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Enhanced FMEA for Supply Chain Risk Identification

Lu Lu[1], Zhou Rong[1], Robert de Souza[1]

1 – National University of Singapore

Supply chain risk identification is fundamental for supply chain risk management. Its main purpose is to find critical risk factors for further attention. The failure mode effect analysis (FMEA) is well adopted in supply chain risk identification for its simplicity. It relies on domain experts' opinions in giving rankings to risk factors regarding three decision factors, e.g. occurrence frequency, detectability, and severity equally. However, it may suffer from subjective bias of domain experts and inaccuracy caused by treating three decision factors as equal. In this study, we propose a methodology to improve the traditional FMEA using fuzzy theory and grey system theory. Through fuzzy theory, we design semantic items, which can cover a range of numerical ranking scores assessed by experts. Thus, different scores may actually represent the same semantic item in different degrees determined by membership functions. In this way, the bias of expert judgement can be reduced. Furthermore, in order to build an appropriate membership function, experts are required to think thoroughly to provide three parameters. As the results, they are enabled to give more reliable judgement. Finally, we improve the ranking accuracy by differentiating the relative importance of decision factors. Grey system theory is proposed to find the appropriate weights for those decision factors through identifying the internal relationship among them represented by grey correlation coefficients. The results of the case study show the improved FMEA does produce different rankings from the traditional FMEA. This is meaningful for identifying really critical risk factors for further management.

Keywords: supply chain risk identification; FMEA; grey system theory; fuzzy set theory

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1 Introduction

Risk identification involving both risk classification and risk ranking can be seen as a fundamental work for risks assessment. It identifies critical risks that need further assessment and treatment (Berman and Putu, 2012). Generally, researchers categorize risks into several groups for systematically risk identification. In our study, risks are classified into three levels—the macro level, the company level and the industry level. Risks on the macro level may influence the whole supply chain's operation; risks on the company level are from operation activities of a company; risks on the industry level are from the development of industry (Zhou et al., 2012).

Subsequently, we still need to identify most relevant risk factors so that only those relevant and important ones are studied further. As a large number of risk factors that may be involved, the easiest way is through risk ranking so that a company can effectively mitigate them (Chopra and Sodhi, 2004). A comparison of nine risk ranking techniques is shown in Table 1, where techniques are compared in five attributes—complexity of application, risk consequence analysis, risk probability analysis, quantified output, and objectivity.

Table 1: Comparison of different techniques

Techniques	Complexity of application	Risk consequence analysis	Risk probability analysis	Quantitative output	Objectivity
Structured "What-if"(SWIFT)	Low	A	A	No	Low
Fault tree analysis	Medium	NA	A	Yes	High
Cause and consequence analysis	High	A	A	Yes	High
Cause and effect analysis	Medium	A	NA	No	Medium
Decision tree	High	A	A	Yes	Medium
FMEA	Medium	A	A	Yes	Medium
Hazard analysis and critical control points	Medium	A	NA	No	Medium
Analysis hierarchy process	Medium	NA	NA	Yes	High
Bayesian statistics and Bayes nets	High	A	NA	Yes	High

According to the above table, risk ranking techniques can be classified into four big categories. The first category is a supporting method, which can only give a general analysis about the risks. For example, SWIFT uses a series of "What if" questions to identify the deviations from normal conditions with the help of a predefined checklist. The second category uses scenario analysis, which is good at analyzing the causes of risks. Fault tree analysis, cause and consequence analysis, cause and effect analysis, and decision tree belong to this category (Dakas et al., 2009, Hauptmanns, 2010, Hichem and Pepijn, 2007). The third category is function analysis method including FMEA, hazard analysis, and critical control points. They focus on analyzing the effects of risks. The final category is the statistical method, which applies the statistical knowledge into the analysis process. AHP and BBN belong to this category.

FMEA has been adopted widely as it can produce quantitative output, which is desirable for risk ranking. However, it may be biased as the opinions of domain experts can be subjective. The target of the current study is to improve FMEA for its objectivity using fuzzy set theory and grey system theory.

The structure of the paper is as follows. The next section describes the traditional FMEA; section 3 presents the enhanced FMEA. A case study is provided in section 4. Finally, conclusions are made in section 5.

2 The Traditional FMEA

FMEA identifies failure modes and mechanisms as well as their effects. There are several types of FMEA, e.g. design FMEA, system FMEA, process FMEA, service FMEA, software FMEA, etc. The current study adopts the FMEA methodology. In the study, the system means the supply chain while the failure mode refers to the potential supply chain risk. For each risk, experts give three scores between one and ten regarding the risk's occurrence frequency (OF), detectability and severity. Then the risk priority number (RPN) can be calculated through multiplying these three score and represents the risk impact of the risk factor. The higher is the RPN, the more critical is the risk.

Table 2: Scores marked by experts

Risk	Experts	OF	Detectability	Severity
Risk 1	B1	4	5	9
	B2	5	1	5
	B3	2	2	8
	Average	3.7	2.7	7.3
Risk 2	B1	9	3	4
	B2	6	2	2
	B3	8	3	5
	Average	7.7	2.7	3.7

2.1 An Example

We assume that there are three domain experts—B1, B2 and B3, who give ranks regarding the risk impacts of two risk factors: risk 1 and risk 2 in a scale of 1 to 10. The greatest rank, 10, refers to the greatest risk impact. The summary of scores marked by experts is shown in Table 2.

Then, using the average numbers of three experts' rankings, RPNs for risks 1 and 2 can be calculated as RPN_1=3.7*2.7*7.3=7.3 and RPN_2=7.7*2.7*3.7=7.7, respectively. Since RPN_2 is greater than RPN_1, risk 2 is more risky than risk 1 according to those three experts.

2.2 Limitations of Traditional FMEA

Through the above example, three limitations of the traditional FMEA can be recognized. Firstly, there may be ranking differences among experts, which can lead to the inaccuracy of outcomes. For example, for the same degree of risk impact, expert B1 may score 9 while expert B2 scores 7. Secondly, the approach depends on the experience and knowledge of experts to a large degree and the outcome can be very subjective. Finally, the RPN formula above does not consider the relative importance of three decision factors. The severity of a risk factor could be more important than OF or detectability while in the current approach, three decision factors are treated as equal. As a result, the above RPN may not be able to give accurate risk rankings.

3 Improved FMEA

To reduce the limitations of the traditional FMEA, we propose to improve it using fuzzy set theory and grey relation analysis. The primary procedure of the improved FMEA is as follows.

— Identify the relevant risk factors (regarding the risk categories) and domain experts.

— Reduce the expert bias using Fuzzy Set theory.

— Experts reach consensus for each risk.

— Improve assessment precision through Grey Correlation Analysis.

— Ranking risk factors.

Specially, we use Fuzzy Set theory in step 2 to reduce experts' ranking difference and Grey Correlation Analysis in step 4 to improve assessment precision through applying appropriate weightages to decision factors.

3.1 Fuzzy Set

In the classical discrete sets, an element either belongs to a set or it does not. But for fuzzy sets, their elements have degrees of membership according to certain membership functions (Abdelgawad and Fayek, 2011). There are many types of membership functions based on the graphs, e.g. triangular, trapezoidal, Gaussian, generalized bell, sigmoid, and others. We choose the triangular membership function to improve the traditional FMEA. A triangular membership function is specified by three parameters, a, b, and c in formula (1):

$$M(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{x-a}{b-a}, & b \leq x \leq c \\ 0, & c \leq x \end{cases} \tag{1}$$

where M refers to the membership of score x. The value of the membership ranges from 0 to 1. The value of 1 represents the full membership.

3.2 Grey Relation Analysis

Grey system theory was first developed in 1982 (Deng, 1982). A grey system generally refers to a system lacking certain information, e.g. structure message, operation mechanism, or behavior document. The aims of the grey system theory are to provide theory, techniques, notions and ideas for resolving latent and intricate systems (Deng, 1982). This study adopts the grey relation analysis, which describes the relationships between one main factor and all the other factors in a given system. The degree of correlation among different factors is measured by their grey correlation coefficient. The greater is the value of coefficient, the closer relationship is between the two factors.

4 Case Study

In this section, we use a case study to improve the traditional FMEA through the proposed methodology. Assuming there are three risk factor, e.g. raw material shortage, labour availability, and natural disaster as well as three experts, e.g. B1, B2, B3, the ranking process follows the five steps illustrated in sections 4.1 to 4.5.

4.1 Identify the Relevant Risks List and Experts

Table 3 summarizes the risk factors and experts, which are identified for the ranking process.

Risks identified are raw material shortage (R1), labor availability (R2), and natural disaster (R3) while three experts, B1, B2 and B3 are from supply chain, operation, and R&D departments, respectively.

Table 3: Risks and experts identified

Potential Risks	Experts	Department
Raw material shortage (R1)	B1	Supply chain department
Labor availability (R2)	B2	Operation department
Natural disaster (R3)	B3	R&D department

4.2 Reduce Experts Bias Using Fuzzy Set Theory

The process of reducing expert bias (ranking difference) includes 1) setting up the fuzzy semantic assessment set, 2) determining membership functions for fuzzy semantic items, and 3) calculating specific numbers for fuzzy semantic items through defuzzification.

4.2.1 Set up the fuzzy semantic assessment set (Faisal and Sarah, 2015)

In the study, the fuzzy semantic assessment set is designed to include the sematic items of “very high”, “high”, “medium”, “low”, and “very low”. The implications of the five semantic items in terms of three decision factors, occurrence frequency, detectability, and severity are illustrated in Table 4.

The definitions of semantic items can guide experts to score a risk factor. In the above table, the semantic item “very high” means “occurs in high frequency” for occurrence frequency, “very hard to detect” for detectability, and “lead to failure of whole supply chain” for severity.

The purpose of the fuzzy sematic assessment set is to provide a few number of semantic items like “very high”, “high”, etc. to reflect experts’ numerical rankings from 1-10. For example, given the same level of risk impact, different experts may give different numerical scores of “7” or “9”. But in terms of semantic items, these scores can be translated to either “high” or “very high” with certain degrees of membership. In this way, the ranking difference, e.g. the bias of experts can be reduced.

Table 4: Implication of semantic items

Semantic items	Occurrence frequency	Detectability	Severity
Very high	Occurs in high frequency	Very hard to detect	Lead to failure of whole supply chain
High	Occurs frequently	Hard to detect	Lead to the failure of critical parts of supply chain
Medium	Occurs occasionally	Can be detected occasionally	Lead to the failure of non-essential parts of supply chain
Low	Occurs in less times relatively	Easy to detect	A little influence on the supply chain
Very Low	Unlikely to occur	Very easy to detect	Mainly no influence on the supply chain

4.2.2 Determine membership functions of fuzzy semantic items

The membership functions for the five semantic items, “very low (VL)”, “low (L)”, “medium (M)”, “high (H)”, and “very high (VH)” are given in Figure 1 regarding equation (1).

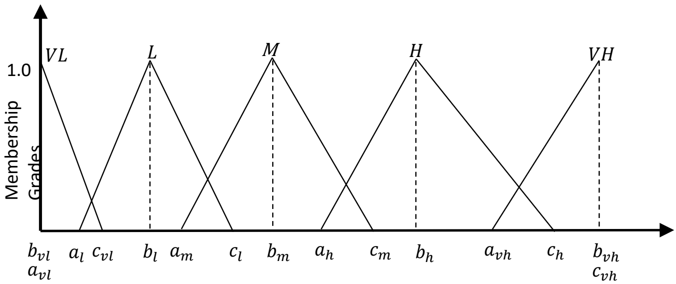

Figure 1: The structure of membership functions

Each membership function is determined by three parameters describing the range of membership. For example, risk factors with scores from a_l to c_l can be generally considered as low risk factors. Score b_l represents full “low risky” membership. For risk factors with scores close to a_l become less “low” but more “very low” risky. Similarly, those with scores close to c_l become less “low” but more “medium” risk. Three parameters determining a membership function are important and need domain experts’ inputs to find out their values.

Thus, instead of giving only one number representing absolute “low” risk, an expert should think over and give a range of numbers which can also be considered as “low” risk but with different degrees. In this way, experts are enabled to think thoroughly and give more feasible ranks of risks. Table 5 collects the inputs of three parameters for each semantic item from three experts (B1, B2, and B3). The last row is the average of three scores.

Subsequently, we have three parameters for each membership function through Table 5:

- For semantic item “very low”: $a_{vl} = 0, b_{vl} = 0, c_{vl} = 2.6$;

Table 5: Experts' inputs regarding three parameters

Expert	Very low	Low	Medium	High	Very high
B1	0, 0, 2.8	1.6, 3.3, 4.8	3.8, 5.8, 7.8	6.8, 8.3, 9.8	8.8, 10,10
B2	0, 0, 2.6	1.2, 3.4, 5.8	3.5, 5.5, 7.6	6.1, 7.8, 9.8	8.6, 10, 10
B3	0, 0, 2.4	1.4, 3.5, 5.1	3.5, 5.5, 8.0	6.6, 8.6, 9.8	8.5, 10, 10
Average	0, 0, 2.6	1.4, 3.4, 5.2	3.6, 5.6, 7.8	6.5, 8.2, 9.8	8.6, 10, 10

- For semantic item "low": $a_l = 1.4, b_l = 3.4, c_l = 5.2$;
- For semantic item "medium": $a_m = 3.6, b_m = 5.6, c_m = 7.8$;
- For semantic item "high": $a_h = 6.5, b_h = 8.2, c_h = 9.8$;
- For semantic item "very high": $a_{vh} = 8.6, b_{vh} = 10, c_{vh} = 10$.

4.2.3 Calculate the specific number of fuzzy semantic item

The aim of the current step is to obtain the specific number, representing a semantic item in one number. Defuzzification is introduced to transfer the values of three parameters into one specific number and the formula (2) adopted is as follow(Chen, 2010).

$$I = \frac{a + ab + c}{4} \tag{2}$$

We then have the specific number of each semantic item as follows.

- For semantic item "very low": $I_{vl} = 0.65$;
- For semantic item "low": $I_l = 3.4$;

— For semantic item "medium": $I_m = 5.7$;

— For semantic item "high": $I_h = 8.2$;

— For semantic item "very high": $I_{vh} = 9.7$;

In summary, the target of the current step is to reduce bias from experts in two aspects. On the one hand, we establish a judgment standard using a fuzzy semantic assessment set so that we can have the same semantic item (very low, low, medium, high, and very high) from the ranges of scores given by experts. On the other hand, in order to establish membership functions, each expert should give three numbers for each fuzzy semantic item describing the extension of membership. This enables them to think thoroughly and subsequently reduces subjectivity of judgment.

4.3 Establish the Judgment Matrix

Now, experts can rank risks R1 to R3 using semantic items ("very low", "low", "medium", "high", and "very high") in terms of their occurrence frequency, detectability and severity. The outcomes of experts' rankings are given in Table 6.

$$x = \begin{bmatrix} x_{o1} & x_{o2} & x_{o3} & x_{o4} & x_{o5} \\ x_{d1} & x_{d2} & x_{d3} & x_{d4} & x_{d5} \\ x_{s1} & x_{s2} & x_{s3} & x_{s4} & x_{s5} \end{bmatrix} \tag{3}$$

Where "o", "d", and "s" represent decision factors "occurrence frequency", "detectability", and "severity", respectively. The first row represents an expert's rankings of "occurrence frequency" in terms of five semantic items "very high", "high", "medium", "low", and "very low", respectively. Similarly, the second and third rows are the experts' rankings of "detectability" and "severity".

Thus, according to Table 6, we can summarize three experts' judgements on three risks regarding three decision factors in tables 8-10. Each entry records the total counts/percentage of same judgement from experts. For example, in Table 7, 3 out 3 (100%) experts think that the "occurrence frequency" of Risk 1 is "very high"; only 1 out 3 (33%) of them think that the "severity" of Risk 1 is "high".

Table 6: Judgment of experts

Expert	Risk	Occurrence frequency	Detectability	Severity
B1	R1	M	L	VH
	R2	H	L	M
	R3	L	M	H
B2	R1	M	M	VH
	R2	M	M	M
	R3	M	L	VH
B3	R1	M	L	H
	R2	H	M	M
	R3	M	L	H

Table 7: Three experts' average judgment for risk 1

	VH	H	M	L	VL
Occurrence frequency	0	0	3 (100%)	0	0
Detectability	0	0	1(33%)	2(67%)	0
Severity	2(67%)	1(33%)	0	0	0

Table 8: Three experts' average judgment for risk 2

	VH	H	M	L	VL
Occurrence frequency	0	2(67%)	1(33%)	0	0
Detectability	0	0	2(67%)	1(33%)	0
Severity	0	0	3(100%)	0	0

Table 9: Three experts' average judgment for risk 3

	VH	H	M	L	VL
Occurrence frequency	0	0	2(67%)	1(33%)	0
Detectability	0	0	1(33%)	2(67%)	0
Severity	1(33%)	2(67%)	0	0	0

$$x^1 = \begin{bmatrix} x^1_{o1}\, x^1_{o2}\, x^1_{o3}\, x^1_{o4}\, x^1_{o5} \\ x^1_{d1}\, x^1_{d2}\, x^1_{d3}\, x^1_{d4}\, x^1_{d5} \\ x^1_{s1}\, x^1_{s2}\, x^1_{s3}\, x^1_{s4}\, x^1_{s5} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0.33 & 0.67 & 0 \\ 0.67 & 0.33 & 0 & 0 & 0 \end{bmatrix} \tag{4}$$

$$x^2 = \begin{bmatrix} x^2_{o1}\, x^2_{o2}\, x^2_{o3}\, x^2_{o4}\, x^2_{o5} \\ x^2_{d1}\, x^2_{d2}\, x^2_{d3}\, x^2_{d4}\, x^2_{d5} \\ x^2_{s1}\, x^2_{s2}\, x^2_{s3}\, x^2_{s4}\, x^2_{s5} \end{bmatrix} = \begin{bmatrix} 0 & 0.67 & 0.33 & 0 & 0 \\ 0 & 0 & 0.67 & 0.33 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{5}$$

$$x^3 = \begin{bmatrix} x^3_{o1}\, x^3_{o2}\, x^3_{o3}\, x^3_{o4}\, x^3_{o5} \\ x^3_{d1}\, x^3_{d2}\, x^3_{d3}\, x^3_{d4}\, x^3_{d5} \\ x^3_{s1}\, x^3_{s2}\, x^3_{s3}\, x^3_{s4}\, x^3_{s5} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0.67 & 0.33 & 0 \\ 0 & 0 & 0.33 & 0.67 & 0 \\ 0.33 & 0.67 & 0 & 0 & 0 \end{bmatrix} \tag{6}$$

Subsequently, the judgment matrices for risks 1, 2 and 3 are listed in matrices of (4) (5) and (6). They represent the rankings from three experts given in terms of five semantic items.

4.4 Improve Precision through Grey System Theory

In the current section, we firstly establish an assessment matrix based on step 3 and then a reference matrix using the most risky semantic item. Subsequently, the degree of relevancy is measured through the grey correlation coefficient. Finally, we apply weights to decision factors (occurrence frequency, detectability, and severity) to differentiate their relevant importance.

4.4.1 Establishment of assessment matrix and reference matrix

The assessment matrix is built based on the judgment matrices of (4) (5) and (6) and specific numbers of sematic items. The assessment matrix for three risks are formed as follow:

$$R = \begin{bmatrix} r_{1o} & r_{1d} & r_{1s} \\ r_{2o} & r_{2d} & r_{2s} \\ r_{3o} & r_{3d} & r_{3s} \end{bmatrix} \tag{7}$$

Where

$r_{io} = I_{vh} \times x^i_{o1} + I_h \times x^i_{o2} + I_m \times x^i_{o3} + I_l \times x^i_{o4} + I_{vl} \times x^i_{o5}$ is the score of "occurrence frequency" for risk i.

$r_{id} = I_{vh} \times x^i_{d1} + I_h \times x^i_{d2} + I_m \times x^i_{d3} + I_l \times x^i_{d4} + I_{vl} \times x^i_{d5}$ is the score of "detectability" for risk i.

$r_{is} = I_{vh} \times x^i_{s1} + I_h \times x^i_{s2} + I_m \times x^i_{s3} + I_l \times x^i_{s4} + I_{vl} \times x^i_{s5}$ is the score of "severity" for risk i.

With specific numbers for five sematic items, e.g. $I_{vl} = 0.65, I_l = 3.4, I_m = 5.7$, $I_h = 8.2$, and $I_{vh} = 9.7$, we have:

- For risk 1, $r_{1o} = 5.7, r_{1d} = 4.2, r_{1s} = 8.9$;
- For risk 2, $r_{2o} = 7.4, r_{2d} = 4.9, r_{2s} = 5.7$;
- For risk 3, $r_{3o} = 4.9, r_{3d} = 4.2, r_{3s} = 8.7$;

Then, we have the assessment matrix in (8).

$$R = \begin{bmatrix} r_{1o} & r_{1d} & r_{1s} \\ r_{2o} & r_{2d} & r_{2s} \\ r_{3o} & r_{3d} & r_{3s} \end{bmatrix} = \begin{bmatrix} 5.7 & 4.2 & 8.9 \\ 7.4 & 4.9 & 5.7 \\ 4.9 & 4.2 & 8.7 \end{bmatrix} \tag{8}$$

Furthermore, we use the specific number of semantic item "very high", e.g. 9.7 to establish the reference matrix in (9).

$$R_f = \begin{bmatrix} r_{fo} & r_{fd} & r_{fs} \end{bmatrix} = \begin{bmatrix} 9.7 & 9.7 & 9.7 \end{bmatrix} \tag{9}$$

This reference matrix represents a very risky situation of a risk factor where the "occurrence frequency", "detectability", and "severity" are all "very high" (Table 4).

4.4.2 Calculating the grey correlation coefficient

Now with the assessment matrix R in (8) and the reference matrix R_f in (9), we can calculate the grey correlation coefficient between them using the grey correlation coefficient function (10) (Du et al., 2011):

$$\lambda(x_{fj}, x_{ij}) = \frac{\underset{i}{\min}|x_{fj} - x_{ij}| + v\underset{i}{\max}|x_{fj} - x_{ij}|}{|x_{fj} - x_{ij}| + v\underset{i}{\max}|x_{fj} - x_{ij}|} \tag{10}$$

Where

i refers to risk i;

j refers to decision factor j;

f refers to the reference matrix entry;

$\lambda(x_{fj}, x_{ij})$ refers to the grey correlation coefficient of entries x_{fj} and x_{ij};

v is the distinguishing coefficient; its value is within [0,1] and normally $v = 0.5$.

Table 10 presents the results of all $|x_{fj} - x_{ij}|$ and the minimal and maximal values are $\underset{i}{\min}|x_f - x_i| = 0.8$ and $\underset{i}{\max}|x_f - x_i| = 5.5$.

Thus, we have

$$\lambda_{1o} = \frac{\underset{i}{\min}|x_{fj} - x_{ij}| + 0.5\underset{i}{\max}|x_{fj} - x_{ij}|}{|x_{fj} - x_{ij}| + 0.5\underset{i}{\max}|x_{fj} - x_{ij}|} = \frac{0.8 + 0.5 \times 5.5}{4 + 0.5 \times 5.5} = 0.52 \tag{11}$$

Table 10: Results of all $|x_{fj} - x_{ij}|$

No.	Occurrence frequency	Detectability	Severity
$\Delta_{1j} = \|x_{fj} - x_{1j}\|$	$\|x_{fo} - x_{1o}\|= 4$	$\|x_{fd} - x_{1d}\|= 5.5$	$\|x_{fs} - x_{1s}\|= 0.8$
$\Delta_{2j} = \|x_{fj} - x_{2j}\|$	$\|x_{fo} - x_{2o}\|= 2.3$	$\|x_{fd} - x_{2d}\|= 4.8$	$\|x_{fs} - x_{2s}\|= 4$
$\Delta_{3j} = \|x_{fj} - x_{3j}\|$	$\|x_{fo} - x_{3o}\|= 4.8$	$\|x_{fd} - x_{3d}\|= 5.5$	$\|x_{fs} - x_{3s}\|= 1$

Similarly, we can get the grey correlation coefficient matrix (12).

$$\lambda = \begin{bmatrix} \lambda_{1o} & \lambda_{1d} & \lambda_{1s} \\ \lambda_{2o} & \lambda_{2d} & \lambda_{2s} \\ \lambda_{3o} & \lambda_{3d} & \lambda_{3s} \end{bmatrix} = \begin{bmatrix} 0.52 & 0.43 & 1 \\ 0.7 & 0.47 & 0.52 \\ 0.47 & 0.43 & 0.95 \end{bmatrix} \tag{12}$$

Furthermore, assuming the weights of decision factors are given in matrix (13).

$$\omega = \begin{bmatrix} 0.3 & 0.2 & 0.5 \end{bmatrix} \tag{13}$$

Where ω_o is the weight of Occurrence frequency, ω_d the weight of detectability, and ω_s the weight of severity.

We have

$$G = \begin{bmatrix} \omega_o\lambda_{1o} + \omega_d\lambda_{1d} + \omega_s\lambda_{1s} \\ \omega_o\lambda_{2o} + \omega_d\lambda_{2d} + \omega_s\lambda_{2s} \\ \omega_o\lambda_{3o} + \omega_d\lambda_{3d} + \omega_s\lambda_{3s} \end{bmatrix} = \begin{bmatrix} 0.742 \\ 0.564 \\ 0.702 \end{bmatrix} \tag{14}$$

Matrix G is the final rankings of three risks regarding three decision factors considering three experts' judgement. The final scores of risks 1, 2, and 3 are 0.742, 0.564, and 0.702, respectively. As the 0.742 is the greatest, R1 is the most risky one while R3 is the second and R2, the third. In summary, from the highest to the lowest in term of risk impacts, the ranking of studied risks is R1>R3>R2.

4.5 Compare the Traditional and the Improved FMEA

For the assessment matrix R (8), the RPN applying the traditional FMEA is as follows.

$$RPN = \begin{bmatrix} r_{1o} \times r_{1d} \times r_{1s} \\ r_{2o} \times r_{2d} \times r_{2s} \\ r_{3o} \times r_{3d} \times r_{3s} \end{bmatrix} = \begin{bmatrix} 5.7 \times 4.2 \times 8.9 \\ 7.4 \times 4.9 \times 5.7 \\ 4.9 \times 4.2 \times 8.7 \end{bmatrix} = \begin{bmatrix} 213 \\ 206 \\ 179 \end{bmatrix} \tag{15}$$

Thus, the ranking of risks is R1>R2>R3, which is different from the outcome of the improved FMEA in matrix (14). The reason is that the improved FMEA considers weights (matrix (13)) for three decision factors.

Furthermore, if we directly include those weights into the assessment matrix (8) without applying the grey correlation coefficient. The result is as follows.

$$RPN^1 = \begin{bmatrix} 5.7 \times 0.3 \times 4.2 \times 0.2 \times 8.9 \times 0.5 \\ 7.4 \times 0.3 \times 4.9 \times 0.2 \times 5.7 \times 0.5 \\ 4.9 \times 0.3 \times 4.2 \times 0.2 \times 8.7 \times 0.5 \end{bmatrix} = \begin{bmatrix} 6.39 \\ 6.18 \\ 5.37 \end{bmatrix} \tag{16}$$

The new ranking becomes the same as the one from the traditional FMEA, e.g. R1>R2>R3, but different from the improved FMEA. This emphasizes the importance of including the grey correlation coefficient in allocating appropriate weightages to decision factors.

5 Conclusion

In this study, the methodology to improve FMEA for supply chain risk identification is proposed in order to reduce the bias from domain experts and improve the ranking accuracy.

First of all, the subjective bias in ranking from experts can be reduced through establishing semantic items, which are linked to numerical scores through fuzzy membership functions. In this way, even though experts give difference scores for the same level of risk impact, those scores can still represent the same semantic meaning, perhaps in different degrees. In this way, the bias from experts can be reduced.

Furthermore, in order to build a membership function, three parameters are requested to represent the coverage of a semantic item in terms of numerical scores. This enables experts to think thoroughly and further improves the reliability of their judgement.

Finally, in the traditional FMEA, decision factors are treated equally in their roles to determine the impact of a risk. This may not rational. In the improved FMEA, we differentiate the importance of decision factors in ranking risk impacts. The grey correlation coefficient is adopted to extract appropriate weights for decision factors. This further improves the accuracy of the ranking.

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