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Evaluating Disruption Risk to Foster Resilience in Humanitarian Supply Chain: An Integrated SV-PSI and EDAS Model

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Abstract. The evaluation of the risks in humanitarian supply chain operations is crucial to prevent losses due to disasters. However, many quantitative studies in the literature are aimed at the profit-oriented supply chain, while those in the field are based on the subjective preferences of decision-makers, making risk prioritization less accurate. To fill this gap, this study presents a theoretically improved approach for this purpose by integrating statistical variance, preference selection index (PSI), and EDAS methods into humanitarian supply chain FMEA to prioritize risks. To demonstrate the applicability of the model, numerical calculations and sensitivity tests were conducted using secondary data. The test results indicate that the dimension of risk detection capability is an important dimension for proactive risk prevention. Furthermore, communication in humanitarian disaster response supply chain operations is a very important enabler for the resilience of the humanitarian supply chain. In the future, inclusion of the influence of relationships between decision criteria and between risk factors is recommended as a direction for further research from this study.

Keywords: Humanitarian Supply Chain, Risk Assessment, FMEA, Resilience, EDAS

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1. Introduction

According to previous studies [1] over the last twenty years, the increasing number of natural disasters has caused a large amount of loss of life and economic losses at an alarming rate. This situation can be mitigated by improving, at a methodological level, the reliability of humanitarian response operations by making them free of failures and, consequently, successful [2]. By identifying critical risk factors that affect the malfunctioning of disaster response operations [3], humanitarian decision-makers will be informed about which critical factors should be prioritized for reduction. However, studies in this field have not yet succeeded in this [4]. One of the challenges is determining the weighting of decision criteria that serves as the basis for assessing the level of risk impact in disaster emergency response operations.

In humanitarian supply chain operations, the identification and evaluation of the criticality of risk is important since decision-makers have limited resources to tackle the adverse impact of disaster occurrence. To this end, a supporting approach could be development of the failure mode and effect analysis (FMEA). It is a qualitative risk evaluation tool used to identify and assess the criticality of risks through risk priority number (RPN) and determine appropriate countermeasures to prevent similar risks in the future [5,6]. Since it was introduced almost 70 years ago by the military, FMEA has been applied in various sectors and continuously developed [7]. Despite the applications of the FMEA as a multi-criteria risk assessment tool being variegated across multiple fields, those in the humanitarian supply chain are scarce [8,9]. A compilation study on the development of risk assessment tools using the FMEA method as written by [10] and [11] focuses more on the manufacturing process domain and not on disaster response operations. In the context of disaster management, several studies related to the FMEA method have been conducted. The research work of [12] combined FMEA and Grey Relational Analysis to identify the most critical risks in mitigating the adverse impact of the COVID-19 pandemic. Chukwuka et al. [13] presented the integration of the Analytical Hierarchy Process (AHP) and fuzzy logic for ranking critical risks in an emergency supply chain. The Delphi method and FMEA are utilized to evaluate humanitarian logistical risks by [14]. Although the study of the application of the FMEA method in emergency supply chain continues to evolve as mentioned above, limitations on risk prioritization in humanitarian situations still exist in those studies, and there is a demand for better humanitarian risk prioritization techniques.

Minguito and Banluta [12], despite already using the grey relational analysis method to consider the impact of risk prioritization, based their risk evaluation approach on subjective decision-maker preferences. The study of [13] excludes the influence of objective information contained in the risk criteria data. The scientific work of [14] still heavily relies on the subjectivity of decision-makers in determining the weight of risk criteria. Consequently, it is clear that no previous studies consider decision-makers' subjective and objective information in the risk prioritization criteria data simultaneously in risk evaluation. Reliance only on decision-makers' subjective risk assessment can cause inaccurate risk prioritization [15]. In order to prevent the problem of inaccurate risk prioritization, the integration of the subjective risk prioritization method and the objective risk prioritization approach will be most beneficial.

To fill this gap, this study integrates a statistical variance model and the preference selection index (PSI) method and links it with the EDAS technique to select the most critical risk in the humanitarian supply chain. The novelty of this contribution is to determine the subjective and objective weight of risk decision criteria simultaneously and combine it with the EDAS method, which, to the best of our knowledge, has never been presented in previous contributions in the humanitarian supply chain disaster management literature. The fundamental question underlying this study is how to create a risk evaluation model in the humanitarian supply chain with consideration of decision-makers' subjective preferences and the objectivity of risk criteria data based on the integration of the SV, PSI, and EDAS methods.

2. Methods

2.1. Humanitarian Supply Chain FMEA

Humanitarian supply chain FMEA is one of the FMEA types aimed at evaluating the risks in the humanitarian supply chain in delivering the needs of beneficiaries. Operating under uncertain situations with time pressure, many obstacles are hindering humanitarian operations, causing them to become very prone to being unreliable. Moreover, varying risk factors within the humanitarian supply chain can cause derailment of its operation [16]. The category of risk mode in the disaster management cycle can be referred to Tay et al. [16]. Similar to design and manufacturing FMEA, the criticality of risks in humanitarian supply chain FMEA is measured in a metric called the risk priority number obtained by multiplying the score of the likelihood of failure event occurrence, its detectability, and the scale of its severity. Recently, transforming FMEA as a predictive risk assessment tool, artificial intelligence-based risk prioritization in FMEA is increasingly introduced, as exemplified by the works of [17–20].

2.2. Statistical Variance Method

The statistical variance method is a kind of multi-criteria weight determination based on the score of the information variance of the decision criteria data [22]. Compared to another objective decision criterion, the Shannon entropy, the statistical variance method is simple in its calculation, making it competitive enough to be an alternative objective decision criterion weightage method. The steps to implement this objective weightage decision criteria can be consulted in [23]. Let now V_j represent the objective weight from the statistical variance method, and later it becomes the input to determine hybrid weight criteria combined with subjective weight criteria using the preference selection index.

2.3. Preference Selection Index Method

The Preference Selection Index (PSI) method is typical of multi-criteria decision-making methods. Compared to the pairwise criteria comparison like the AHP and Best Worst Method (BWM), the PSI method is more beneficial since it does not need to undertake decision criteria pairwise comparison and consistency checking, enabling a more efficient decision-making process. The implementing steps to apply the PSI can be consulted in [24]. Now suppose U_j as the subjective risk criteria weight based on the PSI technique. The hybrid of weight criteria W_j, which presents the combination of subjective weight U_j and objective weightV_j, is formulated as in equation (1).

$$W_j = \alpha U_j + (1 - \alpha)V_j \tag{1}$$

In equation (1), α represent the coefficient of the subjective weight of decision criteria and (1- α) denotes the objective weight of every decision criterion. The score of is usually set at 0.5 for the sake of calculation simplicity. Referring to [21] and [22], if the decision-maker does not lean towards any particular approach for determining the criteria weights, then the value of α is set at 0.5.

2.4. EDAS Method

The EDAS method is basically a method resulting from combining the TOPSIS and simple additive weighting. The advantage of the EDAS method lies in its simplicity and the elimination of the determination of positive and negative ideal points, which are difficult to realize in the real world.
The stages of implementing the EDAS method follow the procedure as follows:

2.4.1. Determination of decision matrix X = $|X_{mk}|$ with k criteria and m alternatives with (*k, m* = 1, 2, 3….).

The decision matrix is defined as $X = |x_{ji}|_{mk} = \begin{vmatrix} x_{11} & x_{21} & x_{1m} \\ x_{21} & \ddots & x_2m \\ x_{k1} & x_{k2} & x_{mk} \end{vmatrix}$

2.4.2. Determination of the average solution from the decision matrix X using equation 2.

$$X_m = \frac{\sum_{k=1}^{m} X_{mn}}{m} \tag{2}$$

2.4.3. Evaluating positive deviation (PD) and negative deviation (ND) values by referring to typical attributes.
For attributes that are beneficial attribute, where higher values are more desirable, positive deviation is evaluated using Equation 3.

$$PD_{km} = \frac{max\big(0, (X_{km} - B_m)\big)}{B} \tag{3}$$

Meanwhile, Equation 4 is used to evaluate the negative deviation.

$$ND_{km} = \frac{max\big(0, (B_m - X_{km})\big)}{B_m} \tag{4}$$

For decision criteria that are cost-oriented, the positive deviation (PD) value is determined by the Equation 5.

$$PD_{km} = \frac{max\big(0 - (B_m - X_{mn})\big)}{B_m} \tag{5}$$

The negative deviation (ND) value is counted using Equation 6.

$$ND_{km} = \frac{max\big(0, (x_{mn} - B_m)\big)}{B_m} \tag{6}$$

2.4.4. Determining the weighted total positive deviation and the weighted total negative deviation.
The weighted total positive deviation score P_k and the weighted total negative deviation N_k are determined using the Equation 7 and 8.

$$P_k = \sum_{k=1}^{m} Q_k PD_{km} \tag{7}$$

$$N_k = \sum_{k=1}^{m} Q_k \, ND_{km} \tag{8}$$

2.4.5. Normalization of the weighted positive deviations and weighted negative deviation.
The next step is the normalization of weighted positive deviations and weighted negative deviations. For the weighted positive deviation, Equation 9 is used for normalization.

$$NP_k = \frac{1}{max_k P_k} \tag{9}$$

Meanwhile, for normalization of the weighted negative deviation, equation used is Equation 10.

$$NN_k = 1 - \frac{N_k}{max_k N_k} \tag{10}$$

2.4.6. Determination of the priority score of every decision alternative.
The priority score for every decision option is determined by Equation 11.

$$PS_k = \frac{1}{2}(NP_k + NN_k) \tag{11}$$

The alternative with the highest priority score is then designated as the first priority, followed by other options with lower preference scores as the second choice, and so on. To test the robustness of the decision support model based on the integration of the SV, PSI, and EDAS methods, a sensitivity analysis was conducted by altering the range of input values for decision criteria weights and observing their effect on the ranking order of risk priorities [23]. For illustrative purposes, numerical data from the study of [24] are used as basis to demonstrate the applicability of the proposed model.

3. Results and Discussion

3.1. Determining the risk modes in humanitarian supply chain

Referring to the numerical data from [24] study, ten risk modes in the humanitarian supply chain logistics process are presented in Table 1.

Table 1. The mode of risk factors affecting the delivery of logistics material in the humanitarian supply chain [24]

Risk Factor	Decision Criteria				Rank
	Severity score	Occurrence score	Detection score	Risk Priority score	
Permits to import are taking long (too many bodies, documentation and registration)	7.64	7.89	6.27	378	1
Communication problems between freight forwarders and supply team in receiving country	7.64	7.04	6.89	371	2
Supplier's failure to meet agreed delivery time	7.92	7.13	6.54	369	3
Freight forwarder's failure to collect and ship consignment at agreed time	7.92	7.08	6.56	368	4
Port congestion leading to shipment delays (lack of capacity)	7.29	7.34	6.24	365	5
Manual order processing at port of entry leading to clearing delays	7.28	7.29	6.28	333	6
Trans-shipment delays at transit hubs due to congestion	7.28	7.14	5.93	308	7
Clearing agent's failure to perform customs clearance processes on time	7.29	6.94	6.05	305	8
Exposure to natural disasters and accidents during transit	7.26	6.80	6.06	299	9
Pipeline visibility and tracking problems from port of origin to port of entry	7.26	6.49	5.96	281	10

Table 1 presents the risk modes in the humanitarian logistics supply chain, as cited from [24] with three risk decision criteria, occurrence of risk, detectability of risk and severity of risk impact. The table identifies 10 risk modes in the distribution chain, beginning with risk mode no. 1, which is 'Permits to import are taking long (too many bodies, documentation, and registration),' and ending with risk mode no. 10, which is 'Pipeline visibility and tracking problems from port of origin to port of entry.' Referring to the Risk Priority Number (RPN) scores, the most influential risk mode is risk mode no. 1, with the highest RPN score of 378, followed by risk mode no. 2 with an RPN score of 371, and concluding with a risk mode that has an RPN score of 281. Using the conventional FMEA approach, the most impactful risk is risk mode no. 1 related to permission of product import, followed by risk mode no. 10 related to visibility of imported logistical goods as the least impactful risk.

3.2. Determination of the hybrid risk criteria weight

The hybrid criteria weight is the decision criteria weight derived from the combination of subjective and objective criteria weights. The determination of the objective criteria weight is carried out using the statistical variance method and the subjective decision criteria weight is determined using the PSI method and the results are then presented in Table 2.

Table 2. Hybrid Risk decision criteria from case study

Risk Decision Criteria Weightage Approach	**Risk Decision Criteria**		
	Frequency of risk occurrence	**Detectability of risk occurrence**	**Severity impact of risk occurrence**
Hybrid risk criteria weight	0.2827	0.54820	0.16282

The calculation results in Table 2 show that among the three risk criteria, the detectability risk criterion has the largest criterion weight and is the most influential criterion, followed by the severity criterion in second place and the severity criterion in third place.

3.3. Risk Ranking Determination using the EDAS Method

The mechanism for selecting risk rankings through the use of the EDAS method is carried out using Equations 2 to the Equation 11. The calculations' result is presented in Table 3.

Table 3. Risk factor ranking using the EDAS method

Risk Code Number	**Risk Factor**	**Risk Rank**
1	Permits to import are taking long (too many bodies, documentation and registration)	7
2	Communication problems between freight forwarders and supply team in receiving country	1
3	Supplier's failure to meet agreed delivery time	3
4	Freight forwarder's failure to collect and ship consignment at agreed time	2
5	Port congestion leading to shipment delays (lack of capacity)	9
6	Manual order processing at port of entry leading to clearing delays	6
7	Trans-shipment delays at transit hubs due to congestion	10
8	Clearing agent's failure to perform customs clearance processes on time	8
9	Exposure to natural disasters and accidents during transit	5
10	Pipeline visibility and tracking problems from port of origin to port of entry	4

Table 4 presents the ranking results using the EDAS method. The ranking results indicate that the disaster-responsive supply chain risk with the greatest impact is risk factor number 2, which is "Communication problems between freight forwarders and the supply team in the receiving country." Meanwhile, the risk factor with the least impact is risk number 7, namely "Trans-shipment delays at transit hubs due to congestion." Considering the influence of the risk criteria weights, there is a change in the ranking in the evaluation of risk criticality in the logistics supply chain, as reflected in Table 4.

3.4. Comparison of Rankings According to Traditional FMEA and the EDAS Method

To examine whether the weight of criteria affects risk ranking in disaster response supply chains, a comparison of risk rankings was conducted, and the results are presented in Table 4.

Table 4. Comparison of risk influence rankings in the supply chain between conventional FMEA and the EDAS method

Risk Code Number	Risk Factor	Risk priority number	
		Traditional FMEA	EDAS
1	Permits to import are taking long (too many bodies, documentation and registration)	1	7
2	Communication problems between freight forwarders and supply team in receiving country	2	1
3	Supplier's failure to meet agreed delivery time	3	3
4	Freight forwarder's failure to collect and ship consignment at agreed time	4	2
5	Port congestion leading to shipment delays (lack of capacity)	5	9
6	Manual order processing at port of entry leading to clearing delays	6	6
7	Trans-shipment delays at transit hubs due to congestion	7	10
8	Clearing agent's failure to perform customs clearance processes on time	8	8
9	Exposure to natural disasters and accidents during transit	9	5
10	Pipeline visibility and tracking problems from port of origin to port of entry	10	4

Table 4 presents a comparison of risk rankings in the supply chain using the conventional FMEA method and the FMEA method integrated with the statistical variance-preference score and EDAS methods. The comparison results indicate differences in risk rankings between the conventional FMEA method and the hybrid FMEA method. In the conventional FMEA method, the highest-ranked risk is Risk No. 1, which involves the lengthy process of obtaining import permits for goods, whereas according to the hybrid multi-criteria method, the most significant risk is communication between teams within the humanitarian logistics supply chain network. This difference in risk ranking arises from the differing operational mechanisms of the two methodologies. In the traditional FMEA method, all three risk decision criteria are considered to have equal weight, whereas in the hybrid model based on the integration of the statistical variance, preference score, and EDAS methods, the influence of criteria weight. This differentiating factor causes a shift in the ranking between the conventional FMEA method and the hybrid FMEA method based on the integration of the SV, PSI, and EDAS methods. The numerical calculations produced show similarity with the study by [25], which indicates that communication factors become very important operational enablers for the smooth operation of disaster response supply chain.

3.5. Sensitivity Analysis

The sensitivity testing of the model is intended to examine the robustness of the model against changes in the weights of risk decision criteria. The sensitivity testing mechanism is conducted by referring to the study by [26] and by altering the weights of decision criteria across various scenarios. The first scenario relates to the weights of the criteria obtained from the combination of the SV and PSI methods. The second scenario pertains to a situation where decision-makers place more importance on the frequency aspect of risk factors. The third scenario concerns a situation where the detection aspect of risk events is considered more important by decision-makers. Subsequently, the fourth scenario relates to a situation where the impact aspect of risk is deemed more important by decision-makers. The final scenario is a situation where decision-makers remain neutral regarding the influence of criteria weights. The results of the sensitivity tests across these five scenarios are presented in Table 5.

Table 5. Sensitivity Testing of case example

Risk Factor	Scenario type				
	Original Weight O = 0.2827; D = 0.54820; S = 0.16282	Occurrence Focused O=0.500; D= 0.250; S = 0.250	Detection Focused O= 0.25; D = 0.50; S = 0.25	Severity Focused O = 0.25; D = 0.25; S = 0.50	Equal Weight O = 0.333; D = 0.333; S = 0.333
R1	7	10	7	8	10
R2	1	2	1	1	1
R3	3	4	3	5	4
R4	2	3	2	4	3
R5	9	8	9	7	8
R6	6	6	6	3	6
R7	10	9	10	10	9
R8	8	5	8	6	7
R9	5	2	5	2	2
R10	4	1	4	3	5

The sensitivity test results indicate that in dynamic and measurable situations, risk factor R2 is the most influential risk factor on the operational supply of emergency response operation. If there is a possibility of an increase in risk occurrences, decision-makers need to pay attention to risk factor R10. If decision maker leans more toward increasing of risk occurrence frequency, risk factor R10 becomes the most impactful risk, marked as rank 1, while R2 ranks second. If decision-makers prioritize risk detection, the first rank is occupied by risk R2 and a shift occurs between R7 and R8. When the impact factor is considered the most important by decision-makers, risk factor R2 remains the main priority, and risk factors R9 and R10 become crucial to consider. Among all scenarios, the risk factor R7 is a typical risk that has the lowest threat compared to other risk factors. The scenario with equal weights still shows that risk factor R2 remains the most influential risk factor, but decision-makers need to pay attention to risk factor R9 and R4 after R2.

In general, the proposed model overcomes the limitations of previous studies in applying risk management tools in humanitarian supply chains, which do not determine the weight of risk prioritization criteria using hybrid-orientated multi-criteria decision-making tools. Using a simpler approach to quantify the weight of risk reprioritization criteria, this paper offers an alternative in lieu of reliance on using pairwise comparison criteria based on the use of the AHP and/or the Analytic Network Process (ANP) techniques. In this regard, the proposed model overcomes some limitations about the practicality and pragmatism of the approaches combining AHP and ANP [27]. The improved model was never presented in previous risk humanitarian supply chain management studies. The merit of the model offered is concerning the inclusion of decision-maker risk ranking preference and risk criteria data objectively in a simultaneous manner using a simpler and more practical approach. It will help decision-makers' determination on the most critical risk factor among competing risks for better preparing the emergency response supply chain.

The proposed model can also be declined in traditional supply chains to make FMEA-based optimization approaches more suitable in the post-pandemic period we are experiencing [28]. In this way, the results of the proposed model can be useful for providing the basis for prospective studies aimed at investigating the repercussions of emergency scenarios on other aspects, such as product development and environmental sustainability [29]. Previous studies regarding the application of the EDAS method, as compiled by [30] and [31], have failed to show the use of the EDAS method in identifying the most influential risks in disaster response supply chains. In relation to sustainability, the theoretical model contributed by this study provides an understanding of which types of risks have the greatest impact on the operational capability of collaborative disaster response operations. By identifying the operational risks that have the most significant impact, decision-makers can focus more on mitigation efforts for the most influential risks. Furthermore, by including sensitivity testing, decision-makers can determine the influence of uncertainty situation dynamics that affect the smooth execution of disaster response operations, which in the end will be beneficial for policy adaptation.

The methodological stages proposed in this research provide emergency disaster operation practitioners with an understanding of how to combine decision-makers' subjective preferences and data-driven decision-making processes to evaluate the impact of risks on humanitarian response operation. The results of this study offer decision guidance in determining the most critical operational risk of the disaster response supply chain among competing risks to be mitigated. Using sensitivity tests enables decision-makers to validate the impact of changing the weight of their decision criteria on the priority of risk mitigation strategy.

4. Conclusion

In this study, statistical variance, PSI and the EDAS method have been integrated into a novel model for assessing criticalities of risks in the humanitarian supply chain. The implementation of the model in a case example highlighted its main strengths and limitations. In general, the model can be considered an answer to the need to prevent the escalation of losses when disastrous events occur in the humanitarian supply chain. The model is more efficient than previous ones in the literature since it is not based on the use of a risk criteria pairwise comparison approach, which obliges one to undertake tedious decision-makers' consistency checking. This study also has limitations that must be taken into account. Considering that the study's analysis is based on secondary data with a setting in Africa, it is highly recommended to replicate the study using primary data from other locations to compare the similarities and differences in typical risks in disaster emergency response. Opportunities for further studies are viable in several directions to overcome the limitations of the proposed model. Considering risk criteria data uncertainty, the embodiment of rough set theory or grey relational analysis into the statistical variance-PSI-based risk prioritization model is the first research opportunity that can be pursued. The second path is concerned with the inclusion of the influence of interrelationships among risk factors in the humanitarian supply chain. At the same time, to improve the validity of the proposed model, the authors recommend reiteration through actual situations.

Supplementary Materials

The data that supports the findings of this study are available in this article.

Declaration of AI and AI assisted technologies in the writing process

Grammarly is used to improve paper readability After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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