



## Article

# An ITARA-TOPSIS Based Integrated Assessment Model to Identify Potential Product and System Risks

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**Abstract:** This is a forward-looking approach that uses a multiple-criteria decision analysis (MCDA) model as an assessment tool for risk identification. This study proposes an indifference threshold-based attribute ratio analysis and technique for order preference by similarity to an ideal solution (ITARA-TOPSIS)-based assessment model to identify critical failure modes in products and systems. The improved indifference threshold-based attribute ratio analysis (ITARA) method can generate more reliable weights for risk factors. In addition, the modified technique for order preference by similarity to an ideal solution (TOPSIS) is used to obtain the risk levels of the failure modes. The gray correlation coefficient is applied to replace the conventional Euclidean distance, and a new index is used to determine the priority of failure modes. The determination of risk factors is based on the failure mode and effect analysis (FMEA) theory, including severity, occurrence, and detection. An important indicator, the expected cost, is also included in the framework. The case of a steam turbine for a nuclear power plant is used to demonstrate the approach, and the analysis results show that the proposed model is practical and effective. Moreover, the advantages of our integrated model are illustrated through model comparisons and sensitivity analysis. This paper can help decision-makers, risk engineers, and related researchers to better understand how a systematic risk assessment can be conducted.

**Keywords:** MCDA; ITARA; TOPSIS; FMEA; risk assessment



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## 1. Introduction

Risk assessment has grown into a separate scientific field over the course of about 40 years, with the establishment of principles, theories, and methods for how to conceptualize, manage, and assess risk. These principles, theories, and methods still profoundly affect the field of risk assessment. New risk assessment studies are constantly appearing, as are significant contributions and new trends in this field. The development of newer, more comprehensive and systematic risk diagnostic tools is the goal in the field of risk management [1]. This involves two main types of tasks: first, to use risk assessment technology to diagnose and explore the potential risk of specific activities, and second, to probe generic risk research and development, related to ideas, theories, concepts, methods, approaches, frameworks, models, and techniques to understand, diagnose, assess, communicate, manage, and summarize risk [2]. In general, the second type of study provides the ideas, methodologies and tools to be used in the specific assessment issues found in the first type of task. Simply put, faced with unknown risk events, decision-makers expect to be able to accurately predict when the risk will occur and then formulate appropriate preventive measures to reduce the damage caused by the risk [3].

Public concern about the field of risk management has expanded in recent years, while risk management has emerged as a systematic and comprehensive procedure to protect human life. Nowadays, risk assessment methods that emphasize quantitative analysis through mathematical logic are popular (e.g., diagrams or algorithms, hazard and operability studies (HAZOPs), and fault tree analysis (FTA). However, it is difficult to collect quantitative data for risk events that have not yet occurred, and even the characteristics, factors, and causes of the events may be unclear [4]. Decision analysis is an alternate approach to improve the accuracy of the risk identification process while determining the optimal alternatives in a scientific manner. Specifically, expert-based decision support systems can effectively obtain more reliable analysis results through the judgments and ideas of experts [5].

In fact, most risk assessment issues involve many complex attributes, factors, and limitations which form a typical multiple-criteria decision analysis (MCDA) problem [6]. The construction of a risk assessment model through MCDA includes three working procedures, namely the construction of the assessment framework, the determination of the weights of the risk factors, and the calculation of the risk scores of the potential failure modes [7]. The creation of the assessment framework usually requires the review of a large amount of literature and discussions with experts to construct assessment risk factors and failure modes. The determination of the risk factor weights is a key step in the MCDA process, because changing the weights may affect the analysis results of the failure modes. Generally speaking, there are two methods for determining weights [8]. One is to obtain subjective weights through information from expert interviews. Some practical issues still need to rely on the subjective ideas of experts. The subjective weighting methods can reflect the preferences of decision-makers so that the evaluation results tend to be what they expect. For example, if a company's business strategy is to reduce operation costs in order to increase profits, then the cost consideration is to give a larger weight [9,10].

Common tools for processing qualitative survey data include the analytic hierarchy process (AHP) [11], Best Worst Method (BWM) [3], analytic network process (ANP) [12], and stepwise weight assessment ratio analysis (SWARA) [13]. The other is to generate objective weights from risk assessment data. For example, the entropy [14], standard deviation, maximizing deviation, and criteria importance through intercriteria correlation (CRITIC) method [15] all fall into this category. The determination of subjective weights is deeply affected by the experts' judgment. If experts lack the experience for answering those subjective weighting methods, the results of the weights will be unreliable [8]. The objective weighting methods have the advantage of not needing to interview experts like the subjective weighting methods do. Using the objective weighting methods can effectively reduce the investigation time and cost of risk analysis. It can also avoid the bias arising from the experts' experience or limited information. The criteria weights obtained by the objective weighting methods reflect the discriminative power of the criteria over the evaluation system [14,15]. Frequently used method for the integration of risk scores in recent years include Vlsekriterijumska Optimizacija i Kompromisno Resenje (VIKOR) [16], the technique for order preference by similarity to an ideal solution (TOPSIS) [7], preference ranking organization method for enrichment evaluation (PROMETHEE) [17], complex proportional assessment of alternatives (COPRAS) [4], weighted aggregated sum product assessment (WASPAS) [18], and additive ratio assessment (ARAS) [19], among others, which can be used to assess the risk scores and provide a basis for ranking the failure modes. The current MCDA follows an important trend in the development of risk assessment technology, that being to develop faster, more effective, and more reliable analysis models for determining the risk factor weights and sorting the failure modes. It is thus a good idea to combine MCDA with failure mode and effect analysis (FMEA). This theoretical framework can be applied to analyze the risks and reliability of components, products, structures, and systems [6]. Such methods have been applied, for example, for the reliability analysis of computer numerical control rotary machines [3], damage detection of rotor blades of an aircraft's turbines [20], and robustness evaluation of audio products [7].

A hybrid MCDA model was proposed by Sofuoğlu [21], who combined indifference threshold-based attribute ratio analysis (ITARA) [22] with multiple methods to discuss material selection issues. The model lays an excellent foundation for ITARA research. Our study extends the ITARA-TOPSIS approach, which uses different concepts to improve and apply it in the field of risk assessment. We propose a novel MCDA risk analysis model that integrates the improved ITARA method and the modified TOPSIS technique. The determination of risk factors is based on the FMEA theory, including severity, occurrence, and detection. An important indicator, the expected cost, is also included in the study. It is feasible to identify the importance of these risk factors through ITARA. We improve the rationality of the original ITARA [22] for practical applications and introduce the standard deviation (SD) and the concept of the aspiration level into the calculation process. The improved ITARA can not only reflect the differences between the alternatives, but also understand the alternative performance to the aspiration level. In addition, the modified TOPSIS is applied to calculate the final risk score of each failure mode. In the conventional TOPSIS [23], the Euclidean distance is used to define the gap between the two failure modes. The Euclidean distance is replaced by the gray correlation coefficient in this study. This allows us to take the degree of correlation between failure modes under multiple risk factors to obtain a more reliable gap measurement. Moreover, the ranking index of TOPSIS developed by Kuo [24] can generate more reasonable ranking results. The proposed model overcomes some of the limitations and shortcomings of previous MCDA models and enhances the analysis capability of the model. The innovative features of this model are outlined below:

1. The proposed model is new because it integrates an improved ITARA method with the modified TOPSIS technique to overcome some shortcomings of conventional FMEA. Reviewing the risk management literature, we found limited articles combining ITARA with TOPSIS to formulate the risk analysis model;
2. This study improves the original ITARA method to more effectively identify critical risk factors and generate more reliable weights. In addition, we replace the gray correlation coefficient and aspiration level in the TOPSIS technique to obtain more reasonable ranking results for the failure modes;
3. In this study, the input data is based on qualitative information from the expert surveys, and the amount of data depends on the number of experts, failure modes, and risk factors. The quality and efficiency of the solution obtained from the proposed model are not affected by the amount of data;
4. The results of the sensitivity analysis of weight changes for the improved ITARA method indicate that this MCDA model has the robustness for practical applications.

The remainder of this paper is organized as follows. Section 2 reviews the MCDA-based risk assessment and the FMEA literature. Section 3 describes the proposed ITARA-TOPSIS integrated assessment model. Section 4 introduces a real application to illustrate the feasibility of this model. Section 5 discusses the findings and contributions of this study, followed by a summary of the discussion and some directions for future research.

## 2. A Brief Literature Review of MCDM Combined with FMEA

There are many methods used in MCDA to analyze and rank the determined alternatives or solutions with respect to the important criteria, factors, or indexes [25,26]. MCDA allows for the simultaneous integration of qualitative information and quantitative data and is particularly suitable for processing objective data or subjective judgments. Such an approach is especially useful for environments where risk is uncertain or where experts or decision-makers must rely upon opinions or judgments to expand their evaluation [5,27,28].

The main purpose of MCDA applied in risk management is to construct a structured risk analysis framework and to enhance decision-makers' understanding of specific decision risk issues. The following list includes a collection of risk management themes that can be dealt with through MCDA [5,29]:

- Screening risk improvement strategies: The time and cost of risk assessments are considerable, so eliminating as many extraneous considerations as possible from improvement programs is desirable.
- Classing and sorting risk prevention measures: Sometimes, risk prevention requires a combination of several measures to maximize the effectiveness of its defense mechanism.
- Searching for the design, identity, or creation of a new alternative, strategy, or measure to meet the goals: Establish an innovative, unique, or novel risk assessment framework for specific issues.
- Detecting potential failure modes or failure factors: From expert interviews or instrument measurements, potential failure factors are summarized and ranked (from highest to lowest, according to a chosen algorithm), and engineers design a product or system of production and eliminate the cause of failure.
- Planning the optimal combination of parameters: Use multi-objective programming tools to find the optimal parameter design and maximize product or system reliability.

Risk engineers will use different methods for risk assessment and internal reporting in different problem situations [4]. Evaluation approaches used to determine the criteria, guidelines, and factors include the checklist, brainstorming, HAZOP, FMEA, structured what if technique (SWIFT), root cause analysis (RCA), primary hazard analysis (PHA), FTA, event tree analysis (ETA), and Ishikawa diagram approaches [30].

The literature review shows many risk assessment studies combining FMEA and MCDA to develop various evaluation models for risk control and improvement in various industries [31–33]. The FMEA method is an efficient tool for risk assessment and accident prevention. It has been applied to discover, control, and eliminate recognized or potential failure modes and to improve the robustness of complex systems [32]. In contrast to other risk assessment methods, the major emphasis of FMEA is to engage in proactive treatment of the product or system, rather than finding a solution after the risk has happened. This can help risk engineers to adjust programs, increase compensating provisions, employ the recommended ways, reduce the likelihood of failures, and avoid hazardous accidents [33]. Conventionally, the most common method for evaluating failure risk in FMEA is by developing the risk priority number (RPN). The RPN is the product of the severity (S), occurrence (O) and detection (D) difficulty rates. However, the crisp RPN method has some limitations when applied in real-world cases. The shortcomings of the conventional FMEA are listed below [3,4,32]:

- The three risk factors used in FMEA calculations do not encompass the entire range of causal factors;
- Measuring risk factors (e.g., severity and detection) is very subjective, and a holistic description of group opinion or judgment is lacking;
- The three factors are hard to precisely evaluate in numerical form;
- The three risk factors are often given equal relative weights;
- The mathematical formula for calculating the conventional RPN is questionable;
- RPN values are not continuous with many holes in the scaling, and there is no mechanism to interpret the meaning of the differences between different RPNs;
- Different combinations of the three risk factors may lead to an identical RPN value, causing some high-risk failure modes to be ignored;
- Many of the scores in the range of 1–1000 cannot be formed from the product of the three risk factors;
- Small variations in each rating may lead to tremendously different effects on the RPN.

The FMEA method has been proven to be one of the most important analytical tools for early preventative initiatives in a system, process, or service. However, the limitations above might reduce the reliability of conventional FMEA. The ITARA-TOPSIS-based assessment model was proposed to remedy these shortcomings in the conventional FMEA method.

The three risk factors used in FMEA calculations do not encompass the entire range of causative factors. Some decision-makers are taking the expected cost into account when

making this type of decision [31]. Therefore, to comprehensively evaluate the failure modes, the proposed FMEA described is not limited to the original three risk factors. The expected cost is added in the model for risk analysis. The expected cost is the maintenance cost that must be paid when the failure mode occurs. During the process of risk evaluation, experts choose a linguistic term to describe the degree of four risk factors for every failure mode. The corresponding linguistic term scores are shown in Table 1. For example, if the expert considers that the expected cost to fix a specific failure mode is almost close to the original price of the product, then the relative score for the expected cost (E) for the failure mode is 10.

**Table 1.** Corresponding ratings of linguistic terms.

Severity	Occurrence	Detection	Expected Cost	Rating
No	Almost never	Almost certain	Nearly no cost	1
Very slight	Remote	Very high	Remote	2
Slight	Very slight	High	Low	3
Minor	Slight	Moderately high	Relatively low	4
Moderate	Low	Moderate	Moderate	5
Significant	Medium	Low	Moderately high	6
Major	Moderately high	Very low	High	7
Extreme	High	Remote	Very high	8
Serious	Very high	Very remote	Extremely high	9
Hazardous	Almost certain	Absolute uncertainty	Almost close to original price	10

### 3. The ITARA-TOPSIS-Based Integrated Assessment Model

This section introduces the proposed model and analysis procedures. First, the improved ITARA method is developed to generate weights for the risk factors, and then the modified TOPSIS method is used to integrate and rank the risk scores of the failure modes.

#### 3.1. Improved ITARA

The original ITARA method proposed by Hatefi et al. [22] is applied to generate objective weights for the risk factors. The importance of the risk factors is assigned based on two parameters: dispersion logic (DL) and the indifference threshold (IT). The so-called DL is mainly used to measure the degree of dispersion among failure modes. If the risk rating dispersion of all failure modes in a risk factor is low, the generated weight will be relatively small. This indicates that the criterion has little discriminative power on the evaluation system (i.e., it cannot distinguish between good and bad alternatives). The IT is a threshold value which indicates the degree of allowable dispersion among failure modes. When the degree of dispersion between two adjacent failure modes is less than the threshold, it means that the decision-makers can tolerate the gap. Conversely, when the degree of dispersion exceeds the IT, it means that the corresponding risk factor has significant discriminative power.

However, the original ITARA method only considers the distance between failure modes and ignores their degree of separation relative to the aspiration level (lowest rating). A simple example is to illustrate the shortcomings of the original ITARA method. Assume that there are four failure modes. The risk ratings of four failure modes under the two risk factors are  $\{3, 1, 2, 2\}$  and  $\{9, 7, 8, 8\}$ , and the lowest rating is 1. Although the internal dispersions of the two sets of data are the same, they are significantly different from the lowest rating. In the original ITARA method, the weights of the two criteria will be equal, but this violates the principle of rationality for practical applications. The improved ITARA method can effectively alleviate this shortcoming by adding the coefficient of variation (CV) as a parameter to reflect the overall degree of dispersion. When the risk rating of the failure mode is farther away from the lowest rating, the corresponding risk factor should be assigned a higher weight, which means that this risk factor should be valued by decision-makers. The improved ITARA method proposed in this study is a semi-objective weighting

method, because some parameters in the calculation procedure need to be determined by the decision-makers or experts. The steps of the improved ITARA method are discussed in detail below.

- Step 1: Obtain the assessment matrix  $X$ .

Assume that there are  $m$  failure modes ( $M_i$ ) assessed through  $n$  risk factors ( $C_j$ ) to obtain the assessment matrix  $X$ , as shown in Equation (1). Here, an aspiration level ( $x_{aspire,j}$ ) is added as an item:

$$X = [x_{ij}] = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{aspire,1} & x_{aspire,2} & \cdots & x_{aspire,n} \end{bmatrix}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (1)$$

where  $x_{ij}$  represents the risk rating of the  $i$ th failure mode under the  $j$ th risk factors.

- Step 2: Set the indifference threshold ( $IT_j$ ).

The decision-makers formulate a reasonable  $IT_j$  for risk factors,  $j = 1, 2, \dots, n$ .  $IT_j$  reflects the allowable range of decision-makers for the degree of dispersion.

- Step 3: Calculate the normalized matrix  $A$ .

Normalization can unify the assessment units of all risk factors, so the range of elements in the matrix  $A$  is between 0 and 1, as shown in Equation (2):

$$A = [a_{ij}] = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \\ a_{aspire,1} & a_{aspire,2} & \cdots & a_{aspire,n} \end{bmatrix}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (2)$$

where  $a_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}$ .

Here,  $NIT_j$  can also be obtained through the normalization of  $IT_j$ , as shown in Equation (3):

$$NIT_j = \frac{IT_j}{\sum_{i=1}^m x_{ij}}, j = 1, 2, \dots, n \quad (3)$$

- Step 4: Sort the elements of matrix  $A$  (ascending order).

Under the same risk factors, the elements in matrix  $A$  are sorted in ascending order to form matrix  $\beta$ , as shown in Equation (4). Here, the rows of matrix  $\beta$  do not represent the  $m$  failure modes, which are used as the base of the normalized values to assess the weights of risk factors. The aspiration level  $\beta_{aspire,j}$  must be the minimum value, so it will be sorted as the first one:

$$\beta = [\beta_{ij}] = \begin{bmatrix} \beta_{aspire,1} & \beta_{aspire,2} & \cdots & \beta_{aspire,n} \\ \beta_{11} & \beta_{12} & \cdots & \beta_{1n} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{m1} & \beta_{m2} & \cdots & \beta_{mn} \end{bmatrix}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (4)$$

- Step 5: Calculate the dispersion degree of the adjacent values in each column.

The dispersion degree of the adjacent values in each column can be defined by Equation (5):

$$\gamma_{ij} = \beta_{i+1,j} - \beta_{ij} \quad (5)$$

- Step 6: Determine the distance between  $\gamma_{ij}$  and  $NIT_j$ .

When  $\gamma_{ij} > NIT_j$ , the degree of dispersion between the adjacent values in each column is beyond the acceptable range of the decision-makers. Therefore,  $\delta_{ij}$  is used to represent the distance between  $\gamma_{ij}$  and  $NIT_j$ . Conversely, when  $\gamma_{ij} \leq NIT_j$ , it means that  $\gamma_{ij}$  is not significant, so  $\delta_{ij}$  is set to 0. The calculation is as shown in Equation (6):

$$\delta_{ij} = \begin{cases} \gamma_{ij} - NIT_j, & \gamma_{ij} > NIT_j \\ 0 & , \gamma_{ij} \leq NIT_j \end{cases} \tag{6}$$

- Step 7: Generate the weights of the risk factors.

The original ITARA method only calculated the distance between the adjacent values in each column. It did not consider the deviation among the failure modes. Therefore, the CV parameter is added to generate a set of reliable weights, as shown Equation (7):

$$w_j = \alpha \left( \frac{v_j}{\sum_{j=1}^n v_j} \right) + (1 - \alpha) \left( \frac{cv_j}{\sum_{j=1}^n cv_j} \right) \tag{7}$$

where  $v_j = \left( \sum_i^m \delta_{ij}^2 \right)^{\frac{1}{2}}$  and  $cv_j = \frac{\sigma_j}{\bar{x}_j}$ . Here, the calculation of the standard deviation  $\sigma_j$ , and the average  $\bar{x}_j$  does not include the aspiration level, while  $\alpha$  is a proportional parameter whose range is between 0 and 1. In general, when the decision-makers consider the importance of the distance of two neighbors and the CV simultaneously, the  $\alpha$  is set to 0.5. If the decision-makers focus on the distance between two neighbors,  $\alpha$  will be set to a value greater than 0.5.

### 3.2. Modified TOPSIS

The TOPSIS is an effective MCDA method that is used to integrate the performance values of the solutions. The technique mainly determines positive and negative ideal solutions (PIS and NIS) in the solution combinations. Then, we calculate the relative position of each solution by measuring the gaps between each solution and the PIS and NIS. The best solution is closest to the PIS and farthest away from the NIS. The TOPSIS has been widely used in many practical decision-making problems [34]. However, it uses the Euclidean distance to define the distance, which is not suitable for multi-dimensional data [35], and it lacks the amount of information needed to measure potential uncertainty. In order to overcome the above problems, this study uses the gray correlational coefficient to determine the distance between each solution and the PIS and NIS. This is a method for judging the degree of correlation between solutions based on the similarity of multi-dimensional geometric shapes [36].

After the weights of the risk factors are generated by the improved ITARA method, the modified TOPSIS is used to prioritize the failure modes. The procedures of the modified TOPSIS for determining the ranking of the failure modes is outlined below.

- Step 1: Obtain the assessment matrix  $X$ .

This is the same as Step 1 in the improved ITARA method.

- Step 2: Calculate the normalized matrix  $Y$ .

Here, the highest rating ( $y_j^* = 10$ ) is used as the denominator instead of the maximum value used in the previous method ( $y_j^* = \max_i x_{ij}$ ). This can truly reflect the real gap. The normalized matrix  $Y$  (Equation (8)) is indicated as follows:

$$Y = [y_{ij}] = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{8}$$

where  $y_{ij} = \frac{x_{ij}}{10}$ .

- Step 3: Derive the weighted normalized matrix  $F$ .

A weighted normalized matrix is obtained by multiplying the risk factor weights by the normalized matrix  $Y$ , as shown in Equation (9):

$$Y = [f_{ij}] = \begin{bmatrix} y_{11} \cdot w_1 & y_{12} \cdot w_2 & \cdots & y_{1n} \cdot w_n \\ y_{21} \cdot w_1 & y_{22} \cdot w_2 & \cdots & y_{2n} \cdot w_n \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} \cdot w_1 & y_{m2} \cdot w_2 & \cdots & y_{mn} \cdot w_n \end{bmatrix}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{9}$$

- Step 4: Set the PIS and NIS.

In risk management, the aspiration level is the minimum risk rating, which is regarded as the PIS (Equation (10)). On the other hand, the highest risk rating is the NIS (Equation (11)):

$$r^* = (r_1^*, r_2^*, \dots, r_j^*, \dots, r_n^*) = (1 \cdot w_1, 1 \cdot w_2, \dots, 1 \cdot w_j, \dots, 1 \cdot w_n) \tag{10}$$

$$r^- = (r_1^-, r_2^-, \dots, r_j^-, \dots, r_n^-) = (10 \cdot w_1, 10 \cdot w_2, \dots, 10 \cdot w_j, \dots, 10 \cdot w_n) \tag{11}$$

- Step 5: Calculate the gray correlation coefficient of each failure mode in relation to the PIS and NIS.

The gray correlation coefficient of the failure mode  $i$  in relation to the PIS and NIS is calculated using Equations (12) and (13), respectively. The  $\rho$  is called the distinguished coefficient, which reduces the influence of the maximum absolute difference and adjusts the difference of the correlation coefficient.  $\rho \in [0,1]$ , and in general,  $\rho$  is set as 0.5. The larger the value of  $\rho$  is, the smaller the disintegration capability is:

$$v_i^* = \sum_{j=1}^n \left( \frac{\min_i |f_{ij} - r_j^*| + \rho \max_i |f_{ij} - r_j^*|}{|f_{ij} - r_j^*| + \rho \max_i |f_{ij} - r_j^*|} \right) \tag{12}$$

$$v_i^- = \sum_{j=1}^n \left( \frac{\min_i |f_{ij} - r_j^-| + \rho \max_i |f_{ij} - r_j^-|}{|f_{ij} - r_j^-| + \rho \max_i |f_{ij} - r_j^-|} \right) \tag{13}$$

- Step 6: Calculating the closeness coefficient ( $CC_i$ ).

The  $CC_i$  is the TOPSIS ranking index, ranging in value from  $-1$  to  $1$ . Kuo [24] provided a novel ranking index to overcome the shortcomings of the conventional TOPSIS, as presented as Equation (14):

$$CC_i = w^+ \left( \frac{v_i^-}{\sum_{i=1}^m v_i^-} \right) - w^- \left( \frac{v_i^*}{\sum_{i=1}^m v_i^*} \right) \tag{14}$$

where  $v_i^*$  and  $v_i^-$  are the gray correlation coefficient between the failure mode and the PIS and NIS, respectively. The two values are the main parameters for constructing the  $CC_i$ . The larger the  $CC_i$  (or the larger the  $v_i^-$ ), the closer the failure mode  $i$  is to the NIS, which also means that it has a higher risk. Here,  $w^+$  and  $w^-$  are the weights for  $v_i^-$  and  $v_i^*$ , respectively, and  $w^+ + w^- = 1$  is required. Generally, when the decision-makers do not tend to value the PIS or NIS, both  $w^+$  and  $w^-$  will be set to 0.5 [24].

#### 4. Demonstration of the Model Using a Real Case

The proposed model was applied for the analysis of a steam turbine for a power plant. Today, there are approximately 448 active nuclear power plants in 31 countries around the



world. Nuclear power plants are a type of highly efficient energy output infrastructure, emitting almost no greenhouse gases or carbon dioxide. However, the cost of nuclear power plant construction is very high, and the demand for imported technology is also high. The maintenance costs are higher than other energy supply facilities. Steam turbines are an essential component, and their reliability is important to the operation of the power plant. A steam turbine is essentially a heat engine that performs mechanical work, using steam as the working fluid. Compared with the traditional reciprocating type of steam engines, steam turbines have a greatly improved heat transfer efficiency. Power plants that use steam turbines are commonly known as thermal power plants. They are particularly suitable for fossil fuel-fired thermal power and nuclear power plants. About 80% of the world's electricity is generated by steam turbine engines [37]. To save costs and ensure the reliability of such turbine systems, it is necessary to evaluate the potential failure modes and implement risk assessment.

#### 4.1. Background Description

The effectiveness and practicability of the proposed model was demonstrated by using data from a nuclear power plant in Taiwan. We used the risk factors defined by the FMEA framework as the assessment criteria, including the S, O, D, and E [3,6,7]. The initial decision group consisted of 24 experts, including professors, government regulators, managers, and power plant engineers in related professions. Every expert had many years of experience in the energy industry. Currently, there are two major nuclear power plants in operation in Taiwan. If an unplanned downtime accident occurs at a nuclear power plant, it will have a serious impact on societal activities. Since the pieces of nuclear power plant equipment are numerous and complex, the most critical component, the steam turbine, was selected for investigation. The experts identified nine major potential failure modes in the steam turbine for the nuclear power plant: high temperature of the engine ( $M_1$ ), a clogged lubricating oil system ( $M_2$ ), foreign objects ( $M_3$ ), fracture of the vane ( $M_4$ ), a loose valve ( $M_5$ ), bearing damage ( $M_6$ ), a broken chassis ( $M_7$ ), mechanical transmission breakdown ( $M_8$ ), and rotor breakdown ( $M_9$ ).

#### 4.2. Using Modified ITARA to Generate the Weights of the Risk Factors

After the major potential failure modes were identified, subjective ratings from experts of each failure mode respective to each risk factor were obtained from the questionnaire. We used the following questions to assist experts in making appropriate assessments of failure modes: (1) What is the severity of the damage to the steam turbine after the failure mode occurs? (2) What is the probability of this failure mode occurring? (3) How easy is it to detect the failure mode before it occurs? (4) What are the associated repair costs after the failure mode occurs? All experts followed these questions to complete the questionnaire. The initial questionnaire of Expert 1 is shown in Table A1 in Appendix A. The average assessment matrix of 24 experts is presented in Table 2 (Equation (1)). For the four risk factors, the expert-given threshold  $IT_j$  was set to 0.5. From Equations (2)–(6), Tables 3–6 can be obtained.

Through Equation (7), the  $\alpha$  was set to 0.65 (jointly decided by 24 experts), and the weights of the risk factors could be obtained as follows:  $w_S = 0.2853$ ,  $w_O = 0.2212$ ,  $w_D = 0.2120$ , and  $w_E = 0.2815$ , respectively, as shown in Table 7. Severity was rated as the most important risk factor in this case. In terms of the gap between adjacent values in each risk factor, the expected cost had the highest level of discrimination in the evaluation system ( $v_E = 0.0629$ ). Although the expected cost was not the top factor, it was ranked in second place, which indicates that cost consideration was necessary in a steam turbine risk assessment system. In fact, the company made budget allocations for regular steam turbine maintenance. Overall, the importance of these risk factors was ranked as  $S \succ E \succ O \succ D$ .

**Table 2.** The assessment matrix  $X$  and the indifference threshold  $IT_j$ .

$M_i$	S	O	D	E
$M_1$	5.590	3.475	2.470	4.865
$M_2$	8.160	4.330	3.155	5.425
$M_3$	8.120	4.975	5.065	4.980
$M_4$	9.340	2.865	4.125	6.120
$M_5$	6.185	5.250	3.770	4.605
$M_6$	7.420	3.900	3.255	5.390
$M_7$	6.770	3.415	3.705	5.040
$M_8$	7.070	4.160	3.735	5.395
$M_9$	8.815	3.720	3.080	7.010
Aspire	1	1	1	1
$IT_j$	0.5	0.5	0.5	0.5

**Table 3.** The normalized matrix  $A$  and the normalized threshold  $NIT_j$ .

$M_i$	S	O	D	E
$M_1$	0.0816	0.0937	0.0740	0.0976
$M_2$	0.1192	0.1167	0.0946	0.1089
$M_3$	0.1186	0.1341	0.1518	0.0999
$M_4$	0.1364	0.0772	0.1237	0.1228
$M_5$	0.0903	0.1415	0.1130	0.0924
$M_6$	0.1084	0.1051	0.0976	0.1082
$M_7$	0.0989	0.0921	0.1111	0.1011
$M_8$	0.1033	0.1122	0.1120	0.1083
$M_9$	0.1287	0.1003	0.0923	0.1407
Aspire	0.0146	0.0270	0.0300	0.0201
$NIT_j$	0.007	0.013	0.015	0.010

**Table 4.** The Matrix  $\beta$  (sorted results of matrix  $A$ ).

	S	O	D	E
Sort 1	0.0146	0.0270	0.0300	0.0201
Sort 2	0.0816	0.0772	0.0740	0.0924
Sort 3	0.0903	0.0921	0.0923	0.0976
Sort 4	0.0989	0.0937	0.0946	0.0999
Sort 5	0.1033	0.1003	0.0976	0.1011
Sort 6	0.1084	0.1051	0.1111	0.1082
Sort 7	0.1186	0.1122	0.1120	0.1083
Sort 8	0.1192	0.1167	0.1130	0.1089
Sort 9	0.1287	0.1341	0.1237	0.1228
Sort 10	0.1364	0.1415	0.1518	0.1407

**Table 5.** The degree of dispersion between adjacent values in each column  $\gamma_{ij}$ .

	S	O	D	E
Sort 2-1	0.0670	0.0503	0.0441	0.0723
Sort 3-2	0.0087	0.0148	0.0183	0.0052
Sort 4-3	0.0085	0.0016	0.0022	0.0023
Sort 5-4	0.0044	0.0066	0.0030	0.0012
Sort 6-5	0.0051	0.0049	0.0135	0.0070
Sort 7-6	0.0102	0.0070	0.0009	0.0001
Sort 8-7	0.0006	0.0046	0.0010	0.0006
Sort 9-8	0.0096	0.0174	0.0106	0.0139
Sort 10-9	0.0077	0.0074	0.0282	0.0179

**Table 6.** The distance between  $\gamma_{ij}$  and  $NIT_j$  ( $\delta_{ij}$ ).

	S	O	D	E
1	0.0597	0.0368	0.0291	0.0623
2	0.0014	0.0013	0.0033	0.0000
3	0.0012	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000
6	0.0029	0.0000	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000
8	0.0023	0.0039	0.0000	0.0039
9	0.0004	0.0000	0.0132	0.0078

**Table 7.** The results obtained with the improved indifference threshold-based attribute ratio analysis (ITARA) method.

	S	O	D	E
$v_j$	0.0599	0.0370	0.0321	0.0629
$cv_j$	0.1636	0.1899	0.2049	0.1356
$w_j$	0.2853	0.2212	0.2120	0.2815
Rank	1	3	4	2

4.3. Using Modified TOPSIS to Integrate the Risk Ratings of the Failure Modes

The risk assessment of a product or system is a difficult and complex task., especially for evaluation in an environment with many failure modes and risk factors. A systematic and scientific analysis model is needed to measure the risk of failures. The TOPSIS is effective for dealing with this type of problem because it explores the distance between each failure mode and the PIS and NIS when determining the priority for improvement. The calculation procedures of the proposed modified TOPSIS are described in Section 3.2.

The concept of the aspiration level is introduced into TOPSIS in this study. Using Equations (8) and (9), the normalized matrix  $Y$  and the weighted, normalized matrix  $F$  can be obtained, as shown in Tables 8 and 9.

**Table 8.** The normalized matrix  $Y$  (modified technique for order preference by similarity to an ideal solution (TOPSIS)).

$M_i$	S	O	D	E
$M_1$	0.559	0.348	0.247	0.487
$M_2$	0.816	0.433	0.316	0.543
$M_3$	0.812	0.498	0.507	0.498
$M_4$	0.934	0.287	0.413	0.612
$M_5$	0.619	0.525	0.377	0.461
$M_6$	0.742	0.390	0.326	0.539
$M_7$	0.677	0.342	0.371	0.504
$M_8$	0.707	0.416	0.374	0.540
$M_9$	0.882	0.372	0.308	0.701

The gray correlation coefficients between the failure mode  $M_i$  and the PIS (lowest risk) and NIS (highest risk) can be determined ( $v^*$  and  $v^-$ ) according to Equations (10)–(14), as shown in Tables 10 and 11. It was confirmed that the gray correlation coefficient between the less risky failure mode and the PIS must be larger. Conversely, its gray correlation coefficient with the NIS must be smaller. The sum of the  $CC_i$  was equal to 0. When the  $CC_i$  was greater than 0, it indicated the set among all the failure modes with higher risk, because their assessment results were closer to the high-risk scenario. Table 12 shows the results of the calculation combining the improved ITARA method and the modified TOPSIS. The priority for failure mode improvement is  $M_3 \succ M_9 \succ M_4 \succ M_2 \succ M_8 \succ M_5$

$\succ M_6 \succ M_7 \succ M_1$ . Figure 1 shows a visualization of our evaluation results, which clearly illustrates the relative risk level. Obviously,  $M_3, M_9, M_4$ , and  $M_2$  are all high-risk failure modes, and engineers should set improvement measures to eliminate or control them.

**Table 9.** The weighted normalized matrix  $F$ .

$M_i$	S	O	D	E
$M_1$	0.159	0.077	0.052	0.137
$M_2$	0.233	0.096	0.067	0.153
$M_3$	0.232	0.110	0.107	0.140
$M_4$	0.266	0.063	0.087	0.172
$M_5$	0.176	0.116	0.080	0.130
$M_6$	0.212	0.086	0.069	0.152
$M_7$	0.193	0.076	0.079	0.142
$M_8$	0.202	0.092	0.079	0.152
$M_9$	0.251	0.082	0.065	0.197
$r^*$	0.029	0.022	0.021	0.028
$r^-$	0.285	0.221	0.212	0.281

Note: The “\*” and “-” symbol represent the positive and negative ideals, respectively.

**Table 10.** The gray correlation coefficient of the failure mode  $i$  in relation to the positive ideal solution (PIS).

$M_i$	S	O	D	E	$v^*$
$M_1$	1.000	0.867	1.000	0.962	3.830
$M_2$	0.773	0.731	0.836	0.890	3.231
$M_3$	0.776	0.654	0.574	0.946	2.951
$M_4$	0.700	1.000	0.679	0.814	3.193
$M_5$	0.936	0.626	0.729	1.000	3.292
$M_6$	0.827	0.794	0.817	0.894	3.332
$M_7$	0.881	0.879	0.739	0.938	3.438
$M_8$	0.855	0.755	0.735	0.893	3.238
$M_9$	0.731	0.824	0.852	0.733	3.139

Note: The “\*” symbol represent the positive ideals.

**Table 11.** The gray correlation coefficient of the failure mode  $i$  in relation to the negative ideal solution (NIS).

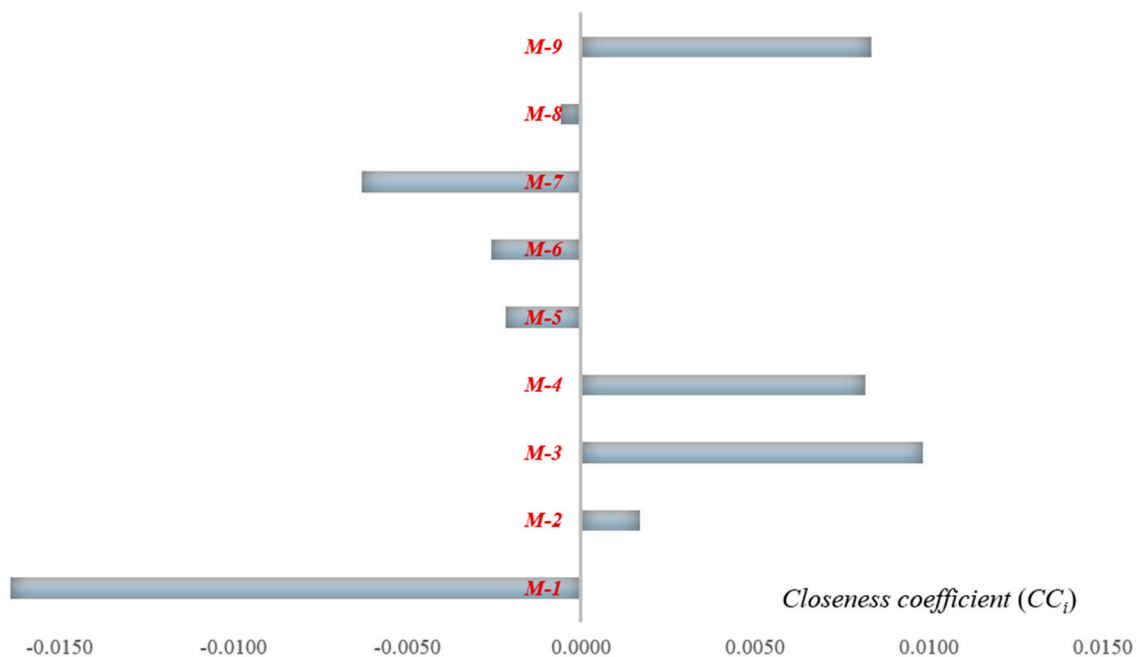
$M_i$	S	O	D	E	$v^-$
$M_1$	0.433	0.824	0.770	0.726	2.754
$M_2$	0.708	0.900	0.820	0.782	3.211
$M_3$	0.701	0.968	1.000	0.737	3.406
$M_4$	1.000	0.777	0.902	0.865	3.544
$M_5$	0.476	1.000	0.870	0.703	3.049
$M_6$	0.599	0.860	0.828	0.778	3.065
$M_7$	0.527	0.819	0.865	0.743	2.954
$M_8$	0.558	0.884	0.867	0.779	3.088
$M_9$	0.845	0.845	0.814	1.000	3.504

Note: The “-” symbol represent the negative ideals.

**Table 12.** The calculation results from the modified TOPSIS.

$M_i$	$v^*$	$v^-$	CC	Rank
$M_1$	3.830	2.754	−0.0164	9
$M_2$	3.231	3.211	0.0017	4
$M_3$	2.951	3.406	0.0098	1
$M_4$	3.193	3.544	0.0082	3
$M_5$	3.292	3.049	−0.0022	6
$M_6$	3.332	3.065	−0.0026	7
$M_7$	3.438	2.954	−0.0063	8
$M_8$	3.238	3.088	−0.0006	5
$M_9$	3.139	3.504	0.0084	2

Note: The “\*” and “−” symbol represent the positive and negative ideals, respectively.



**Figure 1.** Closeness coefficients of the failure modes.

### 5. Discussion and Conclusions

This proposed ITARA-TOPSIS model is suitable for qualitative research on risk assessment in various fields. A review on the MCDA-based hybrid FMEA models for risk management showed only limited articles that considered the inclusion of expected costs for risk maintenance. Although the expected cost is not the top-ranked risk factor, it does affect the failure mode ranking. To the best of our knowledge, this is the first time the ITARA-TOPSIS model has been developed for risk assessment in MCDA research. The developed model is compared with several previous models, including the conventional FMEA, the FMEA with expected costs, AHP-SAW (simple additive weighting method), and the original ITARA -TOPSIS method. Table 13 presents the calculation results for the five models and their failure mode rankings. The results of the FMEA that considers the expected cost are obviously different from those of the conventional FMEA. Although the top failure mode is same, the second-ranking failure modes are  $M_5$  and  $M_9$ , respectively. Moreover, the ranking results obtained with the five methods are different. As mentioned in Section 1, the integrated model proposed in this study should be more reliable and effective than the other four methods because it considers more practical conditions and requirements.

Table 13. Failure mode rankings of the five models.

$M_i$	Conventional FMEA		Conventional FMEA (Including Expected Costs)		AHP-SAW		Original ITARA-TOPSIS		Our Proposed Model	
	RPN	Rank	RPN	Rank	SAW	Rank	CC	Rank	CC	Rank
$M_1$	47.980	9	233.424	9	4.257	9	0.072	9	-0.0164	9
$M_2$	111.475	3	604.752	4	5.482	4	0.361	7	0.0017	4
$M_3$	204.611	1	1018.962	1	5.893	3	0.672	1	0.0098	1
$M_4$	110.381	4	675.533	3	5.896	2	0.629	2	0.0082	3
$M_5$	122.417	2	563.729	6	5.021	7	0.401	5	-0.0022	6
$M_6$	94.193	7	507.701	7	5.187	6	0.339	8	-0.0026	7
$M_7$	85.658	8	431.716	8	4.891	8	0.388	6	-0.0063	8
$M_8$	109.851	5	592.645	5	5.248	5	0.445	4	-0.0006	5
$M_9$	100.999	6	708.001	2	5.964	1	0.488	3	0.0084	2

In order to examine the robustness of the modified TOPSIS, a sensitivity analysis is performed by changing the weights of  $w^+$  and  $w^-$  to observe the ranking results. The  $w^+$  is adjusted from 0.1 to 0.9, with a proportional change in the  $w^-$  weight ( $w^- = 1 - w^+$ ). From the sensitivity analysis results shown in Figure 2, it can be seen that the top failure mode (in run 1 to 6) is still  $M_3$ . However, the top rank is changed after run 6, indicating the importance of  $w^+$  and  $w^-$ . This study recommends that decision-makers set both  $w^+$  and  $w^-$  to be 0.5. Since the core concept of TOPSIS considers the importance to PIS and NIS at the same time, using extreme weight combinations may produce biased results.

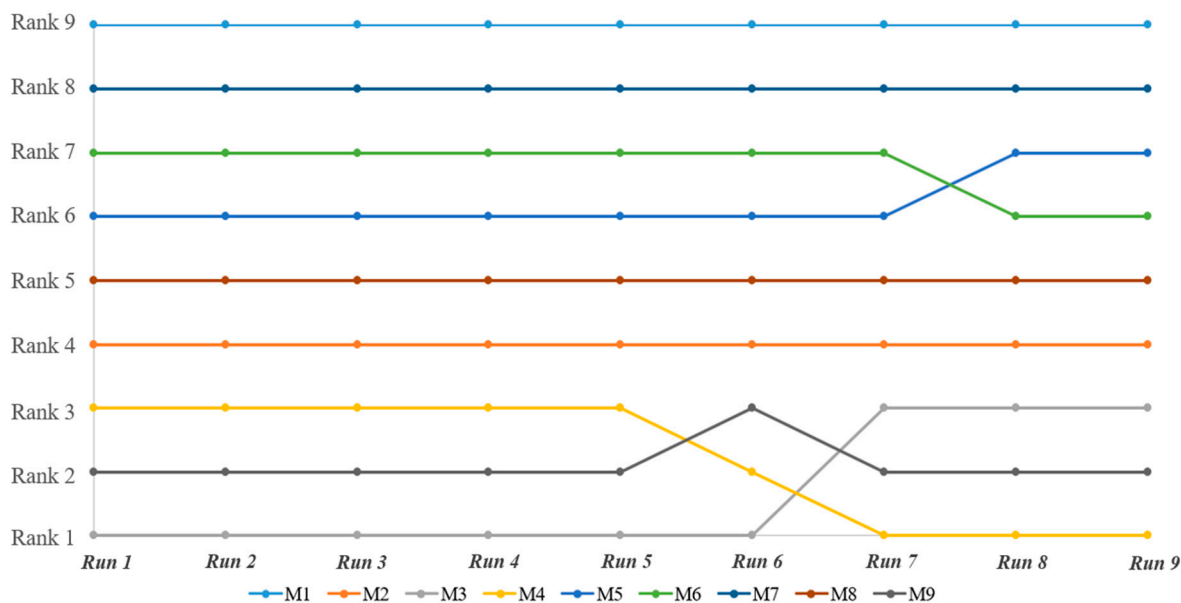


Figure 2. Results of 9 runs of sensitivity analysis.

The weights obtained by the improved ITARA method are based on inherent information, and the index or factor weights are determined by a more objective method. In other words, the proposed method is not only able to consider the weight of every factor, but also determine the weights from a semi-objective point of view. Severity is the most important risk factor from those selected by the 24 decision-makers. Those failure modes identify what needs to be improved first and where to reduce the severity of damage in the system or product.

The steam turbine is the key mechanism for energy conversion in nuclear power plants. Based on the information provided by the 24 engineers and professionals, the factors were selected for the model. The analysis results of the ITARA-TOPSIS integrated

assessment model showed that foreign objects ( $M_3$ ), rotor breakdown ( $M_9$ ), and fracture of the vane ( $M_4$ ) were the top three failures leading to the malfunction of the stream turbine. The modified TOPSIS can obtain the relative risk level of the failure modes through the ranking index ( $CC_i$ ). The purpose of the results of the FMEA is to provide engineers with directions for improvement and take proactive measures before an accident occurs. For the above three failure modes, this study conducted in-depth interviews with the experts to illustrate the prevention methods. For  $M_3$ , better protective nets and fences are constructed to prevent smaller foreign objects from falling in and increase the number of environmental cleanings. For  $M_9$  and  $M_4$ , more detailed checklists are planned to check the two failure modes and prevent unexpected shutdowns. In addition, structural engineers are recommended to use more durable materials to increase the robustness of the steam turbine.

This study makes a contribution to MCDA risk assessment research. This paper not only develops a comprehensive assessment framework for risk management issues, but also proposes a novel, integrated MCDA model to analyze the risk of the failure modes. The three risk factors from FMEA theory are severity, occurrence, and detection. We also included the expected cost as an additional risk factor to make the set of guidelines more complete. The improved ITARA method requires decision-makers or experts' limited input to determine the criteria weights and uses existing risk rating data to generate the weights of the factors. The existing TOPSIS was also modified to improve its practicality. It is feasible to replace the Euclidean distance with the gray correlation coefficient to determine the multi-dimensional geometric distance more accurately. Moreover, the sensitivity analysis and model comparison provide evidence showing the effectiveness and robustness of the proposed model. The procedures described in this paper can be applied to other MCDA issues, as long as the risk factors are added or modified according to different products or systems. We compiled the research results into a report, which was submitted to the maintenance department of a nuclear energy company. They confirmed that this report would be beneficial to the improvement of product reliability.

Although the ITARA-TOPSIS integrated assessment model is innovative and effective, there are still some shortcomings and limitations. First, the model may be too complex for decision-makers in non-MCDA-related fields to apply. It is expected that some software programs can be developed to help decision-makers using this hybrid model. Second, researchers can apply the model to other industries to compare with the current results. Finally, the interaction among the failure modes has not been discussed in this study. Future work can analyze the effects of interaction among failure modes to identify the most influential failure mode.

**Author Contributions:** H.-W.L. designed the research and wrote the paper. C.-C.H. and C.-N.H. collected the data, verified the model, and administered the project. J.J.H.L. co-wrote and made revisions to the paper. All authors have read and agreed to the published version of the manuscript.

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## Appendix A

**Table A1.** The initial questionnaire obtained by Expert 1.

$M_i$	S	O	D	E
$M_1$	6	3	2	3
$M_2$	10	4	4	5
$M_3$	7	3	3	5
$M_4$	10	2	9	6
$M_5$	4	3	3	4
$M_6$	8	5	3	3
$M_7$	5	3	2	3
$M_8$	7	3	5	5
$M_9$	10	2	3	6

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