idea, uses a priority function to compare the advantages and disadvantages of the *FM* one by one, analyzes the coupling relationship between the *FM*, takes into account the objective fact that experts' preferences exist, makes the evaluation of the *FM* more convincing, and avoids the influence of compensatory decisions on the evaluation results [18,19]. Thus, a PROMETHEE II method integrated with a method of the entropy weight [20] of the *RF* and the experts' weight can be studied for a set of conflicting *FMs* in the FMEA process.

The cognitive asymmetry of design experts is mainly due to their differences in knowledge and experience [1], for example, different experts will give very good or moderate ratings for one thing, and the manifestation of cognitive asymmetry for the failure risk of a product is mainly through the heterogeneity of design experts' evaluation information [1,2]. Providing their knowledge and experience is the challenge set for the team experts to derive the risk priority ranking of the *FM*, where the multiple *RF* needs are considered and the priority ranking of the *FM* can be viewed as the problem of multi-attribute decision making. Meanwhile, the complexity of the *RF* leads to an uncertain evaluation value from the team experts. Thus far, numerous approaches have been developed to address these uncertainties for FMEA. Among these methods, AHP, FAHP, and ANP have been utilized to derive the weight of the *RF*. However, a complex procedure and subjective evaluation are needed to obtain consistent results, which seriously hinders the practical application for FMEA. Moreover, some team experts were invited to evaluate the *FM* in the FMEA process. However varied the experiences and backgrounds of the different experts are, the allocation of the expert's weight, *RF* weight, and coupling relationship with the *FM* are the key issues seriously affecting the priority ranking of the *FM*.

Motivated by these issues, an integrated approach was proposed to formulate the feasible priority ranking of the *FM* based on the information entropy [13,14,20], non-linear programming model, and preference ranking organization method for enrichment evaluation (PROMETHEE II) [15,16]. The main contributions of this paper include the following. Firstly, to address the evaluation information of the *RF* within uncertainty and cognitive asymmetry, the interval-valued intuitionistic fuzzy set (IVIFS) was used to express the evaluation values of the team experts. The fuzzy information entropy was used to derive the weight of the team experts to integrate the collective decision matrix to deal with the cognitive asymmetry of evaluation information. Secondly, a non-linear programming model was built to yield the weight of the *RF* or to derive the RPN. Subsequently, the fuzzy PROMETHEE II was utilized to deal with the coupling relationship with the *FM* and the priority ranking of the *FM* was estimated by the net flow. Finally, the proposed approach was elaborated on using a real-world case of a liquid crystal display (LCD).

To sum up, the procedure of a traditional FMEA was carried out as follows: (1) The *FM* information was collected with O, S, and D, which was presented by an accurate number. (2) The multiplication of the RF (O, S, and D) was calculated. (3) The priority ranking of the *FM* was given with the RPN or weighted RPN value. However, the differences between the proposed integrated FMEA and traditional FMEA are summarized as follows: (1) the collecting of the *FM* information: IVIFS is applied to express the evaluation of the RF to reduce the fuzziness and uncertainty of team experts. (2) The weight determination of the RF and the team experts: fuzzy information entropy is utilized to obtain the weight of the team experts to integrate the collective decision matrix to reduce the cognitive asymmetry of the design experts, and a simplified non-linear programming model is utilized to obtain the weight of the RF to derive the weighted preference index of the *FM*. (3) The priority ranking of the *FM*: the coupling relationship within the *FM* is estimated by fuzzy PROMETHEE II, where the net flow is given to estimate the priority ranking of the *FM*.

Based on the above literature, this paper presents an integrated approach for FMEA based on IVIFS, a fuzzy information entropy, a non-linear programming model, and fuzzy PROMETHEE II, so as to solve the failure risk identification problem of cognitive asymmetry from the design experts. The rest of this paper is organized as follows: An in-depth review of IVIFS and the linguistic variables is presented in Section 2. Section 3 elaborates on the new proposed methodology for FMEA. Section 4 describes a real-world case study of an LCD, and the comparison of various methods and the sensitivity analysis demonstrating the effectiveness of the developed approach. The findings and conclusion are summarized in Section 5.

2. Fuzzy Theory and Linguistic Variables

An intuitionistic fuzzy theory was proposed by Atanassov and Gargov [21] to describe the cognitive uncertainty and hesitancy of human beings. An interval-valued intuitionistic fuzzy number (IVIFN) [11] is a special IVIFS, which covers the membership, non-membership, hesitancy degree interval, and a degree of membership [0,1]. An IVIFS is more reasonable and applicable to express the team experts' linguistic assessments of fuzzy context owing to its comprehensiveness [22] and has been widely applied in decision-making problems in recent years [23]. The definitions about IVIFS are described as follows:

Definition 1 ([21]). *Let $X = \{x_1, x_2, \ldots, x_J\}$ be a finite set of elements on the universe of discourse, where an IVIFN on X is represented as $A = \{x_j, \left[u_A^L(x_j),\ u_A^U(x_j)\right], \left[v_A^L(x_j),\ v_A^U(x_j)\right] | x_j \epsilon X$, $j = 1, 2, \ldots, J\}$, $\left[u_A^L(x_j),\ u_A^U(x_j)\right] \subset [0,1]$ and $\left[v_A^L(x_j),\ v_A^U(x_j)\right] \subset [0,1]$ denote the membership degree interval and the non-membership degree interval of x_i to A, respectively, with the conditions: $u_A^L(x_j) \geq 0$, $v_A^L(x_j) \geq 0$, $u_A^U(x_j) + v_A^U(x_j) \leq 1$* for $x_j \in X$, *$(j = 1, 2, \ldots, J)$, where the hesitation degree of an element x_i* in A is presented in the form of $\left[\beta_A^L(x_j), \beta_A^U(x_j)\right] = \left[1 - u_A^U(x_j) - v_A^U(x_j),\ 1 - u_A^L(x_j) - v_A^L(x_j)\right] \subset [0,1]$.

Definition 2 ([24]). *For any given x_j*, let $A = \left\{\left\langle, x_j, \left[u_A^L(x_j),\ u_A^U(x_j)\right], \left[v_A^L(x_j),\ v_A^U(x_j)\right]\right\rangle | x_j \epsilon X, j = 1, 2, \ldots, J\right\}$ and $B = \left\{\left\langle, x_j, \left[u_B^L(x_j),\ u_B^U(x_j)\right], \left[v_B^L(x_j),\ v_B^U(x_j)\right]\right\rangle | x_j \epsilon X, j = 1, 2, \ldots, J\right\}$ *be two IVIFNs, the Euclidean distance d(A, B) between A and B is defined as follows*

$$d(A,\ B) = \left[\frac{1}{4}\sum_{j=1}^{J}\left(\left|u_A^L(x_j) - u_B^L(x_j)\right|^2 + \left|u_A^U(x_j) - u_B^U(x_j)\right|^2 + \left|v_A^L(x_j) - v_B^L(x_j)\right|^2 + \left|v_A^U(x_j) - v_B^U(x_j)\right|^2 + \left|\beta_A^L(x_j) - \beta_B^L(x_j)\right|^2 + \left|\beta_A^U(x_j) - \beta_B^U(x_j)\right|^2\right)\right]^{1/2} \quad (1)$$

If $!_j$ is the weight of the element $x_j \epsilon X$ $(j = 1, 2, \ldots, J)$, which satisfies the normalized conditions: $!_j \epsilon [0, 1]$ $(j = 1, 2, \ldots, J)$ and $\sum_{j=1}^{J} !_j = 1$. Then, the weighted Euclidean distance D(A,B) can be obtained as follows

$$D(A, B) = \left[\frac{1}{4} \sum_{j=1}^{J} !_j \begin{pmatrix} \left|u_A^L(x_j) - u_B^L(x_j)\right|^2 + \left|u_A^U(x_j) - u_B^U(x_j)\right|^2 + \left|v_A^L(x_j) - v_B^L(x_j)\right|^2 + \\ \left|v_A^U(x_j) - v_B^U(x_j)\right|^2 + \left|ß_A^L(x_j) - ß_B^L(x_j)\right|^2 + \left|ß_A^U(x_j) - ß_B^U(x_j)\right|^2 \end{pmatrix} \right]^{1/2} \quad (2)$$

Definition 3 ([25])**.** *For an IVIFS $\tilde{a}_p = [a_p, b_p], [c_p, d_p]$ $(p = 1, 2, \ldots, P)$, the aggregation operator is defined as follows*

$$\mathrm{A}_{\lambda^{\mathrm{P}}}(\tilde{a}_1, \tilde{a}_2, \ldots, \tilde{a}_{\mathrm{p}}) = \left\{ \left[1 - \prod_{\mathrm{p}=1}^{\mathrm{P}} (1 - \mathrm{a_p})^{\lambda_{\mathrm{p}}}, 1 - \prod_{\mathrm{p}=1}^{\mathrm{P}} (1 - \mathrm{b_p})^{\lambda_{\mathrm{p}}} \right], \left[\prod_{\mathrm{p}=1}^{\mathrm{P}} \mathrm{c_p}^{\lambda_{\mathrm{p}}}, \prod_{\mathrm{p}=1}^{\mathrm{P}} \mathrm{d_p}^{\lambda_{\mathrm{p}}} \right] \right\} \quad (3)$$

where $\breve{} = (\breve{}_1, \breve{}_2, \ldots, \breve{}_P)$, $\breve{}_p \epsilon [0, 1]$, $\sum_{p=1}^{P} \breve{}_p = 1$ is the weight vector of experts in this article.

Linguistic variables (given by experts with the cognitive asymmetry) were utilized to express the qualitative evaluation of team experts [26]. In this paper, the qualitative assessments of the linguistic variables for the *RF* are transformed by IVIFN, and the transformed relation (scale of linguistic variables and the corresponding IVIFNs) [27,28] is shown in Table 1.

Table 1. Transformed relations between linguistic variables and IVIFN.

Linguistic Variables	IVIFN
Very High (VH)	$\langle [0.90, 0.95], [0.02, 0.05] \rangle$
High (H)	$\langle [0.70, 0.75], [0.20, 0.25] \rangle$
Fair (F)	$\langle [0.50, 0.55], [0.40, 0.45] \rangle$
Low (L)	$\langle [0.20, 0.25], [0.70, 0.75] \rangle$
Very Low (VL)	$\langle [0.02, 0.05], [0.90, 0.95] \rangle$

3. Proposed Methodology for FMEA

Assume that *P* evaluation experts were invited to evaluate some potential failure modes FM_i $(I = 1, 2, \ldots, I)$ in terms of risk factors RF_j $(j = 1, 2, \ldots, J)$. The expert e^p $(p = 1, 2, \ldots, P)$ is assigned a weight $0 \leq \breve{}_p < 1$ to represent their importance in team. Then, experts express the qualitative linguistic evaluation information, which can be transformed into IVIFNs (as shown in Table 1). If $\tilde{R} = (\tilde{r}_{ij}^p)_{I \times J}$ is an IVIFS, given by the expert e^p, where $\tilde{r}_{ij}^p = \left\langle \left[u_{ij}^{Lp}, u_{ij}^{Up}\right], \left[v_{ij}^{Lp}, v_{ij}^{Up}\right] \right\rangle$ is a translated IVIFN for RF_j of FM_i. Here, we present an improved methodology for FMEA based on the non-linear programming model, fuzzy information entropy, and PROMETHEE II.

3.1. Subsection Non-Linear Programming Model for Weight of Risk Factors

According to the principle of the similarity measure [29,30], the following steps are presented.

Step 1. The qualitative evaluations of linguistic variables for RF_j (O, S, D) can be obtained, then, according to Table 1, the qualitative evaluations can be translated into decision matrix $\widetilde{R} = (\widetilde{r}_j^p)_{P\times J}$

$$\widetilde{R} = \begin{bmatrix} \widetilde{r}_1^1 & \widetilde{r}_2^1 & \dots & \widetilde{r}_J^1 \\ \widetilde{r}_1^2 & \widetilde{r}_2^2 & \dots & \widetilde{r}_J^2 \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{r}_1^P & \widetilde{r}_2^P & \dots & \widetilde{r}_J^P \end{bmatrix} \tag{4}$$

where $\widetilde{r}_j^p = \langle \left[u_j^{Lp}, u_j^{Up}\right], \left[v_j^{Lp}, v_j^{Up}\right] \rangle$ denotes the fuzzy evaluation value of RF_j from e^p.

Step 2. Inspired by the principle of the best worst method [3], the fuzzy reference preferences of the best and worst RF_j are defined as follows

$$\begin{cases} \widetilde{A}_B = (\widetilde{a}_{B1}, \widetilde{a}_{B2}, \dots, \widetilde{a}_{BJ}) \\ \widetilde{A}_W = (\widetilde{a}_{W1}, \widetilde{a}_{W2}, \dots, \widetilde{a}_{WJ}) \end{cases} \tag{5}$$

where $\widetilde{a}_{Bj} = \langle \left[u_{Bj}^L, u_{Bj}^U\right], \left[v_{Bj}^L, v_{Bj}^U\right] \rangle = \langle [1, 1], [0, 0] \rangle$, and $\widetilde{a}_{Wj} = \langle \left[u_{Wj}^L, u_{Wj}^U\right], \left[v_{Wj}^L, v_{Wj}^U\right] \rangle$ $= \langle [0, 0], [1, 1] \rangle$ represent the best and the worst fuzzy preference of RF_{j} in $\widetilde{R}$, respectively.

Step 3. Inspired by the principle of the similarity measure [30], the non-linear programming model is constructed to derive the weight of RF_{j} as follows

$$\begin{cases} Min\, f(!_j^+) = \sum\limits_{j=1}^{J} \sum\limits_{p=1}^{P} \left(!_j^+ d(\widetilde{r}_j^p, \widetilde{a}_{Bj})\right)^2 \\ Max\, f(!_j^-) = \sum\limits_{j=1}^{J} \sum\limits_{p=1}^{P} \left(!_j^- d(\widetilde{r}_j^p, \widetilde{a}_{Wj})\right)^2 \\ s.t. \begin{cases} 0 \le !_j^+ < 1,\ 0 \le !_j^- < 1 \\ \sum\limits_{j=1}^{J} !_j^+ = 1,\ \sum\limits_{j=1}^{J} !_j^- = 1 \\ 0 < d(\widetilde{r}_j^p, \widetilde{a}_{Bj}) < d(\widetilde{r}_j^p, \widetilde{a}_{Wj}) < 1 \end{cases} \end{cases} \tag{6}$$

where, $!_j^+$ and $!_j^-$ represent the weight of RF_j, the $d(\widetilde{r}_j^p, \widetilde{a}_{Bj})$ and $d(\widetilde{r}_j^p, \widetilde{a}_{Wj})$ represent the Euclidean distance between RF_{j} and $\widetilde{A}_B$ and $\widetilde{A}_W$, respectively.

For simplification of above non-linear programming model, a Lagrange function is given as follows

$$Min\, F(!_j^+, !_j^-, `) = \sum_{j=1}^{J} \sum_{p=1}^{P} \left(!_j^+ d(\widetilde{r}_j^p, \widetilde{a}_{Bj})\right)^2 - \left(!_j^- d(\widetilde{r}_j^p, \widetilde{a}_{Wj})\right)^2 + 2`\left(\sum_{j=1}^{J} !_j^+ - 1\right) + 2`\left(\sum_{j=1}^{J} !_j^- - 1\right) \tag{7}$$

Taking the partial derivative of the Formula (6)

$$\begin{cases} \dfrac{\partial L(!_j^+, !_j^-, `)}{\partial !_j^+} = 0 \leftrightarrow \sum\limits_{p=1}^{P} !_j^+ \left(d(\widetilde{r}_j^p, \widetilde{a}_{Bj})\right)^2 + ` = 0 \\ \dfrac{\partial L(!_j^+, !_j^-, `)}{\partial !_j^-} = 0 \leftrightarrow \sum\limits_{p=1}^{P} !_j^- \left(d(\widetilde{r}_j^p, \widetilde{a}_{Wj})\right)^2 + ` = 0 \\ \dfrac{\partial L(!_j^+, !_j^-, `)}{\partial `} = 0 \leftrightarrow \sum\limits_{j=1}^{J} !_j^+ + \sum\limits_{j=1}^{J} !_j^- - 2 = 0 \end{cases} \tag{8}$$

Here, Formula (7) can be simplified as follows

$$\begin{cases} !_j^+ = \dfrac{\left(\sum_{j=1}^{J}\left(\sum_{p=1}^{P}\left(d\left(\tilde{r}_j^p, \tilde{a}_{Bj}\right)\right)^2\right)^{-1}\right)^{-1}}{\sum_{p=1}^{P}\left(d\left(\tilde{r}_j^p, \tilde{a}_{Bj}\right)\right)^2} \\ !_j^- = \dfrac{\left(\sum_{j=1}^{J}\left(\sum_{p=1}^{P}\left(d\left(\tilde{r}_j^p, \tilde{a}_{Wj}\right)\right)^2\right)^{-1}\right)^{-1}}{\sum_{p=1}^{P}\left(d\left(\tilde{r}_j^p, \tilde{a}_{Wj}\right)\right)^2} \end{cases} \tag{9}$$

Finally, the comprehensive weight $!_j$ of RF_j can be derived as follows

$$!_j = \frac{!_j^+ + !_j^-}{2} \tag{10}$$

Here, according to the $!_j$ of RF_j, the weighted RPN_i of FM_i can be calculated as follows

$$RPN_i = S^{!_j^S} \cdot O^{!_j^O} \cdot D^{!_j^D} \tag{11}$$

3.2. Fuzzy Information Entropy for Weight of Experts

Some experts with cognitive asymmetry of knowledge and experiences in different fields are invited to give their linguistic judgments against FM_i with RF_j. Then, the qualitative evaluations are translated into IVIFS matrix $\tilde{R}^{(p)} = (\tilde{r}_{ij}^p)_{I \times J}$ based on Table 1, where $\tilde{r}_{ij}^p = \langle \left[u_{ij}^{Lp}, u_{ij}^{Up}\right], \left[v_{ij}^{Lp}, v_{ij}^{Up}\right] \rangle$ denotes the evaluation of e^p for FM_i in terms of RF_j. With the help of the principle of information entropy [13,14,20], the weight of experts λ_p can be derived using the following steps:

Step 1. Calculate the fuzzy information entropy of e^p with the respect to RF_j on FM_i

$$\begin{cases} e_i^p = 1 - d_i \\ d_i^p = \left|\dfrac{u_i^{Up} - v_i^{Up}}{2}\right| + \left|\dfrac{u_i^{Lp} - v_j^{Lp}}{2}\right| \end{cases} \tag{12}$$

where d_i^p is the score value of an IVIFN.

Step 2. Calculate the λ_p by fuzzy information entropy

$$\begin{cases} \lambda_p = \dfrac{1 - E_i^p}{\sum_{p=1}^{P}\left(1 - E_i^p\right)} \\ E_i^p = \dfrac{1}{I}\sum\limits_{i=1}^{I} e_i^p \end{cases} \tag{13}$$

Then, λ_p with different RF_j can be derived and the weighted decision matrix $R = (\tilde{r}_{ij})_{I \times J}$ can be integrated based on λ_p and $\tilde{R}^p$.

3.3. Fuzzy PROMETHEE II for Priority Ranking of Failure Modes

PROMETHEE method was proposed by Brans, Vincke, and Mareschal [15] as an efficient tool. PROMETHEE II has been applied in decision making based on pairwise comparisons of alternatives [16,17]. The method takes the rank-no-lower relationship as the core idea, uses a priority function to compare the advantages and disadvantages of FM_i one by one, analyzes the coupling relationship between FM_i, takes into account the objective fact that experts' preferences exist, makes the evaluation of FM_i more convincing, and avoids the influence of compensatory decisions on the evaluation results [18,19]. This paper focuses on PROMETHEE II to rank order emerging out of a set of conflicting FM_i. As a well-established decision-making method, here, PROMETHEE II is utilized to rank I FM_i in terms of J RF_j in following steps:

Step 1. Determine the preference function of RF_j.

According to $R = (\tilde{r}_{ij})_{I \times J}$, FM_i and FM_t (i, t = 1, 2, ..., I) are compared in pairs under different RF_j and $!_j$. The result is a preference of one over the other, which is given as an accuracy value of an IVIFN. There are 6 common criteria for determining the preference function, which were summarized and justified by Sun and Zhu [18], where the Gaussian preference function has the characteristic of non-linear variation compared with others and is more in line with the actual decision-making environment. Hence, the Gaussian preference function is chosen in this paper. Here, the Gaussian preference function $p_j(FMi, FMt) \in [0, 1]$ between FM_i and FM_t is given as follows [31]

$$p(d)\begin{cases} 0\ d \le 0 \\ 1 - e^{-d^2/2fl^2}\ d > 0 \end{cases} \tag{14}$$

where $d = d_j(FM_i, FM_t) = FM_i - FM_t, fl = 0.2$.

Step 2. Calculate the weighted preference index of failure mode.

$$H(FM_i, FM_t) = \sum_{j=1}^{J} w_j p_j(FM_i, FM_t) \tag{15}$$

Step 3. Calculate the leaving flow L^+, entering flow L^-, and net flow L^+L^- of weighted preference index [31] of failure mode FM_i

$$\begin{cases} L^+(FM_i) = \sum\limits_{i=1}^{I} H(FM_i, FM_t) \\ L^-(FM_i) = \sum\limits_{i=1}^{I} H(FM_t, FM_t) \\ L^+L^-(FM_i) = L^+(FM_i) - L^-(FM_i) \end{cases} \tag{16}$$

Step 4. Priority ranking of FM_i.

The L^+ denotes the dominance of FM_i over other FM_i and is used to assess the outranking character, and the L^- is the assessment of outranking character. The L^+L^- denotes the comprehensive dominance of FM_i between L^+ and L^-. The larger the value of L^+L^-, the higher is the priority ranking of the FM_i.

3.4. Procedure of Proposed Approach

The flowchart of the proposed approach is shown in Figure 1 and the steps therein are summarized below:

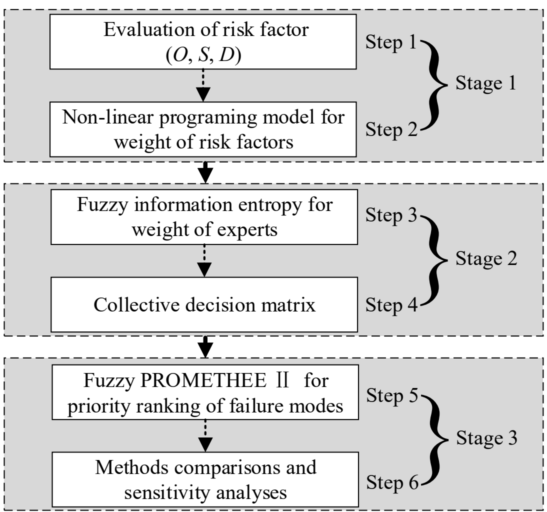

Figure 1. Procedure framework of the proposed approach.

Step 1. For different RF_j on FM_i, experts give their fuzzy qualitative evaluation information based on Table 1.

Step 2. According to the IVIFS evaluation information of RF_j and Equations (6)–(9), the weight w_j of RF_j can be derived by solving Equation (10).

Step 3. The weight of experts λ_p is derived based on Equations (11) and (12).

Step 4. The collective decision matrix $R = (\tilde{r}_{ij})_{I \times J}$ is constructed based on the weight of experts λ_p and Equation (3).

Step 5. Priority ranking of all the FM_i by decreasing the values of net flow, where the preference function of FM_i is calculated based on Equations (13) and (14), and the net flow of FM_i is estimated based on Equation (15).

Step 6. Methods comparisons and sensitivity analyses are conducted to demonstrate the validity of the proposed approach.

4. Case Study

To demonstrate the implementation process of the proposed approach, a real-world display case of an LCD product was undertaken. Moreover, methods comparison and sensitivity analysis were conducted to validate the feasibility of the proposed approach. The risk evaluation data of the LCD display product were collected from a semiconductor manufacturing company, located in the city of Xiamen, China. The company was proposing to launch a series of quality renovations in their LCD products to identify with high reliability the target risky components within the next-generation integrated panel module package to increase customer satisfaction. In the early design stage, the risk components must be identified because the given redesign tasks do not require changing all the components. Since the LCD is comprised of submodules, only the main components of the *FM* were selected for the case study. The three-dimensional diagram of the LCD in display products is shown in Figure 2. The components and descriptions of the *FM* are summarized in Table 2.

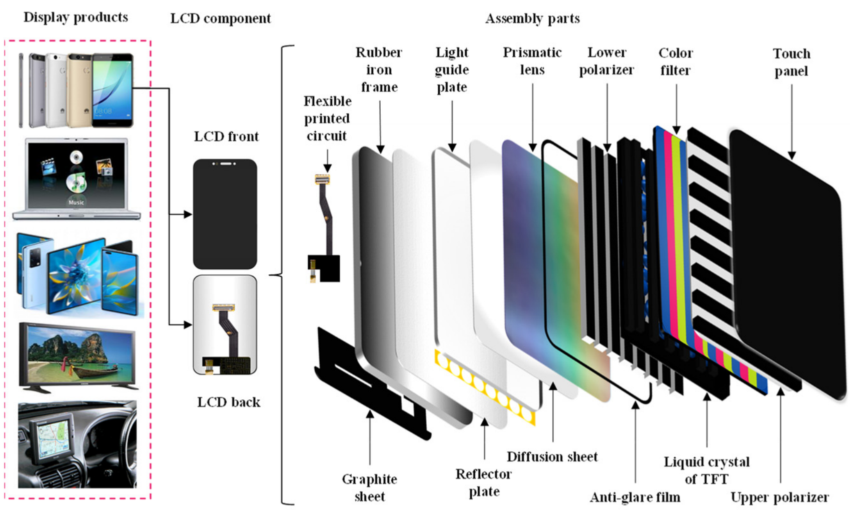

Figure 2. Hierarchical structure of LCD in display products.

Table 2. Components and descriptions of *FM*.

Components of *FM*	Descriptions of *FM*
LCD of TFT: FM_1	Bad point line, picture flicker, extrusion light leakage, power consumption problem, dark line, and serrated display
Back light unit: FM_2	Size deviation, film warping, edge bright line, and unsuitable LCD selection
Module: FM_3	Offset light leakage, LED off, improper tray, fragments, reversed flexible printed circuit (FPC) connection, and foreign bodies in the drum
Integrated circuit: FM_4	Electro-static discharge (ESD) damage, flicker, and excessive power consumption.
Polarizer: FM_5	There are cracks and color differences in polarizer notch
Full cell: FM_6	White screen shows character deviation, gamma offset, and residual shadow
Flexible printed circuit: FM_7	Line break, fracture, pressure deviation, and integrated circuit pin off

4.1. Application of the Proposed Approach

Based on the quality feedback of the LCD, an FMEA team of six experts e^p (p = 1, 2, . . . , 6), working in the design, manufacturing, technology, management, marketing, and service departments, were invited to carry out the risk evaluation of the failure modes FM_i. The priority ranking of the FM_i was then derived as follows:

Step 1. According to Table 1, the importance of the experts' evaluation for RF_j (O, S, D) and for the seven FM_i in terms of the risk factor RF_j are shown in Tables 3 and 4, respectively.

Table 3. Importance of experts' evaluation for RF_j.

	O	*S*	*D*
e^1	VL	H	L
e^2	L	F	H
e^3	F	L	VH
e^4	L	F	H
e^5	H	L	F
e^6	L	F	F
Best	VH	VH	VH
Worst	VL	VL	VL

Table 4. Experts evaluation of RF_j.

	O						*S*						*D*					
	e^1	e^2	e^3	e^4	e^5	e^6	e^1	e^2	e^3	e^4	e^5	e^6	e^1	e^2	e^3	e^4	e^5	e^6
FM_1	VL	F	L	F	F	F	F	H	H	H	F	L	F	VL	VL	VL	VL	VL
FM_2	L	H	H	F	H	F	H	F	F	F	F	H	F	L	L	L	F	F
FM_3	H	F	H	VH	H	VH	F	H	H	H	H	H	L	H	H	H	H	L
FM_4	F	H	H	H	F	F	L	H	F	VH	H	L	L	F	F	F	F	L
FM_5	L	L	VL	F	L	L	L	F	L	H	L	F	F	L	L	H	L	L
FM_6	F	L	VL	L	VL	VL	H	H	VL	H	L	VL	L	VL	L	L	VL	VL
FM_7	H	L	L	VL	F	L	VL	L	F	F	L	F	VL	L	VL	F	F	F

Step 2. With the help of the IVIFS data in Table 3, the fuzzy reference preferences of the best and the worst ($\widetilde{a}_{Bj} = \langle[1, 1], [0, 0]\rangle$ and $\widetilde{a}_{Wj} = \langle[0, 0], [1, 1]\rangle$), the Equations (6)–(9) are solved (or with the help of Lingo 11 software). According to Equation (10), the weights $!_j$ of O, S, and D that are obtained are shown in Table 5.

Table 5. Weights of O, S, D.

	O	S	D
$!_j^+$	0.234863	0.309200	0.455937
$!_j^-$	0.290845	0.322521	0.386634
$!_j$	0.262854	0.31586	0.421286

Stage 3. With the help of the IVIFS data in Table 4, the Equations (12) and (13) are calculated and the weights of the experts $˘_p$ with each different RF_j are derived and are shown in Table 6.

Table 6. Weights of experts with different RF_j.

	e^1	e^2	e^3	e^4	e^5	e^6
E^O	0.5585	0.6142	0.3885	0.5600	0.6157	0.3742
$ˇ^O$	0.1795	0.1974	0.1248	0.1799	0.1978	0.1202
E^S	0.5585	0.6142	0.6157	0.5585	0.6142	0.4300
$ˇ^S$	0.1647	0.1811	0.1815	0.1647	0.1811	0.1267
E^D	0.6157	0.4457	0.4457	0.5585	0.5600	0.3171
$ˇ^D$	0.2092	0.1514	0.1514	0.1898	0.1902	0.1077

Step 4. Taking into consideration the weight of the experts $˘_p$ and Equation (3), the collective decision matrix of the risk assessment is derived and is shown in Table 7.

Table 7. Collective decision matrix risk assessment.

	O	S	D
FM_1	$\langle[0.580, 0.656], [0.268, 0.344]\rangle$	$\langle[0.595, 0.648], [0.298, 0.352]\rangle$	$\langle[0.149, 0.187], [0.760, 0.813]\rangle$
FM_2	$\langle[0.559, 0.614], [0.330, 0.386]\rangle$	$\langle[0.569, 0.621], [0.327, 0.379]\rangle$	$\langle[0.337, 0.388], [0.560, 0.612]\rangle$
FM_3	$\langle[0.761, 0.827], [0.115, 0.173]\rangle$	$\langle[0.674, 0.725], [0.224, 0.275]\rangle$	$\langle[0.591, 0.646], [0.298, 0.354]\rangle$
FM_4	$\langle[0.613, 0.665], [0.282, 0.335]\rangle$	$\langle[0.634, 0.465], [0.479, 0.535]\rangle$	$\langle[0.420, 0.471], [0.478, 0.529]\rangle$
FM_5	$\langle[0.246, 0.295], [0.653, 0.705]\rangle$	$\langle[0.484, 0.540], [0.399, 0.460]\rangle$	$\langle[0.398, 0.453], [0.491, 0.547]\rangle$
FM_6	$\langle[0.196, 0.240], [0.708, 0.760]\rangle$	$\langle[0.338, 0.388], [0.560, 0.612]\rangle$	$\langle[0.124, 0.166], [0.784, 0.834]\rangle$
FM_7	$\langle[0.366, 0.419], [0.524, 0.581]\rangle$	$\langle[0.595, 0.648], [0.298, 0.352]\rangle$	$\langle[0.280, 0.327], [0.620, 0.673]\rangle$

Step 5. According to Table 7 and Equations (14) and (15), the matrix of the weighted preference index of FM_i with RF_j is calculated and shown in Table 8. With the help of Equation (16), the leaving flow $L^+(FM_i)$, entering flow $L^-(FM_i)$, and net flow $L^+L^-(FM_i)$ of the preference index of FM_i are estimated with descending priority ranking of all FM_i, and the results are shown in Table 9.

Table 8. The matrix of weighted preference index of FM_i.

H (FM_i, FM_t)	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7
FM_1	0.0000	0.3949	0.3093	0.4129	0.5580	0.1379	0.3448
FM_2	0.0000	0.0000	0.0000	0.1214	0.1783	0.0865	0.0164
FM_3	0.2801	0.3904	0.0000	0.4044	0.5648	0.3104	0.3988
FM_4	0.0494	0.1275	0.0000	0.0000	0.2430	0.2345	0.1932
FM_5	0.0286	0.0876	0.0000	0.0257	0.0000	0.0000	0.1415
FM_6	0.1176	0.5538	0.3464	0.5089	0.4503	0.0000	0.5149
FM_7	0.0000	0.0688	0.0129	0.2679	0.3085	0.0699	0.0000

Table 9. Priority ranking of FM_i.

	$\boldsymbol{L}^{+}(FM_i)$	$\boldsymbol{L}^{-}(FM_i)$	$\boldsymbol{L}^{+}\boldsymbol{L}^{-}(FM_i)$	**Priority Ranking**
FM_1	2.1557	0.4757	1.6800	2
FM_2	0.4025	1.6229	−1.2204	6
FM_3	2.3488	0.6686	1.6802	1
FM_4	0.8475	1.7410	−0.8935	5
FM_5	0.2834	2.3029	−2.0195	7
FM_6	2.4918	0.8391	1.6526	3
FM_7	0.7280	1.6095	−0.8814	4

Obviously, it is observed that the priority ranking of FM_i was $FM_3 > FM_1 > FM_6 > FM_7 > FM_4 > FM_2 > FM_5$. The calculation results of the proposed approach indicate that FM_3 was assigned the highest risk priorities, which has the most serious failure risk in the redesign of the LCD product.

4.2. Methods Comparison and Sensitivity Analyses

In order to verify the validity of the proposed approach, methods comparison and sensitivity analysis were conducted in two main parts. First, to verify the effectiveness of the proposed approach, we compared our method with other methods. Second, the sensitivity analysis of the main parameters was illustrated to explore the influence of the changing values on the priority ranking of FM_i, where the weight fluctuation in RF_j was performed [32].

4.2.1. Methods Comparison

According to the traditional FMEA, the priority ranking of FM_i was determined in terms of the mathematical Equation $RPN_u = O * S * D$ [33]. Subsequently, the priority ranking of FM_i was determined in terms of another mathematical Equation $RPN_w = S^{\omega_j^S} \cdot O^{\omega_j^O} \cdot D^{\omega_j^D}$ [5]. The respective RPN_u and RPN_w values and their priority ranking of FM_i are exhibited in Table 10. It is evident from Table 10 that except for FM_7, FM_4, and FM_2, the priority ranking of FM_i is still high $FM_3 > FM_1 > FM_6$. The RPN_u derives the priority ranking of FM_i by multiplying RF_j (O, S, and D) without weight; therefore, the method fails to examine the extreme values of RF_j (O, S, and D) for FM_i. For example, FM_2 is ranked ahead of FM_7 and FM_4 because FM_2 has a higher value of RF_j than FM_7 and FM_4. Once the values of O or S or D change, the RPN of FM_2, FM_7, and FM_4 also change, and so does the final priority ranking of FM_i. In addition, the RPN_w derives the priority ranking of FM_i by multiplying RF_j (O, S, and D) with weight where the priority ranking of FM_i is the same as the proposed approach, except for FM_2 and FM_4. The reason is that the evaluation values and the weight of RF_j work together. Accordingly, the three weights of RF_j (O, S, and D) are 0.263, 0.316, and 0.421, respectively, where the weight of D is obviously larger than the weights of O and S. From the original evaluation value, FM_4 is assigned a higher evaluation value than FM_2 as shown in Table 7. It is reasonable for FM_4 to be in front of FM_2. The priority ranking of FM_i with a higher risk level remains unchanged ($FM_3 > FM_1 > FM_6$), which verifies the effectiveness of the proposed approach to some degree. Moreover, the fuzzy information entropy was used to determine the weight of experts in this paper, which differs from the TOPSOS method [34] that requires pairwise comparisons and for which the solving process is tedious.

Table 10. Priority ranking of FM_i with different mathematical equations.

	O	S	D	RPN_u	Priority Ranking	RPN_w	Priority Ranking
FM_1	0.3120	0.2962	0.6179	0.0571	2	0.4093	2
FM_2	0.2280	0.2420	0.2229	0.0123	4	0.2301	5
FM_3	0.6501	0.4493	0.2924	0.0854	1	0.4131	1
FM_4	0.3304	0.4114	0.0581	0.0078	6	0.1702	6
FM_5	0.4081	0.0689	0.0935	0.0026	7	0.1250	7
FM_6	0.5158	0.0820	0.6641	0.0280	3	0.3209	3
FM_7	0.1595	0.2234	0.3423	0.0122	5	0.2447	4

The advantages of the proposed approach were estimated by another two methods, TOPSIS [34] and VIKOR [3,8]. For TOPSIS, the priority ranking of FM_i was determined by the relative closeness degree (RCD), which was ranked with a descending sequence. According to the principle of TOPSIS, the distance measures, RCD, and the priority ranking of FM_i are shown in Table 11. For VIKOR, the priority ranking was defined by the maximum group utility S, the minimum individual regret P, and the comprehensive value Q, which were ranked with an ascending sequence of Q and the compromising conditions [8]. According to the principle of VIKOR, the estimated values of S, P, and Q and the priority ranking of FM_i are shown in Table 11.

Table 11. Priority ranking of FM_i by TOPSIS and VIKOR.

	$D(FM_i, \tilde{A}_B)$	$D(FM_i, \tilde{A}_W)$	RCD_i	Ranking	S_i	P_i	Q_i	Ranking
FM_1	0.2212	0.6161	0.7357	2	1.1230	0.5180	0.3239	2
FM_2	0.4702	0.3651	0.4371	4	1.8295	0.6605	0.7561	4
FM_3	0.0002	0.8350	0.9997	1	0.7716	0.3425	0	1
FM_4	0.3563	0.4787	0.5733	3	1.3431	0.6003	0.4980	3
FM_5	0.5460	0.2890	0.3461	5	1.7510	0.6931	0.7585	6
FM_6	0.7472	0.0878	0.1052	7	2.0172	0.8223	1	7
FM_7	0.6268	0.2082	0.2494	6	1.4699	0.7996	0.7567	5

The TOPSIS showed that the priority ranking of FM_i was totally different from the proposed approach except for FM_3 and FM_1. The reason for this lies in the principle of TOPSIS that the best point should have the shortest distance to the positive ideal solution and the furthest distance to the negative ideal solution. On the other hand, when the distances calculated between the assessment values and the positive ideal solution or negative ideal solution are changing, the values of the RCD fluctuate significantly. For example, FM_1 is ranked ahead of FM_4 because FM_1 presented higher values of D (its assessment value is 0.6179 in Table 10) than FM_4 (its assessment value is 0.0581 in Table 10), and with the help of weight of RF_j (their weights of RF_j were 0.2629, 0.3159, and 0.4212, for O, S, and D, respectively, where the weight of D is obviously larger than that of O and S), FM_1 had more priority than FM_4. Compared with the VIKOR, the result is similar to the preceding. By contrast, VIKOR determined the final priority ranking with three sets of sorting (the maximum group utility S, the minimum individual regret P, and the comprehensive value Q) according to the constraint conditions, which easily derived a compromise solution. The priority ranking of FM_i with a higher risk level remains FM_3 and FM_1, which verifies the effectiveness of the proposed approach to some degree.

4.2.2. Sensitivity Analysis

To explore the influence of the weights' fluctuation on the priority ranking of FM_i, the weight of RF_j was recalculated according to the perturbation principle [5,8,23]: Assume the initial weight of RF_j is $!_j$ (j = 1, 2, 3), then define the new weight of RF_j $!'_j = t!_j$

where $0 < !'_j < 1$, $0 < t < 1/!_j$. As $d = (1 - t!_j)/(1 - !_j)$, change the weight of the rest of the RF_j changes to $!'_k = d!_k$, $(k \neq j,\ k = 1, 2, 3)$, where the adjusted weights satisfy: $!'_j + \sum_{k \neq j,\ k=1}^{J} !'_k = 1$. For each $!_j$ (j = 1, 2, 3), if the value of t changes, the weight of RF_j also changes. Accordingly, when t = 2, 1.7, 1.4, 1.1, 0.8, and 0.5, there are 18 experiments and the updated calculated weights of RF_j are shown in Table 12. According to the updated weight of RF_j, the results of the net flow are recalculated by using the proposed methods (shown in Table 13), and the priority ranking of FM_i with the weights' fluctuation of RF_j are shown in Figure 3.

Table 12. Updated weight of RF_j.

No.	1	2	3	4	5	6	7	…	12	13	14	15	16	17	18
t	2	2	2	1.7	1.7	1.7	1.4	…	1.1	0.8	0.8	0.8	0.5	0.5	0.5
O	0.5257	0.1415	0.0715	0.4469	0.1779	0.1289	0.3680	…	0.2437	0.2103	0.2871	0.3011	0.1314	0.1314	0.3585
S	0.2032	0.6317	0.0859	0.2370	0.5370	0.1549	0.2708	…	0.2929	0.3384	0.2527	0.3618	0.3722	0.1579	0.4308
D	0.2711	0.2268	0.8426	0.3161	0.2851	0.7162	0.3612	…	0.4634	0.4513	0.4602	0.3370	0.4964	0.5185	0.2106

Table 13. Values of net flow after update weights.

	T = 2, 1.7, 1.4, 1.1, 0.8, 0.5							
	1	**2**	**3**	**4**	…	**16**	**17**	**18**
FM_1	0.7464	1.1848	3.4614	1.0271		2.1498	1.9306	0.7923
FM_2	−1.5056	−0.7320	−1.4347	−1.4200		−1.0779	−1.4647	−1.1133
FM_3	2.5234	2.2017	−0.0102	2.2704	…	1.2586	1.4195	2.5255
FM_4	−0.8283	0.5834	−2.7225	−0.8479		−0.9261	−1.6320	0.0210
FM_5	−1.1570	−2.3124	−2.7718	−1.4157		−2.4507	−1.8730	−1.6433
FM_6	1.8222	−0.2585	3.6960	1.7714	…	1.5678	2.6082	0.6310
FM_7	−1.6011	0.6671	−0.2180	−1.3852		−0.5216	−0.9886	−1.2131

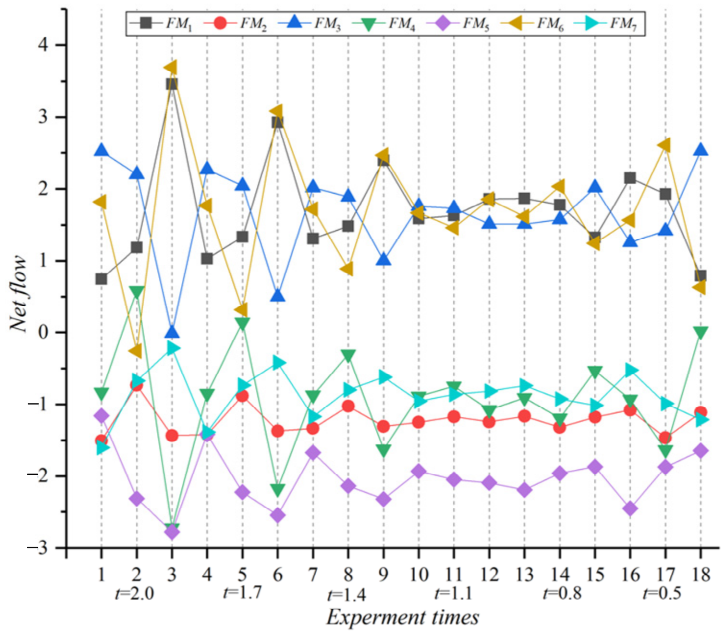

Figure 3. Priority ranking of FM_i with weights' fluctuation of RF_j.

As shown in Figure 3, FM_3, FM_1, and FM_6 retained a higher risk priority with the weights' fluctuation of RF_j (In 18 experiments, FM_3, FM_1, and FM_6 were ranked at the highest risk priority 11, 4, and 3 times, respectively.). Meanwhile, FM_5, FM_2, and FM_4

ranked as the lowest risk priorities (FM_5 16 times). The priority rankings of other FM_i were changed by the weights' fluctuation of RF_j. The weights' fluctuation of RF_j revealed that FM_3 presented the highest risk priority with a different weight of RF_j; therefore, FM_3 should be paid the most attention in the redesign of the product. Meanwhile, considering that the priority ranking of the main FM_i varies with the weight of RF_j, it is necessary and reasonable to determine the weight of RF_j conforming to the actual situation.

In consonance with Tian, Wang, and Zhang [3], for the highest importance degree, the hesitancy degree of RF_j D (shown in Table 7) was reduced to zero $\langle[0.5,\ 0.55],\ [0.4,\ 0.45]\rangle$ in the sensitivity analysis. The priority rankings of FM_i obtained by different methods are shown in Table 14. According to Table 14, despite some differences in the priority ranking of FM_i, FM_3 remained the highest risk priority. The finding revealed the robustness of the proposed approach to some extent.

Table 14. Priority ranking of FM_i without hesitancy degree.

	RCD_i	Ranking	Q_i	Ranking	RPN_u	Ranking	RPN_w	Ranking	Net Flow	Ranking
FM_1	0.6215	3	0.1531	3	0.0571	2	0.4093	2	1.6911	2
FM_2	0.6008	4	0.1992	4	0.0123	4	0.2301	5	0.5823	5
FM_3	0.6888	1	0	1	0.0854	1	0.4131	1	1.9506	1
FM_4	0.6418	2	0.1116	2	0.0078	6	0.1702	6	0.5413	6
FM_5	0.4685	7	0.9114	6	0.0026	7	0.1250	7	0.2260	7
FM_6	0.4781	5	0.9865	7	0.0280	3	0.3209	3	0.8940	3
FM_7	0.4767	6	0.7318	5	0.0122	5	0.2447	4	0.7333	4

To sum up, the advantages of the proposed method include the following:(1) The IVIFS was used to quantify the qualitative evaluation and to reduce the uncertainty of the linguistic information. The weight of the experts, RF_j, was determined by the fuzzy information entropy, which overcomes the subjectivity element in the weight. The weight of RF_j was determined by a simplified non-linear programming model, which can be solved easily and eliminated the subjectivity of the weight. (2) The priority ranking of FM_i was given by the fuzzy PROMETHEE II, which can deal with the coupling relationship with FM_i and obtain a stable and reasonable accuracy degree in decision making. (3) The priority ranking of FM_i was derived by the proposed approach to give the robustness and credibility based on methods comparison and sensitivity analysis, thereby providing a valuable supporting tool in decision making.

5. Conclusions

To identify the potential failure risk and improve the application of FMEA in product and system redesign, this paper presents an integrated approach for FMEA based on IVIFS, a fuzzy information entropy, a non-linear programming model, and fuzzy PROMETHEE II to solve the failure risk identification problem of the cognitive asymmetry from design experts. The qualitative information of the *FM* was quantified by IVIFS. A simplified non-linear programming model was used to derive the weight of the *RF*, and a fuzzy information entropy was used to obtain the weight of the team experts. The fuzzy PROMETHEE II was applied to identify the priority ranking of the *FM*. Finally, the proposed approach was elaborated by the real-world case of an LCD. Methods comparison and sensitivity analyses were carried out to demonstrate the validity and feasibility of the proposed approach, which was more stable than the traditional methods and provided an effective supporting tool for decision making in risk management.

However, the proposed approach can be further improved by considering more data from the products (such as manufacturing data, product maintenance data, and designer preferences), from the failure modes, and from the risk factors for implementing the redesign of products. The limitation of the proposed approach may be that with lots of failure modes in a product, the complexity of the coupling relationship within the *FM* will lead to an excessive amount of calculation. Further exploration will focus on the methods of natural semantic processing, such as stochastic numbers and interval fuzzy sets, which would be utilized to yield qualitative evaluation of FMEA in multi-attribute decision making, and, in the future, a comparative study of methods such as the COMET method or SPOTIS [8] will be applied to the decision making of FMEA.

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