Advances in Industrial Engineering, December 2026, 60(2): 493-516
DOI: 10.22059/aie.2026.409369.1966

RESEARCH PAPER

A Data-Driven Multi-Criteria Group Analysis Model Based on Two New Improved Interval-Valued Fuzzy LMAW and AURA Methods for Project Portfolio Selection Problem

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Received: 03 January 2026, Revised: 27 July 2026, Accepted: 28 August 2026
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Abstract

Among the responsibilities of senior managers in each project-based organization, project portfolio selection (PPS) is critical. Practical optimization and decision-making models play a vital role in facilitating managerial decision-making. In this respect, the current study develops a new data-driven multi-criteria decision-making (MCDM) model for group decision-making in the PPS within the framework of project portfolio management. Mining-specific criteria will help enhance project evaluation and selection, allowing the project manager to make more accurate and efficient decisions. By incorporating interval-valued fuzzy sets (IVFSs) into the decision-making process, this paper addresses uncertainties and ambiguities in experts' judgments, making evaluations more realistic and flexible. A new interval-valued fuzzy weighting method, IVF-LMAW, is developed to determine the relative importance of the criteria, and a new IVF method, IVF-AURA, is presented to prioritize projects, offering higher accuracy and stability than conventional decision approaches. To validate the accuracy and robustness of the model, the criteria weights have been subjected to a sensitivity analysis, and the resulting rankings have been examined. To highlight the practical applicability of the model, a real case study in the mining industry has been performed on a set of projects. The results show that the proposed approach can efficiently, transparently, and reliably support the PPS process by simultaneously considering both financial and non-financial dimensions.

Keywords:
Project Portfolio Selection, Data-Driven Multi-Criteria Decision Making, Interval-Valued Fuzzy Sets, LMAW Method, AURA Method, Mining Industry.

1. Introduction

Project portfolio selection problem (PPS) is a significant decision in project management that helps organizations achieve their strategic goals. Several studies have addressed this area, proposing various approaches and methodologies for selecting an appropriate project portfolio [1]. However, considering all the factors and criteria influencing project selection simultaneously remains a challenging and complex task. This complication is mostly derived from the variety of decision-making dimensions, conflicts among organizational goals, and the multi-criteria nature of the problem, which may lead to confusion and instability in portfolio selection outcomes. Therefore, the development of efficient analytical and decision-making

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approaches capable of accounting for multiple criteria simultaneously in dynamic, real-world environments is of particular importance [2].

Project prioritization and selection within the scope of PPM are usually executed either with the support of managerial techniques or optimization algorithms, focusing on pre-defined project evaluation and selection criteria. The ultimate goal of portfolio development is to align the selected projects with the organization's strategic objectives. As indicated by Dixit and Tiwari [3], this underlines that project portfolio design is inherently a multi-criteria decision-making (MCDM) problem. Broadly speaking, there have been two approaches to the selection of project portfolios. The first approach relies on conventional managerial methods in practice, while the second relies on quantitative analyses using advanced analytical and optimization techniques. The study follows the latter approach, focusing on project portfolio selection through a comprehensive quantitative analysis supported by the MCDM model [4].

MCDM methods are effective tools that incorporate decision-makers' judgments and preferences into the process of evaluating, comparing, and selecting among alternatives to rank them from least desirable to most desirable. Over the past few decades, it has undergone significant development across diverse fields, with extensive applications in complex decision-making. Basically, MCDM problems involve deciding between several competing alternatives with respect to a set of criteria that are usually diverse and often conflicting [5].

The PPS is inherently complex and multi-dimensional, requiring consideration of a set of financial, strategic, technical, and risk-related criteria simultaneously. Given the nature of such criteria, which often conflict and require decision-makers to balance competing objectives, the involvement of MCDM methods in this process is inevitable [6]. MCDM is a structured, quantitative framework that enables project managers to evaluate alternatives against a set of weighted criteria and select the optimal combination of projects consistent with organizational objectives. Furthermore, MCDM can convert decision-makers' subjective judgments into quantifiable data, thereby making decision-making more transparent, rational, and repeatable. Hence, adopting MCDM approaches in project portfolio selection enhances not only the accuracy and validity of decisions but also their alignment with the organization's overarching strategies [7].

MCDM methods have been widely applied in recent years because they break complex problems into smaller components and further evaluate alternatives based on pre-specified criteria. Real situations often arise in which data are imprecise, incomplete, or uncertain, and human judgments may be ambiguous, biased, or wavering. In such situations, the application of fuzzy logic is an effective approach to approximate decision-making models in real life [1].

Fuzzy set theory, especially interval-valued fuzzy sets (IVFSs), has been increasingly applied in complex decision-making due to its ability to handle ambiguous and incomplete data. Due to their advanced fuzzy features, IVFSs can provide more accurate modeling of uncertainties than conventional fuzzy sets. This capability is especially valuable in such a sensitive and dynamic environment, where subjective assessments are influenced by human judgment, variability in environmental conditions, and fluctuations in data [8]. Fuzzy sets theory allows, through the use of indeterminate boundaries, the transformation of linguistic and subjective assessments of decision-makers into quantifiable data, with model outcomes compatible with real situations and practically applicable. Therefore, the use of IVFSs bridges the gap between theoretical models and real-world decision-making, offering substantial advantages in improving the accuracy, flexibility, and reliability of the decision-making process [9].

In this context, the primary objective of this research paper is to propose a new data-driven MCDM approach for group decision-making in the PPS using IVFSs. In this work, we develop two new methodologies with IVFSs: a weighting method, called LMAW, and a ranking technique, called AURA, to facilitate efficient and accurate decision-making based on strategic

criteria in an uncertain environment.

In order to achieve the objectives of this study and comprehensively evaluate the proposed model in the PPS problem, the research questions are presented as follows:

1. What is the impact of using a data-driven model compared to non-data-driven models on the accuracy and reliability of decision-making in the PPS?
2. To what extent does the use of IVF-numbers improve the model's ability to measure the ambiguity and uncertainty of judgments compared to conventional and deterministic fuzzy methods?
3. How does the IVF-LMAW weighting method calculate the weight and relative importance of different criteria based on the aggregation of expert group opinions?
4. What advantage does the IVF-AURA ranking method offer in correctly prioritizing projects compared to conventional methods?

Regarding the subject of literature, Wheelwright and Clark [10] categorized projects into four types: breakthrough, platform, derivative, and research and development (R&D). They argued that an effective project portfolio should include a balanced selection of projects drawn from all these categories. According to [11], organizations often need to estimate, evaluate, and select a group of projects simultaneously to align with their strategic objectives. In this regard, the PPS methods can be employed to efficiently allocate available budgets and resources among the chosen projects. Lee et al. [6] examined a project portfolio selection problem in the automobile industry, particularly because of its direct connection to environmental concerns.

Selecting project portfolios is highly important because there is a strong need for alignment between project portfolios and the strategies of the organization. In fact, effective project portfolios can be treated as a powerful strategic weapon for an organization [3]. Zahedirad et al. [9] discussed an integrated model using fuzzy goal programming in project portfolio and contractor selection. Uncertainty could be modeled using fuzzy preference relations to capture the priority levels of various objectives. From the case study results, it was concluded that applying fuzzy preferences in FGP improves solution performance for multi-objective problems.

Chen and Askin [12] formulated and analyzed project selection and task scheduling simultaneously. Additionally, various concepts such as research and development (R&D), financial performance measures, and different solution techniques, including goal programming and genetic algorithms, have been incorporated into project selection problems. To make use of this as a practical case study, Wu et al. [1] applied both fuzzy multi-attribute decision-making and fuzzy multi-objective programming to optimize strategic objectives for photovoltaic companies.

A dynamic two-stage mathematical programming approach was presented, in which a fuzzy technique for order preference by similarity to ideal solution (TOPSIS) was used to evaluate alternative projects under uncertain conditions. The authors then derived a bi-objective mixed-integer linear program to optimize profit and qualitative values for each portfolio, including project synergies and additional criteria across multiple scenarios [8]. Mohammed [7] presented a fuzzy-based approach for optimal project selection in project portfolio management. In this research, he determined the criteria weights using the fuzzy AHP method, while project ranking was done through the use of fuzzy TOPSIS. From an evaluation of 20 oil industry projects, it has been found that this approach enhances decision accuracy and improves the overall quality of project portfolio management.

Ma et al. [5] proposed a project selection model for a sustainable portfolio that uses a multiple-criteria decision model. In the current research, economic, environmental, and social dimensions were considered as core sustainability indicators. The proposed model was developed using fuzzy logic and the TOPSIS method; it was also implemented as a case study in a paper manufacturing company. Marques et al. [13] presented an innovative approach to

project portfolio selection through the FITradeoff method. This interactive and flexible technique examines the portfolio selection problem by incorporating partial information on decision-makers' preferences. Computational results indicated that the proposed model improved the efficiency of multi-criteria decision-making by reducing both computational effort and cognitive workload.

Karimi et al. [14] developed a stochastic fuzzy project portfolio selection model incorporating asset growth and coupled revenue, as well as costs, that can be solved by a strong possibilistic method. Souza et al. [15] developed a hybrid method that combines fuzzy AHP and VIKOR for project selection in the pharmaceutical industry, accounting for process uncertainties. In the model, strategic priorities were represented using fuzzy AHP, and fuzzy VIKOR was used for ranking. From the case study analysis, the developed method improved decision-making accuracy and effectiveness.

In the study by Fernandez et al. [28], fuzzy-LMAW method was used to deal with uncertainty in expert judgments. This methodology determines the relative importance of each criterion by converting linguistic scales into fuzzy numbers and applying logarithmic functions. Key features of this approach include reducing computational complexity and maintaining high consistency in group decision-making, thereby transforming qualitative opinions into numerical coefficients for prioritizing sustainable development goals. Demir et al. [29] introduced the LMAW method, providing a systematic framework for determining criteria weights. This methodology calculates the relative importance of criteria based on expert opinions using a logarithmic transformation and the Bonferroni operator, thereby eliminating rank reversal and improving the reliability of the weighting process. Morshed et al. [30] used the Dombi-LMAW method for the accurate weighting of criteria. This method avoids the rank inversion problem by combining a logarithmic transformation with the Dombi operator and ensures stable results. This technique is superior to traditional MCDM models in terms of uncertainty management and computational accuracy.

Seo et al. [31] used the AURA method as the main methodology of their research. This method overcomes the ethical and privacy challenges associated with real hospital data by generating synthetic videos using text-to-video diffusion models. It uses body posture estimation techniques to identify high-risk movement patterns, such as touching sensitive areas and patient restlessness, with high accuracy. Zaman et al. [32] introduced the AURA method as a multi-criteria decision-making method based on distance-based comparative scoring. The main focus of this method is to integrate benefit, cost, and objective criteria into a single, interpretable formula and to make option evaluation more flexible by dynamically defining reference, ideal, and anti-ideal points. The methodological advantage of AURA is that it ranks options under different data conditions, especially for criteria with a limited range or an unbalanced distribution, while maintaining appropriate stability and efficiency, without relying on complex mechanisms.

Kumar [33] presented a multi-criteria decision-making framework based on interval-valued fuzzy sets, with the main goal of modeling uncertainty and ambiguity in MCDM problems more accurately. In this method, fuzzy membership functions are defined as intervals, and this structure is then integrated into the TOPSIS, VIKOR, and ELECTRE frameworks to evaluate options more robustly under conditions of incomplete data and weak expert consensus. The main advantage of this method compared to conventional fuzzy approaches is its greater ability to represent uncertainty, reduced sensitivity to rank reversal, and maintained computational efficiency in real problems. Karami and Mousavi [34] developed an interval-valued fuzzy group decision-making model based on IVF-LBWA and IVF-MAIRCA for sustainable project selection. This integrated approach, using interval-valued fuzzy numbers, improves the accuracy of criteria weighting and project ranking under uncertainty. Its main advantage is that it produces stable and consistent results, making it a reliable framework for sustainable project

portfolio selection.

A critical review of the existing literature reveals that, despite considerable developments in MCDM methods and fuzzy-based approaches, there are significant lacunas in previous works. Many studies have focused on the application of either classical or widely used hybrid methods for project prioritization and selection; similarly, many have relied solely on traditional fuzzy sets to handle uncertainties. On the other hand, real-world decision-making regarding the selection of industrial and mining project portfolios is inherently ambiguous, multi-criteria, and multi-decision-maker in nature, thus requiring the application of advanced fuzzy approaches such as IVFSs. The review of related literature shows that IVFSs have been applied infrequently in project portfolio selection models and have not fully exploited their potential to handle uncertainty, aggregate group judgments, and improve decision reliability.

Besides, in previous studies, the weighting methods have often used either crisp data with numerical weights or conventional techniques. This limitation keeps the derived weights from reflecting the diversity of decision-makers' opinions and the range of uncertainty involved. Moreover, previously used ranking methods are often based on conventional fuzzy techniques, lacking mechanisms to improve ranking stability and accuracy in group decision-making environments. Thus, there is a pressing need to develop new IVFS-based methods for weighting and ranking that can effectively handle complex uncertainty structures.

In addition to the gaps mentioned above, the review of past studies indicates that most studies have used subjective or judgment-based data. At the same time, data-driven approaches, which may strengthen decision-making mechanisms and enhance the accuracy of project evaluations, have been rarely considered. In actual project portfolio selection problems, decision-making models should use real, cleaned, and analytically processed data, particularly in industries that handle large volumes of technical, operational, and economic data, such as the mining industry. This gap highlights that an MCDM framework, coupled with a data-driven approach, can significantly enhance the accuracy, realism, and reliability of decision-making.

In addition, most existing models lack a clear structure for group decision-making during the weighting and ranking stages. Limiting group decision-making to only part of the process may bias outcomes and lower the overall ranking quality. Thus, the literature calls for a model that would integrate group decision-making throughout both the weighting and ranking stages.

Given these gaps, the current study proposes a new fuzzy, data-driven multi-criteria decision-making model for the PPS problem that meaningfully addresses the shortcomings of previous studies. The proposed model has the following novelties:

1. Development of a new data-driven framework is presented in the process of group decision-making that will improve accuracy in data evaluation and analysis.
2. A new interval-valued fuzzy aggregated weighting is proposed, IVF-LMAW, able to handle more realistically interval uncertainties and differences in opinions by decision-makers.
3. A new interval-valued fuzzy ranking methodology, namely IVF-AURA, is proposed within an IVFS environment, which provides more accuracy, along with robustness against changes in criteria weights compared to existing models.
4. Two weighting and ranking stages of group decision-making provide more transparency and reliability in the results simultaneously.
5. Performing an industrial case study in the mining industry can provide empirical proof of the operational capability of the model in a practical way.

These innovations enable the proposed model to bridge key gaps in the literature and provide a broad, reliable, and practically adaptable framework for the PPS problem.

The structure of this article is as follows: Section 2 introduces the concepts of IVFSs; Section 3 describes the proposed methodology; Sections 4 and 5 present the case study and analyses; Section 6 provides managerial insights. Section 7 concludes the paper and outlines future research directions.

2. Interval-Valued Fuzzy Numbers

When it comes to complex decision-making tasks that involve uncertainties and vague information, linguistic values have a major edge. As conceptualized by the pioneers of this art, works such as those by Zadeh [16] and Zimmermann [17] demonstrate how linguistic values help decision makers quantify uncertainties effectively. Nevertheless, conventional fuzzy sets may have limitations in this respect, as they consider only a single value per element.

As stated in the classic definition by Gorzałczany [18], IVFS on the domain of real numbers can be written as:

$$\tilde{A} = \{X, [\mu_{\tilde{A}^L}(x), \mu_{\tilde{A}^U}(x)]\}, x\epsilon(-\infty \text{و} + \infty) \tag{1}$$

In this definition, $\mu_{\tilde{A}^L}(x)$ and $\mu_{\tilde{A}^U}(x)$ represent the lower and upper bounds of the membership function for element (x), respectively, and the condition $\mu_{\tilde{A}^L}(x) \leq \mu_{\tilde{A}^U}(x)$ must always hold [19].

One of the most widely used forms of IVFS is the interval-valued triangular fuzzy number (IVTFN). Due to their simple yet powerful structure, these numbers are highly popular in multi-criteria decision-making modeling [20]. An interval-valued triangular fuzzy number $\tilde{A}$, as described by Yao and Lin [21] and depicted in Figure 1, is generally represented below:

$$\tilde{A} = [\tilde{A}_X^L, \tilde{A}_X^U] = [(a^L, b^L, c^L; \hat{w}_{\tilde{A}}^L), (a^U, b^U, c^U; \hat{w}_{\tilde{A}}^U)] \tag{2}$$

$(\tilde{A}_X^L)$ represents the interval for the lower bound, and $(\tilde{A}_X^U)$ represents the interval for the upper bound of the fuzzy number. $\mu_{\tilde{A}^L}(X) = \hat{w}_{\tilde{A}}^L$ and $\mu_{\tilde{A}^U}(X) = \hat{w}_{\tilde{A}}^U$ are the lower and upper membership functions, respectively [22].

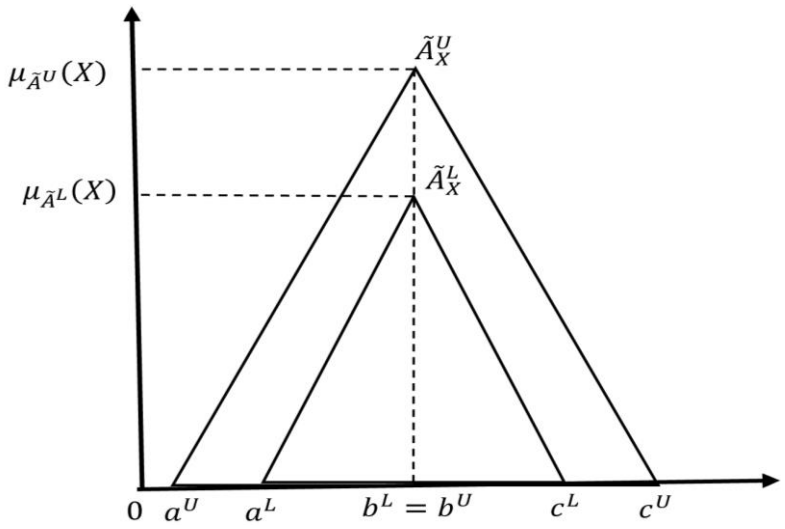


Figure 1: An interval-valued triangular fuzzy number

A defined set of mathematical operations is used to analyze and aggregate these numerical values. Suppose we have two interval-valued triangular fuzzy numbers below:

$$\tilde{A} = [(a_1^u, a_1^l); a_2; (a_3^l, a_3^u)] \tag{3}$$
$$\tilde{X} = [(x_1^u, x_1^l); x_2; (x_3^l, x_3^u)] \tag{4}$$

The main mathematical operations between these two numbers, based on the works of Chen

and Chen [23], are below:

A. Addition (⊕):

$$\begin{aligned}\tilde{A} \oplus \tilde{X} &= \left[\left(a_1^u, a_1^l\right); a_2; \left(a_3^l, a_3^u\right)\right] \oplus \left[\left(x_1^u, x_1^l\right); x_2; \left(x_3^l, x_3^u\right)\right] \\ &= \left[\left(a_1^l + x_1^l, a_1^u + x_1^u\right), (a_2 + x_2), (a_3^l + x_3^l, a_3^u + x_3^u)\right]\end{aligned} \tag{5}$$

B. Subtraction (⊖):

$$\begin{aligned}\tilde{A} \ominus \tilde{X} &= \left[\left(a_1^u, a_1^l\right); a_2; \left(a_3^l, a_3^u\right)\right] \ominus \left[\left(x_1^u, x_1^l\right); x_2; \left(x_3^l, x_3^u\right)\right] \\ &= \left[\left(a_1^l - x_3^l, a_1^u - x_3^u\right), (a_2 - x_2), (a_3^l - x_1^l, a_3^u - x_1^u)\right]\end{aligned} \tag{6}$$

C. Multiplication (⊗):

$$\begin{aligned}\tilde{A} \otimes \tilde{X} &= \left[\left(a_1^u, a_1^l\right); a_2; \left(a_3^l, a_3^u\right)\right] \otimes \left[\left(x_1^u, x_1^l\right); x_2; \left(x_3^l, x_3^u\right)\right] \\ &= \left[\left(a_1^l \times x_1^l, a_1^u \times x_1^u\right), (a_2 \times x_2), (a_3^l \times x_3^l, a_3^u \times x_3^u)\right]\end{aligned} \tag{7}$$

D. Generalized division (⊘):

$$\begin{aligned}\tilde{A} \oslash \tilde{X} &= \left[\left(a_1^u, a_1^l\right); a_2; \left(a_3^l, a_3^u\right)\right] \oslash \left[\left(x_1^u, x_1^l\right); x_2; \left(x_3^l, x_3^u\right)\right] \\ &= \left[\left(\frac{a_1^l}{x_3^l}, \frac{a_1^u}{x_3^u}\right), \left(\frac{a_2}{x_2}\right), \left(\frac{a_3^l}{x_1^l}, \frac{a_3^u}{x_1^u}\right)\right]\end{aligned} \tag{8}$$

This computational framework not only facilitates the mathematical handling of uncertainty but also markedly improves the capacity to analyze, evaluate, and prioritize options in an interval-valued fuzzy decision-making context. These attributes have established IVFSs as a fundamental and indispensable instrument in group multi-criteria decision analysis under conditions of structured uncertainty [24].

3. Proposed Methodology

The evaluation and selection of an optimal project portfolio involve broad, complex analyses that include forecasting the performance indicators of different project alternatives and ranking them. A new approach is proposed in this paper that combines data science techniques with multi-criteria decision-making methods to identify, prioritize, and reduce the most significant performance indicators for candidate projects. The aim of such an approach is to allow only a few high-potential projects to proceed to advanced stages of evaluation, thereby avoiding the need to conduct numerous time-consuming and expensive feasibility studies for all proposed projects. This approach therefore significantly reduces the overall cost, risk, and time required to select and initiate appropriate projects.

To accomplish this objective, the evaluation criteria and functional characteristics of potentially viable projects must first be defined by experts from relevant organizational units, based on their insights and judgments. Following this step, managers and planners prepare a list of proposed projects. During the initial screening, certain infeasible projects are eliminated due to factors such as excessive implementation costs, insufficient resources, or misalignment with strategic organizational priorities.

Subsequently, using available data from similar projects, whether developed internally or undertaken by competing organizations, the functional indicators of new project alternatives are estimated through analytical, data-driven models, such as Artificial Neural Networks

(ANNs). In the final stage, the projects are evaluated, scored, and ranked using the AURA method. Those alternatives achieving the highest rankings are then selected as the optimal project portfolio for further in-depth assessment and eventual implementation. Figure 2 shows the design of the research flowchart. In this figure, the data-driven method and the weighting method are presented as inputs to the ranking method.

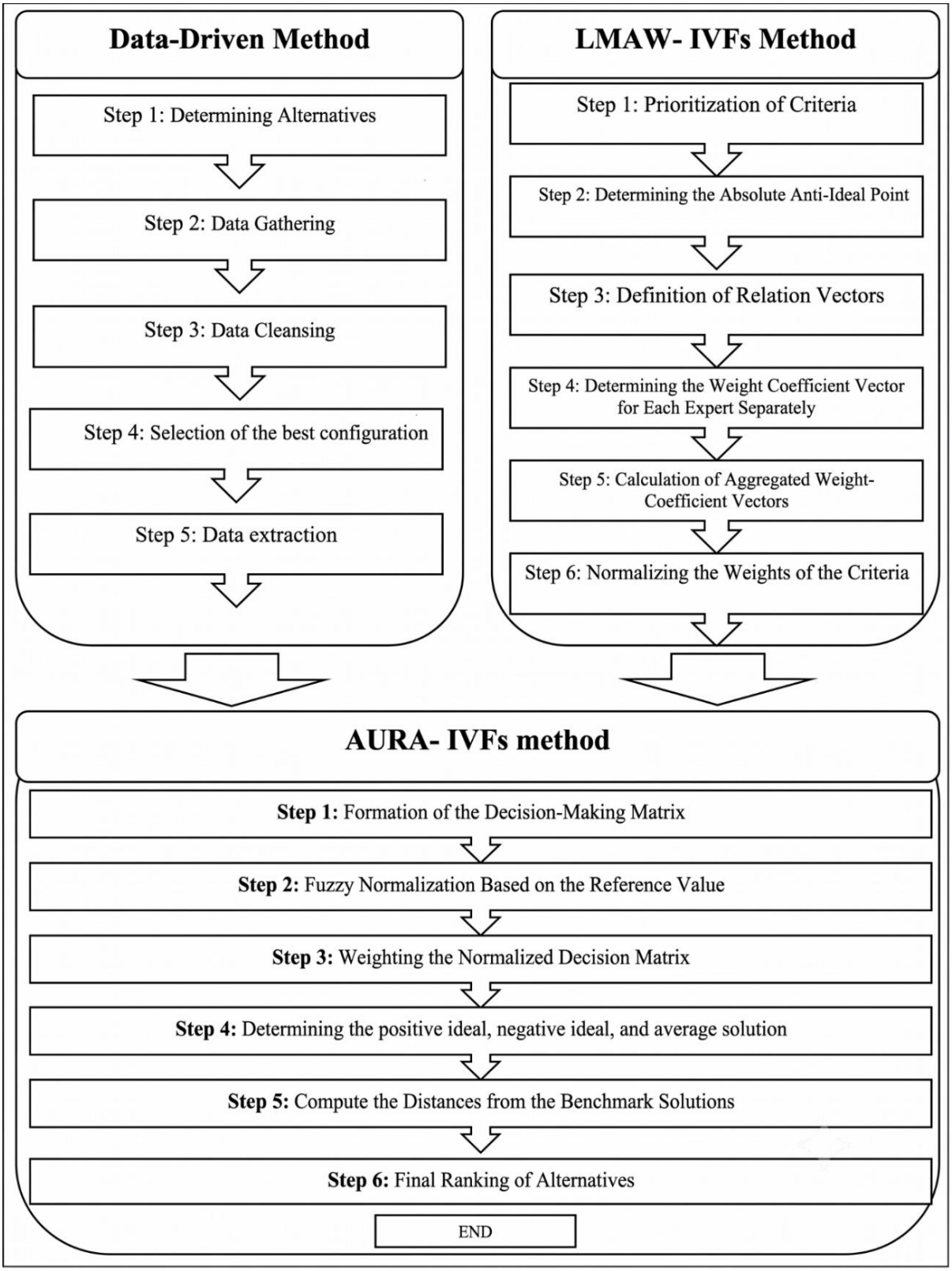


Figure 2: Flowchart of the proposed research

3.1. Data-Driven Method

In this section, the proposed approach is presented based on the study by Arabi et al. [25], and the steps of the method are as follows:

Step 1: Determining Alternatives

Experts have selected the available alternatives based on their importance and added value, so that the presented method can make an informed choice and identify the best alternative based on the extracted criteria. This selection is essential and enables the alternatives to be compared on multiple dimensions, ensuring the best alternative is chosen based on the criteria.

Step 2: Data Gathering

To evaluate the alternatives, decision makers and opinion leaders in the field must rate each alternative according to each selected criterion. This rating can be either quantitative or qualitative based on linguistic variables. If a qualitative assessment is used, a linguistic variable table is applied, and the qualitative values are converted to quantitative values.

Step 3: Data Cleansing

In this section, all outliers and data outside the decision matrix range are removed. This action makes the data more uniform and aligned.

Step 4: Selection of the Best Configuration

In this section, a set of forecasting models with different configurations is examined to estimate the output variables with the highest possible accuracy. For each configuration, the mean square error in Equation (9) is calculated to determine the difference between the actual and predicted values. Then, the normalized error values are obtained using Equation (10), and their weighted sum is computed according to Equation (11).

$$MSE_{ij} = \frac{1}{m}\sum_{i}\sum_{j}\left(y_{ij} - \hat{y}_j\right)^2 \ \forall\, i = 1,2,\dots,m\,, j = 1,2,\dots,n \tag{9}$$

$$NMSE_{ij} = \frac{MSE_{ij} - \underset{i}{\text{Min}}\, MSE_{ij}}{\underset{i}{\text{Max}}\, MSE_{ij} - \underset{i}{\text{Min}}\, MSE_{ij}} \ \forall\, i = 1,2,\dots,m\,, j = 1,2,\dots,n \tag{10}$$

$$WNMSE_{ij} = W_j' \times NMSE_{ij} \ \forall\, i = 1,2,\dots,m, j = 1,2,\dots,n \tag{11}$$

Step 5: Data Extraction

In this step, the input data from the previous step are extracted for the decision matrix, and the modified decision matrix is obtained.

3.2. Proposed IVF-LMAW Method

Given that ranking methods require the calculation of criterion weights, this study uses the LMAW method developed by Pamučar et al. [26]. Unlike many common MCDM methods, LMAW can simultaneously determine the weights of the criteria and rank the alternatives. In this study, only the weighting part of the method is used; therefore, only the weighting steps are presented. Given the problem's inherent uncertainty, an interval-valued fuzzy approach is applied. This approach is considered an essential extension of the method and has been adopted by experts, further improving its applicability.

While traditional weighting methods often require exhaustive pairwise comparisons, LMAW employs a logarithmic transformation that streamlines computation while maintaining high mathematical consistency and mitigating rank-reversal issues [26]. However, standard crisp or single-point fuzzy implementations struggle to capture the full spectrum of expert

hesitation in complex decision environments. To overcome this limitation, this study extends LMAW into an interval-valued fuzzy framework (IVF-LMAW). By using double-bounded membership functions, IVF-LMAW incorporates upper and lower bounds on uncertainty, preventing information loss during group aggregation and providing a more realistic assessment of criterion weights. The steps of the method are as follows:

Step 1: Prioritization of Criteria

In this section, based on each expert's opinion, the value assigned to each criterion is determined, and the criteria's prioritization is derived from these values. The corresponding relationship is presented in Equation (12).

$$\tilde{o}_{kj} = \begin{bmatrix} \tilde{o}_{11} & \cdots & \tilde{o}_{k1} \\ \vdots & \ddots & \vdots \\ \tilde{o}_{1N} & \cdots & \tilde{o}_{kN} \end{bmatrix} \quad \forall k = 1,2,\dots,K \ , j = 1,2,\dots,N \tag{12}$$

Where $\tilde{o}_{kj}$ is IVFN and can be represented as $\tilde{o}_{kj} = \left[\left(o_{kj}^1, o_{kj}^2\right); o_{kj}^3; \left(o_{kj}^4, o_{kj}^5\right)\right]$

Step 2: Determining the Absolute Anti-Ideal Point

The absolute anti-ideal point is calculated as the lowest value for each criterion and is presented in Equation (13).

$$\widetilde{zo}_j = \min_k \tilde{o}_{kj} \quad \forall \quad j = 1,2,\dots,N \tag{13}$$

Where $\widetilde{zo}_j$ is IVFN and can be represented as $\widetilde{zo}_j = \left[\left(\min_k o_{kj}^1, \min_k o_{kj}^2\right); \min_k o_{kj}^3; \left(\min_k o_{kj}^4, \min_k o_{kj}^5\right)\right]$

Step 3: Definition of Relation Vectors

In this step, the rank of each criterion is divided by the elements with absolute anti-ideal points. The aim of this step is to reduce the magnitude of the criterion scores, and these vectors are formed using Equation (14).

$$\tilde{p}_{kj} = \left(\frac{\tilde{o}_{kj}}{\widetilde{zo}_j}\right) \quad \forall k = 1,2,\dots,K \ , j = 1,2,\dots,N \tag{14}$$

Where $\tilde{p}_{kj}$ is IVFN and can be represented as $\tilde{p}_{kj} = \left[\left(\frac{o_{kj}^1}{zo_j^5}, \frac{o_{kj}^2}{zo_j^4}\right); \frac{o_{kj}^3}{zo_j^3}; \left(\frac{o_{kj}^4}{zo_j^2}, \frac{o_{kj}^5}{zo_j^1}\right)\right]$

Step 4: Determining the Weight Coefficient Vector for each Expert Separately

First, the natural logarithm is calculated for all relation vectors. Then, this value is divided by the product of all criteria for each decision maker within the relation vectors, and the natural logarithm of the result is computed. This step is shown in Equation (15).

$$\tilde{q}_{kj} = \left(\frac{\ln \tilde{p}_{kj}}{\ln\left(\prod_j \tilde{p}_{kj}\right)}\right) \quad \forall k = 1,2,\dots,K \ , j = 1,2,\dots,N \tag{15}$$

Where $\tilde{q}_{kj}$ is IVFN and can be represented as $\tilde{q}_{kj} = \left[\left(\frac{\ln p_{kj}^1}{\ln\left(\prod_j p_{kj}^5\right)}, \frac{\ln p_{kj}^2}{\ln\left(\prod_j p_{kj}^4\right)}\right); \frac{\ln p_{kj}^3}{\ln\left(\prod_j p_{kj}^3\right)}; \left(\frac{\ln p_{kj}^4}{\ln\left(\prod_j p_{kj}^2\right)}, \frac{\ln p_{kj}^5}{\ln\left(\prod_j p_{kj}^1\right)}\right)\right]$

Step 5: Calculation of Aggregated Weight-Coefficient Vectors

To calculate the aggregated vectors of weight coefficients, the Bonferroni aggregator is used. This equation is presented in (16).

$$\tilde{s}_j = \left(\frac{1}{n(n-1)} \sum_{\substack{j \\ j \neq j'}} \tilde{q}_{kj} \tilde{q}'_{kj'} \right)^{\frac{1}{v+u}} \quad \forall\, j = 1,2,\dots,N \tag{16}$$

Where $\tilde{s}_j$ is IVFN and can be represented as $\tilde{s}_j = \left(\frac{1}{n(n-1)}\left[\left(\sum_{\substack{j \\ j \neq j'}} q^1_{kj} q'^1_{kj'}, \sum_{\substack{j \\ j \neq j'}} q^2_{kj} q'^2_{kj'}\right); \sum_{\substack{j \\ j \neq j'}} q^3_{kj} q'^3_{kj'}; \left(\sum_{\substack{j \\ j \neq j'}} q^4_{kj} q'^4_{kj'}, \sum_{\substack{j \\ j \neq j'}} q^5_{kj} q'^5_{kj'}\right)\right]\right)^{\frac{1}{v+u}}$

Step 6: Normalizing the Weights of the Criteria

In this section, the final weight is obtained by normalizing the calculated weight. This value is given in Equation (17).

$$\widetilde{w}_j = \frac{\tilde{s}_j}{\sum_j \tilde{s}_j} \; \forall\, j = 1,2,\dots,N \tag{17}$$

Where $\widetilde{w}_j$ is IVFN and can be represented as $\widetilde{w}_j = \left[\left(\frac{s^1_j}{\sum_j s^5_j}, \frac{s^2_j}{\sum_j s^4_j}\right); \frac{s^3_j}{\sum_j s^3_j}; \left(\frac{s^4_j}{\sum_j s^2_j}, \frac{s^5_j}{\sum_j s^1_j}\right)\right]$

3.3. Proposed IVF-AURA Method

The adaptive efficiency ranking algorithm (AURA) is the MCDM framework used to evaluate alternatives. This approach uses distance measures to select the best alternative based on the criteria and their importance (weights). The approach is derived from the article by Zaman et al. [27]. An important aspect of this research is the use of the interval-valued fuzzy approach, which represents a new extension of the method. In addition, incorporating decision makers is another innovation in this method and can enhance its effectiveness.

Unlike conventional ranking techniques, such as TOPSIS or VIKOR, which evaluate alternatives strictly against positive- and negative-ideal solutions, the AURA algorithm incorporates an average reference solution as a third benchmark [27]. This adaptive utility structure improves discrimination power, particularly when separating alternatives with marginal score differences or handling unbalanced data distributions. By extending AURA into an interval-valued fuzzy setting (IVF-AURA), this study combines its tri-benchmark reference mechanism with interval distance metrics. This enhancement enables the model to better accommodate linguistic ambiguity, ensuring that the final project rankings remain robust to minor fluctuations in expert preferences. The steps of the AURA method are presented below:

Step 1: Formation of the Decision-Making Matrix

At this stage, the decision-making matrix is formed based on the number of alternatives and the number of criteria. This matrix is obtained from the output of the data-driven method and serves as the input for the decision makers. The decision-makers' matrix is presented in Equation (18). First, the decision makers' opinions are aggregated in Equation (19), and then the decision-making matrix is formed. The aggregated decision-making matrix is presented in Equation (20).

$$\widetilde{A}' = \begin{bmatrix} \tilde{a}'_{11k} & \cdots & \tilde{a}'_{m1k} \\ \vdots & \ddots & \vdots \\ \tilde{a}'_{1nk} & \cdots & \tilde{a}'_{mnk} \end{bmatrix} \ \forall i = 1,2,\dots,M \ , j = 1,2,\dots,N, k = 1,2,\dots,K \quad (18)$$

$$\tilde{a}_{ij} = \frac{\tilde{a}'_{ijk}}{K} \ \forall\, j = 1,2,\dots,N \quad (19)$$

$$\tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \cdots & \tilde{a}_{M1} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{1N} & \cdots & \tilde{a}_{MN} \end{bmatrix} \ \forall i = 1,2,\dots,M, \ \ j = 1,2,\dots,N \quad (20)$$

Where $\tilde{a}_{ij}$ is IVFN and can be represented as $\tilde{a}_{ij} = \left[\left(a_{ij}^1, a_{ij}^2\right); a_{ij}^3; \left(a_{ij}^4, a_{ij}^5\right)\right]$

Step 2: Fuzzy Normalization Based on the Reference Value

The main logic of the AURA method is based on normalization with respect to each criterion's reference value, so that the proximity of each alternative to the criterion's desired value is measured. Normalization is performed using two components: the reference value and the range between the maximum and minimum values. The reference distance is calculated using Equation (21). In addition, the distance between the maximum and minimum is calculated using Equation (22), and the normalization relationship is obtained from Equation (23).

$$\tilde{k}_j = \begin{cases} [(1,1); 1; (1,1)], & x \in Benefit \\ [(0,0); 0; (0,0)], & x \in Cost \end{cases} \quad (21)$$

$$\tilde{h}_j = \max_i\left(\tilde{a}_{ij}\right) - \min_i\left(\tilde{a}_{ij}\right) \ \forall\, j = 1,2,\dots,N \quad (22)$$

Where $\tilde{h}_j$ is IVFN and can be represented as $\tilde{h}_j = \left[\left[\left(h_j^1, h_j^2\right); h_j^3; \left(h_j^4, h_j^5\right)\right]\right]$and the values h_j^1, h_j^2, h_j^3, h_j^4, and h_j^5, which are components of the interval-valued fuzzy numbers, are respectively $\tilde{h}_j = \max_i\left(a_{ij}^1\right) - \min_i\left(a_{ij}^5\right)$, $h_j^2 = \max_i\left(a_{ij}^2\right) - \min_i\left(a_{ij}^4\right)$, $h_j^3 = \max_i\left(a_{ij}^3\right) - \min_i\left(a_{ij}^2\right)$, $h_j^4 = \max_i\left(a_{ij}^4\right) - \min_i\left(a_{ij}^2\right)$, and $h_j^5 = \max_i\left(a_{ij}^5\right) - \min_i\left(a_{ij}^1\right)$.

$$\tilde{r}_{ij} = \begin{cases} 1 - \dfrac{\tilde{k}_j - \tilde{a}_{ij}}{\tilde{h}_j}, & x \in Benefit \\ 1 - \dfrac{\tilde{a}_{ij} - \tilde{k}_j}{\tilde{h}_j}, & x \in Cost \end{cases} \quad (23)$$

Where $\tilde{r}_{ij}$ is IVFN and can be represented as $\tilde{r}_{ij} = \begin{cases} \left[\left(1 - \frac{1-a_{ij}^5}{h_j^5}, 1 - \frac{1-a_{ij}^4}{h_j^4}\right); 1 - \frac{1-a_{ij}^3}{h_j^3}; \left(1 - \frac{1-a_{ij}^2}{h_j^2}, 1 - \frac{1-a_{ij}^1}{h_j^1}\right)\right], & x \in Benefit \\ \left[\left(1 - \frac{a_{ij}^1-0}{h_j^5}, 1 - \frac{a_{ij}^2-0}{h_j^4}\right); 1 - \frac{a_{ij}^3-0}{h_j^3}; \left(1 - \frac{a_{ij}^4-0}{h_j^2}, 1 - \frac{a_{ij}^5-0}{h_j^1}\right)\right], & x \in Cost \end{cases}$

Step 3: Weighting the Normalized Decision Matrix

In this step, each normalized value is multiplied by the weight of its corresponding criterion. In Equation (24), the weighted values are calculated. In Equation (25), the interval-valued fuzzy weighted values are converted into crisp values.

$$\tilde{c}_{ij} = \widetilde{w}_j \times \tilde{r}_{ij} \ \forall\, i = 1,2,\dots,M \ \ j = 1,2,\dots,N \quad (24)$$

Where $\tilde{c}_{ij}$ is IVFN and can be represented as $\tilde{c}_{ij} = \left[\left(w_j^1 \times r_{ij}^1, w_j^2 \times r_{ij}^2\right); w_j^3 \times r_{ij}^3; \left(w_j^4 \times r_{ij}^4, w_j^5 \times r_{ij}^5\right)\right]$

$$c_{ij} = \frac{c_{ij}^1 + c_{ij}^2 + c_{ij}^3 + c_{ij}^4 + c_{ij}^5}{5} \quad (25)$$

Step 4: Determining Positive Ideal, Negative Ideal, and Average Solutions

In this step, three indices are calculated: the positive ideal, the negative ideal, and the average solution. Each of these indices is obtained from a weighted normalized matrix of interval-valued fuzzy numbers. The positive ideal determines the maximum value among the bins for each index. The negative ideal determines the minimum value within each bin for each index, and the average solution determines the mean value of the alternatives for each criterion. The positive ideal is presented in Equation (26), the negative ideal in Equation (27), and the average solution in Equation (28). Finally, the conversion of interval-valued fuzzy numbers into crisp numbers for all three indices is presented in Equation (29).

$$d_j^+ = \max_i \tilde{c}_{ij} \ \forall j = 1,2,\dots,N \quad (26)$$

$$d_j^- = \min_i \tilde{c}_{ij} \ \forall j = 1,2,\dots,N \quad (27)$$

$$d_j^a = \sum_i \tilde{c}_{ij} \ \forall j = 1,2,\dots,N \quad (28)$$

Where $\tilde{c}_{ij}$ is IVFN and can be represented as $\tilde{d}_j = \left[\left(d_j^1, d_j^2\right); d_j^3; \left(d_j^4, d_j^5\right)\right]$

$$d_j = \frac{d_j^1 + d_j^2 + d_j^3 + d_j^4 + d_j^5}{5} \quad (29)$$

Step 5: Compute Distances from the Benchmark Solutions

In this step, the distance of each alternative from the three calculated reference points, namely the positive ideal, the negative ideal, and the average solutions, is computed. This distance is calculated based on the difference between the weighted values of the indicators and the initial distance. This relationship is presented in Equation (30). In this equation, d_j may represent one of the values d_j^+, d_j^-, or d_j^a. In this case, the value of $p \geq 2$ will be used. Next, a correction coefficient is calculated to adjust the distance, as shown in Equation (31). Finally, based on the initial distance and the correction coefficient, the corrected distance from the reference point is obtained. This corrected distance is presented in Equation (32).

$$e_i(s) = \left(\sum_j \left|c_{ij} - d_j\right|^p\right)^{1/p} \ \forall i = 1,2,\dots,M \quad (30)$$

$$f = \max_i\left(e_i(s)\right) - \min_i\left(e_i(s)\right) \quad (31)$$

$$g_i = e_i(s) + f e_i(s)^2 \ \forall i = 1,2,\dots,M \quad (32)$$

Step 6: Final Ranking of Alternatives

In this step, the final ranking of the alternatives is determined based on the corrected distance. This value is obtained using Equation (33). The linearization weight value is $\alpha \in [0,1]$.

$$g_i = \frac{\alpha(g_i^+ - g_i^-) + (1-\alpha)(g_i^a)}{2} \ \forall i = 1,2,\dots,M \quad (33)$$

4. Case Study

The case study examines the project portfolio selection process within a major state-owned mining organization in Iran, where capital-intensive operations, high operational risks, and geological uncertainties necessitate highly structured decision-making. From an initial pool of 35 mining projects encompassing exploration, extraction, processing, and infrastructure development, the organization screened and selected 10 major candidate projects representing its largest and most strategic operations. Each project is evaluated based on geological data, reserve capacity and quality, investment and operational costs, and initial economic potential.

To evaluate these 10 candidate projects against the main criteria, a decision-making framework was established involving three Vice Presidents of the organization as domain experts, each possessing over 20 years of executive experience in the mining sector. To ensure a balanced assessment, these decision-makers provided complementary expert perspectives: the first expert focused on infrastructure and logistics, the second on financial and economic aspects, and the third on health, safety, and environmental (HSE) performance.

Selecting a project portfolio in such an environment is of strategic importance, as evaluating the entire set of projects rather than assessing each individually allows for an integrated analysis of interactions, synergies, and resource dependencies. Effective project portfolio management enables the organization to allocate financial, human, and equipment resources optimally, avoiding projects that are overly risky or of low impact. Consequently, overall investment returns are enhanced, and decision-makers can steer development in alignment with the organization's strategic objectives and actual capabilities.

In this study, ten main criteria are considered for selecting a mining contractor's project portfolio; most of them are directly derived from practical mining project experience. These criteria include proximity to the central depot, mine reserves, contract extendability, fleet suitability, fleet age, mine access route, mine infrastructure, health, safety and environmental (HSE) risks, employer's goodwill and synergy with the employer. Proximity to the central depot is vital because shorter distances usually simplify project machinery and logistics management and reduce ancillary costs. Mine reserves relate to the project's economic aspects and indicate whether it is short-term or sustainable. The issue of contract extendability is also of great importance from the contractor's perspective, as the possibility of continuing cooperation beyond the initial contract can reduce decision-making risk. Fleet suitability refers to whether the requested fleet type is compatible with the company's existing equipment; in practice, greater compatibility minimizes the pressure to procure new equipment. In addition, fleet age reflects the level of wear and tear on machinery, and experience has shown that younger fleets typically cause fewer operational problems. Access to the mine is not only a technical issue but also important for safety and the continuity of operations, especially in adverse seasonal conditions. The mine infrastructure includes facilities such as electricity, water, fuel, and support services; the absence or weakness of any of these can pose serious challenges to project implementation. Health, safety and environmental (HSE) risks relate to the likelihood of accidents, occupational hazards and environmental consequences, and reducing these risks usually means more sustainable working conditions. Ultimately, the client's goodwill and the level of synergy with the contractor, which result from experience in collaboration and executive interaction, play an important role in the success or failure of the project. The selection criteria in this study were derived from actual project selection conditions and expert research. To provide a practical classification, these ten criteria are grouped into two categories: financial and non-financial. The financial criteria include mine reserves, proximity to the central depot, and contract extendability, which directly relate to costs, project scale, and commercial stability. Meanwhile, the non-financial criteria cover technical criteria (fleet suitability and fleet age), site criteria (access routes and infrastructure), safety criteria (HSE risks), and relationship

criteria (employer goodwill and synergy).

In this research, ten copper mining and tailings projects are considered decision-making Alternatives for this study; each is defined in real mining conditions and is not completely similar to the others in terms of size, implementation method, and technical issues. The decision to focus on copper projects stems from the role this metal plays in the country's industry. Copper is one of the materials whose presence is quite noticeable from extraction through final consumption across various production sectors, and the dispersion of its reserves across different regions of Iran has created significant mining capacity. However, the importance of copper is not limited to the amount of reserves or production. The widespread use of this metal across various industries has led decisions about copper projects to extend beyond the mine area. Industries such as electricity, electronics, construction, automotive, and industrial equipment manufacturing depend on the continuous supply of copper; for this reason, any interruption, misstep, or unrealistic decision in this area can create ripple effects across other sectors.

A real case study of ten major mines in Iran has been used. The largest copper reserves in Iran are located in the two provinces of Kerman and East Azerbaijan, and significant reserves are also found in other provinces. Given the specific conditions of the mines and the confidential information provided by the decision-makers, it is not possible to explicitly name the mines. Table 1 presents the decision-making matrix. This matrix was completed by three experts, who provided their evaluations for each mine based on the important criteria for selecting the extraction project.

Table 1. Decision-making matrix

Alternative / Criteria	Expert	Proximity	Reserve	Contract Stability	Fleet Compatibility	Fleet Age	Access Quality	Infrastructure	HSE Risk	Client Reliability	Synergy
Project Mine-1	Expert 1	VH	VH	VH	VH	MH	H	VH	MH	H	H
	Expert 2	H	VH	H	VH	H	H	VH	MH	H	H
	Expert 3	VH	VH	H	MH	H	VH	VH	H	H	MH
Project Mine-2	Expert 1	L	VH	H	MH	H	M	H	M	H	ML
	Expert 2	L	VH	H	MH	H	M	H	M	H	ML
	Expert 3	L	VH	H	M	H	M	H	M	H	L
Project Mine-3	Expert 1	H	H	H	H	MH	MH	H	MH	H	MH
	Expert 2	H	H	H	H	MH	H	H	H	H	H
	Expert 3	H	H	H	H	MH	MH	H	H	H	MH
Project Mine-4	Expert 1	MH	MH	MH	MH	M	M	MH	M	H	MH
	Expert 2	MH	H	MH	MH	MH	M	MH	M	MH	MH
	Expert 3	MH	MH	MH	M	M	M	MH	M	MH	MH
Project Mine-5	Expert 1	ML	M	M	ML	M	ML	ML	ML	M	L
	Expert 2	M	ML	M	ML	M	ML	ML	L	ML	L
	Expert 3	ML	M	M	L	ML	ML	M	L	ML	L
Project Mine-6	Expert 1	H	H	H	MH	M	M	MH	M	H	MH
	Expert 2	H	H	H	H	M	M	MH	M	H	MH
	Expert 3	H	H	H	MH	M	M	MH	M	H	MH
Project Mine-7	Expert 1	MH	MH	MH	MH	M	M	MH	M	H	MH
	Expert 2	MH	MH	MH	MH	M	M	M	ML	MH	M
	Expert 3	MH	MH	MH	MH	ML	M	M	ML	MH	M
Project Mine-8	Expert 1	ML	MH	MH	M	M	M	M	M	M	ML
	Expert 2	ML	MH	MH	M	M	M	ML	ML	M	ML
	Expert 3	L	MH	M	ML	ML	M	ML	ML	M	L
Project Mine-9	Expert 1	MH	M	M	MH	M	ML	MH	M	M	M
	Expert 2	MH	M	M	MH	M	M	MH	M	M	M
	Expert 3	MH	M	M	M	M	ML	MH	M	M	M
Project Mine-10	Expert 1	M	ML	ML	M	M	M	M	M	M	ML
	Expert 2	M	ML	ML	ML	M	M	M	ML	M	ML
	Expert 3	ML	ML	L	ML	M	M	ML	ML	M	L

In this study, for weighting the criteria, the LMAW method requires expert opinions for each criterion. This index reflects the importance of each criterion in selecting the project portfolio and its significance in the implementation process. Three experts were used for this evaluation. In Table 2, the scores for each criterion are derived from the experts' opinions.

Table 2. Score of each criterion based on the opinions of the experts

Expert	Proximity	Reserve	Contract Stability	Fleet Compatibility	Fleet Age	Access Quality	Infrastructure	HSE Risk	Client Reliability	Synergy
Expert 1	MH	H	MH	H	M	M	MH	MH	H	MH
Expert 2	MH	H	H	VH	M	H	H	M	H	M
Expert 3	M	H	MH	MH	MH	MH	MH	VH	H	M

Given that the expert opinions were extracted qualitatively and based on linguistic variables, converting these linguistic variables into quantitative values requires a linguistic variable table that maps each qualitative term to its corresponding quantitative value. Table 3 presents the limits of the linguistic variables. Quantitative values are represented as sets of interval-valued fuzzy numbers.

Table 3. IVFNs corresponding to linguistic variables

Linguistic variables	Symbol	Triangular interval-valued fuzzy numbers
Very low	VL	[(0, 0); 0; (0.1, 0.15)]
Low	L	[(0, 0.05); 0.1; (0.25, 0.35)]
Medium low	ML	[(0, 0.15); 0.3; (0.45, 0.55)]
Medium	M	[(0.25, 0.35); 0.5; (0.65, 0.75)]
Medium high	MH	[(0.45, 0.55); 0.7; (0.8, 0.95)]
High	H	[(0.55, 0.75); 0.9; (0.95, 1)]
Very high	VH	[(0.85, 0.95); 1; (1, 1)]

The data is extracted and becomes ready for use in the LMAW method. Given the requirement for criterion weights in the AURA method, the criteria' weights are calculated using the LMAW method, and the final project selection is obtained using the AURA method.

5. Results Analysis and Validation

A case study was used in the presented methods, and the final score and rank of each copper mine project were obtained from the project portfolio. This selection facilitates the final project selection. In Table 4, the score and rank of each project are calculated. Finally, this selection helps the decision-maker properly evaluate the projects based on the criteria.

As shown in Table 4, rank 1 is assigned to Project Mine-3, and rank 5 is assigned to Project Mine-5. Based on the initial assessment and the decision-makers’ perspective, Project Mine-1 and Project Mine-2 are considered the best choices because they are among the largest mines in Iran. However, by using the presented method and considering key criteria, this selection changes, and the country’s flagship projects are placed in subsequent ranks. This result indicates that the largest project does not necessarily mean the best project, and the criterion for selecting the best project should be defined and evaluated using precise engineering criteria, which have been implemented correctly in this study.

Table 4. Results of the proposed model in selecting a mining project portfolio

NO.	Project selection	Final amount	Rank
1	Project Mine-1	-0/014	2
2	Project Mine-2	0/015	7
3	Project Mine-3	-0/015	1
4	Project Mine-4	-0/008	4
5	Project Mine-5	0/041	10
6	Project Mine-6	-0/011	3
7	Project Mine-7	-0/003	5
8	Project Mine-8	0/024	8
9	Project Mine-9	0/006	6
10	Project Mine-10	0/035	9

5.1. Results Analysis

For accurate analysis, results should be compared across different dimensions. Since all three parts of this research have been developed, the evaluation should be conducted from different perspectives. The analysis of the results can be done from various perspectives. In this research, the experts' opinions have been used for the final decision-making. If the decision-making is based on each expert, the scores of each project and their ranks are compared with the results of the proposed model. In Table 5, the results of the proposed approach are compared with the opinions of each expert alone.

Table 5. Comparison of the state of aggregation of expert opinions with the opinion of each of the experts

No.	Project selection	Gathering of expert opinions		Expert 1		Expert 2		Expert 3	
		Final amount	Rank	Final amount	Rank	Final amount	Rank	Final amount	Rank
1	Project Mine-1	-0/014	2	-0/020	1	-0/015	2	-0/011	2
2	Project Mine-2	0/015	7	0/016	7	0/012	7	0/019	7
3	Project Mine-3	-0/015	1	-0/014	2	-0/017	1	-0/012	1
4	Project Mine-4	-0/008	4	-0/004	5	-0/005	4	-0/002	4
5	Project Mine-5	0/041	10	0/051	10	0/051	10	0/046	9
6	Project Mine-6	-0/011	3	-0/008	3	-0/008	3	-0/006	3
7	Project Mine-7	-0/003	5	-0/004	5	0/006	6	0/004	5
8	Project Mine-8	0/024	8	0/023	8	0/029	8	0/037	8
9	Project Mine-9	0/006	6	0/013	6	0/006	5	0/012	6
10	Project Mine-10	0/035	9	0/035	9	0/040	9	0/051	10

As shown, the experts' scores differ, and when each expert's review is compared with the proposed approach, the difference in project ranking is evident. This direct effect of aggregating expert opinions and their placement in the proposed matrix is evaluated, underscoring the high importance of expert opinions.

The next analysis of the results refers to the use of an extended uncertainty approach called the interval-valued fuzzy set. This approach reveals the impact and improvement of using extended uncertainty in this method. Table 6 compares three cases: the extended fuzzy approach, the conventional fuzzy approach, and the deterministic approach.

Table 6. Comparison of the results of the proposed model with other approaches to dealing with uncertainty

No.	Project selection	IVFNs		Conventional fuzzy numbers		Crisp numbers	
		Final amount	Rank	Final amount	Rank	Final amount	Rank
1	Project Mine-1	-0/014	2	-0/014	2	-0/014	2
2	Project Mine-2	0/015	7	0/015	7	0/016	7
3	Project Mine-3	-0/015	1	-0/015	1	-0/015	1
4	Project Mine-4	-0/008	4	-0/005	4	-0/004	4
5	Project Mine-5	0/041	10	0/044	10	0/044	10
6	Project Mine-6	-0/011	3	-0/008	3	-0/007	3
7	Project Mine-7	-0/003	5	0/002	5	0/003	5
8	Project Mine-8	0/024	8	0/026	8	0/027	8
9	Project Mine-9	0/006	6	0/008	6	0/010	6
10	Project Mine-10	0/035	9	0/036	9	0/037	9

By examining the three cases of interval-valued fuzzy numbers, conventional fuzzy numbers, and deterministic values, the results and scores of each project are observed. This change in project selection based on acceptance level is fundamental and underscores the importance of interval-valued fuzzy sets.

To validate the accuracy of the proposed decision-making model, two well-established benchmark multi-criteria decision-making (MCDM) methods (IVF-TOPSIS and IVF-VIKOR) were implemented under the identical interval-valued fuzzy environment. IVF-TOPSIS measures performance based on the shortest distance from the positive-ideal solution and the farthest distance from the negative-ideal solution. In contrast, IVF-VIKOR evaluates accuracy through compromise ranking, balancing maximum group utility and minimum individual regret.

As presented in Table 7, the proposed IVF-AURA method demonstrates high structural consistency with both benchmark methods. Notably, IVF-AURA achieves identical ranking results with IVF-VIKOR across all 10 candidate projects, while showing strong rank alignment with IVF-TOPSIS (maintaining identical top-ranked Project Mine-3 and bottom-ranked Project Mine-5). This high degree of rank correlation confirms the accuracy and reliability of the proposed ranking model compared to common literature methods.

Table 7. Comparison of the proposed ranking method with common methods in the literature

No.	Project selection	IVF-AURA method		IVF-TOPSIS method		IVF-VIKOR method	
		Final amount	Rank	Final amount	Rank	Final amount	Rank
1	Project Mine-1	-0/014	2	0.612	3	0.284	2
2	Project Mine-2	0/015	7	0.438	8	0.517	7
3	Project Mine-3	-0/015	1	0.645	1	0.261	1
4	Project Mine-4	-0/008	4	0.571	5	0.349	4
5	Project Mine-5	0/041	10	0.392	10	0.681	10
6	Project Mine-6	-0/011	3	0.601	4	0.311	3
7	Project Mine-7	-0/003	5	0.548	6	0.402	5
8	Project Mine-8	0/024	8	0.421	9	0.556	8
9	Project Mine-9	0/006	6	0.563	7	0.468	6
10	Project Mine-10	0/035	9	0.405	8	0.603	9

5.2. Sensitivity Analysis

Sensitivity analysis is essential for verifying the stability and robustness of the decision-making model under input variations. In this study, model stability was evaluated through two distinct sensitivity perspectives: expert panel expansion and criteria weight perturbations. First, to test the stability of project rankings against panel size, the number of decision-makers in the LMAW weighting process was systematically expanded from 3 to 96 experts. In Table 8, the

rank of each option is reported for a specific number of experts. As shown in Table 8, the rankings of all 10 candidate projects remain completely stable across all panel sizes, indicating that the final decisions are robust and immune to individual expert variation. Second, the sensitivity of the criteria weights was analyzed using 100 expert weight profiles (Figure 3), further confirming that the primary project rankings remain stable and robust underweight variations.

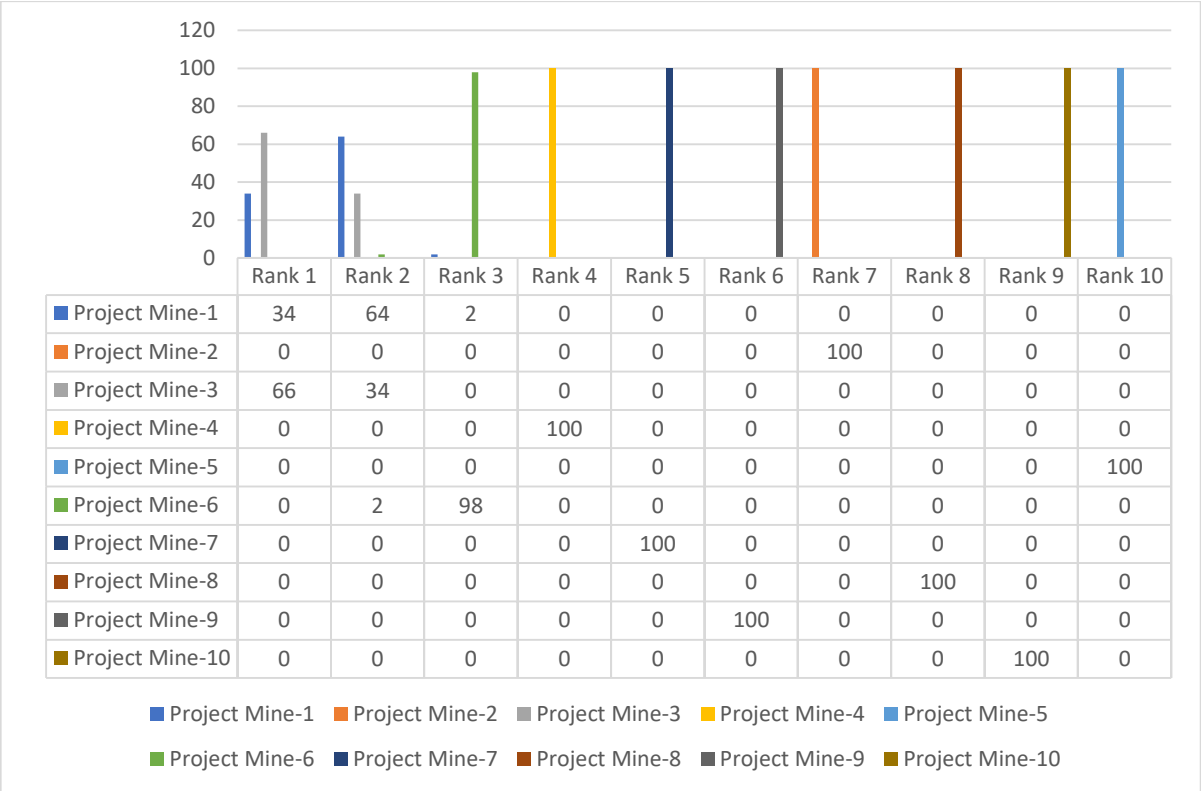
Table 8. Option scores based on the number of experts

Project selection / Expert		**Project Mine-1**	**Project Mine-2**	**Project Mine-3**	**Project Mine-4**	**Project Mine-5**	**Project Mine-6**	**Project Mine-7**	**Project Mine-8**	**Project Mine-9**	**Project Mine-10**
3 Experts	Final value	-0/014	0/015	-0/015	-0/008	0/041	-0/011	-0/003	0/024	0/006	0/035
	Rank	2	7	1	4	10	3	5	8	6	9
6 Experts	Final value	-0/013	0/014	-0/015	-0/007	0/041	-0/011	-0/003	0/023	0/005	0/034
	Rank	2	7	1	4	10	3	5	8	6	9
12 Experts	Final value	-0/013	0/014	-0/015	-0/007	0/041	-0/011	-0/003	0/023	0/005	0/034
	Rank	2	7	1	4	10	3	5	8	6	9
24 Experts	Final value	-0/013	0/014	-0/015	-0/007	0/041	-0/011	-0/003	0/023	0/005	0/034
	Rank	2	7	1	4	10	3	5	8	6	9
48 Experts	Final value	-0/013	0/014	-0/015	-0/007	0/041	-0/011	-0/003	0/023	0/005	0/034
	Rank	2	7	1	4	10	3	5	8	6	9
96 Experts	Final value	-0/013	0/014	-0/015	-0/007	0/041	-0/011	-0/003	0/023	0/005	0/034
	Rank	2	7	1	4	10	3	5	8	6	9

This sensitivity analysis shows that the rank of the options is constant, which is due to the clarity of the criteria and, to a large extent, individual decisions will not affect the rank of the projects. However, it is important that the score of each project reaches a desirable level of stability as the number of experts increases, and that it does not change significantly with a greater number of experts. This issue addresses the stability of each project's score.

Sensitivity analysis of the criteria' weights is of great importance. Accordingly, changes in the weight of each criterion can yield unique results, which can be used to observe each expert's sensitivity to the criteria. In this study, the weights required in the AURA ranking method are calculated using the LMAW weighting method. Accordingly, for ranking the proposed method, the criterion weights were extracted from 100 experts, without the need for an additional weighting method. These weights can be considered as the effect of each criterion and its relationship with the ranking of the options. Figure 3 shows a graph illustrating the rank of each project based on the opinions of 100 experts.

In this sensitivity analysis, the relative changes in each expert's weight and their impact on the project selection results are also observed. As shown, the sensitivity of ranks 1, 2, and 3 is very high, while the remaining ranks show little change. Project Mine-1, Project Mine-3, and Project Mine-6 have experienced the most variations in the final ranking. Project Mine-2, due to its high importance and very significant reserves, is ranked sixth based on the aggregation of 100 expert weights. This result is attributed to the high accuracy in selecting the project portfolio criteria and the reliability of the experts' opinions, which makes the obtained results dependable.



	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Rank 8	Rank 9	Rank 10
Project Mine-1	34	64	2	0	0	0	0	0	0	0
Project Mine-2	0	0	0	0	0	0	100	0	0	0
Project Mine-3	66	34	0	0	0	0	0	0	0	0
Project Mine-4	0	0	0	100	0	0	0	0	0	0
Project Mine-5	0	0	0	0	0	0	0	0	0	100
Project Mine-6	0	2	98	0	0	0	0	0	0	0
Project Mine-7	0	0	0	0	100	0	0	0	0	0
Project Mine-8	0	0	0	0	0	0	0	100	0	0
Project Mine-9	0	0	0	0	0	100	0	0	0	0
Project Mine-10	0	0	0	0	0	0	0	0	100	0

Figure 3. Sensitivity analysis of expert weights on the final rank

5.3. Responses to the Research Questions

1. Answer to Question 1: The proposed data-driven approach, by eliminating the sole reliance on qualitative and subjective judgments of experts, significantly increases the accuracy, transparency, and reliability of project portfolio evaluation and selection. This model operates through a five-step process: identifying options, collecting and cleaning data, removing outliers, selecting the best configuration of forecasting models by minimizing mean squared error, and finally extracting the final data. In this framework, the technical and performance indicators of projects are predicted using artificial intelligence tools and analytical models such as artificial neural networks, based on real data from past projects. This prevents unsuitable projects from entering the final stages and avoids spending time and high costs on feasibility studies for non-priority options.
2. Answer to Question 2: The use of interval-valued fuzzy numbers, due to the presence of upper and lower bounds in the membership function, offers a much greater ability to model ambiguity and uncertainty than conventional fuzzy methods and deterministic values. While deterministic methods are unable to capture uncertainty and conventional fuzzy models consider only a single degree of membership, the interval-valued structure allows environmental fluctuations, the lack of complete consensus among experts, and noise in operational data to be represented flexibly and realistically. Comparative studies in this article also show that this interval-valued approach increases decision-making stability in high-risk situations and reduces the risk of sudden changes or rank reversals.
3. Answer to Question 3: The new IVF-LMAW weighting method calculates the relative importance of criteria through an algorithmic and group process. This method first converts the qualitative scores provided by experts into interval-valued fuzzy numbers, then adjusts the score scale by determining the absolute anti-ideal point and forming relationship vectors. Then, by calculating the natural logarithm of these vectors and applying the Bonferroni operator, the interdependencies between the criteria and the differences in the experts' views are simultaneously aggregated. Finally, by normalizing the obtained weights, the final

criterion weights are extracted without rank inversion while maintaining computational robustness.

4. Answer to Question 4: The IVF-AURA ranking method works by evaluating the distance of options from three reference points, including the positive ideal solution, the negative ideal solution, and the average solution. After forming a data-driven decision matrix and applying criteria weights, this method normalizes using the reference distance and the maximum-minimum range. A comparison of this methodology with conventional methods, such as IVF-TOPSIS and IVF-VIKOR, shows that IVF-AURA offers much better accuracy and discrimination in separating projects with very close scores. Because it does not rely on complex mathematical mechanisms, it also demonstrates higher stability and more reliable behavior in the face of heterogeneous or limited data.

6. Managerial Insights

Implementing a data-driven multi-criteria decision-making model in an interval fuzzy environment for the PPS problem has the following practical implications and guidelines for senior managers and industrial decision-makers:

- Multi-dimensional assessment and avoidance of unidimensional assessments: The findings of this study show that relying solely on traditional indicators such as the scale or volume of a project's reserve can lead to suboptimal decisions. Senior managers should be aware that operational and non-financial criteria, including fleet age and fitness, access routes, infrastructure conditions, and health and safety (HSE) risks, can negate the economies of scale of large projects.
- Reducing evaluation costs and time through data-driven screening: Integrating analytical models and artificial intelligence into the initial evaluation stages enables more accurate predictions of project performance using real-world data. This predictive model allows managers to identify and eliminate non-prioritized options before committing significant financial and time resources to detailed feasibility studies.
- Realistic modeling of structured uncertainties in high-risk environments: Interval-valued fuzzy sets (IVFSs) provide decision-makers with a powerful tool for modeling the ambiguity of qualitative judgments and variable environmental conditions without simplifying or crudely converting them into definite values. This increases the adaptability and flexibility of strategic decisions in the face of operational uncertainties.
- Reducing individual biases and enhancing organizational transparency: Integrating the group decision-making process into both the weighting (IVF-LMAW) and ranking (IVF-AURA) stages provides a robust platform for systematically aggregating expert opinions. This approach minimizes personal biases and individual preferences in resource allocation, creating an objective, repeatable, and defensible decision for stakeholders.
- Ensuring strategic sustainability amid managerial fluctuations: The results of the sensitivity analysis show that the extracted prioritization is highly robust and stable to changes in the weights of the criteria or the number of experts. This feature assures organizations that project portfolio selection strategies will not deviate or become unstable over time or with changes in management personnel.

7. Conclusion

This article introduces a new data-driven IVF-MCDM approach for project portfolio selection and addresses the gaps identified in earlier works. The approach combines a data-driven model and group decision-making processes. It proposes a new fuzzy weighting approach, IVF-LMAW, capable of handling interval uncertainties, and an innovative fuzzy ranking technique,

IVF-AURA, that increases the accuracy and robustness of project outcomes. Through this method, decision-makers can form reliable judgments about projects under uncertain conditions and make portfolio decisions in alignment with the organization's strategic plans and goals. The results gain greater transparency and reliability through a two-stage process of weighting and ranking for the group decisions under uncertainty.

The real case study conducted in the mining industry demonstrates the validity of the proposed model. A number of exploration, extraction, processing, and infrastructure development projects were investigated based on financial, technical-operational, and environmental-social criteria. The results indicate that the model efficiently identifies an optimal project portfolio that maximizes economic value while keeping risk levels and resource limitations within an acceptable management framework. Moreover, a sensitivity analysis of the criterion weights confirms the stability and robustness of the project rankings, demonstrating that the model can deliver reliable, consistent decisions even in the face of variability in expert evaluations.

The study therefore stresses the importance of advanced multi-criteria decision-making techniques for complex, high-risk environments in the context of mineral project portfolio selection. Conventional methods are also limited when considering uncertainties, interdependencies, and the multi-dimensional nature of decision problems. This approach uses interval-valued fuzzy sets within a structured group decision-making framework to provide a realistic, flexible, and rational way to assess projects, incorporating both financial and non-financial factors through a weighting scheme.

Further research might extend this model by considering dynamic interaction among projects over multiple time periods, using real-time data and continuously updating the models to provide real-time decision support, and expanding the framework to other high-risk, capital-intensive industries. Future work should focus on developing hybrid models that combine IVFSs with artificial intelligence or optimization methods to enhance the accuracy of project portfolio selection further and thereby make the decision-making process more efficient.

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