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An Objective Multi-Attribute Decision-Making Framework for Identifying Critical Phases in Automotive Component Manufacturing

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Abstract: Efficient management of production processes in modern manufacturing depends on the timely identification of their most critical phases, as such recognition directly enhances process reliability, productivity, and product quality. To address this need, an objective multi-attribute decision-making (MADM) framework has been developed by integrating the Criteria Importance Through Inter-criteria Correlation (CRITIC) method with Pareto analysis, a well-established approach also referred to as ABC classification. Within this framework, a comprehensive set of evaluation criteria was determined in collaboration with a Process Failure Mode and Effects Analysis (PFMEA) team from a Tier-1 automotive manufacturer. The decision matrix was constructed from data extracted from PFMEA reports that had been subjected to preliminary statistical processing to ensure robustness and comparability. The relative importance of the criteria was then established using the CRITIC method, which objectively derives weights from statistical indicators such as the arithmetic mean, standard deviation, and inter-criteria correlation coefficients. The framework was subsequently applied to the PFMEA report for a rear axle assembly process, encompassing 16 discrete production phases. Pareto analysis was employed to classify the phases according to their criticality, thereby enabling a systematic prioritization of process risks. The resulting classification demonstrated strong consistency with expert evaluations and was confirmed to reflect real-world production conditions accurately. Beyond confirming methodological validity, the findings underscore the advantages of employing a fully objective weighting mechanism combined with a widely recognized prioritization tool, thereby offering a transparent and replicable basis for decision-making in complex manufacturing contexts. This integration not only supports continuous improvement and risk mitigation but also provides a scalable framework applicable to a broad range of industrial processes where critical phase identification is essential.

Keywords: Criteria Importance Through Inter-criteria Correlation; Pareto analysis; Process Failure Mode and Effects Analysis; Classification; Automotive manufacturing; Multi-attribute decision-making

1 Introduction

The automotive industry has always been characterized by a high level of production process complexity and has required the manufacturing and assembly of a large number of components and subassemblies. Modern technologies implemented in next-generation vehicles have significantly improved user experience and customer satisfaction, but they have also considerably increased the complexity of production processes. The advancement of existing production technologies, the introduction of new functionalities, and other changes emerging in the 21st century have necessitated the modernization of production equipment. Taken together, these developments have emphasized the growing need for more effective risk management in the automotive industry.

In addition to product quality, comfort, and reliability, increasing attention is being devoted to passenger safety. All these factors are significantly influenced by the production process itself, or more precisely, by the control of this process. One of the most widely used methodologies for identifying and analyzing potential failure modes in the automotive industry is the Failure Mode and Effect Analysis (FMEA). According to the current handbook [1], which provides guidelines for the application of FMEA, the method can vary depending on whether it is applied during the design phase, production phase, or during field operation monitoring. The version utilized in this study is Process Failure Mode and Effects Analysis (PFMEA), which is applied during the manufacturing phase in automotive industry companies. It is important to note that the application of FMEA is prescribed by the International Automotive Task Force (IATF) 16949 standard [2] and is mandatory for all companies that are suppliers within the automotive supply chain.

PFMEA methodology is based on the identification and evaluation of failure modes. The evaluation is performed based on three risk factors: severity (S), occurrence (O), and detectability (D). These are typically assessed on a scale from 1 to 10, as defined in the handbook [1]. Traditionally, the overall risk, or, as it is sometimes referred to, the overall priority, is determined using the Risk Priority Number (RPN) [3], which is calculated as the multiplication of the three aforementioned risk factors. The latest version of the handbook replaces the RPN with the Action Priority (AP) methodology. Although the RPN approach has several shortcomings [4–6], unlike AP, which classifies failure modes into Low (L), Medium (M), or High (H) priority categories, RPN provides a quantitative indicator, which remains one of its main advantages. For this reason, RPN was used as the basis for analysis in this study.

Although PFMEA is a highly useful analysis that relies on expert knowledge of the production process, available documentation, and historical data, relying solely on individual RPN values or AP priorities for each failure mode may lead to a subjective or incomplete understanding of risks at the process or sub-process level. Therefore, this study proposes an integrated evaluation approach that allows for the assessment of production process phases, rather than just individual failure modes.

The proposed model is based solely on data already available in the PFMEA report and does not require any additional evaluations or expert assessments. Based on the PFMEA report, a total of five criteria were defined: (1) the total number of failure modes within a process phase, (2) the sum of RPN values, (3) the average RPN value, (4) the maximum RPN value, and (5) the number of failure modes with an RPN value exceeding 100. The model was tested on the rear axle assembly process in a Tier 1 supplier company within the automotive supply chain. The production process, from the receipt of raw materials to delivery to the customer, consists of 16 phases, which are presented later in the paper.

The objective of this study is to determine the priority of the production process phases in an objective manner using only data from the PFMEA report. For this purpose, two methods were used. The Criteria Importance Through Inter-criteria Correlation (CRITIC) method [7, 8] was employed to determine the weights of the criteria. This method is known for assigning weights through objective statistical analysis based on input data. Therefore, it does not rely on decision-makers' judgments or the aggregation of their assessments, as was done in some studies that relied on a subjective approach [9]. Pareto analysis, also known as ABC classification [10, 11], was used to determine the priority ranking of each phase. Therefore, the proposed approach can be considered an extension of the PFMEA analysis that does not require additional data collection or analysis but relies exclusively on existing information.

This type of analysis can be of significant value to company management, as it enables an objective assessment of the priority of analyzed phases, thus supporting more efficient resource allocation and directing monitoring efforts toward the most critical segments of the production process.

In the relevant literature, studies can be found where authors combine FMEA with Pareto analysis, whereas the combination of FMEA and the CRITIC method is not present in relevant publications. In two analyzed studies, FMEA and Pareto were used to determine risk priorities in different fields, namely geotechnics [12] and medicine [13]. Additionally, this combination is applied in construction [14], the automotive industry [15], and the food industry [16, 17] to assess process reliability and ensure compliance with standards.

However, the combination of FMEA and multi-attribute decision-making (MADM) methods is not unfamiliar in the literature. On the contrary, such combinations are numerous and are used very frequently [18–22]. There is even a large number of studies in which FMEA has been extended with fuzzy MADM approaches, as demonstrated in the review paper [23].

However, none of the approaches focused on determining risk within each individual phase; instead, risks were analyzed separately for each failure mode, which gives additional significance to the proposed model. Moreover, the proposed model is not a classical extension of PFMEA, but can be seen as a supplement to the analysis itself, utilizing an objective approach and data that already exist in the PFMEA report.

After the introductory chapter, the methodology is explained in Section 2. Section 3 presents the research results, while Section 4 discusses the obtained findings. The most important conclusions of the study are provided in Section 5.

2 Methodology

The proposed methodology builds upon the standard PFMEA analysis by utilizing data extracted from a developed PFMEA report. While the standard report provides detailed information for each identified failure mode, it does not evaluate the process phases as integrated units. In order to identify the most critical stages of the process, such an extended analysis is necessary. This enables risk management efforts to be focused specifically on the most critical phases. In practice, this implies that these phases may require enhanced monitoring, or even redesign and optimization efforts.

Formally, the considered optimization problem can be defined as follows: Process phases are denoted by i, where $i = 1, ..., I$, and I is the total number of analyzed phases. The criteria, defined based on the PFMEA report data, are denoted by j, where $j = 1, ..., J$, and J represents the total number of considered criteria. Each criterion is indexed by j.

The proposed model consists of two phases. First, the weights of the considered criteria were objectively calculated using the CRITIC method. Subsequently, a Pareto analysis was applied to determine the priority of the analyzed process phases. A graphical representation of the proposed model is shown in Figure 1.

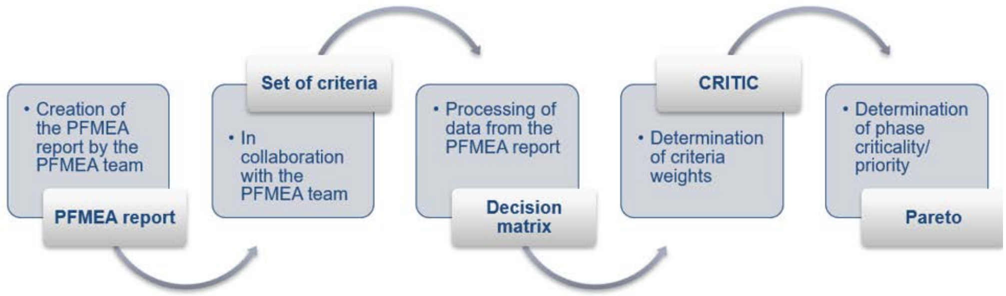

Figure 1. The proposed model

The following section presents the steps for applying the proposed model, namely the CRITIC and Pareto analysis.

2.1 Steps for Applying the CRITIC Method

In this study, the conventional CRITIC method [7] was applied using linear Max normalization [24]. The steps for applying the CRITIC method are as follows:

Step 1—Construct the decision matrix:

$$[D_{ij}]_{I\times J} \tag{1}$$

Step 2—Normalize values and form the normalized decision matrix:

$$[N_{ij}]_{I\times I} \tag{2}$$

where,

$$n_{ij} = \frac{d_{ij}}{d_j^{\max}} \tag{3}$$

Step 3—Calculate the arithmetic mean and standard deviation for each criterion:

$$\bar{n}_j = \frac{n_{ij}}{\sum\limits_{i=1,\ldots,I} n_{ij}} \tag{4}$$

$$S_j = \sqrt{\frac{1}{I-1}\cdot\sum_{i=1,\ldots,l}(n_{ij}-\bar{n}_j)^2} \tag{5}$$

Step 4—Calculate the correlation coefficient for each pair of criteria:

$$r_{jj'} = \frac{\sum\limits_{i=1,\ldots,l}((n_{ij}-\bar{n}_j)\cdot(n_{ij'}-\bar{n}_{j'}))}{\sqrt{\sum\limits_{i=1,\ldots,l}(n_{ij}-\bar{n}_j)^2\cdot\sum\limits_{i=1,\ldots,l}(n_{ij'}-\bar{n}_{j'})^2}} \tag{6}$$

Step 5—Determine the criterion weights:

$$W_j = S_j\cdot\sum_{j=1,\ldots,J}(1-r_{jj'}) \tag{7}$$

$$\omega_j = \frac{W_j}{\sum\limits_{j=1,\ldots,J} W_j} \tag{8}$$

2.2 Steps for Applying the Pareto Analysis

The steps of the standard Pareto analysis [10, 11] were applied in this study. The first two steps are identical to those in the application of the CRITIC method, so the remaining steps are as follows:

Step 1—Weighting the values from the normalized decision matrix and forming the weighted normalized decision matrix:

$$[O_{ij}]_{I \times J} \tag{9}$$

where,

$$o_{ij} = n_{ij} \cdot \omega_j \tag{10}$$

Step 2—Creating the individual value for each considered alternative:

$$v_i = \sum_{j=1}^{J} o_{ij} \tag{11}$$

Step 3—Normalization of the individual values for each considered alternative:

$$f_i = \frac{v_i}{\sum_{i=1}^{I} v_i} \tag{12}$$

Step 4—Sorting the alternatives based on their normalized values, f_i, in descending order.

Step 5—Calculating the cumulative sum of the sorted f_i values, cf_i.

Step 6—Classification according to the Pareto rule into A, B, and C categories. The classification is performed as follows: (1) Class A includes alternatives up to approximately 20% of the cumulative value; (2) Class B covers the range from Class A to approximately 95% of the cumulative value; (3) All remaining alternatives are classified as Class C.

Class A represents the highest-priority phases, which are the most critical. Class B includes medium-priority phases that should still be monitored, while Class C consists of the lowest-priority phases.

3 Results

In this study, the rear axle assembly production process was examined in a company that is a Tier 1 supplier in the supply chain. For the company under consideration, this is not the only product in its production portfolio, but it is regarded as the most important one and is delivered to the most important customer.

All phases were analyzed, from the receipt of materials from suppliers to the delivery of the final product to the customer. The phases were taken from the PFMEA report and are as follows:

- Reception of components and raw materials ($i = 1$);
- Incoming inspection of components and raw materials ($i = 2$);
- Handling and storage of controlled materials ($i = 3$);
- Welding of M12 nut ($i = 4$);
- Heat treatment ($i = 5$);
- Main welding operation (left/right arm) ($i = 6$);
- Laser cutting ($i = 7$);
- CO_2 welding ($i = 8$);
- Visual inspection and manual CO_2 welding ($i = 9$);
- Milling process ($i = 10$);
- Vision system inspection—MAP Vision ($i = 11$);
- Dimensional inspection (convergence and camber) ($i = 12$);
- Sandblasting ($i = 13$);
- Painting ($i = 14$);
- Installation of hydraulic bushing and labeling ($i = 15$); and
- Final delivery ($i = 16$).

As previously mentioned, the priority/criticality of the considered phases is determined based on five criteria. These criteria were defined during daily improvement meetings in collaboration with the company's PFMEA team. Based on constructive discussions, it was concluded that the following criteria are relevant to the problem under consideration:

- Total number of failure modes within a process phase ($j = 1$);
- Sum of RPN values ($j = 2$);
- Average RPN value ($j = 3$);

• Maximum RPN value ($j = 4$); and
• Number of failure modes with an RPN value exceeding 100 ($j = 5$).

This section is divided into two parts. The first part presents the procedure for determining the criteria weights using the CRITIC method, while the second part performs the classification of phases using Pareto analysis. It should be noted that the first two steps, namely, the formation of the decision matrix and the normalization of values, were carried out in the same manner for both methods. For this reason, in the case of the Pareto analysis, the procedure will be presented starting from the third step, i.e., the weighting of the normalized values.

3.1 Determination of Criteria Weights

Based on the processed data from the PFMEA report, a decision matrix was created, which is presented in Table 1. In this case, neither the name of the failure mode nor the individual value of the risk factor is relevant for the analysis under consideration.

Table 1. Decision matrix

i	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$	9	240	26.67	36	0
$i=2$	66	3252	49.27	96	0
$i=3$	8	334	41.75	60	0
$i=4$	9	480	53.33	84	0
$i=5$	5	268	53.60	64	0
$i=6$	21	870	41.43	81	0
$i=7$	14	609	43.50	84	0
$i=8$	93	4094	44.02	105	1
$i=9$	16	847	52.94	81	0
$i=10$	16	1082	67.63	84	0
$i=11$	6	280	46.67	80	0
$i=12$	2	192	96.00	96	0
$i=13$	4	204	51.00	72	0
$i=14$	7	504	72.00	72	0
$i=15$	9	548	60.89	84	0
$i=16$	8	460	57.50	84	0

The normalized values obtained by applying linear max normalization are presented in Table 2.

Table 2. Normalized decision matrix

i	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$	0.097	0.059	0.278	0.343	0.000
$i=2$	0.710	0.794	0.513	0.914	0.000
$i=3$	0.086	0.082	0.435	0.571	0.000
$i=4$	0.097	0.117	0.556	0.800	0.000
$i=5$	0.054	0.065	0.558	0.610	0.000
$i=6$	0.226	0.213	0.432	0.771	0.000
$i=7$	0.151	0.149	0.453	0.800	0.000
$i=8$	1.000	1.000	0.459	1.000	1.000
$i=9$	0.172	0.207	0.551	0.771	0.000
$i=10$	0.172	0.264	0.704	0.800	0.000
$i=11$	0.065	0.068	0.486	0.762	0.000
$i=12$	0.022	0.047	1.000	0.914	0.000
$i=13$	0.043	0.050	0.531	0.686	0.000
$i=14$	0.075	0.123	0.750	0.686	0.000
$i=15$	0.097	0.134	0.634	0.800	0.000
$i=16$	0.086	0.112	0.599	0.800	0.000

Then, the arithmetic mean of the values for each criterion is calculated.

$$\bar{n}_1 = 0.197 \quad \bar{n}_2 = 0.218 \quad \bar{n}_3 = 0.559 \quad \bar{n}_4 = 0.752 \quad \bar{n}_5 = 0.063$$

The standard deviation of the values for each criterion individually is:

$$S_1 = 0.268 \quad S_2 = 0.275 \quad S_3 = 0.163 \quad S_4 = 0.154 \quad S_5 = 0.250$$

The correlation coefficient for each pair of criteria is presented through the inter-criteria correlation matrix, as shown in Table 3.

Table 3. Inter-criteria correlation matrix

	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
j = 1	1	0.993	-0.248	0.540	0.800
j = 2	0.993	1	-0.173	0.585	0.758
j = 3	-0.248	-0.173	1	0.451	-0.164
j = 4	0.540	0.585	0.451	1	0.430
j = 5	0.800	0.758	-0.164	0.430	1

Through the subsequent procedure of the conventional CRITIC method, the weights of the criteria were determined, as illustrated in Figure 2.

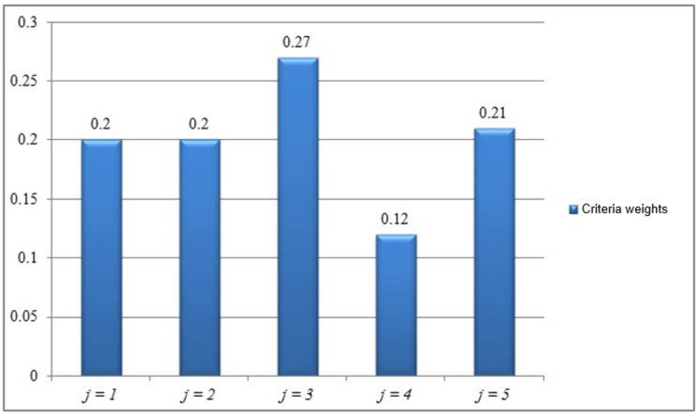

Figure 2. Criteria weights

The weights of the criteria can also be formally expressed as follows: $\omega_1 = 0.2$, $\omega_2 = 0.2$, $\omega_3 = 0.27$, $\omega_4 = 0.12$, and $\omega_5 = 0.21$.

3.2 Classification of Process Phases

The first two steps, namely the decision matrix and the normalized decision matrix, are taken from the CRITIC method. Thus, the weighting procedure is first applied, as presented in Table 4.

Table 4. Weighted normalized decision matrix

i	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$
$i=1$	0.019	0.012	0.075	0.041	0.000
$i=2$	0.142	0.159	0.139	0.110	0.000
$i=3$	0.017	0.016	0.117	0.069	0.000
$i=4$	0.019	0.023	0.150	0.096	0.000
$i=5$	0.011	0.013	0.151	0.073	0.000
$i=6$	0.045	0.043	0.117	0.093	0.000
$i=7$	0.030	0.030	0.122	0.096	0.000
$i=8$	0.200	0.200	0.124	0.120	0.210
$i=9$	0.034	0.041	0.149	0.093	0.000
$i=10$	0.034	0.053	0.190	0.096	0.000
$i=11$	0.013	0.014	0.131	0.091	0.000
$i=12$	0.004	0.009	0.270	0.110	0.000
$i=13$	0.009	0.010	0.143	0.082	0.000
$i=14$	0.015	0.025	0.203	0.082	0.000
$i=15$	0.019	0.027	0.171	0.096	0.000
$i=16$	0.017	0.022	0.162	0.096	0.000

Furthermore, by applying the conventional Pareto analysis procedure, the cumulative sum of the sorted f_i values was calculated, as shown in Table 5.

Table 5. Cumulative sum of the sorted f_i values

i	f_i	Normalized f_i	cf_i
$i = 8$	0.854	0.158	0.158
$i = 2$	0.549	0.102	0.260
$i = 12$	0.393	0.073	0.333
$i = 10$	0.373	0.069	0.402
$i = 14$	0.324	0.060	0.462
$i = 9$	0.317	0.059	0.521
$i = 15$	0.313	0.058	0.579
$i = 16$	0.297	0.055	0.634
$i = 6$	0.297	0.055	0.689
$i = 4$	0.289	0.054	0.743
$i = 7$	0.278	0.052	0.795
$i = 11$	0.249	0.046	0.841
$i = 5$	0.248	0.046	0.887
$i = 13$	0.244	0.045	0.932
$i = 3$	0.220	0.041	0.973
$i = 1$	0.147	0.027	1.000

The analysis of the obtained results was conducted in the following section. It is important to note that the results are applicable exclusively to the analyzed company and the specific PFMEA report under consideration. In any other case, since the CRITIC method is applied, the criterion weights would change depending on the input data. In this way, the proposed model is sufficiently flexible to be applied in any research or practical context.

4 Discussion

Based on Table 5, the considered process phases can be classified. In Pareto analysis, the boundaries often cannot be strictly defined at a specific percentage, and small deviations are allowed. In this case, through constructive discussion with the company's PFMEA team members, as well as consultations with production and maintenance managers, the classes of the considered phases were formed and are presented in Figure 3.

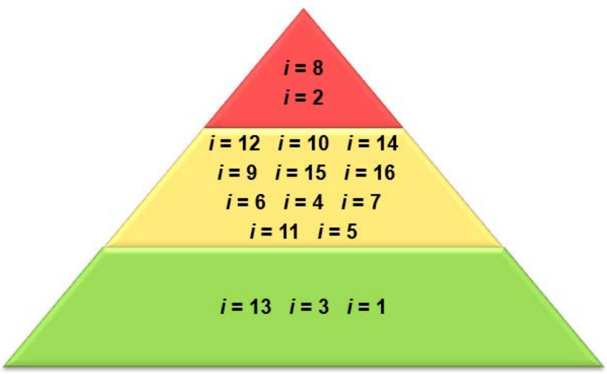

Figure 3. Classification of process phases based on Pareto analysis

Based on the conducted Pareto analysis, as well as consultations with experts from the analyzed company, it was determined that the CO_2 welding phase ($i = 8$) and the incoming inspection of components and raw materials phase ($i = 2$) are the most critical in the entire process. These phases require special attention through the implementation of appropriate preventive actions, control, and monitoring. The mentioned phases have been classified as Class A.

Phases that are not critical, i.e., those that are unlikely to significantly disrupt the process, include Sandblasting ($i = 13$), Handling and storage of controlled materials ($i = 3$), and Reception of components and raw materials ($i = 1$). These phases have been classified as Class C.

All other phases (the majority) have been classified as Class B, and these phases should be monitored and controlled, especially those positioned closer to the top of the ranking list.

The obtained results have also been confirmed by experts from the analyzed company. The CO_2 welding phase ($i = 8$) is, objectively speaking, based on experience and practice, highly critical due to its complexity, the number of operations involved, the required precision, and the fact that errors in this phase are often detected only in subsequent phases, which then requires product rework.

Similarly, the incoming inspection of components and raw materials phase ($i = 2$) represents the first and a very important control point in the production process. If low-quality materials pass through this phase undetected, there is a high possibility that this will generate problems in the subsequent stages of the process.

5 Conclusions

This paper explores the applicability of a combined CRITIC–Pareto approach for classifying process phases within the production process of an automotive company, based on their criticality and overall impact on the production system. The model was tested in a company from the automotive industry, specifically within the rear axle assembly production process. Based on the obtained results, which align with the opinions of experts from the analyzed company, two phases were identified as the most critical. Therefore, the phases that pose the highest risk to process quality are the CO_2 welding phase and the incoming inspection of components and raw materials phase.

These two phases can be designated as key control points that require enhanced monitoring and the implementation of preventive measures, primarily because the manifestation of failure modes in these phases may directly or indirectly affect other stages of the process.

The key contribution of this research is practical in nature. The main contributions of this research are:

• A systematic approach is proposed for classifying process phases based on quantitative criteria generated from an existing PFMEA report.

• This approach consists of the objective CRITIC method for determining the weights of the criteria, and a simple yet effective Pareto analysis for classification.

• It is important to emphasize that the proposed model is applicable to any PFMEA report and can be implemented through four basic phases: (1) data generation from the PFMEA report, (2) data processing, (3) application of the CRITIC method, and (4) application of Pareto analysis.

• The model is very simple and does not require additional evaluations by expert teams (decision-makers).

• It can be applied in any research or practical domain.

A key limitation of this research lies in the fact that the model was tested on only one case study. However, since the CRITIC method is flexible and depends solely on the input data, in this case, the information from the PFMEA report, the weights of the criteria are adapted to the specific problem being analyzed. What may pose a challenge is the definition of the set of criteria, which can vary from one company to another.

Future research should focus on testing the model in different sectors, particularly those where FMEA analysis is commonly used, such as energy and chemical industry, healthcare, information technology, etc. In addition, it is important to conduct comparative analyses using other MADM methods, as well as to perform various types of sensitivity analysis.

Author Contributions

Conceptualization, N.K. and D.M.; methodology, N.K. and D.M.; validation, D.M.; formal analysis, N.K.; investigation, N.K.; resources, N.K.; data curation, D.M. and N.K.; writing—original draft preparation, N.K.; writing—review and editing, D.M.; visualization, N.K.; supervision, D.M.; project administration, D.M. All authors were actively involved in discussing the findings and refining the final manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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