Cureus Journal of Engineering
https://doi.org/10.7759/s44388-026-00153-z

Original Article

Best Holistic Adaptable Ranking of Attributes Technique-2 for Fuzzy Decision-Making in Industry 4.0: A Robust and Computationally Efficient Multi-Attribute Decision-Making Approach

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Received: March 23, 2026 | Review began: April 01, 2026 | Review ended: June 09, 2026 | Published: July 07, 2026

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Abstract

Real-world decision-making in the Industry 4.0 era, such as the selection of logistics service providers and manufacturing partners, is increasingly influenced by uncertainty, vagueness, and imprecise data. Conventional fuzzy multi-attribute decision-making (MADM) approaches, including Fuzzy Analytic Hierarchy Process (AHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution, often involve high computational complexity, extensive pairwise comparisons, and parameter dependency, which may limit their applicability in large-scale and time-sensitive decision environments. To address these limitations, this study proposes the Best Holistic Adaptable Ranking of Attributes Technique-2 (BHARAT-2), a computationally efficient framework for solving fuzzy MADM problems.

In the proposed approach, fuzzy evaluations are processed directly within the BHARAT-2 framework during criteria weighting and composite score computation. Subsequently, the arithmetic mean is applied only to the final composite fuzzy scores for ranking the alternatives. Three real-world case studies are analyzed to demonstrate the applicability and effectiveness of the proposed framework. The obtained weights and rankings are compared with several established approaches, including equal weights, rank-inverse, rank-centroid, direct assignment, pairwise comparison, and AHP methods.

The comparative results demonstrate strong agreement between BHARAT-2 and conventional techniques, with rank correlation values of 0.9762, 0.9000, and 0.8909-0.9909 for Case Studies 1, 2, and 3, respectively, indicating high consistency in decision outcomes. Although minor ranking variations are observed due to sensitivity to small weight changes, BHARAT-2 exhibits comparatively stable ranking behavior and lower variability across all case studies. Furthermore, the proposed framework offers reduced computational complexity and improved decision consistency while maintaining methodological simplicity and scalability. These characteristics make BHARAT-2 a reliable and efficient decision-support framework for complex decision-making applications in Industry 4.0, healthcare, banking, and related domains.

Categories: Supply Chain and Logistics Management, Sustainable Technologies, Design and Manufacturing

Keywords: industry 4.0, multi-attribute decision making, weight selection, bharat-2, fuzzy problem

Introduction

The rapid advent of Industry 4.0 has transformed the manufacturing and industrial landscape, enabling unprecedented levels of automation, interconnectivity, and data-driven decision-making. This transformation is driven by the integration of advanced digital technologies such as cyber-physical systems, Internet of Things (IoT), big data analytics, and artificial intelligence as described by Kagermann et al. [1]. In such complex and dynamic environments, industries face multiple,

often conflicting criteria when making operational, strategic, and technological choices. Zhou et al. [2] explained that these scenarios necessitate systematic decision-making frameworks capable of evaluating diverse alternatives across multiple quantitative and qualitative attributes.

Tzeng and Huang [3] explained that Multi-Criteria Decision-Making (MCDM) has emerged as a critical discipline to address these challenges by structuring and solving problems that involve balancing multiple objectives. Within MCDM, Multi-Attribute Decision-Making (MADM) focuses on problems where a discrete set of alternatives must be ranked, selected, or evaluated based on several attributes or criteria, as discussed by Triantaphyllou [4]. Calik [5] depicted that the importance of MADM in Industry 4.0 lies in its ability to integrate human expertise, computational efficiency, and rigorous analytical frameworks for decisions in areas such as supplier selection, material evaluation, technology adoption, and production planning.

Over the decades, researchers have developed various MADM methods, among which the Analytic Hierarchy Process (AHP) proposed by Saaty [6] and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) introduced by Tzeng and Huang [3] remain the most widely used. Aljinovic et al. [7] used AHP for selection in the selection process for the manual assembly line. AHP is favored for its intuitive pairwise comparison mechanism and structured hierarchy. However, Ishizaka and Labib [8] explained that AHP suffers from high computational complexity in problems involving a large number of criteria and alternatives, and is sensitive to inconsistency in judgments. TOPSIS is appreciated for its conceptual simplicity and ability to identify the closest-to-ideal alternative; however, Behzadian et al. [9] had explained that it assumes precise numerical inputs, making it less suitable for uncertain, imprecise, or linguistic evaluations. Similarly, Duc Trungl [10] had applied MACROS with weighting methods like EW, RR, RS, and ROC to milling, grinding, and turning processes, showcasing the decision accuracy of the MACROS method, but they too rely on crisp inputs, limiting their applicability in real-world settings where fuzziness is inherent.

To address uncertainty, fuzzy set theory introduced by Zadeh [11] has been integrated with classical MADM methods, leading to the combination of fuzzy theory with AHP and TOPSIS by Van Laarhoven and Pedrycz [12] and Chen [13]. Cengiz et al. [14] explained that these fuzzy extensions allow decision-makers to use linguistic terms and membership functions to express imprecise judgments, making them more suitable for complex industrial decision-making. Recent advancements have extended fuzziness to other methods, such as those developed by Guo and Zhao [15]. Evans et al. [16] had developed a fuzzy decision tree approach for the selection of manufacturing technology. Pour et al. [17] used Fuzzy AHP and Fuzzy TOPSIS to solve the selection problem in manufacturing systems. Sadat et al. [18] used Fuzzy AHP-TOPSIS in Barrier analysis of solar PV for Iran. However, despite their flexibility, these fuzzy methods often involve complicated mathematical formulations, defuzzification steps, and parameter tuning, which increase computational burden and may reduce interpretability for practitioners, as discussed by Fanian [19].

From the literature, it is evident that researchers have also proposed hybrid and novel approaches to overcome the shortcomings of both crisp and fuzzy MADM methods. However, Rao [20] described that many of these methods remain parameter-dependent, computationally intensive, or challenging for industry practitioners to implement without specialized knowledge. Moreover, comparative studies by Nath and Sarkar [21] highlighted that when multiple methods are applied to the same problem, inconsistencies in rankings can occur, making result interpretation more difficult for decision-makers.

Although several fuzzy MADM methods exist in the literature, many approaches involve high computational complexity, extensive parameter dependence, or complicated fuzzy aggregation procedures. To address these limitations, the proposed BHARAT-2 framework aims to provide a computationally simple yet effective rank-based decision-making structure capable of handling uncertain and fuzzy environments while preserving discrimination capability among alternatives.

To bridge these gaps, the BHARAT-2 was developed as a parameter-free, computationally simple, and easily interpretable MADM technique. Unlike AHP, it does not require exhaustive pairwise comparisons; unlike TOPSIS and MACROS, it can handle uncertain evaluations; and unlike fuzzy-based methods, it avoids complex fuzzification and defuzzification processes. The method's design focuses on practical applicability in Industry 4.0 contexts, enabling decision-makers to

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quickly process multi-attribute evaluations while maintaining transparency and consistency in results. The present study applies weights of different methods, such as equal weights, rank sum, rank inverse, rank of centroid, Decision Analysis Table, pairwise, AHP, and BHARAT-2, to multiple industrial case studies, comparing their performance with established methods to demonstrate their effectiveness in modern industrial decision environments. The remainder of the paper is organized as follows: different weight determination methods are presented first, followed by the working of BHARAT-2, the description of the case studies, the discussion of results, and the concluding remarks.

Materials And Methods

The weight assignment can be performed in two ways: (1) by giving preference to the decision-maker and, according to these preferences, assigning ranks, after which weights are allocated according to the preference (subjective weights); and (2) by solving mathematical equations based on the given data (objective weights).

Numerous scenarios exist where employing ranked weights is justifiable, prompting the development of various techniques to handle ranked weights and determine choices or rank alternatives. The concept of relative criteria weights is rooted in the idea that a universal correlation exists between criteria ranks and average weight values. This transformation relies on employing different formulas.

Ranking criteria by importance may prove simpler than delineating other imprecise weight types, such as bounded weights. This circumstance arises, for instance, in scenarios characterized by time constraints, the qualitative nature of criteria, knowledge gaps, imprecision, incomplete or partial information, and limitations in decision makers' attention and information processing capabilities.

Equal weights

The equal weight method (EW) works with minimal input from decision-makers regarding criteria priorities. When decision-makers lack information about true weights, true weights can be illustrated as a uniform distribution on the unit n-simplex of weights, as defined by specific conditions. The n-simplex of weight is a geometric object. For example, n=2, then the weights will be $W_1 = W_2 = \frac{1}{2}$ The general formula is as follows:

$$W_i(EW) = \frac{1}{n} \quad \text{where } i = 1, 2, \ldots n \tag{1}$$

Rank sum method

The Rank Sum (RS) procedure employs weights obtained from individual ranks, which are then normalized by dividing each rank by the sum of all ranks. The formula generating the weights W_i(RS) with rank r_i is as follow [22]:

$$w_i(RS) = \frac{(n - r_i + 1)}{\sum_{k=1}^{n}(n - r_k + 1)} = \frac{2(n + 1 - r_i)}{n(n+1)}, \quad \text{where } i = 1, 2, \ldots, n \tag{2}$$

Rank-inverse method

The rank-inverse (RR) method, involves assigning weights to items based on the reciprocal of their ranks, normalized by dividing each term by the sum of the reciprocals. The formula for this method can be expressed as follows:

$$w_i(RR) = \frac{\left(\frac{1}{r_i}\right)}{\sum_{k=1}^{n}\left(\frac{1}{r_k}\right)}, \quad \text{where } i = 1, 2, \ldots, n \tag{3}$$

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Rank order centroid method

The Rank Order Centroid (ROC) weight approach aims to derive weights that minimize the maximum error of each weight by identifying the centroid of all potential weights while preserving the rank order. Sriram [23] observed that this method yields highly stable weights. When considering the rank order of true weights without specific quantitative data, one can assume a uniform distribution of weights across the rank-order weight simplex. In this representation, each weight is assigned an equal value, while maintaining each item's rank order of importance. This assumption implies equal significance for all items in the absence of precise weight information.

$$w_i(ROC) = \frac{1}{n}\sum_{k=i}^{n}\frac{1}{r_k} \tag{4}$$

The term "rank-order centroid" is derived from the idea that these weights mirror the centroid, or central point, of the simplex created by the criteria rankings. As the number of criteria grows, the error associated with ranked criteria decreases substantially.

Direct assignment technique (DAT)

In this technique, the user directly assigns points to the attributes based on preference [24]. For instance, there are five attributes, and the user has to assign points up to 100, so they assign points such as 40,30,20,6,4 so the total is 100 points. The weight is the ratio of individual to total, i.e., $\frac{40}{100}$= 0.4, $\frac{30}{100}$ = 0.3, $\frac{20}{100}$ = 0.2, $\frac{6}{100}$= 0.06, and $\frac{4}{100}$= 0.04. So, these are the weights used for solving the problem.

Pairwise comparison

In pairwise comparison, attributes are compared systematically based on importance [24]. A point is assigned to a more important attribute for each pairwise comparison. At the end, the weight assigned to an attribute is the ratio of points assigned to an individual attribute to the total points. For example, if there are five attributes, then there will be $\frac{5*(5-1)}{2}$ = 10 comparisons performed, so for N attributes, $\frac{N*(N-1)}{2}$ comparisons are performed.

Analytic hierarchy process

The AHP uses a scale of absolute numbers that captures individual preferences concerning qualitative and quantitative attributes [6]. Then, it is converted into the ratio scale and combined into a linear additive weight for each alternative. Further, AHP provides a relative comparison of attributes and, based on it, gives weight to the attributes.

Best holistic adaptable ranking of attributes technique (BHARAT-2)

Numerous scenarios exist where employing ranked weights is justifiable, prompting the development of various techniques to handle ranked weights and determine choices or rank alternatives. The ranks depend on weights assigned to the attributes. If the weight determination is subject to anchoring bias, it can lead to skewed judgments or decisions, as people tend to adjust their evaluations around the anchor rather than objectively assessing all information [25]. The decision-maker should ensure that the weights are not biased. The concept of relative criteria weights is rooted in the idea that a universal correlation exists between criteria ranks and average weight values. This transformation relies on employing different formulas.

By their importance, ranking criteria may prove simpler than delineating other imprecise weight types, such as bounded weights. This circumstance arises, for instance, in scenarios characterized by time constraints, the qualitative nature of criteria, imprecision, knowledge gaps, incomplete or partial information, and limitations in decision-makers' attention and information processing capabilities.

A straightforward and efficient approach to multi-criteria decision-making is known as the "Best Holistic Adaptable Ranking of Attributes Technique (BHARAT-2)," developed by Rao [25] in 2024. When using decision-making methods that involve multiple characteristics, a decision table with weighted attributes typically includes attributes, performance

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measures for each option, and the options themselves. The decision-maker is tasked with evaluating each option and determining the most favorable choice depending on the information in the decision table and the selected decision-making approach. Here's a breakdown of the steps in the recommended decision-making method.

Step 1: Identify the decision-making context, relevant attributes A_i where and the available alternatives B_i where These features encompass both beneficial and non-beneficial factors. This task can be undertaken by either a group of decision-makers or an individual decision-maker. Non-beneficial attributes are those where lower values are preferred, while beneficial attributes are those where higher values are preferred.

Step 2: In different situations, ranking weights can offer various ranking methodologies. Ranks are commonly favored over weights because they tend to be more agreeable to experts and non-experts, enhancing their reliability in determining attribute weights. Decision-makers usually place greater trust in attribute ranks compared to their weights. Sorting attributes by importance is straightforward. To determine attribute weights W_i where i = 1, 2, … n, attributes are ordered by their perceived significance, using ranks such as 1, 2, 3, 4, 5, 6, and so forth. When multiple (two, three, or more attributes) are deemed equally significant, they are assigned an average rank. For this purpose, the BHARAT 2 [26] employs the R-method, as proposed by Rao and Lakshmi [27]. For instance, if three attributes, A, B, and C, are ranked as 1, 2, and 3, respectively, their weights are calculated as follows:

$$A1 = \begin{matrix} A \\ B \\ C \end{matrix} \begin{bmatrix} 1 & 2 & 3 \\ 1/2 & 1 & 3/2 \\ 1/3 & 2/3 & 1 \end{bmatrix} \tag{5}$$

The matrix A1 shows the rank relation, where diagonal elements are 1 and the elements in the lower triangular are the reciprocal of their rank relations. The arithmetic mean of rows are [(1 + 2 + 3)/3] = 2, [(1/2 + 1 + 3/2)/3] = 1, [(1/3 + 2/3 + 1)/3] = 0.66, respectively. The total of all the row is 2 + 1 + 0.66 = 3.66. Now, divide each row total with the grand total i.e., Row 1 = 2/3.66 = 0.54, Row 2 = 1/3.66 = 0.27 and Row 3 = 0.66/3.66 = 0.18.

To check the consistency of the weights, A2 = $\boldsymbol{A1} * \begin{bmatrix} \mathbf{0.54} \\ \mathbf{0.27} \\ \mathbf{0.18} \end{bmatrix} = \begin{bmatrix} \mathbf{1.62} \\ \mathbf{0.81} \\ \mathbf{0.54} \end{bmatrix}$. Now, divide A2 matrix with [0.54,0.27,0.18].

$$\boldsymbol{A3} = \frac{\begin{bmatrix} \mathbf{1.62} \\ \mathbf{0.81} \\ \mathbf{0.54} \end{bmatrix}}{\begin{bmatrix} \mathbf{0.54} \\ \mathbf{0.27} \\ \mathbf{0.18} \end{bmatrix}} = \begin{bmatrix} \mathbf{3} \\ \mathbf{3} \\ \mathbf{3} \end{bmatrix} \tag{6}$$

The maximum eigen value $\boldsymbol{\lambda_{max} = average\ of\ A3 = [3+3+3]/3 = 1.}$ The Consistency Index (CI) = $\boldsymbol{\lambda_{max} - m/(m-1) = (3-3)/(3-1) = 0.}$ The consistency index 0 shows that the rank relation given in A1 matrix is absolutely consistent and there is no error present in the judgements of rank relations. As a result, weights of 0.54, 0.81, and 0.18 can be assigned to the attributes A, B, and C, respectively. This approach allows for the inclusion of any number of attributes by assigning ranks to them, which helps calculate their weights. Unlike AHP and Best Worst Method, which often lack absolute consistency in evaluating relative importance, the proposed method is more reliable.

Step 3: Evaluate the performance x_{ji} of each alternative for a specific attribute. These performances can be quantitatively or qualitatively expressed. In group decision-making, take note of the qualitative descriptions provided by a team of decision-makers for each qualitative attribute. Convert the qualitative data, represented by linguistic terms, into quantitative data using a straightforward scale without resorting to fuzzy logic.

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Step 4: Normalize the data of each attribute based on the "best" value of that attribute across various alternatives. Repeat this normalization procedure for all attributes to obtain the normalized dataset. Here, "best" indicates the highest value for beneficial attributes and the lowest value for non-beneficial attributes.

The performance measures of alternatives x_{ji} where $(j = 1, 2, 3, \ldots, n)$ and $(i = 1, 2, 3, \ldots, m)$ are to be normalized. The normalized value $(x_{ji})_{\text{normalized}}$ of an alternative corresponding to a beneficial attribute is $\left(\frac{x_{ji}}{(x_i)_{\text{best}}}\right)$, and it is $\left(\frac{(x_i)_{\text{best}}}{x_{ji}}\right)$ for non-beneficial attributes. Here,$(x_i)_{\text{best}}$ represents the best value of the i^{th} attribute. This normalization method concerning the "best" values effectively demonstrates the relative positions of the alternatives regarding the "best" attribute values.

Step 5: The total score of an alternative is determined by adding together the products of the attribute weights and the corresponding normalized data $(x_{ji})_{\text{normalized}}$. This procedure entails multiplying the attribute weights by the normalized attribute data for each alternative. As a result, the calculation provides the total scores for the alternatives. In the case of fuzzy triangular, we will get three values of the composite score, calculating the arithmetic mean of the composite score.

Step 6: Arrange the arithmetic mean in decreasing order. The alternative with the highest overall score is considered the best option in the decision-making scenario. Figure *1* provides a graphical representation of the BHARAT-2.

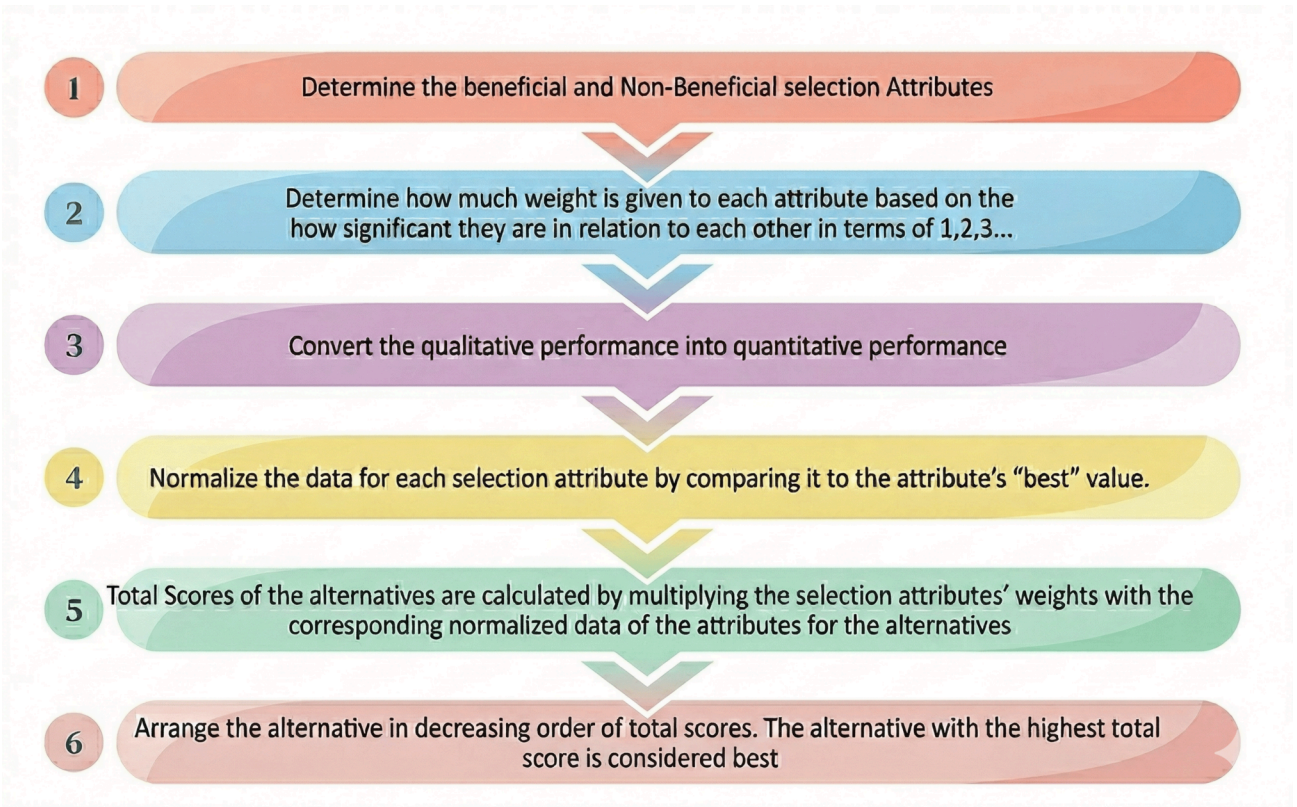


FIGURE 1: Flowchart of BHARAT-2

The BHARAT-2 is straightforward, transparent, adaptable, and simple. It does not rely on intricate fuzzy logic for translating linguistic expressions or qualitative data into quantitative data. It can be applied across diverse decision-making scenarios, facilitating faster decision-making and offering practical solutions. This enhances its credibility as a decision-making tool for assigning weights. This simplicity reduces the burden on decision-makers during the decision-

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making process. The conversion of ranks into weights provides a direct and efficient way to assign importance to alternatives and attributes. The complete computational procedure of BHARAT-2 is summarized in Algorithm 1 to improve reproducibility and implementation clarity.

Algorithm for BHARAT-2

Step 1: Identify beneficial and non-beneficial criteria

Step 2: Define the set of alternatives and criteria $A = \{A_1, A_2, \ldots, A_m\}, and C = \{C_1, C_2, \ldots, C_n\}$

Step 3: Convert qualitative values into quantitative values and construct the fuzzy decision matrix $\tilde{X} = [\tilde{x}_{ij}]_{m \times n}$
where $\tilde{x}_{ij}$ represents the fuzzy performance value of alternative A_i with respect to criterion C_j.

Step 4: Normalize the fuzzy decision matrix based on the beneficial and non-beneficial to obtain $\tilde{R} = [\tilde{r}_{ij}]_{m \times n}$

Step 5: Construct the BHARAT-2 rank relation matrix
$B = [b_{ij}]_{n \times n}$
using pairwise rank comparison among criteria.

For each criterion pair (C_i, C_j)

If C_i is preferred over C_j

Rank $C_i > C_j$

Else

Assign reciprocal

End For

Step 6: Compute row totals of the BHARAT-2 relation matrix: $S_i = \sum_{j=1}^{n} b_{ij}$

Determine criteria weights:
$w_i = \frac{S_i}{\sum_{i=1}^{n} S_i}$

Step 7: Construct the weighted normalized decision matrix: $V = [v_{ij}] where\, v_{ij} = w_j \tilde{r}_{ij}$

Step 8: Calculate the composite performance score for each alternative and find the arithmetic mean of composite scores: $P_i = \sum_{j=1}^{n} v_{ij}$

Step 9: Arrange all alternatives according to descending order of P_i. and select the alternative having the highest composite score as the best alternative.

Unlike conventional rank-based weighting approaches such as Rank Sum, Rank-Inverse, and ROC methods, which directly transform ordinal ranks into normalized weights using predefined mathematical expressions, the proposed BHARAT-2 framework employs a structured relational ranking mechanism for evaluating attribute importance. The method emphasizes computational simplicity, ranking stability, and reduced elicitation burden while preserving the comparative dominance structure among attributes. In contrast to AHP and pairwise comparison-based techniques, BHARAT-2 avoids extensive pairwise comparison matrices and consistency ratio calculations, thereby reducing computational complexity and improving applicability for large-scale fuzzy MADM problems.

Results And Discussion

Case studies

In this section, three case studies are solved using BHARAT-2 method using different weights obtained by different methods and comparison is performed based on the rank obtained.

Case Study: 1. Industry 4.0 Selection Framework for Manufacturing System

Aluminium extrusion is a vital manufacturing process because of its ability to produce lightweight, durable, and recyclable products that find extensive applications in construction, automotive, aerospace, and electrical sectors. The process is, however, highly energy-intensive and quality-sensitive, making the selection of appropriate Industry 4.0 technologies crucial to reduce setup time, minimize rework, optimize energy consumption, and improve overall efficiency. To address this, researchers have increasingly turned to MADM frameworks. Pour et al. [17] applied a fuzzy AHP and fuzzy TOPSIS framework to select Industry 4.0 technologies for aluminium extrusion, balancing operational, environmental, social, and financial criteria. Other studies have employed alternative MADM approaches: Fernández et al. [28] used VIKOR for ranking sustainable materials and processes in extrusion environments, while Quezada et al. [29] applied COPRAS and CODAS to prioritize manufacturing technologies under uncertainty, especially in energy-intensive sectors such as aluminium and steel. Tanane et al. [30] introduced a hybrid decision framework integrating quality management with Industry 4.0 adoption, demonstrating its applicability to extrusion and metal processing industries. Mathew et al. [31] integrated Fuzzy sets with AHP and TOPSIS to solve advanced manufacturing system selection problems.

Additionally, comparative analyses in recent literature highlight that those fuzzy extensions of classical MADM methods (AHP, TOPSIS, VIKOR, COPRAS, CODAS) are most effective in capturing the linguistic judgments of experts in aluminium extrusion, where trade-offs between sustainability, efficiency, and profitability are complex and uncertain. Collectively, these contributions show that aluminium extrusion not only necessitates advanced decision frameworks for technology adoption but also serves as a benchmark case for testing the robustness of MADM methodologies in real-world industrial applications.

The case study in this study is extracted from Pour et al. [17] for the selection of technology for the firm of aluminium extrusion, where data are in fuzzy form, so they have used Fuzzy AHP and Fuzzy TOPSIS to solve the problem, which has four criteria that are further divided into 10 sub-criteria with eight alternatives. The criteria are Production, Environment, Social and Economic. The production criteria are divided into three sub criteria i.e., rework ratio, setup ratio and production process ratio. I11 - Rework Ratio: It is used to find the amount of product which did not pass the quality requirement, I12 - Setup Ratio: It is the ratio of time require to set up the machine and actual process time, I13 - Production Process Ratio: It is an attribute used measure the overall efficiency of production by taking ratio of order execution time by production time.

The environment criteria are divided into three sub-criteria, i.e., direct GHG emissions, Energy consumption within organization and material used by weight or volume. I21 - Direct GHG Emissions: It shows the total amount of greenhouse gases emitted directly in air. I22 - Energy Consumption within Organization: It is the total amount of fuel required to run an organization, including renewable and non-renewable sources. I23 - Material used by weight or volume: It represents the amount of reduction in energy consumption using initiatives which leads to energy conservation.

The Social criteria is divided into two sub-criteria, i.e., work related injuries and hazard identification, risk assessment and incident investigation. I31 - Work-related Injuries: It shows the number of work-related injuries, I32 - Hazard Identification, Risk Assessment, and Incident Investigation: It identifies work related hazards and the associated risks associated with them.

The Economic criteria is divided into two sub-criteria, i.e., price earnings ratio and return on assets. I41 - Price Earnings Ratio (P/E): It is a financial indicator for firms calculated by taking ratio of market price per share by earnings per share. I42 - Return on Assets (ROA): It shows a firm's financial performance by determining the firm's profitability for stockholders. It is calculated by taking the ratio of net income to the stockholder by the stockholder's equity investment in the firm.

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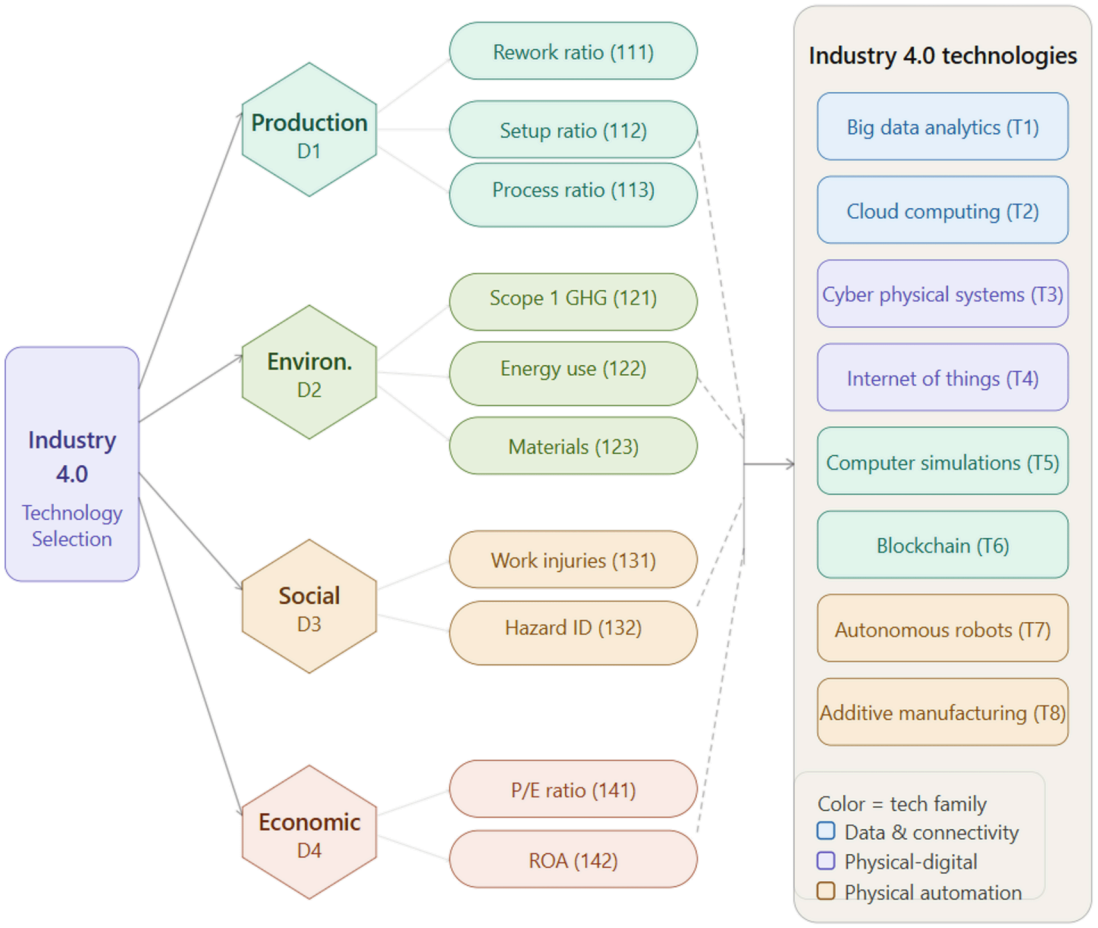


FIGURE 2: Framework for case study 1

The problem has eight alternatives' technologies ranging from T1 to T8 described below:

T1 - Big Data Analytics: Big data analytics handles and analyses the raw data for the industry. It assists the decision-makers by giving them analyses.

T2 - Cloud Computing: This technology provides additional storage space for manufacturing firms to store essential data.

T3 - Cyber-Physical Systems: A group of technologies that helps connect physical and digital components within one firm. This helps digitize production lines. The technology consists of sensors that collect data from the physical components, and the actuators will interact with the physical components.

T4 - Internet of Things: IoT is a popular technology used in Industry 4.0, and it acts as a bridge between different components and industries. It helps reduce manufacturing costs and production time.

T5 - Computer Simulation: This technology helps the firm simulate the process on the computers before the actual manufacturing. This will reduce the losses a firm goes through during the testing phase. For example, Digital Twin is a computer simulation that helps the firm predict manufacturing processes.

T6 - Blockchain: This technology ensures secure and transparent transactions.

T7 - Autonomous/Industrial Robots: Robotics and Autonomous systems are integrated parts of industry. Robots reduce error, automates repetitive jobs, and assist in work.

T8 - Additive Manufacturing: It is a rapidly growing technology for Industry 4.0. This technology benefits manufacturing firms and reduced production costs these are the alternative technologies used in the study and are shown in Figure *2* [17]. The decision-maker asked experts to fill in their opinion in fuzzy TOPSIS survey in linguistic terms such as Very Low Impact (VLI) - (1,1,3), Low Impact (LI) - (1,3,5), Medium Impact (MI) - (3,5,7), High Impact (HI) - (5,7,9), Very High Impact (VHI) - (7,9,9) for 8*10 matrix, as shown in Table *1*.

	I11	I12	I13	I21	I22	I23	I31	I32	I41	I42
T1	HI	MI	VHI	MI	VHI	HI	HI	LI	MI	HI
T2	MI	LI	MI	MI	MI	LI	LI	LI	LI	LI
T3	VHI	HI	VHI	MI	HI	VHI	VHI	MI	MI	HI
T4	LI	LI	LI	LI	LI	VLI	VLI	VLI	VLI	VLI
T5	LI	LI	HI	MI	MI	LI	LI	LI	VLI	VLI
T6	MI	LI	VLI	LI	LI	MI	MI	MI	LI	LI
T7	HI	HI	HI	MI	LI	VHI	VHI	VHI	LI	LI
T8	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI

TABLE 1: Fuzzy decision matrix in linguistic terms

Table *1* is converted into its numerical value based on VLI, LI, MI, HI, and VHI values, as shown in Table *2*.

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	I11	I12	I13	I21	I22	I23	I31	I32	I41	I42
T1	(5,7,9)	(3,5,7)	(7,9,9)	(3,5,7)	(7,9,9)	(5,7,9)	(5,7,9)	(1,3,5)	(3,5,7)	(5,7,9)
T2	(3,5,7)	(1,3,5)	(3,5,7)	(3,5,7)	(3,5,7)	(1,3,5)	(1,3,5)	(1,3,5)	(1,3,5)	(1,3,5)
T3	(7,9,9)	(5,7,9)	(7,9,9)	(3,5,7)	(5,7,9)	(7,9,9)	(7,9,9)	(3,5,7)	(3,5,7)	(5,7,9)
T4	(1,3,5)	(1,3,5)	(1,3,5)	(1,3,5)	(1,3,5)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)
T5	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)	(3,5,7)	(1,3,5)	(1,3,5)	(1,3,5)	(1,1,3)	(1,1,3)
T6	(3,5,7)	(1,3,5)	(1,1,3)	(1,3,5)	(1,3,5)	(3,5,7)	(3,5,7)	(3,5,7)	(1,3,5)	(1,3,5)
T7	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(1,3,5)	(7,9,9)	(7,9,9)	(7,9,9)	(1,3,5)	(1,3,5)
T8	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)	(1,1,3)

TABLE 2: Fuzzy decision matrix

Steps for BHARAT-2

Step 1: Identify the number of attributes and alternatives, here there are 10 attributes and 8 alternatives and all the attributes are beneficial in this case for which the higher values are preferred. It should be noted that some indicators, such as rework ratio, setup ratio, direct GHG emissions, energy consumption, and work-related injuries, are commonly classified as cost criteria in MADM problems. However, to maintain consistency with the benchmark formulation reported by Pour et al. [17], the criterion directions adopted in the original study have been retained.

Step 2: Giving ranks to the attributes where I42 has the highest priority because it shows the financial performance of the firm, followed by attribute I13, which shows the production efficacy of the firm in such a way the priorities are as follows: I42>I13>I31>I11>I22>I41>I12>I23>I32>I21, where I21 has the lowest priority as given by Pour et al. [17]. Based on these priorities, the rank relation matrix is generated as shown in Table *3*. Based on that, the weights are obtained.

	I42	I13	I31	I11	I22	I41	I12	I23	I32	I21	Sum	Weights
I42	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00	55.00	0.34
I13	0.50	1.00	0.67	0.50	0.40	0.33	0.29	0.25	0.22	0.20	4.36	0.03
I31	0.33	1.50	1.00	0.75	0.60	0.50	0.43	0.38	0.33	0.30	6.12	0.04
I11	0.25	2.00	1.33	1.00	0.80	0.67	0.57	0.50	0.44	0.40	7.97	0.05
I22	0.20	2.50	1.67	1.25	1.00	0.83	0.71	0.63	0.56	0.50	9.84	0.06
I41	0.17	3.00	2.00	1.50	1.20	1.00	0.86	0.75	0.67	0.60	11.74	0.07
I12	0.14	3.50	2.33	1.75	1.40	1.17	1.00	0.88	0.78	0.70	13.65	0.08
I23	0.13	4.00	2.67	2.00	1.60	1.33	1.14	1.00	0.89	0.80	15.56	0.10
I32	0.11	4.50	3.00	2.25	1.80	1.50	1.29	1.13	1.00	0.90	17.47	0.11
I21	0.10	5.00	3.33	2.50	2.00	1.67	1.43	1.25	1.11	1.00	19.39	0.12
											161.09	1.00

TABLE 3: Weights determination matrix for case study 1

Step 3: The fuzzy data are considered directly and normalized using the beneficial attribute normalization expression $\left(\frac{x_{ji}}{(x_i)_{\text{best}}}\right)$. In this case study, all attributes are treated as beneficial criteria, consistent with the formulation adopted by Pour et al. [17]. For Example, for T1 = (5,7,9)/(7,9,9) = (0.7193,0.7778,1). Similarly, we will calculate the normalized value for all alternatives.

Step 4: Multiply the weights of the corresponding attribute with this column in order to get composite score. The composite score is obtained by the product of the normalized value with its corresponding weight. For instances (0.7143 × 0.0494 + 0.6 × 0.0847 + 1 × 0.0271 + 1 × 0.1204 + 1 × 0.0611 + 0.7143 × 0.0966 + 0.7143 × 0.0380 + 0.1429 × 0.1085 + 1 × 0.0729 + 1 × 0.3414 = 0.8206), this gives the first value obtained in the composite score in the similar manner the composite score is calculated.

Step 5: Now, to obtained rank we need to defuzzify the fuzzy composite score so we can used arithmetic mean for instance geometric mean for 0.8206,0.8626,0.9930 is 0.8721 for T1, using BHARAT-2. Similarly, we can calculate the arithmetic mean for all the alternative ranges from T1 to T8.

Step 6: Rank the alternative based on the decreasing order of the arithmetic mean the ranks are obtained as T3>T1>T7>T2>T6>T5>T4>T8 as shown in Table *4*.

Weights	**0.0494**	**0.0847**	**0.0271**	**0.1204**	**0.0611**	**0.0966**	**0.0380**	**0.1085**	**0.0729**	**0.3414**	**1.0000**		
	I11	I12	I13	I21	I22	I23	I31	I32	I41	I42	Composite Score	Arithmetic Mean	Rank
T1	(0.7143,0.7778,1)	(0.6,0.7143,0.7778)	(1,1,1)	(1,1,1)	(1,1,1)	(0.7143,0.7778,1)	(0.7143,0.7778,1)	(0.1429,0.3333,0.5556)	(1,1,1)	(1,1,1)	(0.8206,0.8626,0.9930)	0.8721	2
T2	(0.4286,0.5556,0.7778)	(0.2,0.4286,0.5556)	(0.4286,0.5556,0.7778)	(1,1,1)	(0.4286,0.5556,0.7778)	(0.1429,0.3333,0.5556)	(0.1429,0.3333,0.5556)	(0.1429,0.3333,0.5556)	(0.3333,0.6,0.7143)	(0.2,0.4286,0.5556)	(0.3236,0.5042,0.6512)	0.4930	4
T3	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(0.7143,0.7778,1)	(1,1,1)	(1,1,1)	(0.4286,0.5556,0.7778)	(1,1,1)	(1,1,1)	(0.9206,0.9382,0.9756)	0.9449	1
T4	(0.1429,0.3333,0.5556)	(0.2,0.4286,0.5556)	(0.1429,0.3333,0.5556)	(0.3333,0.6,0.7143)	(0.1429,0.3333,0.5556)	(0.1429,0.1111,0.3333)	(0.1429,0.1111,0.3333)	(0.1429,0.1111,0.3333)	(0.3333,0.2,0.4286)	(0.2,0.1429,0.3333)	(0.2040,0.2447,0.4355)	0.2948	7
T5	(0.1429,0.3333,0.5556)	(0.2,0.4286,0.5556)	(0.7143,0.7778,1)	(1,1,1)	(0.4286,0.5556,0.7778)	(0.1429,0.3333,0.5556)	(0.1429,0.3333,0.5556)	(0.1429,0.3333,0.5556)	(0.3333,0.2,0.4286)	(0.2,0.1429,0.3333)	(0.3172,0.3725,0.5495)	0.4131	6
T6	(0.4286,0.5556,0.7778)	(0.2,0.4286,0.5556)	(0.1429,0.1111,0.3333)	(0.3333,0.6,0.7143)	(0.1429,0.3333,0.5556)	(0.4286,0.5556,0.7778)	(0.4286,0.5556,0.7778)	(0.4286,0.5556,0.7778)	(0.3333,0.6,0.7143)	(0.2,0.4286,0.5556)	(0.2876,0.4844,0.6452)	0.4724	5
T7	(0.7143,0.7778,1)	(1,1,1,1)	(0.7143,0.7778,1)	(1,1,1)	(0.1429,0.1111,0.3333)	(1,1,1)	(1,1,1)	(1,1,1)	(0.3333,0.6,0.7143)	(0.2,0.4286,0.5556)	(0.6040,0.7180,0.8003)	0.7074	3
T8	(0.1429,0.1111,0.3333)	(0.2,0.1429,0.3333)	(0.1429,0.1111,0.3333)	(0.3333,0.2,0.1429)	(0.0611,0.0611,0.0966)	(0.1429,0.0.1111,0.3333)	(0.1429,0.0.1111,0.3333)	(0.1429,0.0.1111,0.3333)	(0.3333,0.2,0.4286)	(0.2,0.1429,0.3333)	(0.2040,0.1418,0.3517)	0.2325	8

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TABLE 4: Normalized matrix with Fuzzy composite score

The T3 Cyber-Physical Systems obtained the highest value of arithmetic mean. Hence, it is ranked 1, which shows that in an aluminum extrusion firm, it is important to connect the physical devices with technology to reduce the labor load. On the other hand, T8 Additive manufacturing obtained the lowest value of the arithmetic mean. Hence, it is ranked last, which shows that in this type of firm, this technology is least impactful. With the help of the BHARAT-2, the decision-makers of manufacturing firms can better understand which Industry 4.0 technologies have the most impact on their firm so that they can have better profit and production.

Table *5* depicts the ranks obtained by BHARAT-2 method with weights obtained by different methods such as equal weights, rank sum, rank inverse, DAT, pairwise, AHP and BHARAT-2 different methods. The results show a minor variation in RR, ROC and AHP for rank 5 and 6, while EW, RS, DAT, pairwise and BHARAT-2 methods obtained same ranking as obtained by Pour et al. [17]. Further, the correlation is also calculated from Table *5*.

	EW	RS	RR	ROC	DAT	Pairwise	AHP	BHARAT-2
T1	2	2	2	2	2	2	2	2
T2	4	4	4	4	4	4	4	4
T3	1	1	1	1	1	1	1	1
T4	7	7	7	7	7	7	7	7
T5	6	6	5	5	6	6	5	6
T6	5	5	6	6	5	5	6	5
T7	3	3	3	3	3	3	3	3
T8	8	8	8	8	8	8	8	8

TABLE 5: Ranks obtained by BHARAT-2 using weights obtained by different methods

ROC, Rank Order Centroid; DAT, Direct assignment technique; EW, equal weight; RS, Rank Sum; RR, rank-inverse; AHP, Analytic Hierarchy Process

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	EW	RS	RR	ROC	DAT	Pairwise	AHP	BHARAT-2
EW	1.0000							
RS	1.0000	1.0000						
RR	0.9762	0.9762	1.0000					
ROC	0.9762	0.9762	1.0000	1.0000				
DAT	1.0000	1.0000	0.9762	0.9762	1.0000			
Pairwise	1.0000	1.0000	0.9762	0.9762	1.0000	1.0000		
AHP	0.9762	0.9762	1.0000	1.0000	0.9762	0.9762	0.9762	
BHARAT-2	1.0000	1.0000	0.9762	0.9762	1.0000	1.0000	1.0000	1.0000

TABLE 6: Rank corelation for case study 1

ROC, Rank Order Centroid; DAT, Direct assignment technique; EW, equal weight; RS, Rank Sum; RR, rank-inverse; AHP, Analytic Hierarchy Process

Table *6*, shows the rank correlation of EW, RS, RR, ROC, DAT, Pairwise, AHP and BHARAT-2. The rank correlation of EW vs RR is 0.9762 because of the variation observed in rank 5 and 6. Similarly, for EW vs ROC the value is 0.9762. Here, the arithmetic mean is an approach used to normalize the fuzzy composite score. Further, these ranks are compared with the ranks obtained by Pour et al. [17] i.e., T3>T1>T7>T2>T5>T6>T4>T8 the ranks are almost similar, as seen in Table *5*. From Table *5*, we can conclude that the BHARAT-2 is able to solve the fuzzy problems, and for the defuzzifing the fuzzy data, we can use any approach. It is not necessary to take the arithmetic mean; the ranks obtained will be the same for all the approaches as the ranks to the alternatives depend on the attributes' priorities. If the decision-maker can change his/her priorities for the attributes, the ranks will be changed. The ranks obtained by the BHARAT-2 with different weights could conclude that ranks are sensitive to weights minor variation in weights can lead to alternation in ranks.

Case study: 2. Third-party logistics services provider problem

The selection of an appropriate third-party logistics (3PL) provider has emerged as one of the most crucial strategic decisions for organizations operating in highly competitive and globalized markets. An efficient 3PL provider not only enhances supply chain performance through cost reduction, timely delivery, and flexibility but also supports firms in achieving customer satisfaction, sustainability, and long-term competitiveness. Given its importance, researchers have extensively investigated the 3PL selection problem using different MCDM approaches, often under fuzzy environments to address uncertainty in expert judgments. For instance, Zarbakhshnia et al. [32] tackled this problem using a hybrid framework of Fuzzy SWARA and Fuzzy COPRAS, which enabled both criteria weighting and ranking of alternatives under imprecise conditions. Wang et al. [33] adopted Fuzzy AHP in combination with Fuzzy VIKOR to capture the hierarchical structure of decision criteria and provide a compromise ranking solution. Extending this line of research, Wang and Dang [34] proposed an integrated method of Fuzzy AHP and Fuzzy MARCOS, demonstrating its applicability in handling complex evaluation environments. Singh et al. [35] addressed the specialized context of cold chain management, where reliability and temperature control are critical, by applying Fuzzy AHP and Fuzzy TOPSIS for selecting the most suitable

3PL provider. Similarly, Keshavarz et al. [36] advanced the literature by employing the CRITIC-WASPAS method in a Type-2 fuzzy environment, thereby improving robustness in capturing higher degrees of uncertainty. Furthermore, Nila and Roy [37] highlighted that sustainability considerations - such as environmental performance, social responsibility, and long-term economic viability - are increasingly becoming essential dimensions in 3PL provider selection, reflecting the broader paradigm shift toward sustainable supply chain management.

Wang and Dang [34] have conducted a case study of a manufacturing company in Vietnam which have their specialization in electronic devices, smart components, and other technological devices. For continued production, they are involved in the high manufacturing, which requires adaption of Industry 4.0, for which the company needs to enhance the logistics by selecting a third-party logistics, which has modern standards and digital innovations. For this purpose, the company allows a panel of 15 experts to weigh the criteria and rank the 3PLs. These experts have more than 5 years of experience in the industry, having domains such as logistics and supply chain, technology, industry insights, and compliance.

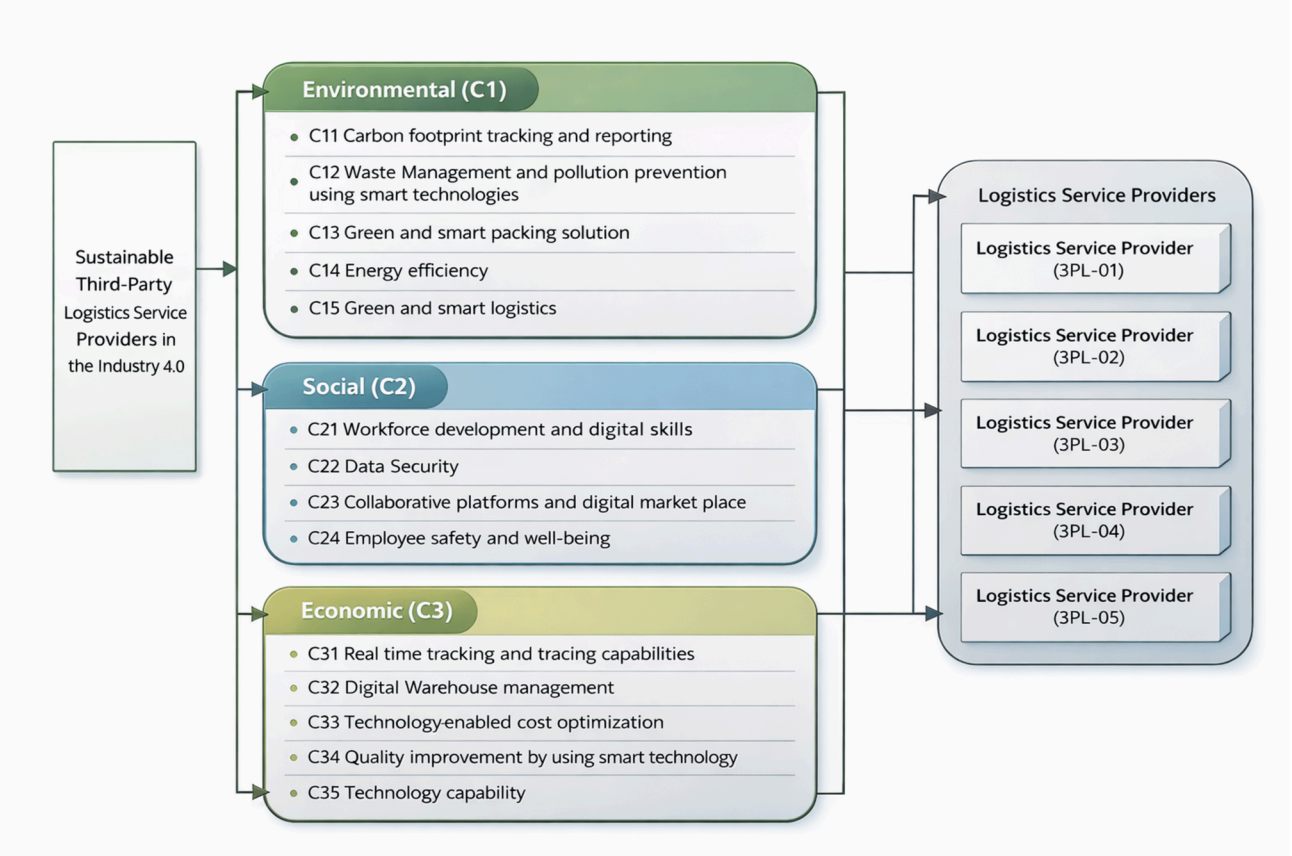


FIGURE 3: Framework for case study 2

There are major three criteria, i.e., C1 - Environmental, C2 - Social and C3 - Economic and these criteria are divided into subcategory as follows:

C1 - Environmental category:

C11 - Tracking and reporting of carbon footprint

C12 - Using smart technology waste and pollution management with prevention

C13 - Smart and green packaging

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C14 - Energy efficiency

C15 - Smart and green logistics

C2 - Social Category:

C21 - Digital skills and workforce development

C22 - Data security

C23 - Digital marketplaces and Collaborative platforms

C24 - Employee well-being and safety

C3 - Economic Category:

C31 - Real-time tracing and tracking capabilities

C32 - Digital warehouse management

C33 - Technology enabled cost optimization

C34 - Using smart technologies quality improvement

C35 - Technology capability

C36 - Supply chain visibility

Steps of BHARAT-2:

Step 1: Identify the number of attributes and alternatives. Here there are 15 attributes and 5 alternatives as shown in Figure *3* and all the attributes are beneficial in this case for which the higher values are preferred. Table *7* shows the fuzzy data 5 alternatives for 15 criteria. The data are in fuzzy triangular form.

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	C11			**C12**			**C13**		
3PL-01	5.2862	6.2219	7.3192	4.7729	5.4649	6.8428	3.9193	5.1093	6.0478
3PL-02	3.8740	4.9959	6.0136	5.4062	6.3270	7.4428	5.7203	6.5799	7.7403
3PL-03	5.2252	6.1185	7.2777	5.2252	6.2219	7.2777	4.8287	5.7203	6.8818
3PL-04	2.9542	4.3597	5.1648	5.1648	6.3270	7.2365	3.2888	4.4107	5.4649
3PL-05	4.8287	5.9828	6.8818	3.2888	4.7729	5.4649	3.1787	4.4107	5.3437
	C14			C15			C21		
3PL-01	2.7597	4.0289	4.9382	4.0082	5.1093	6.1500	4.6670	5.8501	6.7291
3PL-02	3.9395	4.8287	5.9828	3.9295	5.1093	5.9828	3.6613	4.7215	5.7825
3PL-03	5.2252	6.0839	7.2777	5.0502	6.1185	7.1163	4.0760	5.2862	6.1185
3PL-04	4.0760	4.9959	6.1185	3.9395	4.9382	5.9828	4.2630	5.3437	6.3270
3PL-05	2.5648	3.8076	4.7729	2.8553	4.0760	5.0502	5.1690	5.9828	7.1976
	C22			C23			C24		
3PL-01	3.3057	4.2171	5.4062	4.0760	4.9959	6.1185	4.7215	5.7203	6.7674
3PL-02	5.2862	6.2573	7.3192	4.0289	5.3481	6.0839	3.9395	4.8287	5.9828
3PL-03	5.3481	6.1185	7.3608	3.4202	4.4622	5.5288	4.0289	4.9959	6.0839
3PL-04	4.5144	5.7203	6.5444	4.4107	5.4062	6.4706	4.2172	4.8287	6.2573
3PL-05	3.0722	4.2172	5.2252	4.5635	5.7203	6.6173	3.2888	4.6130	5.4649
	C31			C32			C33		
3PL-01	3.7881	4.8287	5.9137	4.5107	5.5288	6.5799	4.0082	5.2252	6.1500
3PL-02	5.2862	6.2219	7.3119	6.1185	7.2777	8.1393	3.6613	4.8287	5.7825
3PL-03	4.0760	4.8851	6.1185	4.7729	5.7825	6.8428	5.4062	6.3270	7.4428
3PL-04	4.6670	5.4975	6.7291	2.3038	3.6801	4.5107	4.5635	5.4062	6.6173
3PL-05	5.9828	7.0379	8.0040	2.6536	4.0289	4.8811	5.9828	6.9981	8.0040
	C34			C35			C36		

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3PL-01	5.2252	6.2573	7.2777	5.1093	5.8501	7.1568	4.8287	5.8501	6.8818
3PL-02	4.7729	5.5889	6.8428	4.8287	5.8501	6.8818	4.1684	5.2252	6.2219
3PL-03	4.9382	5.8501	6.9981	5.7203	6.4339	7.7403	5.1690	6.1185	7.1976
3PL-04	3.4799	4.8247	5.6833	5.3437	6.6173	7.4007	5.7203	6.8818	7.7403
3PL-05	4.4107	5.2862	6.4706	4.1203	4.8811	6.1867	3.3057	4.3633	5.4062

TABLE 7: Fuzzy decision matrix for 3PLs

Step 2: Giving ranks to the attributes by considering the expert opinion, the C34, C35, C33, C22, and C15 are the top five criteria for evaluation of 3PLs, which covers almost 50% of the total weight for 3PLs selection from a total of 15 criteria. However, the decision-maker can change the priorities of these criteria according to the aims and objectives of the firm. The rank 1 is given to C35, i.e., Technology capability followed by C34, i.e., using smart technologies quality improvement in such a way the priorities are as follows: C35>C34>C33>C22>C15>C23>C31>C13>C14>C21>C24>C12>C11>C36>C32 where C32 has the least priorities given by Wang and Dang [31]. Based on these ranks of the attributes, the weights are calculated using the BHARAT-2 and the priorities given by the experts are used generate the weight determination matrix, as shown in Table *8*.

	C35	C34	C33	C22	C15	C23	C31	C13	C14	C21	C24	SUM	WEIGHTS
C35	1.0000	2.0000	3.0000	4.0000	5.0000	6.0000	7.0000	8.0000	9.0000	10.0000	11.0000	120.0000	0.3014
C34	0.5000	1.0000	1.5000	2.0000	2.5000	3.0000	3.5000	4.0000	4.5000	5.0000	5.5000	60.0000	0.1507
C33	0.3333	0.6667	1.0000	1.3333	1.6667	2.0000	2.3333	2.6667	3.0000	3.3333	3.6667	40.0000	0.1005
C22	0.2500	0.5000	0.7500	1.0000	1.2500	1.5000	1.7500	2.0000	2.2500	2.5000	2.7500	30.0000	0.0753
C15	0.2000	0.4000	0.6000	0.8000	1.0000	1.2000	1.4000	1.6000	1.8000	2.0000	2.2000	24.0000	0.0603
C23	0.1667	0.3333	0.5000	0.6667	0.8333	1.0000	1.1667	1.3333	1.5000	1.6667	1.8333	20.0000	0.0502
C31	0.1429	0.2857	0.4286	0.5714	0.7143	0.8571	1.0000	1.1429	1.2857	1.4286	1.5714	17.1429	0.0431
C13	0.1250	0.2500	0.3750	0.5000	0.6250	0.7500	0.8750	1.0000	1.1250	1.2500	1.3750	15.0000	0.0377
C14	0.1111	0.2222	0.3333	0.4444	0.5556	0.6667	0.7778	0.8889	1.0000	1.1111	1.2222	13.3333	0.0335
C21	0.1000	0.2000	0.3000	0.4000	0.5000	0.6000	0.7000	0.8000	0.9000	1.0000	1.1000	12.0000	0.0301
C24	0.0909	0.1818	0.2727	0.3636	0.4545	0.5455	0.6364	0.7273	0.8182	0.9091	1.0000	10.9091	0.0274

How to cite this article:
Rao R V, Bajaj K (July 07, 2026) Best Holistic Adaptable Ranking of Attributes Technique-2 for Fuzzy Decision-Making in Industry 4.0: A Robust and Computationally Efficient Multi-Attribute Decision-Making Approach. Cureus J Eng 3 : es44388-026-00153-z. DOI https://doi.org/10.7759/s44388-026-00153-z

C12	0.0833	0.1667	0.2500	0.3333	0.4167	0.5000	0.5833	0.6667	0.7500	0.8333	0.9167	1.0000	1.0833	1.1667	1.2500	10.0000	0.0251
C11	0.0769	0.1538	0.2308	0.3077	0.3846	0.4615	0.5385	0.6154	0.6923	0.7692	0.8462	0.9231	1.0000	1.0769	1.1538	9.2308	0.0232
C36	0.0714	0.1429	0.2143	0.2857	0.3571	0.4286	0.5000	0.5714	0.6429	0.7143	0.7857	0.8571	0.9286	1.0000	1.0714	8.5714	0.0215
C32	0.0667	0.1333	0.2000	0.2667	0.3333	0.4000	0.4667	0.5333	0.6000	0.6667	0.7333	0.8000	0.8667	0.9333	1.0000	8.0000	0.0201
																398.1875	

TABLE 8: Weight determination matrix for criteria of 3PLs

Step 3: The data of Table *7* is to be normalized based on beneficial and non-beneficial criteria. In this case, all the attributes are beneficial and so using $\left(\frac{x_{ji}}{(x_i)_{\text{best}}}\right)$

Table *5* is normalized. For instance, (5.2892,6.2219,7.3192)/(5.2892,6.2219,7.3192) = (1,1,1). Similarly, we will calculate the normalized value for all.

Step 4: The weights obtained from Table *8* is multiplied by the normalized value of the criteria, as all the criteria are beneficial the normalized value is calculated as follows: For instance, $1 \times 0.0232 + 0.08829 \times 0.0251 + 0.06852 \times 0.0377 + 0.5282 \times 0.0334 + 0.7637 \times 0.0603 + 0.9029 \times 0.0301 + 0.6181 \times 0.0753 + 0.8932 \times 0.0502 + 1 \times 0.0274 + 0.6332 \times 0.0430 + 0.7372 \times 0.0201 + 0.6700 \times 0.1004 + 1 \times 0.1507 + 0.8932 \times 0.3014 + 0.8441 \times 0.02156 = 0.8301$ which is the first value of composite score and in the similar way the other values are calculated.

Step 5: Now to obtained rank we need to defuzzify the fuzzy composite score so we can used arithmetic mean. For instance, geometric mean for 0.8301,0.8534,0.8816 is 0.8550 for 3PL-01, using BHARAT-2. Similarly, we can calculate the arithmetic mean for all the alternative ranges from 3PL-01 to 3PL-05.

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Weights	0.0232	0.0251	0.0377	0.0335	0.0603	0.0301	0.0753	0.0502	0.0274	0.0431	0.0201	0.1005	0.1507	0.3014	0.0215	Composite Score	Arithmetic Mean	Rank
	C11	C12	C13	C14	C15	C21	C22	C23	C24	C31	C32	C33	C34	C35	C36			
3PL-01	(1.0000,1.0000,1.0000)	(0.8829,0.8637,0.9194)	(0.6852,0.7765,0.7813)	(0.5282,0.6622,0.6785)	(0.7937,0.8351,0.8642)	(0.9029,0.9778,0.9349)	(0.6181,0.6739,0.7345)	(0.8932,0.8734,0.9246)	(1.0000,1.0000,1.0000)	(0.6332,0.6861,0.7388)	(0.7372,0.7597,0.8084)	(0.6700,0.7467,0.7684)	(1.0000,1.0000,1.0000)	(0.8932,0.8841,0.9246)	(0.8441,0.8501,0.8891)	(0.8301,0.8534,0.8816)	0.8550	3
3PL-02	(0.7329,0.8030,0.8216)	(1.0000,1.0000,1.0000)	(1.0000,1.0000,1.0000)	(0.7539,0.7937,0.8221)	(0.7781,0.8351,0.8407)	(0.7083,0.7892,0.8034)	(0.9884,1.0000,0.9943)	(0.8829,0.9349,0.9194)	(0.8344,0.8441,0.8841)	(0.8836,0.8841,0.9135)	(1.0000,1.0000,1.0000)	(0.6120,0.6900,0.7225)	(0.9134,0.8932,0.9402)	(0.8441,0.8841,0.8891)	(0.7287,0.7593,0.8038)	(0.8423,0.8723,0.8885)	0.8677	2
3PL-03	(0.9885,0.9834,0.9943)	(0.9665,0.9834,0.9778)	(0.8441,0.8694,0.8891)	(1.0000,1.0000,1.0000)	(1.0000,1.0000,1.0000)	(0.7885,0.8836,0.8501)	(1.0000,0.9778,1.0000)	(0.7495,0.7801,0.8355)	(0.8533,0.8734,0.8990)	(0.6813,0.6941,0.7644)	(0.7801,0.7646,0.8407)	(0.9036,0.9041,0.9299)	(0.9451,0.9349,0.9616)	(1.0000,0.9723,1.0000)	(0.9036,0.8891,0.9299)	(0.9319,0.9271,0.9519)	0.9370	1
3PL-04	(0.5589,0.7007,0.7057)	(0.9553,1.0000,0.9723)	(0.5749,0.6703,0.7060)	(0.7801,0.8212,0.8407)	(0.7801,0.8071,0.8407)	(0.8247,0.8932,0.8790)	(0.8441,0.9142,0.8891)	(0.9665,0.9451,0.9778)	(0.8932,0.8441,0.9246)	(0.7801,0.7811,0.8407)	(0.3765,0.5057,0.5542)	(0.7628,0.7725,0.8267)	(0.6660,0.7711,0.7809)	(0.9342,1.0000,0.9561)	(1.0000,1.0000,1.0000)	(0.8144,0.8696,0.8718)	0.8519	4
3PL-05	(0.9135,,0.9616,0.9	(0.6083,0.7544,0.7	(0.5557,0.6703,0.6	(0.4909,0.6258,0.6	(0.5654,0.6662,0.7	(1.0000,1.0000,1.0	(0.5744,0.6740,0.7	(1.0000,1.0000,1.0	(0.6966,0.8064,0.8	(1.0000,1.0000,1.0	(0.4337,0.5536,0.5	(1.0000,1.0000,1.0	(0.8441,0.8448,0.8	(0.7203,0.7376,0.7	(0.5779,0.6340,0.6	(0.7596,0.7987,0.8	0.7969	5

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	40 2)	34 3)	90 4)	55 8)	09 7)	00 0)	09 9)	00 0)	07 5)	00 0)	99 7)	00 0)	89 1)	99 3)	98 4)	32 4)		

TABLE 9: Normalized matrix with Fuzzy composite score for 3PLs

Step 6: Rank the alternative based on the decreasing order of the arithmetic mean. The ranks obtained are 3PL-03> 3PL-02>3PL>01>3PL-04>3PL-05, where 3PL-03 is highest, and hence ranked 1, followed by 3PL-02, 3PL-03, 3PL-04, and the last rank is given to 3PL-05. 3PL-03 has consistently maintained its position as the preferred 3PL.

The arithmetic mean is used to rank the PLs using BHARAT-2. The ranks obtained are same as ranked by Wang and Dang [34], i.e., 3PL-03> 3PL-02>3PL>01>3PL-04>3PL-05. They used Fuzzy AHP to find the weight and then Fuzzy MACROS to find the ranks, which is a very complex method, so the BHARAT-2 can be used to solve this type of fuzzy problem. From Table *9*, we can conclude that any approach can be used to defuzzied the composite score. It is not necessary to use arithmetic mean as the ranks to the alternatives depends on the attributes' priorities.

Table *10* depicts the ranks obtained by BHARAT-2 method with weights obtained by different methods such as equal weights, rank sum, rank inverse, DAT, pairwise, AHP and BHARAT-2 methods. The results show a minor variation in RS, ROC, and pairwise for rank 3 and 4 while EW, RR, DAT, and BHARAT-2 methods obtained same ranking as given by Wang and Dang [34]. Further, the correlation is also calculated from Table *11*.

	EW	RS	RR	ROC	DAT	Pairwise	AHP	BHARAT-2
3PL-01	3	4	3	4	3	4	3	3
3PL-02	2	2	2	2	2	2	2	2
3PL-03	1	1	1	1	1	1	1	1
3PL-04	4	3	4	3	4	3	4	4
3PL-05	5	5	5	5	5	5	5	5

TABLE 10: Ranks obtained by BHARAT-2 using weights obtained by different methods

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	EW	RS	RR	ROC	DAT	Pairwise	AHP	BHARAT-2
EW	1							
RS	0.9	1						
RR	1	0.9	1					
ROC	0.9	1	0.9	1				
DAT	1	0.9	1	0.9	1			
PAIRWISE	0.9	1	0.9	1	0.9	1		
AHP	1	0.9	1	0.9	1	0.9	1	
BHARAT-2	1	0.9	1	0.9	1	0.9	1	1

TABLE 11: Rank corelation for case study 2

ROC, Rank Order Centroid; DAT, Direct assignment technique; EW, equal weight; RS, Rank Sum; RR, rank-inverse; AHP, Analytic Hierarchy Process

Table *11* shows the rank correlation of EW, RS, RR, ROC, DAT, Pairwise, AHP, and BHARAT-2. The rank correlation of EW vs RS is 0.9 because of the variation observed in rank 3 and 4. Similarly, for EW vs ROC the value is 0.9. From Table *11*, we can conclude that the BHARAT-2 is able to solve the fuzzy problems, and for the defuzzifing the fuzzy data. The ranks obtained will vary from alternative to alternative as these alternatives depend on the attributes' priorities. If the decision-maker can change his/her priorities for the attributes, the ranks will be changed. The ranks obtained by the BHARAT-2 with different weights could conclude that ranks are sensitive to weights minor variation in weights that can lead to alternation in ranks.

Case study: 3. digital sustainable supply chain problem

Supply change risk management had gained critical importance due to digital transformation, globalization, and sustainability concerns. The traditional supply chain faces risk such as operations, supply, demand, environment and social responsibility but, with the rise of digital era, the challenges shift toward green technology, e-waste, data security, etc. Ahuja and Kaur [38] had developed an integrated fuzzy MADM framework to analyze and prioritize risk mitigation strategies for a digitally sustainable electronic supply chain. The study identified 25 risk factors and 22 mitigation strategies through expert consultation and literature synthesis. Using the Fuzzy Delphi Method (FDM), significant risks and strategies were refined, followed by Fuzzy TOPSIS based on Z-numbers to rank the most effective mitigation measures. Ahuja and Kaur [38] had taken an Indian electronics industry case study, revealed that adopting advanced technology, embracing green practices, enhancing agility, maintaining responsive pricing, and fostering stakeholder collaboration are the most influential strategies for building supply chain resilience. According to Tang [39] and Aqlan and Lam [40], effective supply chain risk management involves systematic identification, assessment, and mitigation of potential risks through coordination among supply chain participants to ensure profitability and resilience.

The emergence of the digital supply chain (DSC), powered by Industry 4.0 technologies such as the IoT, artificial intelligence, and big data analytics, has transformed supply chain operations by enhancing connectivity, visibility, and responsiveness. However, digitalization has also introduced new categories of risks, including data breaches, technological failures, and cybersecurity threats, while simultaneously amplifying traditional risks such as supply shortages and demand fluctuations. Moreover, growing environmental and social awareness has compelled industries to adopt sustainable and responsible practices that minimize ecological footprints, reduce waste, and improve social welfare. This evolution has led to the concept of a Digitally Sustainable Supply Chain - one that harmonizes digital transformation with the pillars of sustainability: economic viability, environmental stewardship, and social equity.

Existing literature has identified a wide range of supply chain risks spanning environmental, economic, operational, informational, and societal dimensions [41,42]. Environmental risks include the unavailability of green materials, inefficient energy usage, and waste generation [43], whereas social risks involve unethical labor practices, lack of employee safety, and poor stakeholder relations. Economic and operational risks such as raw material price volatility, delivery delays, and quality issues also remain prominent [44,45]. In response, researchers have proposed numerous risk mitigation strategies, including supplier diversification, technological innovation, stakeholder collaboration, and agile response mechanisms [46,47]. Yet, determining the most suitable set of strategies under uncertainty remains a multi-dimensional and subjective problem requiring robust decision-support models.

To address such decision complexity, several MADM techniques - such as the AHP, Decision-Making Trial and Evaluation Laboratory, Analytic Network Process, and the TOPSIS - have been utilized in SCRM. Among these, Fuzzy TOPSIS stands out for its ability to handle linguistic and imprecise information effectively, reflecting the ambiguity inherent in human judgment. The integration of Z-numbers further enhances the model's reliability by incorporating the confidence level of decision-makers' assessments [48]. Hsu and Hu [49] and Rezaei et al. [50] had demonstrated the effectiveness of fuzzy-based MADM in prioritizing risks, selecting suppliers, and evaluating sustainability performance. However, there is still a research gap in combining digital transformation, sustainability, and risk mitigation within a unified decision-making framework, particularly for the electronics manufacturing sector, where issues such as e-waste, technological obsolescence, and green investment risks are critical.

For this case study, Ahuja and Kaur [38] had taken five decision-makers who have more than 10 years of experience in productions, operation and logistics, marketing and procurement. There are 12 risk factor (attributes) and 11 Mitigation strategies (Alternatives).

Environmental Risks

R1 - Supply risk: Supply insufficiently green material for production.

R2 - Energy Consumption: Risk of inefficient energy use.

R3 - Green Technological Changes: Risk of implementing green technologies.

R4 - Hazardous waste generation: Inefficacy use of resources leads to production of harmful waste.

R5 - Lack of environmental policy: Risk involves noncompliance with government imposing environment laws and regulations.

R6 - Green Supplier failure: Supplier fails to provide green material.

Social Risks

R7 - Failure to fulfil social commitments: Risk associate with breaching social obligations.

R8 - Training of employees: Risk associate with training of employees.

Economic Risks

R9 - Demand issues: Risk associated with changing demands.

R10 - Raw material price uncertainty: Price of raw material is uncertain that infer with procurement.

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Rao R V, Bajaj K (July 07, 2026) Best Holistic Adaptable Ranking of Attributes Technique-2 for Fuzzy Decision-Making in Industry 4.0: A Robust and Computationally Efficient Multi-Attribute Decision-Making Approach. Cureus J Eng 3 : es44388-026-00153-z. DOI https://doi.org/10.7759/s44388-026-00153-z

R11 - Delivery delays: Supplier fails to deliver on time or there are ongoing delays.

R12 - Transportation risks: Risk associate with delay in delivery, damage of product during delivery or expensive shipping.

Mitigation Strategies

MS1 - Hazardous substance management: Substitution, caution and lowering of harmful waste and chemical usage.

MS2 - Fulfilling social responsibility: Responsible for carry out their civic obligation which must be benefit for the society.

MS3 - Strong association with stakeholders: Organization must have a good and open relation with its supplier and client.

MS4 - Risk Planning-Putting into action a methodology is divided into three phase (i) identification, measurement and assessment, (ii) evaluation, mitigation and emergency plan, and (iii) control and monitoring.

MS5 - Developing agility: Agility refers to the ability to respond swiftly and effectively to unexpected changes. In today's competitive, unstable, and uncertain market environment, organizations must build agility into their supply chains to ensure the continuous and efficient delivery of goods and services.

MS6 - Use of advanced technology: Leveraging advanced technologies can enable businesses to efficiently handle large volumes of data and make informed, data-driven decisions based on the insights obtained.

MS7 - Implementation of regulation and regulatory compliance: Compliance with sustainability standards and certifications.

MS8 - Flexible and multimodal transportation: Employing diverse transportation modes (such as air, sea, rail, road, and small carriers), along with multiple logistics partners and routes, helps mitigate supply chain disruptions and enhance operational resilience.

MS9 - Responsive pricing: Managing and controlling the demand for specific products.

MS10 - Adoption of green practices: Implementation of green practices across all supply chain partners in design, procurement, production, warehousing, and distribution processes.

MS11- Robust supply chain Strategies: Strategies aimed at reducing the frequency and severity of risks at both the organizational and supply chain levels.

Steps of BHARAT-2:

Step 1: Identify the number of attributes and alternatives. Here there are 12 attributes and 11 alternatives and all the attributes are beneficial in this case for which the higher values are preferred. Table *12* shows the fuzzy value given by decision-makers for 12 attributes, the data are in fuzzy triangular form.

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	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
DM1	(0.418 3,0.58 57,0.7 530)	(0.639 0,0.82 16,0.8 216)	(0.418 3,0.58 57,0.7 530)	(0.251 0,0.41 83,0.5 857)	(0.418 3,0.58 57,0.7 530)	(0.273 9,0.45 64,0.6 390)	(0.418 3,0.58 57,0.7 530)	(0.456 4,0.63 90,0.8 216)	(0.585 7,0.75 30,0.7 530)	(0.418 3,0.58 57,0.7 530)	(0.418 3,0.58 57,0.7 530)	(0.639 0,0.82 16,0.8 216)
DM2	(0.639 0,0.82 16,0.8 216)	(0.639 0,0.82 16,0.8 216)	(0.495 0,0.63 64,0.6 364)	(0.212 1,0.35 36,0.4 950)	(0.251 0,0.41 83,0.5 857)	(0.418 3,0.58 57,0.7 530)	(0.456 4,0.63 90,0.8 216)	(0.418 3,0.58 57,0.7 530)	(0.456 4,0.63 90,0.8 216)	(0.251 0,0.41 83,0.5 857)	(0.585 7,0.75 30,0.7 530)	(0.639 0,0.82 16,0.8 216)
DM3	(0.456 4,0.63 90,0.8 216)	(0.418 3,0.58 57,0.7 530)	(0.585 7,0.75 30,0.7 530)	(0.251 0,0.41 83,0.5 857)	(0.353 6,0.49 50,0.6 364)	(0.456 4,0.63 90,0.8 216)	(0.639 0,0.82 16,0.8 216)	(0.273 9,0.45 64,0.6 390)	(0.251 0,0.41 83,0.5 857)	(0.251 0,0.41 83,0.5 857)	(0.639 0,0.82 16,0.8 216)	(0.585 7,0.75 30,0.7 530)
DM4	(0.639 0,0.82 16,0.8 216)	(0.456 4,0.63 90,0.8 216)	(0.418 3,0.58 57,0.7 530)	(0.070 7,0.21 21,0.3 536)	(0.418 3,0.58 57,0.7 530)	(0.212 1,0.35 36,0.4 950)	(0.639 0,0.82 16,0.8 216)	(0.585 7,0.75 30,0.7 530)	(0.212 1,0.35 36,0.4 950)	(0.418 3,0.58 57,0.7 530)	(0.456 4,0.63 90,0.8 216)	(0.418 3,0.58 57,0.7 530)
DM5	(0.585 7,0.75 30,0.7 530)	(0.418 3,0.58 57,0.7 530)	(0.251 0,0.41 83,0.5 857)	(0.070 7,0.21 21,0.3 536)	(0.251 0,0.41 83,0.5 857)	(0.418 3,0.58 57,0.7 530)	(0.353 6,0.49 50,0.6 364)	(0.585 7,0.75 30,0.7 530)	(0.585 7,0.75 30,0.7 530)	(0.456 4,0.63 90,0.8 216)	(0.639 0,0.82 16,0.8 216)	(0.585 7,0.75 30,0.7 530)

TABLE 12: Fuzzy data by group decision-makers

Step 2: Giving ranks to the attributes by considering the expert opinion, the ranks are aggregated based on the five decision makers. R12 is ranked the highest, followed by R1, R11, R2, R7, R8, R3, R9, R10, R6, R5, and R4 is ranked the last. However, the decision-maker can change the priorities of these criteria according to the aims and objectives of the firm. Based on these ranks of the attributes, the weights are calculated using the BHARAT-2 and the priorities given by the experts are used generate the weight determination matrix, as shown in Table *13*.

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	R12	R1	R11	R2	R7	R8	R3	R9	R10	R6	R5	R4	SUM	Weights
R12	1.0000	2.0000	3.0000	4.0000	5.0000	6.0000	7.0000	8.0000	9.0000	10.0000	11.0000	12.0000	78.0000	0.3222
R1	0.5000	1.0000	1.5000	2.0000	2.5000	3.0000	3.5000	4.0000	4.5000	5.0000	5.5000	6.0000	39.0000	0.1611
R11	0.3333	0.6667	1.0000	1.3333	1.6667	2.0000	2.3333	2.6667	3.0000	3.3333	3.6667	4.0000	26.0000	0.1074
R2	0.2500	0.5000	0.7500	1.0000	1.2500	1.5000	1.7500	2.0000	2.2500	2.5000	2.7500	3.0000	19.5000	0.0806
R7	0.2000	0.4000	0.6000	0.8000	1.0000	1.2000	1.4000	1.6000	1.8000	2.0000	2.2000	2.4000	15.6000	0.0644
R8	0.1667	0.3333	0.5000	0.6667	0.8333	1.0000	1.1667	1.3333	1.5000	1.6667	1.8333	2.0000	13.0000	0.0537
R3	0.1429	0.2857	0.4286	0.5714	0.7143	0.8571	1.0000	1.1429	1.2857	1.4286	1.5714	1.7143	11.1429	0.0460
R9	0.1250	0.2500	0.3750	0.5000	0.6250	0.7500	0.8750	1.0000	1.1250	1.2500	1.3750	1.5000	9.7500	0.0403
R10	0.1111	0.2222	0.3333	0.4444	0.5556	0.6667	0.7778	0.8889	1.0000	1.1111	1.2222	1.3333	8.6667	0.0358
R6	0.1000	0.2000	0.3000	0.4000	0.5000	0.6000	0.7000	0.8000	0.9000	1.0000	1.1000	1.2000	7.8000	0.0322
R5	0.0909	0.1818	0.2727	0.3636	0.4545	0.5455	0.6364	0.7273	0.8182	0.9091	1.0000	1.0909	7.0909	0.0293
R4	0.0833	0.1667	0.2500	0.3333	0.4167	0.5000	0.5833	0.6667	0.7500	0.8333	0.9167	1.0000	6.5000	0.0269
													242.0504	1

TABLE 13: Weight determination matrix for criteria of risk mitigation strategies

Step 3: The data of Table *14* shows the fuzzy data of the industrial problem, Table *10* is to be normalized based on beneficial and non-beneficial criteria. In this case, all the attributes are beneficial so using $\left(\frac{x_{ji}}{(x_i)_{\text{best}}}\right)$ Table *10* is normalized. For instance, (4.3052,6.0395,7.4392)/ (5.5074,7.2722,7.9415) = (0.7817,0.8304,0.9367). Similarly, we will calculate the normalized value for all.

How to cite this article:
Rao R V, Bajaj K (July 07, 2026) Best Holistic Adaptable Ranking of Attributes Technique-2 for Fuzzy Decision-Making in Industry 4.0: A Robust and Computationally Efficient Multi-Attribute Decision-Making Approach. Cureus J Eng 3 : es44388-026-00153-z. DOI https://doi.org/10.7759/s44388-026-00153-z

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
MS1	(4.3052, 6.0395, 7.4392)	(5.2184, 7.0137, 8.0787)	(5.1118, 6.8765, 7.9415)	(5.1422, 6.9070, 7.9415)	(4.6704, 6.4047, 7.8043)	(2.9361, 4.6704, 6.4047)	(3.2708, 5.0051, 6.7393)	(1.5974, 3.3317, 5.0660)	(2.2363, 3.9706, 5.7049)	(4.3357, 6.0700, 7.8043)	(2.6014, 4.3357, 6.0700)	(2.6014, 4.3357, 6.0700)
MS2	(5.5074, 7.2722, 7.9415)	(5.3702, 7.1045, 7.8043)	(6.0700, 7.8043, 7.8043)	(5.1644, 6.8164, 7.4339)	(3.6664, 5.4007, 7.1350)	(5.7049, 7.4392, 7.8043)	(2.2668, 4.0011, 5.7354)	(1.7782, 3.4302, 5.0821)	(3.6359, 5.3702, 7.1045)	(2.9361, 4.6704, 6.4047)	(1.5974, 3.3317, 5.0660)	(5.4769, 7.2417, 7.9415)
MS3	(3.2708, 5.0051, 6.7393)	(3.6359, 5.3702, 7.1045)	(2.9818, 4.7466, 6.5114)	(3.9249, 5.6287, 7.3325)	(4.3357, 6.0700, 7.8043)	(2.8904, 4.5942, 6.2980)	(3.3470, 5.1118, 6.8765)	(2.3027, 3.8724, 5.4421)	(4.4119, 6.1767, 7.9415)	(2.6472, 4.4119, 6.1767)	(1.9474, 3.7121, 5.4769)	(3.3775, 5.1422, 6.9070)
MS4	(4.2885, 5.9709, 7.2883)	(2.9361, 4.6704, 6.4047)	(2.6929, 4.4881, 6.2834)	(3.1458, 4.7764, 6.4071)	(5.0813, 6.8460, 7.9415)	(5.0051, 6.7393, 7.8043)	(2.1753, 3.8486, 5.5220)	(2.1586, 3.8410, 5.5235)	(5.1873, 6.8606, 7.5299)	(5.1873, 6.8606, 7.5299)	(2.1753, 3.8486, 5.5220)	(5.1873, 6.8606, 7.5299)
MS5	(2.9818, 4.7466, 6.5114)	(1.0040, 2.2058, 3.9401)	(2.6929, 4.4881, 6.2834)	(1.4435, 3.0955, 4.7475)	(2.6014, 4.3357, 6.0700)	(3.3013, 5.0355, 6.7698)	(3.4232, 5.2184, 7.0137)	(4.6247, 6.3285, 7.6671)	(1.6279, 3.4232, 5.2184)	(1.9626, 3.7579, 5.5531)	(2.6624, 4.4577, 6.2529)	(1.6279, 3.4232, 5.2184)
MS6	(3.5887, 5.2711, 6.9536)	(0.5020, 1.5106, 3.1930)	(3.6359, 5.3702, 7.1045)	(1.1607, 2.8126, 4.4646)	(1.9169, 3.6816, 5.4464)	(5.1118, 6.8765, 7.9415)	(4.9593, 6.6631, 7.6671)	(5.8420, 7.6068, 7.9415)	(1.1454, 2.7669, 4.3884)	(1.1454, 2.7669, 4.3884)	(0.8108, 2.4323, 4.0538)	(0.4761, 1.7782, 3.4302)
MS7	(5.1888, 6.8713,	(0.9263, 2.0351,	(4.4424, 6.2072,	(3.3844, 5.0059,	(1.6127, 3.3775,	(2.9666, 4.7009,	(3.8410, 5.5235,	(3.2708, 5.0051,	(5.8886, 7.5711,	(4.8228, 6.6181,	(1.4542, 3.0238,	(3.8715, 5.5540,

	7.5711)	3.6353)	7.6068)	6.6274)	5.1422)	6.4352)	7.2060)	6.7393)	7.5711)	8.0787)	4.5935)	7.2364)
MS8	(5.0821, 6.7341, 7.4339)	(4.3662, 6.1005, 7.4696)	(4.3662, 6.1005, 7.4696)	(3.9760, 5.5457, 6.7807)	(3.3013, 5.0355, 6.7698)	(5.4769, 7.2417, 7.9415)	(1.7309, 3.3311, 4.9312)	(2.2820, 4.0468, 5.8116)	(4.4119, 6.1767, 7.9415)	(4.5942, 6.2980, 7.6671)	(2.8126, 4.4646, 6.1166)	(4.8526, 6.5260, 7.5299)
MS9	(4.7771, 6.5419, 7.6068)	(2.9720, 4.5417, 6.1114)	(4.0468, 5.8116, 7.5763)	(3.6359, 5.3702, 7.1045)	(1.5365, 3.2708, 5.0051)	(1.2018, 2.9361, 4.6704)	(2.2668, 4.0011, 5.7354)	(1.5670, 3.3013, 5.0355)	(5.2335, 6.9673, 7.6671)	(6.0700, 7.8043, 7.8043)	(3.7648, 5.4168, 7.0688)	(2.0199, 3.5895, 5.1592)
MS10	(3.1260, 4.7779, 6.4299)	(2.8889, 4.5713, 6.2538)	(4.1833, 5.8566, 7.1953)	(3.5902, 5.2940, 6.9978)	(1.6127, 3.3775, 5.1422)	(1.5822, 3.3470, 5.1118)	(1.6852, 3.2549, 4.8245)	(1.2018, 2.9361, 4.6704)	(4.7475, 6.3995, 7.4339)	(4.6704, 6.4047, 7.8043)	(1.9062, 3.5887, 5.2711)	(3.3470, 5.1118, 6.8765)
MS11	(5.1888, 6.8713, 7.5711)	(3.8486, 5.5220, 7.1953)	(5.4464, 7.2112, 7.9415)	(4.7475, 6.3995, 7.4339)	(1.5670, 3.3013, 5.0355)	(1.2171, 2.9818, 4.7466)	(2.2210, 3.9249, 5.6287)	(1.5517, 3.3165, 5.0813)	(4.3357, 6.0700, 7.8043)	(3.8486, 5.5220, 7.1953)	(3.8486, 5.5220, 7.1953)	(4.1833, 5.8566, 7.5299)

TABLE 14: Fuzzy decision matrix for risk mitigation strategies

Step 4: The weights obtained from Table *13* are multiplied by the corresponding normalized fuzzy values of each criterion. Since all the criteria are beneficial, the beneficial normalization formula is used. For the first alternative, the fuzzy composite score is calculated as: 0.1611 × (0.8642,0.7859,0.6925) + 0.0806 × (0.3960,0.2153,0.0962) + 0.0460 × (0.7913,0.6526,0.5269) + 0.0269 × (0.5618,0.4074,0.2256) + 0.0293 × (0.6410,0.5106,0.3290) + 0.0322 × (0.7293,0.6289,0.4094) + 0.0644 × (0.7156,0.6505,0.5153) + 0.0537 × (0.9221,0.8812,0.7524) + 0.0403 × (0.7692,0.6969,0.5122) + 0.0358 × (0.5624,0.4557,0.2642) + 0.1074 × (0.6685,0.5609,0.3116) + 0.3222 × (0.5653,0.4100,0.1830). Thus, the fuzzy composite score of the first alternative is (0.6657,0.5462,0.3686). The fuzzy composite scores for the remaining alternatives are calculated in the same manner.

Step 5: Now, to obtain rank we need to defuzzify the fuzzy composite score and hence used arithmetic mean. For instance, geometric mean (0.6657,0.5462,0.3686) is 0.5268 for MS1, using BHARAT-2. Similarly, we can calculate the arithmetic mean for all the alternative ranges from MS1 to MS11 as shown in Table *15*.

Alternative	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	Composite Score (l, m, u)	Mean	Rank
Weights	0.1611	0.0806	0.046	0.0269	0.0293	0.0322	0.0644	0.0537	0.0403	0.0358	0.1074	0.3222	-	-	-
MS1	(0.86, 0.79, 0.69)	(0.40, 0.22, 0.10)	(0.79, 0.65, 0.53)	(0.56, 0.41, 0.23)	(0.64, 0.51, 0.33)	(0.73, 0.63, 0.41)	(0.72, 0.65, 0.52)	(0.92, 0.88, 0.75)	(0.77, 0.70, 0.51)	(0.56, 0.46, 0.26)	(0.67, 0.56, 0.31)	(0.57, 0.41, 0.18)	(0.6657, 0.5462, 0.3686)	0.5268	7
MS2	(0.81, 0.65, 0.54)	(0.41, 0.21, 0.09)	(0.80, 0.58, 0.44)	(0.60, 0.41, 0.22)	(0.70, 0.61, 0.42)	(0.60, 0.39, 0.21)	(0.84, 0.81, 0.74)	(0.92, 0.86, 0.68)	(0.62, 0.52, 0.32)	(0.69, 0.59, 0.39)	(0.80, 0.73, 0.51)	(0.43, 0.25, 0.09)	(0.6347, 0.4882, 0.3337)	0.4855	11
MS3	(0.95, 0.95, 0.91)	(0.45, 0.28, 0.14)	(0.97, 0.95, 0.90)	(0.61, 0.50, 0.30)	(0.64, 0.54, 0.35)	(0.74, 0.64, 0.42)	(0.70, 0.64, 0.50)	(0.86, 0.76, 0.52)	(0.55, 0.45, 0.26)	(0.71, 0.63, 0.43)	(0.74, 0.66, 0.42)	(0.43, 0.25, 0.09)	(0.6512, 0.5405, 0.3905)	0.5274	6
MS4	(0.88, 0.79, 0.70)	(0.50, 0.32, 0.17)	(1.00, 1.00, 1.00)	(0.70, 0.59, 0.37)	(0.63, 0.48, 0.30)	(0.60, 0.44, 0.24)	(0.87, 0.85, 0.77)	(0.85, 0.76, 0.56)	(0.58, 0.40, 0.22)	(0.58, 0.40, 0.22)	(0.73, 0.63, 0.37)	(0.46, 0.26, 0.09)	(0.6567, 0.5217, 0.3646)	0.5143	8
MS5	(0.99, 1.00, 1.00)	(0.81, 0.69, 0.50)	(1.00, 1.00, 1.00)	(0.94, 0.91, 0.80)	(0.82, 0.75, 0.59)	(0.69, 0.58, 0.36)	(0.69, 0.62, 0.49)	(0.61, 0.46, 0.26)	(0.84, 0.81, 0.70)	(0.79, 0.74, 0.58)	(0.65, 0.55, 0.30)	(0.66, 0.52, 0.29)	(0.7626, 0.6777, 0.5199)	0.6534	2
MS6	(0.92,	(1.00,	(0.88,	(1.00,	(0.92,	(0.59,	(0.63,	(0.59,	(1.00,	(1.00,	(1.00,	(1.00,	(0.9209, 0.88	0.8849	1

	0.90, 0.83)	1.00, 1.00)	0.84, 0.74)	1.00, 1.00)	0.89, 0.80)	0.43, 0.24)	0.49, 0.34)	0.39, 0.21)	1.00, 1.00)	1.00, 1.00)	1.00, 1.00)	1.00, 1.00)	87, 0.8451)		
MS7	(0.85, 0.69, 0.57)	(0.88, 0.74, 0.54)	(0.83, 0.72, 0.61)	(0.67, 0.56, 0.34)	(0.97, 0.97, 0.95)	(0.73, 0.62, 0.41)	(0.67, 0.59, 0.44)	(0.69, 0.59, 0.37)	(0.58, 0.37, 0.19)	(0.54, 0.42, 0.24)	(0.88, 0.80, 0.56)	(0.47, 0.32, 0.12)	(0.6863, 0.5567, 0.3782)	0.5404	5
MS8	(0.87, 0.71, 0.59)	(0.43, 0.25, 0.12)	(0.84, 0.74, 0.62)	(0.66, 0.51, 0.29)	(0.74, 0.65, 0.47)	(0.59, 0.41, 0.22)	(0.98, 0.98, 0.97)	(0.80, 0.73, 0.53)	(0.55, 0.45, 0.26)	(0.57, 0.44, 0.25)	(0.66, 0.54, 0.29)	(0.46, 0.27, 0.10)	(0.6380, 0.4952, 0.3338)	0.489	10
MS9	(0.85, 0.73, 0.62)	(0.52, 0.33, 0.17)	(0.83, 0.77, 0.67)	(0.63, 0.52, 0.32)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(0.84, 0.81, 0.74)	(0.93, 0.89, 0.77)	(0.57, 0.40, 0.22)	(0.56, 0.35, 0.19)	(0.57, 0.45, 0.22)	(0.66, 0.50, 0.24)	(0.7178, 0.5917, 0.4186)	0.576	4
MS10	(1.00, 0.99, 0.95)	(0.51, 0.33, 0.17)	(0.87, 0.77, 0.64)	(0.64, 0.53, 0.32)	(0.97, 0.97, 0.95)	(0.91, 0.88, 0.76)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(0.59, 0.43, 0.24)	(0.56, 0.43, 0.25)	(0.77, 0.68, 0.43)	(0.50, 0.35, 0.14)	(0.7229, 0.6289, 0.4866)	0.6128	3
MS11	(0.85, 0.69, 0.57)	(0.44, 0.27, 0.13)	(0.79, 0.62, 0.49)	(0.60, 0.44, 0.24)	(0.99, 0.99, 0.98)	(0.98, 0.98, 0.99)	(0.86, 0.83, 0.76)	(0.92, 0.89, 1.00)	(0.56, 0.46, 0.26)	(0.61, 0.50, 0.30)	(0.56, 0.44, 0.21)	(0.46, 0.30, 0.11)	(0.6426, 0.5170, 0.3762)	0.5119	9

TABLE 15: Normalized matrix with Fuzzy composite score for risk mitigation strategies

Step 6: Rank the alternative based on the decreasing order of the arithmetic mean. The ranks obtained are MS6>MS5>MS10>MS9>MS7>MS3>MS1>MS4>MS11>MS8>MS2, where the MS6 (use of advance technology) is highest, and hence is ranked 1, followed by MS5, MS10, MS9, MS7, MS3, MS1, MS4, MS11, MS8 and the last rank is given to MS2 (Fulfilling social responsibility). MS6 has consistently maintained its position as the preferred mitigation strategies.

How to cite this article:
Rao R V, Bajaj K (July 07, 2026) Best Holistic Adaptable Ranking of Attributes Technique-2 for Fuzzy Decision-Making in Industry 4.0: A Robust and Computationally Efficient Multi-Attribute Decision-Making Approach. Cureus J Eng 3 : es44388-026-00153-z. DOI https://doi.org/10.7759/s44388-026-00153-z

The arithmetic mean was used to rank the mitigation strategies with BHARAT-2. The ranking produced by Ahuja and Kaur [38], who used the FDM and Fuzzy TOPSIS, is: MS6>MS5>MS10>MS9>MS11>MS3>MS7>MS4>MS1>MS2>MS8. BHARAT-2 produces a slightly different ordering: MS6>MS5>MS10>MS9>MS7>MS3>MS1>MS4>MS11>MS8>MS2. The top three positions are identical in both approaches (MS6, MS5, MS10). However, BHARAT-2 places MS2 (fulfilling social responsibility) last, while Ahuja and Kaur rank MS8 (flexible and multimodal transportation) last. We argue that MS8 should be ranked higher than MS2: although organizations might occasionally deprioritize social responsibility, a lack of flexibility in transportation can cause severe customer loss. Therefore, the BHARAT-2 ranking appears more precise and justifiable in this context. Furthermore, because Ahuja and Kaur employed the comparatively complex FDM and Fuzzy TOPSIS to derive weights and ranks, BHARAT-2 offers a simpler yet effective alternative for solving this kind of fuzzy decision problem.

Table *16* depicts the ranks obtained by BHARAT-2 method with weights obtained by different methods such as equal weights, rank sum, rank inverse, DAT, pairwise, AHP and BHARAT-2 methods. The results show a variation in EW, RS, ROC, DAT, pairwise, and AHP, while minor variation is observed between RR and BHARAT-2 for rank 5 and 6. Further, the correlation is also calculated from Table *17*.

	EW	RS	RR	ROC	DAT	Pairwise	AHP	BHARAT-2
MS1	9	9	7	8	9	9	8	7
MS2	11	10	11	10	10	10	10	11
MS3	7	6	6	6	6	6	6	5
MS4	8	7	8	7	7	7	7	8
MS5	2	2	2	2	2	2	2	2
MS6	1	1	1	1	1	1	1	1
MS7	6	5	5	5	5	5	4	6
MS8	10	11	10	11	11	11	11	10
MS9	4	4	4	4	4	4	5	4
MS10	3	3	3	3	3	3	3	3
MS11	5	8	9	9	8	8	9	9

TABLE 16: Ranks obtained by BHARAT-2 using weights obtained by different methods

ROC, Rank Order Centroid; DAT, Direct assignment technique; EW, equal weight; RS, Rank Sum; RR, rank-inverse; AHP, Analytic Hierarchy Process

	EW	RS	RR	ROC	DAT	Pairwise	AHP	BHARAT-2
EW	1.0000							
RS	0.9364	1.0000						
RR	0.9000	0.9636	1.0000					
ROC	0.9000	0.9909	0.9818	1.0000				
DAT	0.9364	1.0000	0.9636	0.9909	1.0000			
Pairwise	0.9364	1.0000	0.9636	0.9909	1.0000	1.0000		
AHP	0.8818	0.9818	0.9727	0.9909	0.9818	0.9818	1.0000	
BHARAT-2	0.8909	0.9545	0.9909	0.9727	0.9545	0.9545	0.9545	1.0000

TABLE 17: Rank corelation for case study 3

ROC, Rank Order Centroid; DAT, Direct assignment technique; EW, equal weight; RS, Rank Sum; RR, rank-inverse; AHP, Analytic Hierarchy Process

Table *17* shows the rank correlation of EW, RS, RR, ROC, DAT, Pairwise, AHP and BHARAT-2. The rank correlation of EW vs RS is 0.9364 because of the variation observed in rank 5, 6, 7, and 8. Similarly, for EW vs RR the value is 0.9. From Table *17*, the ranks obtained will vary from alternative to alternative as these alternatives are depend on the attributes' priorities. If the decision-maker can change his/her priorities for the attributes, the ranks will be changed. The ranks obtained by the BHARAT-2 with different weights could conclude that ranks are sensitive to weights. Minor variation in weights can lead to alternation in ranks.

Results and discussion

In MADM problems, most of the researchers have used Fuzzy AHP to give weights to the Fuzzy problem. This is a complex process, as the number of criteria increases the complexity because the crisp data is converted into the fuzzy data, and then the pairwise comparison is performed. If we assume the data are fuzzy triangular for five criteria then when it is converted into fuzzy form, it will be $3 \times 5 = 15$ criteria. So, the complexity increases three times for fuzzy triangular data. The fuzzy numbers are of many different forms, such as triangular, trapezoidal, signum, Gaussian, intrinsic fuzzy, and many more so. According to the type of fuzzy data, the complexity of Fuzzy AHP increases, whereas in BHARAT-2 weights only depend on the priorities of the attributes. These weights are not converted into the fuzzy numbers, which show that BHARAT-2 is better than Fuzzy AHP for obtaining weights for the attributes. The weights obtained by EW, RR, RS, ROC, DAT, and Pairwise are formulated based on some mathematical formula. Fuzzy TOPSIS is dependent on Fuzzy AHP for weights of the attributes, and problems in weight allocation will lead to incorrect ranks, while the BHARAT-2 uses the weights generated by the weight determination matrix. This proves that the BHARAT-2 is a better approach than Fuzzy AHP, Fuzzy TOPSIS, and other traditional methods. The detailed comparison is shown in Table *18*.

How to cite this article:
Rao R V, Bajaj K (July 07, 2026) Best Holistic Adaptable Ranking of Attributes Technique-2 for Fuzzy Decision-Making in Industry 4.0: A Robust and Computationally Efficient Multi-Attribute Decision-Making Approach. Cureus J Eng 3 : es44388-026-00153-z. DOI https://doi.org/10.7759/s44388-026-00153-z

Criteria	BHARAT-2	Fuzzy AHP	Fuzzy TOPSIS
Complexity	**Simple and computationally efficient**	**Involves complex pairwise comparisons**	**Requires multiple distance calculations**
Handling Uncertainty	Can handles uncertainty directly.	Handles uncertainty via fuzzy pairwise comparisons	Handles uncertainty using distance measures
Consistency Checking	Consistency can be verify using CI	Requires CR (Consistency Ratio) check	No direct consistency check
Computational Cost	Lower, as it avoids large matrices	Higher, due to pairwise comparisons	Moderate, due to similarity calculations
Suitability for Large Data	Highly scalable	Becomes inefficient with large criteria sets	Efficient but computationally expensive
Interpretability	Results are easier to understand and analyze	Can be complex to interpret due to multiple calculations	Results are easy to interpret

TABLE 18: Comparison of BHARAT-2 with Fuzzy AHP and Fuzzy TOPSIS

AHP, Analytic Hierarchy Process

In the case of study 1, Pour et al. [17] used Fuzzy AHP and Fuzzy TOPSIS to solve the problem, but there is a high number of pairwise comparisons, and the weights obtained by the fuzzy AHP depended on the selection of fuzzy number (i.e., triangular or trapezoidal), whereas in BHARAT-2 the weight determination is independent of a fuzzy number. Then, while solving the problem using Fuzzy TOPSIS, the geometric mean is used to defuzzify the data, while in the BHARAT-2, we can use any approach to defuzzify the data. It can be the Arithmetic mean or geometric mean. So we can conclude that the BHARAT-2 is simple and logical. We can also use weights obtained by any methods such as EW, RR, RS, ROC, DAT, or pairwise; this will show whether the ranks obtained by the alternatives are sensitive to weights given by the decision-maker to the attributes. In case study 1, there was a minor variation in ranks 5 and 6, which led to a decrease in the rank correlation value from 1 to 0.9.

In case study 2, Wang and Dang [34] have solved the 3 PLs selection problem using Fuzzy AHP and Fuzzy MACROS, which increases their computational complexity as they have applied two methods, one for weight determination and another for ranking the alternatives. Further, the Fuzzy MACROS method is also dependent on the weights assigned by Fuzzy AHP and we cannot check the consistency in fuzzy MACROS. Wang and Dang [34] had also used geometric mean for defuzzied the data for final ranking while in BHARAT-2 we can used any approach to defuzzied the data. Fuzzy AHP is excellent for structured decision-making, and Fuzzy TOPSIS is useful for ranking alternatives based on their proximity to the ideal solution, but to solve any MADM problem, researchers have to combine these methods. Conversely, BHARAT-2 can be used to solve any type of MADM problem as it reduces the pairwise comparison, and we can check the consistency of weights using the CI ratio. The computational complexity of BHARAT-2 is $O(n^2 + mn)$, whereas the complexity of Fuzzy AHP is approximately $O\left(n^3\right)$ and that of the integrated Fuzzy AHP-Fuzzy TOPSIS approach is $O(n^3 + mn)$, where n and denote the numbers of criteria and alternatives, respectively. Therefore, BHARAT-2 offers improved scalability and lower computational burden than AHP-based approaches. Furthermore, the method preserves simplicity in implementation while producing results that are highly consistent with established MADM techniques.

In the case of study 3, Ahuja and Kaur [38] employed the FDM in combination with Fuzzy TOPSIS to evaluate and rank the mitigation strategies. The FDM is typically used to derive the most relevant criteria or to refine expert opinions through multiple rounds of surveys, ensuring consensus among decision-makers. However, this process is highly iterative and time-consuming, requiring significant expert involvement at every stage. Moreover, the determination of fuzzy weights in FDM and subsequent ranking through Fuzzy TOPSIS largely depends on the selection of fuzzy numbers - triangular or trapezoidal - and the chosen defuzzification technique. Such dependency may introduce subjectivity and inconsistency in the final results. In contrast, the BHARAT-2 method simplifies this entire process by eliminating the dependency on fuzzy number selection and iterative expert feedback.

In the BHARAT-2 framework, fuzzy evaluations are retained throughout the computational process. The fuzzy decision matrix is normalized, weighted, and aggregated directly using fuzzy values without converting them into crisp values at the initial stage. The resulting composite scores are therefore obtained in fuzzy form. To facilitate the final ranking of alternatives, the composite fuzzy scores are subsequently transformed into crisp values using the arithmetic mean method. Thus, defuzzification is performed only at the final ranking stage, while the weighting and aggregation procedures operate directly on fuzzy information. Furthermore, while Fuzzy TOPSIS typically employs the geometric mean for defuzzification, BHARAT-2 allows the use of any defuzzification approach, such as the arithmetic or geometric mean, depending on the nature of the data and decision-maker preference. This flexibility enhances the robustness and interpretability of the results. Hence, compared to the FDM-Fuzzy TOPSIS approach used by Ahuja and Kaur [38], BHARAT-2 provides a more straightforward, transparent, and computationally efficient framework. It reduces the burden of expert elicitation and simplifies the decision-making process while producing ranking outcomes that are highly consistent with established MADM approaches. These characteristics make BHARAT-2 a practical and computationally efficient framework for complex fuzzy decision-making problems.

Conclusions

Choosing the right logistics providers, service partners, and manufacturers represents one of the most pressing challenges in modern decision-making, and by its very nature, this challenge falls under the domain of MADM. As these problems have grown increasingly complex, a wide range of MADM techniques has emerged to address them. While fuzzy adaptations of established methods like AHP, TOPSIS, and MACROS improve how uncertainty is handled, they tend to bring added layers of complexity - introducing extra parameters, repeated calculations, and reliance on subjective input. This study applies BHARAT-2 to tackle fuzzy MADM problems through a variety of weighting strategies: EW, RR, RS, ROC, AHP, DAT, pairwise, and BHARAT-2 derived weights. The effectiveness of this framework is validated through three real-world case studies - Industry 4.0 selection framework for manufacturing system, assessing third-party logistics (3PL) providers, and prioritizing risk mitigation strategies for a digital supply chain.

A key finding of this research is the strong agreement between the rankings produced by BHARAT-2 and those obtained using established weighting methods. The correlation analysis indicates that, in Case Study 1, BHARAT-2 exhibits a high correlation of 0.9762 with the rankings generated using alternative weighting schemes. In Case Study 2, the correlation values are approximately 0.90, indicating strong consistency between BHARAT-2 and the compared methods. Similarly, in Case Study 3, the correlation values range from 0.8909 to 0.9909, with the lowest correlation observed between BHARAT-2 and Equal Weighting (0.8909) and the highest between BHARAT-2 and Rank Reciprocal (0.9909). These high correlation values demonstrate that the rankings obtained using BHARAT-2 are largely consistent with those generated by well-established MADM weighting approaches, thereby supporting the reliability and robustness of the proposed framework. The comparative analysis indicates that BHARAT-2 exhibits stable ranking behavior across the considered case studies, with only minor variations resulting from changes in weighting schemes. The high rank correlation values obtained with established weighting methods further demonstrate the robustness of the proposed framework. In addition, the computational complexity analysis shows that BHARAT-2 has a complexity of $O(n^2 + mn)$, which is lower than that of Fuzzy AHP $O(n^3)$ and integrated Fuzzy AHP-Fuzzy TOPSIS $O(n^3 + mn)$. This reduced computational burden is achieved by avoiding extensive pairwise comparisons, consistency calculations, and iterative procedures, making BHARAT-2 suitable for large-scale MADM applications.

How to cite this article:
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This level of rank stability is rarely achieved by conventional fuzzy MADM methods and it clearly demonstrates the robustness and reliability of the proposed approach under uncertainty. Owing to its simplicity, scalability, and strong quantitative performance, BHARAT-2 is well suited for a wide range of MADM applications in manufacturing, healthcare, supply chain management, and other Industry 4.0-driven domains. Although the priority rankings of the attributes were adopted from the original benchmark case studies to ensure consistency and comparability. Future research may investigate the robustness of the proposed BHARAT-2 framework under different attribute priority structures and decision-maker preferences. Further, it may focus on integrating BHARAT-2 with machine learning techniques to further automate and enhance adaptive decision-making. Overall, BHARAT-2 represents a robust, efficient, and reliable decision-support framework capable of delivering highly consistent and computationally efficient decisions in complex and uncertain environments.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Kartik Bajaj, Ravipudi V. Rao

Acquisition, analysis, or interpretation of data: Kartik Bajaj, Ravipudi V. Rao

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Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request. Data sharing is not applicable. This work is theoretical; no datasets were generated or analyzed.

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