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Adaptive Utility Ranking Algorithm for Evaluating Blockchain-Enabled Microfinance in Emerging - A New MCDM Perspective

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ABSTRACT

Blockchain integration in microfinance is beginning to reshape the scenario of financial inclusion and economic empowerment in emerging markets. To support a strategic decision on adoption, the study introduces the Adaptive Utility Ranking Algorithm (AURA), a newly established Multi-Criteria Decision-Making (MCDM) method to be used in evaluating blockchain-based alternatives relevant to microfinance in Malaysia. AURA stands apart from traditional MCDM techniques in that it has a distance function that is flexible and a normalization scheme that is dynamic by nature, thereby making it capable of offering the decision maker more leverage in terms of adaptability to actual economic conditions. For demonstrating the methodology, a simulated dataset based on eight blockchain-modeled alternatives and six criteria considered important in economic performance was constructed. These criteria were used for sensitivity analysis; the application of comparative evaluation of well-known MCDM methods such as TOPSIS, VIKOR, and COBRA; and robustness checks with the simulation methodology, all of which helped attest to the reliability of AURA. Even though it was based on synthetic data, the study has provided strong conceptual insight into the possibility of financial institutions being able to prioritize options from the technology perspective under complex economic constraints. Portraying AURA as a competitive decision-support tool for technology evaluation in microfinance will certainly make an impact.

1. Introduction

The decision-making framework of Multiple Criteria Decision Making (MCDM) has existed for decades to evaluate various alternatives, including strategy, policy, and choice to solve problems [1].

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Generally, the researcher(s) or decision-maker(s) need to find the best alternatives by examining multiple criteria in MCDM [2]. In other words, MCDM can also be explained as a process of evaluating and selecting the alternatives based on the importance of the criteria on the alternatives [3]. Ati *et al.,* [4] stated that the MCDM methods give advantages to the decision-maker(s) because it gives more objective decisions and it practical in helping the decisionmaker(s) to rank and select the best alternatives. MCDM field can be divided into two categories which are multi-objective decision-making (MODM) and multi-attribute decision-making (MADM) [5]. MODM involves developing a strategy that optimally balances multiple objectives to achieve the decision maker's goals while MADM refers to the procedure of choosing the best choice among a predetermined group of options based on several criteria.

Over the years, there have developed many MCDM methods to cope with complex decision making issues, with each method having its own distinct way of aggregating and ordering alternatives. Classical methods like Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijuska Optimizacija I Komoromisno Resenje (VIKOR), and Simple Additive Weighting (SAW) are being used extensively previously until recently. Kaya [6] stated that TOPSIS targets the determination of solutions that are near the ideal solution, but far from the worst-

case scenario and these are among the most regularly used MCDM methods. Other techniques such as Multi-Objective Optimization by Ratio Analysis (MOORA), Weighted Aggregated Sum Product Assessment (WASPAS) and lately emerging innovations in distance-oriented MCDM, Comprehensive Distance-Based Ranking (COBRA) have been developed contributing to significant rises in decision making accuracy. The evaluation process in MCDM approaches typically has four steps. The procedure is given by (i) determining which criteria and alternatives are relevant for the problem, (ii) weighting each criterion based on its importance, (iii) rating individual performance for every option on each measure as well as (iv) evaluating every option against these criteria and ranking them based on their overall performance measures [7], [8]. Step 2, which is weighting each criterion based on its importance, is an important aspect in MCDM even though it is not the main focus in this study. Techniques like Entropy, CRITIC, and MEREC are used to extract weights starting from data characteristics and being more data driven [9]. Some applications that focus on weight are Pythagorean Neutrosophic Method Based on the Removal Effects of Criteria (PNMEREC) [10], and also integration of objective weight in material selection [9]. Steps 3 and 4 are mainly discussed in this study. We can say that it is one of the most critical and difficult processes in a solution of MCDM problems, as it influences the accuracy and reliability of a solution, since we evaluate individual performance for every alternative and aggregate their overall ranking.

The approaches of MCDM have evolved quite considerably, to include such innovations as data-driven models, fuzzy-based schemes, and hybrid techniques to enhance decision-making efficiency and flexibility in practice application [11]. Applications in MCDM has grown to different industries, one of which is business and management such as MCDM model for personnel selection in tourism sector [12], textile supply chain management [13], and selection of an optimal ERP software in organization [14]. Apart from that, the MCDM is broadly used in engineering and logistics industries. For example, MCDM techniques for improvement sustainability engineering processes [15], Selection of Warehouse Location with Octagonal Neutrosophic Application [16], and MCDM methodology to logistics location problems [17]. One area in which MCDM is an emerging field in safety and security is that it uses structured decision-making procedures to enhance security procedures and safety measures in a wide range of situations. MCDM methods support public security [18], construction safety [19], analysis of safety transport system [20], and security forces operations [21]. All these developments in MCDM lead to the emergence of trends.

Emerging trends in MCDM as technology develops and the decision context grows more complex, are emerging trends in MCDM that respond to the environment of decision-making tendencies. To make them more useful and more effective in several areas, MCDM techniques are being modified and combined with new technologies. As the world continues to become digital, the use of blockchain technology and IoT is gradually introduced using MCDM techniques to deliver dynamic and real-time decision making and increases of big data analytics [22]. Improved decision making is facilitated by this integration, particularly in such areas as environmental management and health care. In the crisis of COVID-19 pandemic, when resources needed to be maximized and wise choices to be made, MCDM techniques were applied and proved themselves applicable in fast paced, high stakes situations [23]. In addition, the creation of hybrid models such as m-polar fuzzy soft expert sets has been developed to solve tricky decision-making situations that involve various experts and criteria [24]. Given that new methods are being developed every few months, it is difficult to identify the exact extent of such MCDM approaches contained in literature, although there are over fifty of such approaches. However not every approach is taken up by researchers and professionals. The applicability of every approach depends on, how well it fits a given problem and resources required that include time, money, and human experience. Despite these advances, there are apparent limitations of current MCDM methods with regards to their complexity, computation burden, and the inability to normalize results flexibly enough. For example, COBRA uses two distance formulas, Euclidean and Taxicab, complicating the process further. Furthermore, many classical methods provide the best ideal solution as strictly optimal either maximum or minimum value, which may not be observed in real world data sets where ideal value lies in the middle.

Considering this gap to understand how technology or application can support the cross-cultural processes of value formation, this research suggests a new approach, the Adaptive Utility Ranking Algorithm (AURA). AURA is the target of reducing the computational steps in the pattern matching during decision making, the use of a single distance measure instead of a combination of them, and adoption of a flexible normalization that allows the ideal solution to be dynamically searched in the data range. This improves the flexibility and reliability of the method in real-world decision-making situations. The focal point of this work is the ease by which the aggregation and ranking processes in MCDM will be simplified without sacrificing accuracy of decision outcomes. AURA also increases the objectivity and clarity of distance-based ranking approaches and makes the latter both effective and applicable for practitioners working in complex decision environments.

The remainder of this paper is organized as follows. Section 2 discusses the literature review of current MCDM approaches. Section 3 presents an introduction to the proposed AURA method, presenting its conceptual framework and algorithmic steps. Section 4 presents computational analysis such as numerical case study, sensitivity analysis, and comparison with other established MCDM methods. Finally, Section 5 summarizes the paper and presents possible directions for further research.

2. Literature Review of MCDM methods

The MCDM Method is an important tool for dealing with complex decision-making problems involving multiple and often conflicting criteria. These methods have evolved significantly over time, combining both traditional and modern methods to improve decision-making processes across multiple fields [17]. The traditional methods can be classified into different groups according to similar characteristics such as scoring, distance-based, pairwise comparison, outranking, utility or valuate, and others [25]. Table 1 presents numerical grouping of MCDM methods, and it shows some of the MCDM methods within their groups.

Table 1
MCDM Methods

MCDM Group	MCDM Method	Acronym	References
Scoring	“Simple additive weighting”	SAW	[26]
	“Weighted Sum Model”	WSM	[27]
	“Weighted Product Model”	WPM	[28]
	“Complex Proportional Assessment”	CORPAS	[26]
Distance-Based	“Technique for Order of Preference by Similarity to Ideal Solution”	TOPSIS	[29]
	“VIšeKriterijumska OptimizacijaI Kompromisno Rešenje”	VIKOR	[30]
	“Multi-Objective Optimization by *Ratio Analysis (plus the full MULTIplicative form)”	(MULTI)MOORA	[31]
	“Weighted Aggregated Sum Product Assessment”	WASPAS	[28]
	“Comprehensive Distance-Based Ranking”	COBRA	[32]
Pairwise Comparison	“Analytic Hierarchy Process”	AHP	[33]
	“Analytical Network Process”	ANP	[34]
	“Measuring Attractiveness through a Categorical-Based Evaluation Technique”	MACBETH	[35]
	“FUll Consistency Method”	FUCOM	[36]
Outranking	“Preference Ranking Organization METHod for Enrichment of Evaluations”	PROMETHEE	[37]
	“ÉLimination et Choix Traduisant la REalité”	ELECTRE	[38]
	“Multi-Attributive Border Approximation area Comparison”	MABAC	[39]
	“Indifference Threshold-based Attribute Ratio Analysis”	ITARA	[40]
Utility/Valuate	“Multi-Attribute Utility Theory”	MAUT	[41]
	“Multi-Attribute Value Theory”	MAVT	[41]
Others	“Quality Function Development”	QFD	[42]

Penadés-Plà *et al.,* [25] mentioned that the most basic MCDM techniques are the scoring techniques. Their foundation is evaluating the options using basic mathematical concepts. The basic concept behind the distance-based method is to calculate the distance between every alternative and a specific point. The pairwise comparison methods help obtaining the weight of the different criteria and compare alternatives with respect to a subjective criterion. Establishing a preference relation on several alternatives that shows the level of dominance among them is the basis of outranking methods. The utility methods define expressions that determine the degree of satisfaction of the criteria.

The method created in this study belongs to the distance-based MCDM methods like TOPSIS, VIKOR, MOORA, WASPAS, and COBRA, special attention is given to these methods among the ones mentioned above. All these approaches use the same ranking logic, which assesses alternatives according to different kinds of distances from a reference alternative. Since SAW, a scoring method, is still one of the most widely used traditional MCDM techniques, proving its ongoing relevance and applicability, it is also included in the comparative study.

It is common practice in the field of Multiple Criteria Decision-Making (MCDM) to employ the SAW method. It is applied in various disciplines to evaluate alternatives based on several criteria to present an easy way of making decisions. In the SAW approach each criterion is associated with the weight, the scores of the alternatives are normalized and weighted sum is calculated to determine the preferred alternative. Its simplicity and effectiveness in solving decision-making problems in various uncertain environments make this method particularly appreciated. SAW method has proved to be successfully implemented in ranked educational institutes using fuzz logic to address the issue of uncertainty [43]. Additionally, SAW method is combined with the recurrent neural networks (RNN) to ensure the optimalization of resource allocation among cloud computing domains [44]. The SAW method is revised and applied for manufacturing environments [45]. The SAW method, however, has its own weakness despite being faulted for ease of use and efficiency. The approach may not fully reflect the complexity of criteria relation because it assumes a linear nature of criteria weighting. By providing more complex evaluations under an uncertain environment, the SAW method's expansion such as those which invoke fuzzy logic or hybrid methods try to address these defects [46].

The TOPSIS method ranks alternatives according to their geometric closeness degree to the positive-ideal and negative-ideal solutions. The simplest as well as most logically consistent, accurate, adaptable, and having the simplest, straightforward mathematical formulation, the given one is also the most popular option of the decision-making process. Nevertheless, the technique described by TOPSIS has some flaws. The ranking procedure is most literal, though without regard to the relative distance importance, a simple addition of distances from the positive and negative ideal solutions. In addition, it is not always an optimal strategy to approach the positive ideal solution and thus avoid the negative one in making some decision [47]. The TOPSIS approach is applied here in a few industries such as in choosing the suppliers that are green [48], selection of the waste to energy technology [49], vehicle routing [50], and evaluating the cost effectiveness of the green infrastructure [51].

Just as in case of TOPSIS method, the VIKOR approach considers the utility, regret, and distance from ideal and worst solution to compare options. VIKOR significantly outperforms TOPSIS in compromising towards the choice. The incorporation of the advantage rates ensures that the alternative in the highest rank is the most like the optimal answer, something which is not always the case with the TOPSIS technique [52]. The VIKOR approach has proven numerous applications in many areas, recent ones are web-based expert system chatbot [53], medical diagnostic [54], and sequencing three-way classification ranking [55].

The MOORA approach orders the alternatives in proportion to the square root of distance with the reference point. The calculation time using mathematical calculations is reduced by the MOORA method [56]. Further, it is easy to learn and to use, consistently provides results, and does not need such additional parameters as the parameter v in the VIKOR approach [57]. Provided below are some of the latest applications of the MOORA method, such as the project selection of the renewable energies [58], the decision supporting for the selection of the computer lecturer[59], and the determination of the pilot area [60].

The WASPAS method is a combination of the weighted sum model and the weighted product model. The WASPAS approach is very reliable for process parameter settings based on current data combinations, eliminating the need for decision makers to evaluate them further [61]. Its simplicity has led to widespread application in fields such as selecting head of study program [62], selecting a prospective librarian [63], and designing a used goods donation system to reduce waste accumulation [64].

Within the field of MCDM, the COBRA MCDM method is a particular technique for evaluating and ranking alternatives according to several criteria. The COBRA method combines all the advantages of the few other distance-based MCDM methods, eliminating the need to discuss according to which distance and in relation to which solution the alternatives should be ranked [32]. After criteria weights have been established using another approach, like MEREC, the COBRA method which is explicitly stated in the context of choosing an e-commerce development strategy is a Comprehensive Distance Based Ranking method that helps with the final evaluation and ranking of alternatives [65]. As an application, IVPNS-COBRA approach has been applied to e-commerce development strategies and IT supplier selection considering 5-point and 7-point linguistic scales together with Euclidean and Hamming distances to boost the precision of alternative evaluations in decision-making setups [66].

As mentioned earlier, these methods are similar in that they rank the alternatives according to a distance measure from a reference point. It is hard to determine which of these approaches is superior to the others, or, to put it another way, if it is preferable to utilize Manhattan or Euclidean distances or to compute distances from the ideal, anti-ideal, both ideal and anti-ideal, or average solutions. The method to rank the options based on the integration of multiple distance types from different reference points has not yet been specified in the literature, which is precisely the research gap that this work seeks to address. Therefore, a new distance-based method AURA has been developed in this study. AURA was developed to make distance-based MCDM techniques, such as COBRA, easier to use and more effective. By proposing a more flexible normalization technique and utilizing a single distance formula rather than two, AURA increases computational efficiency without reducing accuracy. The most optimal ideal solution can be located anywhere in the intermediate range using AURA, which makes it more flexible for real-world decision-making situations than typical MCDM techniques that define ideal solutions at extreme values. The primary motivation for implementing the AURA approach in this study, in addition to some of the earlier ones, is to make the decision-making process more thorough, broader, and more reliable.

The paper is structured as follows. Section 2 provides the proposed MCDM method. Section 3 explains computational analysis where it includes numerical example, sensitivity analysis, and comparative analysis. The final section summarizes the paper.

3. Proposed Method

The Adaptive utility Ranking Algorithm (AURA) is a MCDM framework that is developed to quantify and compare alternatives based on their performance in multiple criterions. It proposes a flexible normalization approach, weighting system and integrated distance-based ranking mechanism which enhances computational efficiency without compromising with high accuracy. The following describes the AURA procedure in six systematic steps as shown in Figure 1.

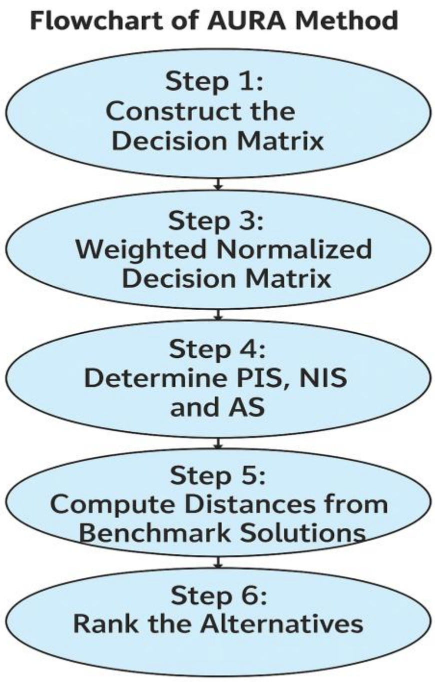

Fig. 1. AURA Method Flowchart

Step 1: Construct the Decision Matrix.

In AURA method, the decision-making process starts from declaring a set of alternatives $i(i=1,...,m)$ with respect to criterion $j(j=1,...,n)$, thus the decision matrix is obtained:

$$A=\begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}, \tag{1}$$

In which n, is the total number of criteria, and m is the number of total alternatives taken into consideration. The decision matrix is the basis of the analysis. It summarizes raw data or expert assessments in many criteria such as the benefits-type, the cost-type, proximity-based measures may be applied. Before employing the AURA method, it is necessary to absolutely guarantee that the decision matrix is constructed well. This includes validating the data, imputing the missing values, and matching scales of evaluation in the criteria.

By creating this matrix, AURA provides an explicit reference point from which to convert the raw data, possibly of varied characteristics into a structured comparable template for the following normalization phase.

Step 2: Normalized the Decision Matrix.

After that, the AURA method requires normalizing of the decision matrix A for the relevant criteria to be dimensionless and comparable. This normalization removes the effect of different units of measurements (i.e. cost, percentage, or ratings) and levels up all the criteria on a standardized scale ranging from 0 to 1. The AURA method uses normalization formula based on proximity. Form a decision matrix in a normalized table Δ:

$$\Delta=\left[\psi_{ij}\right]_{m\times n}, \tag{2}$$

where

$$\psi_{ij}=1-\frac{\left|a_{ij}-k_j\right|}{h_j}, \tag{3}$$

Where k_j is a reference value specified by the decision maker for criterion j and could be a target, benchmark, or desired performance. h_j is the range of values for criterion j where $h_j=\left(\max\left(a_j\right)-\min\left(a_j\right)\right)$. This formula normalizes the score depending on how close they are to the reference value k_j with the closest scores to gain higher normalized values. The normalization is flexible, as it can accommodate for the best value not necessarily being simply the maximum or the minimum but rather in between which is a monetization tool that improves AURA's ability to be applicable in the real world in decision making. As an example, benefit criteria can adopt k_j as the highest value, whereas cost criteria can adopt k_j as the minimum, or a target value that is flexible and a coordinated method in dealing with both kinds of criteria.

The normalized matrix Δ is hence derived in which each entry indicates the relative proximity of alternative to the ideal reference for each criterion, transiting the path to the next step in using weights.

Step 3: Weighted Normalized Decision Matrix.

After normalization, the relative importance of each decision criterion is integrated into the AURA method by determining the weighted normalized decision matrix. This step makes sure that criteria that carry more weightages can impose more weightage on the final ranking. The weighted normalized decision matrix Δ_ω is given:

$$\Delta_\omega = \left[\omega_j \times \psi_{ij}\right]_{m\times n}, \tag{4}$$

Where ω_j is an indicative weight of criterion j, and it suggests its relative importance, with $\sum_{j=1}^{n}\omega_j = 1$. This process leads to the matrix where $V = \left[v_{ij}\right]$, $v_{ij} = \omega_j \times \psi_{ij}$. Weights ω_j are able to be determined using methods such as expert judgement, objective techniques such as entropy, or a combination of both. Introducing weights into the AURA method is a mechanism for incorporation of stakeholder priorities within the ranking method and the fair-relative balance of the importance of all criteria in the process.

Step 4: Determine the Positive Ideal (PIS), Negative Ideal (NIS) and Average Solution (AS).

On this step, AURA finds three main reference points for each criterion to use as benchmarks when measuring proximity of alternatives:

$$PIS = S_j^{+} = \max_i\left(v_{ij}\right), \forall j = 1,\dots,n, \tag{5}$$

$$NIS = S_j^{-} = \min_i\left(v_{ij}\right), \forall j = 1,\dots,n, \tag{6}$$

$$AS = S_j^{a} = \frac{\sum_{i=1}^{m}\left(v_{ij}\right)}{m}, \forall j = 1,\dots,n, \tag{7}$$

Where PIS and NIS both represent the best and the worst and AS reflects average performance for weighted normalized value of the alternatives for the criterion j. By computing these three benchmark values, AURA plans to compare how far apart each of the alternatives is from the ideal, the worst and the average solutions. The tri-benchmark approach provides the method with greater flexibility and a greater sensitivity to small differences between the alternatives, particularly in complex or uncertain environments.

Step 5: Compute the Distances from the Benchmark Solutions.

In this step the AURA method calculates the distance of each alternative from the positive ideal solution (PIS), negative ideal solution (NIS) and average solution (AS). This step offers a good evaluation of the extent each alternative matches the best, worst, and normal performance, across all criteria.

The distances of alternative i from a benchmark S_j are computed as:

$$d_i\left(S\right) = \left(\sum_{j=1}^{n}\left|v_{ij} - S_j\right|^{p}\right)^{\frac{1}{p}}, \tag{8}$$

Where S_j represents S_j^{+}, S_j^{-}, and S_j^{a}. The parameter p is a distance parameter to keep sensitiveness to large deviations in check. Furthermore, AURA applies a correction coefficient σ to the distances:

$$\sigma = \max\left(d_i\left(S\right)\right) - \min\left(d_i\left(S\right)\right) \tag{9}$$

The correction coefficient is put in the distance formula thus:

$$D_i\left(S\right) = d_i\left(S\right) + \sigma \cdot d_i\left(S\right)^2 \tag{10}$$

By using this scaling, AURA highlights slight and significant differences between alternatives, proving that alternatives that are close or far from the benchmarks are meaningfully distinguished. This step forms the basis of a strong and detailed ranking process at the final stage.

Step 6: Rank the Alternatives.

Finally, AURA scores a comprehensive ranking score.

$$dR_i = \frac{\alpha \cdot \left(D_i\left(S^+\right) - D_i\left(S^-\right)\right) + (1-\alpha) \cdot D_i\left(S^a\right)}{2} \tag{11}$$

Where $\alpha \in [0,1]$, allows the decision makers have the option to weigh the closeness to the ideal versus the effect of the average solution. Thus, the alternatives are ranked from lowest to highest where a lower value is better.

3. Computational Analysis

In this section, we present four sub-sections where the first sub-section uses a numerical example to demonstrate the way of using the AURA method. Second sub-sections perform sensitivity analysis where we examine the impact of varying parameter values on the ranking outcomes and, we do a sensitivity analysis on the ranking across weight scenarios. Third sub-sections perform comparative analysis to show that AURA methods are valid and congruent with other MCDM methods. The fourth sub-section presents a simulation-based analysis to test the stability of the results obtained by AURA.

3.1 Numerical Example

Six beneficial criteria that are selected to evaluate the performance of blockchain-based models in enhancing social capital within Malaysian microfinance systems include transparency C_1 which is valued for its ability to increase openness and accountability in financial transactions, promoting trust among stakeholders. Security C_2 is prioritized to ensure strong protection against fraud, data breaches, and cyber threats, thereby safeguarding user information and assets. Operational Efficiency C_3 is also provided to induce solutions that will minimize the consuming time of a transaction and its cost, thus more timely rapid and cost-effective services. Financial Inclusion C_4 tries to address inequitable access to financial services for minority and under-served classes harmonizing with the social purpose of microfinance. Scalability C_5 is important to check whether solution can be scaled to be used in different institutions and across geographic locations as well, so that the impact is better. Finally, Regulatory Compliance C_6 makes sure that solutions put forward comply with Malaysian financial laws and regulations making it easier to deploy them on the legal framework in place.

To assess these criteria, eight blockchain-based microfinance alternatives are examined. These include Smart Contracts for Loan Disbursement A_1, which are automated and enforce loan agreement without the need for intermediaries. Decentralized Identity Verification A_2, which increases trust by means of secure user-controlled identity management. Blockchain-Based Credit Scoring A_3, which helps obtain open and unalterable records that facilitate credit rating. Cryptocurrency for Microfinance Payments A_4, offering low cost, borderless payments. Peer-to-Peer (P2P) Lending on Blockchain A_5, enabling direct lending between individuals without traditional banking intermediaries. Tokenized Assets for Collateral A_6, which allows borrowers to use digital representations of assets as security for loans. Hyperledger-Based Consortium Model A_7, promoting permissioned networks for collaborative microfinance efforts, and Public Blockchain for Financial Transparency A_8, which ensures open access to transaction histories for increased accountability.

To illustrate the procedure of utilizing AURA method, we use a simple decision matrix in this sub-section. In this current example criteria are all numerical and of benefit type. However, the proposed method can flexibly treat benefit and cost-type criteria because k_j can be changed as the reference value. The weights assigned to the criteria were determined through consultations with stakeholders, and Table 2 below summarizes the criteria and their corresponding weights.

Table 2
The Weights of each criterion for blockchain based microfinance

Criterion	Weight (ω_j)
C_1	0.12
C_2	0.2
C_3	0.16
C_4	0.32
C_5	0.15
C_6	0.05

Step 1: Construct the Decision Matrix.

Table 3 presents the 8×6 decision matrix where there are 8 alternatives and 6 criteria.

Table 3
The decision matrix of the numerical example

Alt.	C_1	C_2	C_3	C_4	C_5	C_6
A_1	4	8	8	7	9	8
A_2	6	7	7	8	9	6
A_3	7	6	5	8	7	4
A_4	6	6	4	6	5	4
A_5	9	9	4	6	6	7
A_6	7	9	8	8	7	8
A_7	8	8	9	8	6	9
A_8	9	4	7	5	8	6

Step 2: Normalized the Decision Matrix.

Decision-maker(s) use Equation (3) to find the normalized decision matrix. Decision-maker(s) has set reference values k_j for each criterion as $k = [9,9,9,8,9,9]$. Table 4 represents this matrix.

Table 4
The normalized decision matrix of the numerical example

Alt.	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0	0.8	0.8	0.6667	1	0.8
A_2	0.4	0.6	0.6	1	1	0.4
A_3	0.6	0.4	0.2	1	0.5	0
A_4	0.4	0.4	0	0.3333	0	0
A_5	1	1	0	0.3333	0.25	0.6
A_6	0.6	1	0.8	1	0.5	0.8
A_7	0.8	0.8	1	1	0.25	1
A_8	1	0	0.6	0	0.75	0.4

Normalization ensure that all raw scores are converted into a common, dimensionless scale so no single criterion can dominate the results.

Proximity-based type:

C_2 where the $k_1 = 9$

$\psi_{12} = 1 - \frac{|8-9|}{5} = 0.8$, $\psi_{23} = 1 - \frac{|7-9|}{5} = 0.6$

C_4 where the $k_4 = 8$

$\psi_{14} = 1 - \frac{|7-8|}{3} = 0.6667$, $\psi_{24} = 1 - \frac{|8-8|}{3} = 1$

Step 3: Weighted Normalized Decision Matrix.

Compute the weighted normalized decision matrix following the Equation (4). The weights for the criteria are $\omega = [0.12, 0.2, 0.16, 0.32, 0.15, 0.05]$. Table 5 represents the matrix.

Table 5
The weighted normalized decision matrix of the numerical example

Alt.	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*
A1	0	0.16	0.128	0.2133	0.15	0.04
A2	0.048	0.12	0.096	0.32	0.15	0.02
A3	0.072	0.08	0.032	0.32	0.075	0
A4	0.048	0.08	0	0.1067	0	0
A5	0.12	0.2	0	0.1067	0.0375	0.03
A6	0.072	0.2	0.128	0.32	0.075	0.04
A7	0.096	0.16	0.16	0.32	0.0375	0.05
A8	0.12	0	0.096	0	0.1125	0.02

Each alternative is calculated as follows:

For $v_{11} = 0 \cdot 0.12 = 0$

For $v_{23} = 0.6 \cdot 0.16 = 0.096$

Step 4: Determine the Positive Ideal (PIS), Negative Ideal (NIS) and Average Solution (AS).

Determine the PIS, NIS and AS using the Equation (5), (6), and (7) respectively. Table 6 shows the result of it.

Table 6
The PIS, NIS, and AS for each criterion

	C1	*C2*	*C3*	*C4*	*C5*	*C6*
S_j^+	0.12	0.2	0.16	0.32	0.15	0.05
S_j^-	0	0	0	0	0	0
S_j^a	0.072	0.125	0.08	0.2133	0.0797	0.025

In this step, we calculate the maximum, minimum and average value for each criteria column. The result shows that in C_1, we get $S_j^+ = 0.12$, $S_j^- = 0$, and $S_j^a = 0.072$. Then we proceed the same for other criteria.

Step 5: Compute the Distances from the Benchmark Solutions.

Determine the distance from the $D_i\left(S^+\right), D_i\left(S^-\right)$, and $D_i\left(S^a\right)$ for each of the alternatives using Equation (8), (9), and (10). Let parameter $p = 2$. Table 7 shows the distance $d_i\left(S^+\right)$, $d_i\left(S^-\right)$, and $d_i\left(S^a\right)$ for each alternative where we calculate it using Equation (8).

Table 7

The distance $d_i\left(S^+\right)$, $d_i\left(S^-\right)$, and $d_i\left(S^a\right)$ for each alternative

Alt.	$d_i\left(S^+\right)$	$d_i\left(S^-\right)$	$d_i\left(S^a\right)$
A_1	0.1688	0.3341	0.1178
A_2	0.1288	0.3889	0.1312
A_3	0.2030	0.3473	0.1279
A_4	0.3401	0.1417	0.1654
A_5	0.2901	0.2609	0.1659
A_6	0.0951	0.4138	0.1398
A_7	0.1218	0.4083	0.1483
A_8	0.3857	0.1915	0.2546

Calculating the distance for $d_i\left(S^+\right)$, $d_i\left(S^-\right)$, and $d_i\left(S^a\right)$ alternatives:

For $d_1\left(S^+\right)=\left(\sum_{j=1}^{n}\left|v_{ij}-S_j\right|^p\right)^{1/p}$

$$d_1\left(S^+\right)=\begin{pmatrix}\left|0-0.12\right|^2+\left|0.16-0.2\right|^2+\left|0.128-0.16\right|^2+\\ \left|0.2133-0.32\right|^2+\left|0.15-0.15\right|^2+\left|0.04-0.05\right|^2\end{pmatrix}^{1/2}=0.1688$$

For $d_1\left(S^-\right)=\left(\sum_{j=1}^{n}\left|v_{ij}-S_j\right|^p\right)^{1/p}$

$$d_1\left(S^+\right)=\begin{pmatrix}\left|0-0\right|^2+\left|0.16-0\right|^2+\left|0.128-0\right|^2+\\ \left|0.2133-0\right|^2+\left|0.15-0\right|^2+\left|0.04-0\right|^2\end{pmatrix}^{1/2}=0.3341$$

For $d_1\left(S^a\right)=\left(\sum_{j=1}^{n}\left|v_{ij}-S_j\right|^p\right)^{1/p}$

$$d_1\left(S^a\right)=\begin{pmatrix}\left|0-0.072\right|^2+\left|0.16-0.125\right|^2+\left|0.128-0.08\right|^2+\\ \left|0.2133-0.2133\right|^2+\left|0.15-0.0797\right|^2+\left|0.04-0.025\right|^2\end{pmatrix}^{1/2}=0.1178$$

Then we apply a correction coefficient σ as in Equation (9) to the distances and the results is shown in Table 8.

Table 8

The correction coefficient based on the $d_i\left(S\right)$

	$d_i\left(S^+\right)$	$d_i\left(S^-\right)$	$d_i\left(S^a\right)$
σ	0.2906	0.2720	0.1367

The correction coefficient is put in the distance formula which is Equation (10) and the result is presented in Table 9.

Table 9
The distance $D_i\left(S^+\right)$, $D_i\left(S^-\right)$, $D_i\left(S^a\right)$ for each alternative

Alt.	$D_i\left(S^+\right)$	$D_i\left(S^-\right)$	$D_i\left(S^a\right)$
A_1	0.1771	0.3644	0.1197
A_2	0.1336	0.4300	0.1335
A_3	0.2150	0.3801	0.1301
A_4	0.3738	0.1472	0.1691
A_5	0.3146	0.2795	0.1696
A_6	0.0978	0.4603	0.1425
A_7	0.1261	0.4537	0.1513
A_8	0.4290	0.2015	0.2634

The calculation for the first alternative is as follows:

For $D_1\left(S^+\right)=d_i\left(S^+\right)+\sigma\cdot d_i\left(S^+\right)^2=0.1688+0.2906\cdot 0.1688^2=0.1771$

For $D_1\left(S^-\right)=d_i\left(S^-\right)+\sigma\cdot d_i\left(S^-\right)^2=0.3341+0.2720\cdot 0.3341^2=0.3644$

For $D_1\left(S^a\right)=d_i\left(S^a\right)+\sigma\cdot d_i\left(S^a\right)^2=0.1178+0.1367\cdot 0.1178^2=0.1197$

Step 6: Rank the Alternatives.

Rank the alternative using Equation (11), parameter $\alpha=0.5$. Table 10 shows the final ranking result using AURA method. The alternatives are ranked in ascending order, where a lower value indicates a better alternative.

Table 10
Final ranking using AURA method

Alt.	Ranking Score	Rank
A_1	-0.0169	4
A_2	-0.0407	3
A_3	-0.0088	5
A_4	0.0989	7
A_5	0.0512	6
A_6	-0.0550	1
A_7	-0.0441	2
A_8	0.1227	8

Let $\alpha=0.5$,

$$dR_1=\frac{0.5\cdot\left(0.1771-0.3644\right)+\left(1-0.5\right)\cdot 0.1197}{2}=-0.0169$$

$$dR_2=\frac{0.5\cdot\left(0.1336-0.4300\right)+\left(1-0.5\right)\cdot 0.1335}{2}=-0.0407$$

$$dR_3=\frac{0.5\cdot\left(0.2150-0.3801\right)+\left(1-0.5\right)\cdot 0.1301}{2}=-0.0088$$

The final ranks and scores with $A_6>A_7>A_2>A_1>A_3>A_5>A_4>A_8$ are shown in Figure 2.

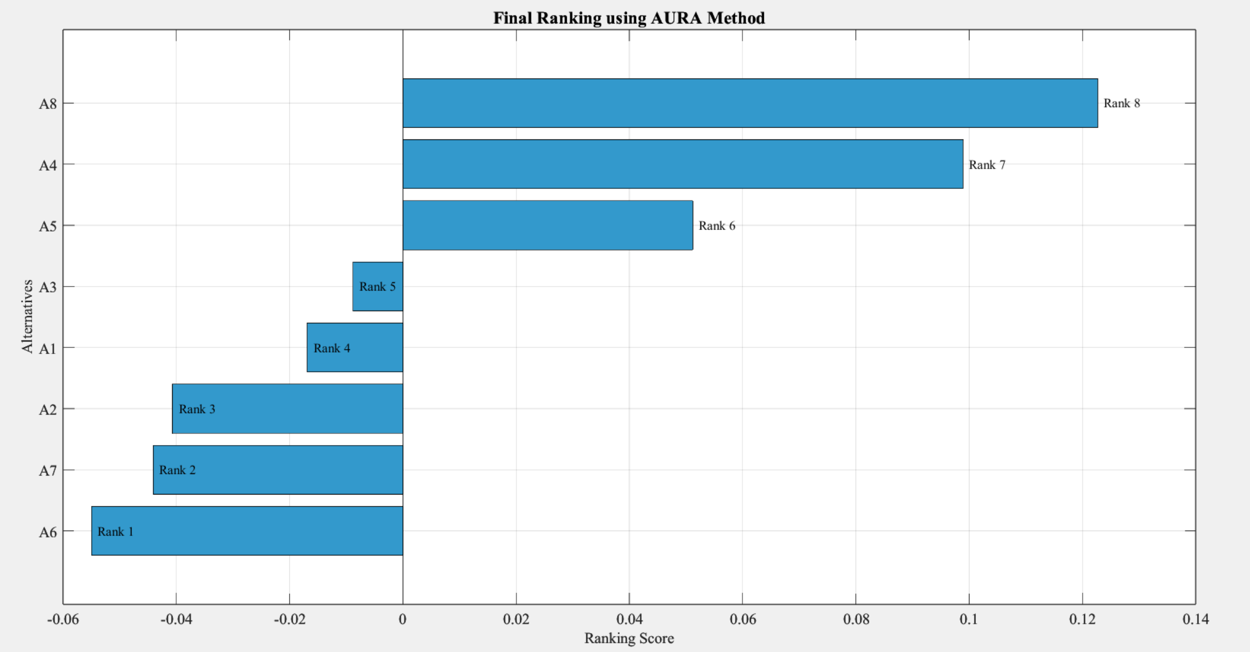

Fig 2. Final ranking using AURA method

The horizontal bar chart in Figure 2 above depicts the final ranking of eight alternatives by using the AURA method, ranking scores are plotted along the x-axis, alternatives along the y-axis and accompanied by rank annotations. According to the analysis, A_6, A_7, and A_2 are among the best performing alternatives and have obtained the lowest or most favorable ranking scores -0.0550, -0.0441, and -0.0407 which suggest overall good performance. Alternatives in the middle status, such as $A_{1,} A_{3,}$ and A_5 show moderate performance while A_4 and A_8 hold the lowest ranks implying huge deviation from the best solution and poor performance. The spread of results in negative and positive values shows the major gap in performance from the alternatives. This thorough example demonstrates AURA's resilience and suitability for the best alternatives. AURA offers a valuable tool for intricate decision-making situations requiring the evaluation and balancing of numerous parameters.

3.2 Sensitivity Analysis

This section examines the impact of varying parameter values on `the ranking outcomes in the example provided and the impact of changing weight on ranking. The calculation on this analysis is calculated using EXCEL Software and MATLAB. The graph and simulation are from MATLAB.

We will demonstrate the impact of varying α in the AURA method. The trade-off between the PIS, NIS and AS is largely determined by the balance parameter α. We can examine the stability of rankings and determine which alternatives are more prone to shifts in decision preferences by adjusting α. The parameter p was set at 2 for this analysis, whereas α was varied between 0 and 0.25, 0.5, 0.75, and 1. The $D_i\left(S^a\right)$ is the main basis for rankings when $\alpha = 0$, but the $\left(D_i\left(S^+\right) - D_i\left(S^-\right)\right)$ are a major factor when $\alpha = 1$. Hence, middle value $\alpha = 0.5$ offers a balanced approach. Figure 3 show the effect of α on rankings.

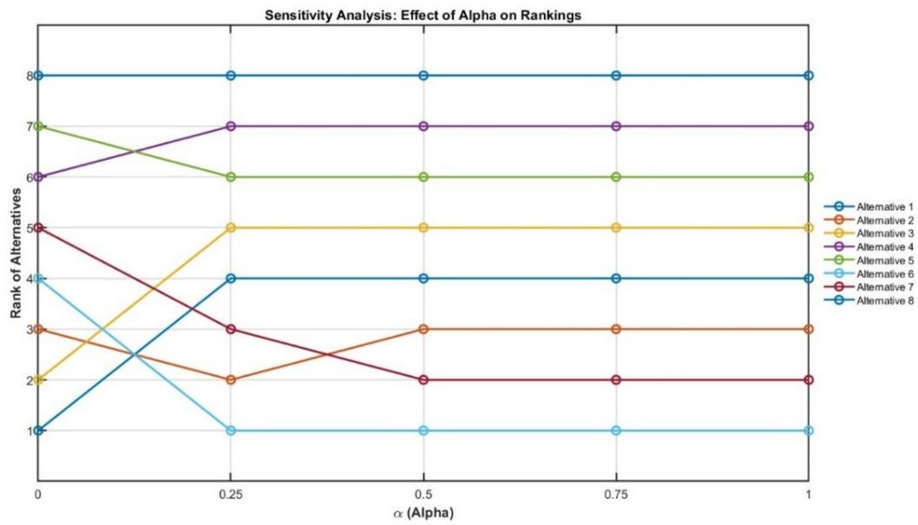

Fig. 3. Effect of α on Rankings

Based on Figure 3, certain alternatives show notable rank fluctuations, while others stay constant regardless of the α value. The ranking of alternatives 5, 6, 7, and 8 varies very little, indicating that they are resilient to different parameter values. Nevertheless, Alternatives 1, 2, 3, and 4 exhibit rank reversals, suggesting that the selection of α has a significant impact on their ranking positions. This observation is clearly shown in the sensitivity graph, where stable alternatives are indicated by flat horizontal lines and changes in ranking order are represented by crossing lines. A sensitivity to decision-maker preferences is highlighted by alternatives that change ranks often, underscoring the necessity of carefully choosing α to provide a fair evaluation.

According to the results, $\alpha = 0.5$ is appropriate for preserving ranking stability and guaranteeing a fair evaluation of both ideal and average solutions. If proximity to the best and worst options is a deciding factor, a higher α value such as 0.75 or 1 is better. However, a lower α value like 0 or 0.25, which is more risk-averse, can be suitable for a more balanced ranking strategy. The findings show that rankings are significantly impacted by α, with certain options being more sensitive than others.

Another sensitivity to demonstrate the impact of varying parameter p is being conducted and Figure 4 shows the effect of p on ranking.

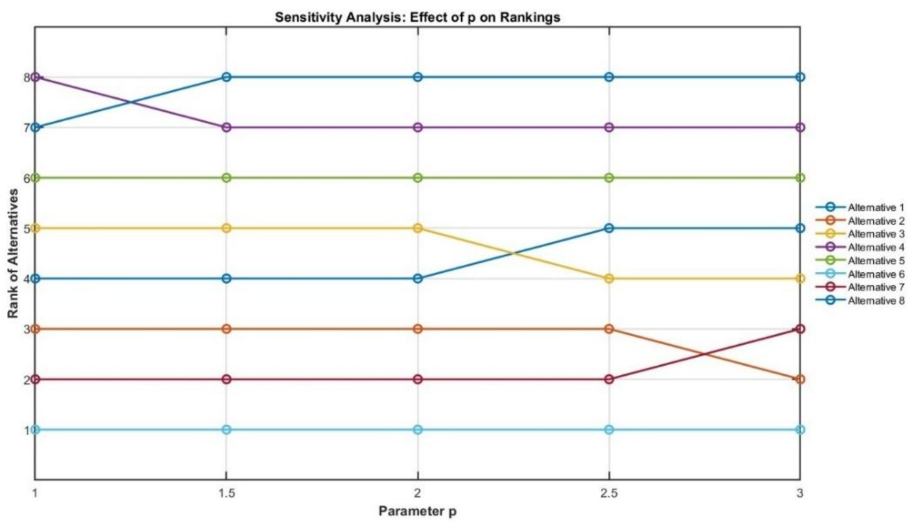

Fig. 4. Effect of p on Rankings

Figure 4 shows the impact of varying parameter p in the AURA method. It is crucial since parameter p determines how deviations between alternatives and ideal solutions are measured. To evaluate the effect of p on ranks, p was varied across 1, 1.5, 2, 2.5, and 3, while the parameter α was set at 0.5. A smaller p value like $p = 1$, gives individual deviations more weight and increases the sensitivity of the ranking to slight variations in the criterion values. On the other hand, higher p value like $p = 3$, highlight bigger variances and lessen the impact of small variations across alternatives.

Figure 4 shows that even though some alternatives show rank reversals, the ranks of most alternatives are consistent across a range of p values. Alternatives 1, 3, 4, 5, and 6 exhibit little to no change, indicating their resilience to changes in distance. Nevertheless, we can see changes in the rankings of alternatives 2, 7, and 8, with alternatives 2 and 7 moving up and down in relation to p. These rank reversals are highlighted in the plotted sensitivity graph on Figure 2, where changes in ranking order are indicated by crossing lines. While alternatives with intersecting lines are more sensitive to various distance standards, those with flat lines in the graph show stability, indicating that their ranks are unaffected by changes in p.

According to these results, when $p = 2$, it minimizes significant ranking shifts while offering a balanced distance measure. It may be more suitable to use a higher p value if decision-makers want to highlight the differences between alternatives. In contrast, a lower p value can be appropriate if a fairer comparison of deviations is desired. The findings show that while the AURA technique is typically not very sensitive to p, rankings for some alternatives can be greatly impacted by p selection.

Next, we perform another sensitivity analysis to determine the effect of weight variation on the relativity of the alternatives. Figure 5 shows the result of changing weight.

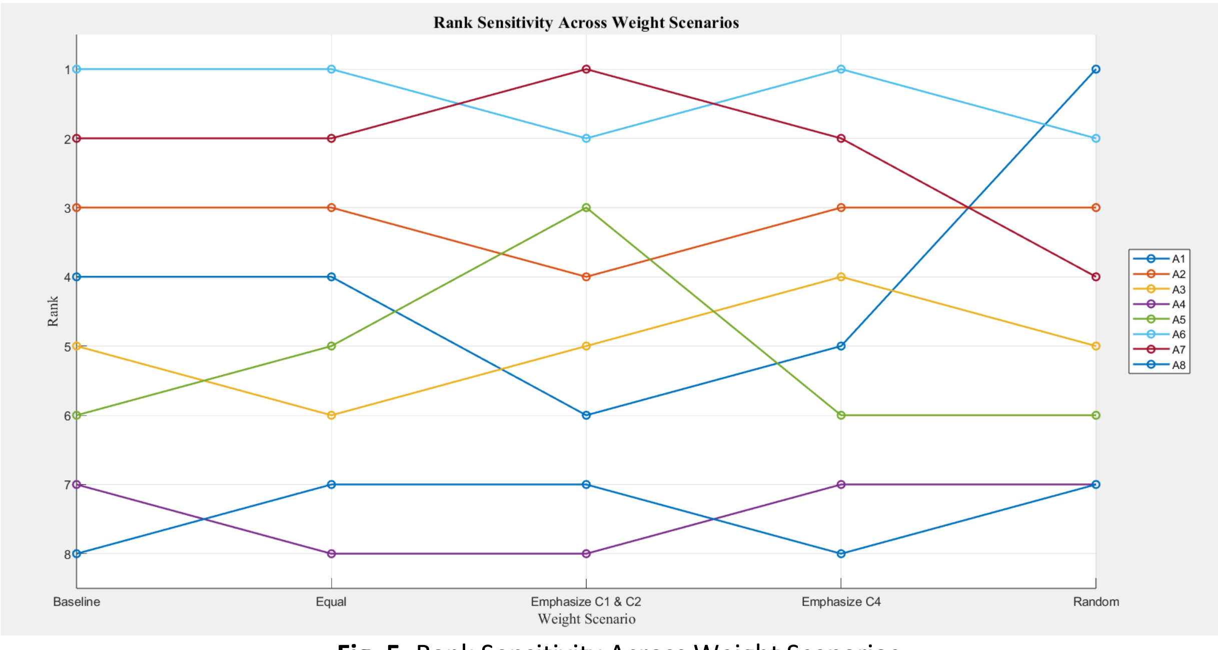

Fig. 5. Rank Sensitivity Across Weight Scenarios

Shown in Figure 5 above is the rank sensitivity of eight alternatives over five different weight situations namely Baseline, Equal, Emphasize on C1 & C2, Emphasize C4 and Random. The line chart shows distinct trends of stability and variation of alternatives as the weighting schemes vary. Alternatives A_6 and A_7 always hold first place with second spots, this is almost in all scenarios, this shows positive robustness and in sensitivity to weight changes. Conversely, we have the alternatives A_4 and A_8 which hold consistently the lowest ranks showing poor performance, irrespective of the weight configuration. Remarkably, alternatives A_1, A_3, and A_5 show moderate rank variability indicating that these alternatives are moderately sensitive to the prescribed weights in ranking. For instance, under Random weight, A_1 is notably at the top rank, whereas under Emphasize C1 & C2, A_5 achieves its best performance. Such fluctuations underline the necessity of weighing decisions because they can really affect the benchmarking results for middle-tier options. Overall, this sensitivity analysis demonstrates the stability provided by AURA method in respect with consistently strong and weak alternatives and inherent ability of the method to identify alternatives whose differential performance is sensitive to preferences and weight configurations of the decision-makers.

3.3 Comparative Analysis

In this section, we want to evaluate the effectiveness and reliability of the newly introduced AURA method against existing methods. To validate the results obtained by applying new AURA method in the illustrative example, the same problem has been solved by other existing methods such as COBRA, MOORA, SAW, TOPSIS, VIKOR, and WASPAS. The results obtained are presented in Table 11 and Figure 6.

Table 11
Comparison of AURA with other MCDM methods

Alt.	AURA	COBRA	MOORA	SAW	TOPSIS	VIKOR	WASPAS
A_1	4	4	4	4	4	4	4
A_2	3	3	3	3	3	2	3
A_3	5	5	6	5	5	5	5
A_4	7	8	8	8	8	7	8
A_5	6	6	5	6	6	6	6
A_6	1	1	1	1	1	1	1
A_7	2	2	2	2	2	3	2
A_8	8	7	7	7	7	8	7

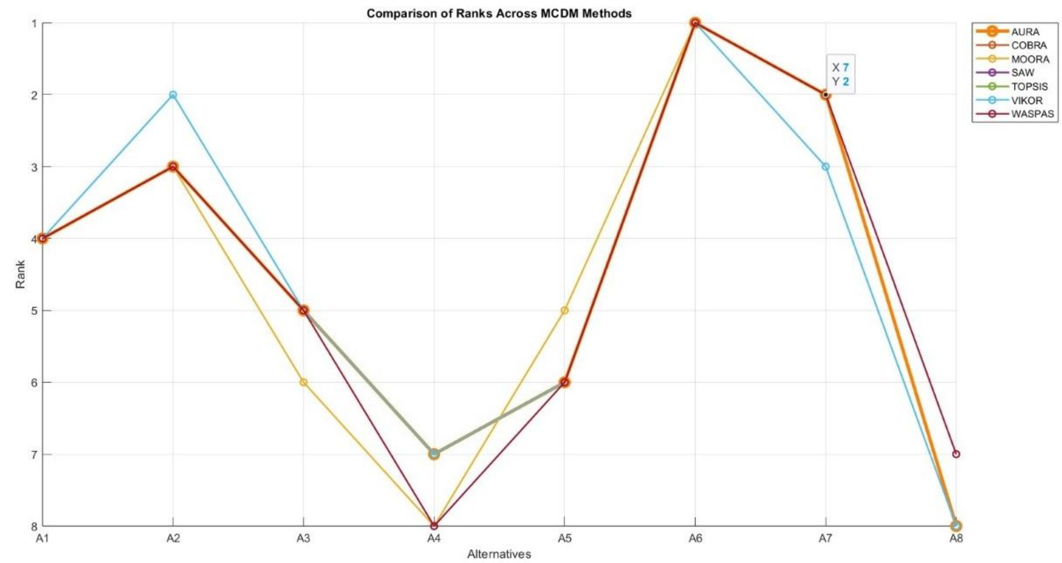

Fig. 6. Comparison of AURA with other MCDM methods

Analysis of the ranking comparison amongst MCDM methods above shows that the rankings given by various methods are very similar. We can see that A_6 continuously earns the rank 1 across all methods, demonstrating a clear trend of significant preference for this alternative during the decision-making process. On the other hand, A_8 is consistently ranked among the least suitable options, showing that all methods concur with its weakness. These consistent rankings indicate that the methods largely align in their assessment criteria, reinforcing the robustness of their decision-making frameworks.

Although the rankings are generally consistent, there are some fluctuations, especially for A_3, A_4, and A_5 where different methodologies produce somewhat different ranks. A very same ranking pattern is displayed by COBRA, SAW, and WASPAS algorithms, indicating that they use similar weight aggregation strategies. Nevertheless, MOORA and VIKOR add some unpredictability, particularly for A_2 and A_7, where VIKOR gives A_2 a Rank 2 instead of the Rank 3 that most other methods get. Furthermore, A_3 receives Rank 6 via MOORA whereas it receives Rank 5 from most other methods, suggesting minor variations in the criteria used for making decisions. Although it adds subtle differences, the AURA method highlighted in bold in Figure 3 aligns closely with COBRA and SAW and reflects a slightly different weighting technique. Overall ranking trends show that although the majority of MCDM approaches align well, minor ranking differences may result from changes to method specific criteria.

To quantify this similarity, Spearman's rank correlation coefficient was used, and the results are presented in Figure 7. The average Spearman correlation coefficient for AURA method is 0.9509. This shows that AURA has a very high degree of complying with other MCDM methods, which supports the idea that the new proposed method is highly adaptable and competitive with the other methods.

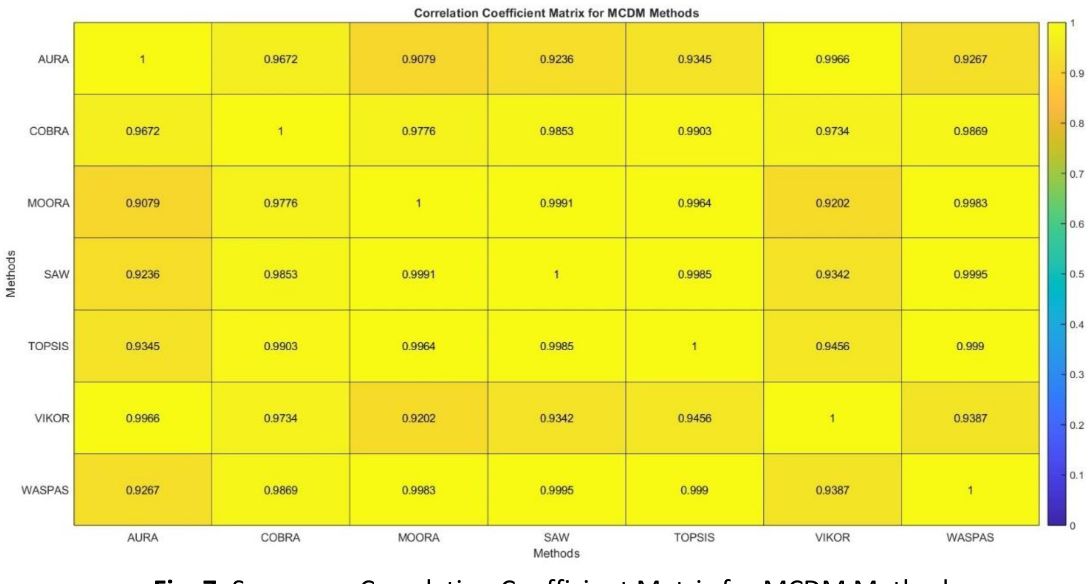

Fig. 7. Spearman Correlation Coefficient Matrix for MCDM Methods

Figure 7 shows a significant degree of agreement in ranking patterns and is indicated by the matrix, which shows that the majority of methods have high correlations. To illustrate their consistency in decision-making, SAW and WASPAS with spearman's rank correlation of 0.9995 and MOORA and SAW with 0.9991 have nearly identical rankings indicating that these methods adhere to similar ranking criteria. VIKOR (0.9966), COBRA (0.9672), TOPSIS (0.9345), WASPAS (0.9267) and

SAW (0.9236) show excellent positive correlations with AURA, suggesting that it generates very consistent ranking results with these methodologies. AURA is a stable and dependable decision support tool, as it appears to be strongly aligned with other MCDM methods. However, it has a bit lower correlation (0.9079) with MOORA in the matrix, suggesting that MOORA has a somewhat different weighting system or ranking structure than AURA. The minor distinctions between AURA and other methods demonstrate their potential versatility in evaluating options, which makes it helpful in situations requiring a balance between similarity and flexibility. In the end, the results indicate that using several MCDM techniques improves decision reliability and offers an in-depth evaluation method that allows for both method specific and highly aligned ranking alterations.

3.4 Simulation-Based Analysis

This sub-section examines the stability of the proposed method using a simulation-based analysis. 3 different types of decision matrices are generated using MATLAB software to test how AURA performs under different conditions. Small matrix (5 x 5) meaning that the matrix has 5 alternatives and 5 criteria. Followed by Medium (10 x 10) and large (20 x 20). The results are presented through statistical measures which mean standard deviation and ranking variance in Table 12 and Table 13 respectively, and boxplots to visualize ranking fluctuations in Figure 8. The objective is to assess whether AURA provides stable rankings, particularly as the problem size increases.

Table 12
Mean standard deviation

Matrix size	Mean Standard Deviation
5X5	1.4286
10X10	2.8868
20X20	5.7808

Table 13
Ranking Variance

Matrix size	Variance
5X5	2.0408
10X10	8.3333
20X20	33.417

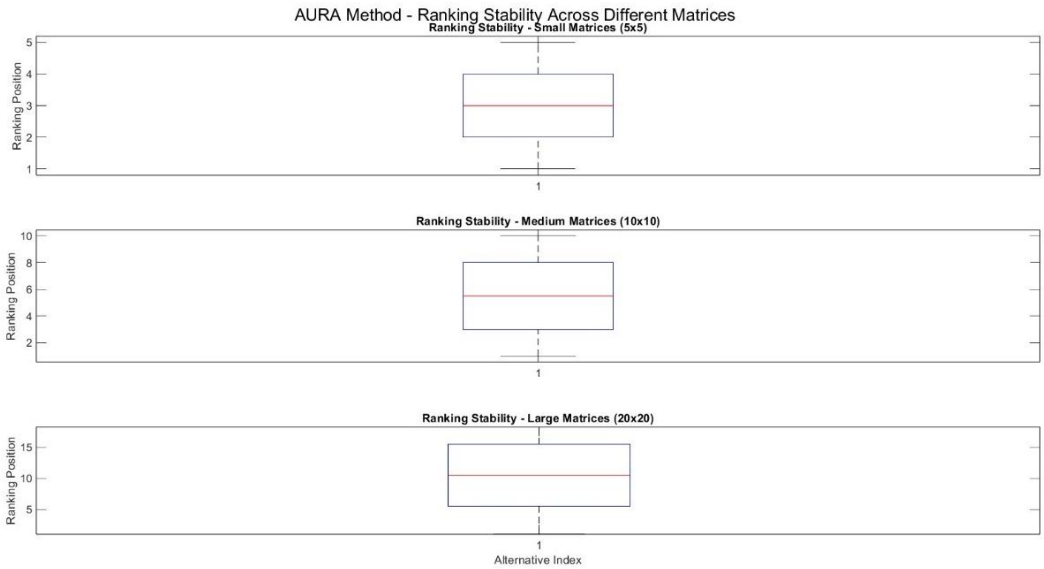

Fig. 8. Ranking stability across different matrices

The mean standard deviation of ranks, which quantifies the extent of fluctuation in rankings across trials, is shown in Table 12. The standard deviation for the small matrix, according to the data, is 1.4286, suggesting that rankings do not change much. The standard deviation doubles to 2.8868 as the matrix size grows to medium, indicating a significant degree of ranking variation. The standard deviation for the large matrix, however, rises to 5.7808, indicating significant ranking shifts across different trials. This implies that as the number of alternatives and criteria rises, AURA becomes progressively prone to shifts in the input data.

The ranking variance, which measures the total variation in ranking positions, is shown in Table 13. Rankings do not change much with only the variance of a small matrix is 2.0408 showing this. The variance for the medium matrix, however, increases visibly to 8.3333, indicating that the rankings start to diverge. The deviation grows to 33.417 in the large matrix, so AURA does not seem to be very good at maintaining the similarity of rankings when faced with more complicated decision making. Having consistency important in real-world decision-making application, this large variance implies that even minor differences in input values can lead to substantial changes in rank.

The box-plot results in Figure 8 give visual confirmations of these findings. The small interquartile range (IQR) and whiskers in the small matrix boxplot show how the rankings hold up well through several trials. The medium matrix boxplot also maintains the spread fairly contained despite showing a greater IQR and thus greater shifts in ranking. The rankings are however much less predictable as the large matrix boxplot shows the largest variation with long whiskers. AURA can be volatile at a large-scale decision matrix; small changes in input can lead to large discrepancies in ranking as evidenced by the wide range of the large matrix.

In general, the study demonstrates that the AURA method loses stability for large-scale problems, is rather stable for medium ones and is extremely stable for small-scale ones. AURA's performance may suffer under usage on complicated decision matrices as suggested by growing variance and changing ranks.

4. Conclusions

An improved MCDM method called the Adaptive Utility Ranking Algorithm (AURA) is proposed in this study to enhance choice flexibility, computational effectiveness, and ranking consistency. Unlike the COBRA distance-based MCDM, AURA uses one common distance formula to reduce the rapidity of the ranking process while maintaining reliability and accuracy. The proposed method's innovative normalization technique renders it possible that the same method will offer greater flexibility for a variety of decision-making situations if the optimal choice will be the middle range.

With simulation-based analysis, comparison analysis and sensitivity analysis AURA proved reliable and has strong correlation with established MCDM methods. The results indicate that although there are some minor differences in ranking from larger scale applications, AURA is functional in small-medium decision matrices. The ability of its output to provide credible rankings in different scenarios can be taken as a mark of its latent power as a tool in decision support.

However, AURA is not without any limitations. Its operation in large and high-dimensional matrices is yet to be widely verified, and the reliability of ranking generated by it may fragment whenever the number of alternatives and criteria increase. Furthermore, the approach is slightly affected by parameter tuning since inappropriate parameters or normalization settings could affect the final scores. These limitations all point to the need for future extensions, for adaptive or self-tuning mechanisms and more extensive testing regimes.

Further investigation should explore AURA's integration with real time applications, hybrid decision making frameworks and large data sets to further justify its scalability despite its improvement in computing efficiency and ranking reliability. Generally, AURA is an interesting

MCDM, which is a simple but effective substitute for handling complicated decision-making problems in numerous fields.

Author Contributions

M.M.K.Z.: Method, software, formal analysis, investigation, data curation, visualization, writing-original draft preparation, and verification. Z.MD.R.: Conceptualization; resources; supervision; project administration; funding acquisition; writing review & editing; and validation. Y.A.: Validation. A.W.G.: Writing—review and editing. N.A.S.: Writing—review and editing. Z.M.S.: Writing—review and editing. J.M.M.: Writing—review and editing. All authors have confirmed the final published version of this manuscript.

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Data Availability Statement

All data supporting the findings of this study are included within the article.

Conflicts of Interest

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

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References

[1] Bhole, G. P. (2018). Multi Criteria Decision Making (MCDM) Methods and its applications. International Journal of Research in Applied Science and Engineering Technology, 6(5), 899–915. https://doi.org/10.22214/IJRASET.2018.5145

[2] Köksalan, M., Wallenius, J., & Zionts, S. (2016). An early history of multiple criteria decision making. International Series in Operations Research and Management Science, 233, 3–17. https://doi.org/10.1007/978-1-4939-3094-4_1

[3] Yücenur, G. N., & Maden, A. (2024). Sequential MCDM methods for site selection of hydroponic geothermal greenhouse: ENTROPY and ARAS. Renewable Energy, 226. https://doi.org/10.1016/J.RENENE.2024.120361

[4] Ati, A., Bouchet, P., & Ben Jeddou, R. (2024). Using multi-criteria decision-making and machine learning for football player selection and performance prediction: A systematic review. Data Science and Management, 7(2), 79–88. https://doi.org/10.1016/J.DSM.2023.11.001

[5] Abdulgader, F. S., Eid, R., & Rouyendegh, B. D. (2018). Development of decision support model for selecting a maintenance plan using a fuzzy MCDM approach: A theoretical framework. Applied Computational Intelligence and Soft Computing, 2018. https://doi.org/10.1155/2018/9346945

[6] Kaya, N. (2024). Multi-criteria decision-making methods (MCDM): A bibliometric analysis (1974-2024). Journal of Business, Economics and Finance. https://doi.org/10.17261/PRESSACADEMIA.2024.1940

[7] Roszkowska, E. (2013). Rank Ordering Criteria Weighting Methods – A Comparative Overview. Optimum. Studia Ekonomiczne, 5(65), 14–33. https://doi.org/10.15290/OSE.2013.05.65.02

[8] Alfares, H. K., & Duffuaa, S. O. (2016). Simulation-Based Evaluation of Criteria Rank-Weighting Methods in Multi-Criteria Decision-Making. International Journal of Information Technology & Decision Making, 15(1), 43–61. https://doi.org/10.1142/S0219622015500315

[9] Van Dua, T., Van Duc, D., Bao, N. C., & Trung, D. D. (2024). Integration of objective weighting methods for criteria and MCDM methods: Application in material selection. EUREKA: Physics and Engineering, 2024(2), 131–148. https://doi.org/10.21303/2461-4262.2024.003171

[10] Kamari, M. S. M., Rodzi, Z. M., & Kamis, N. H. (2025). Pythagorean Neutrosophic Method Based on the Removal Effects of Criteria (PNMEREC): An Innovative Approach for Establishing Objective Weights in Multi-Criteria Decision-Making Challenges. Malaysian Journal of Fundamental and Applied Sciences, 21(1), 1678–1696. https://doi.org/10.11113/MJFAS.V21N1.3600

[11] Sahoo, S. K., & Goswami, S. S. (2023). A Comprehensive Review of Multiple Criteria Decision-Making (MCDM) Methods: Advancements, Applications, and Future Directions. Decision Making Advances, 1(1), 25–48. https://doi.org/10.31181/DMA1120237

[12] Genç, E., Keleş, M. K., & Özdağoğlu, A. (2024). A hybrid MCDM model for personnel selection based on a novel Gray AHP, Gray MOORA and Gray MAUT methods in terms of business management: An application in the tourism sector. Journal of Decision Analytics and Intelligent Computing, 4(1), 263–284. https://doi.org/10.31181/JDAIC10024122024G

[13] Alimohammadi, M., Salehi, A., & Babaei, A. (2024). A Comprehensive Review of MCDM Applications in Enhancing Textile Supply Chain Management. https://doi.org/10.20944/PREPRINTS202409.0599.V1

[14] Van Thanh, N. (2022). Designing a MCDM Model for Selection of an Optimal ERP Software in Organization. Systems, 10(4), 95. https://doi.org/10.3390/SYSTEMS10040095

[15] Zavadskas, E. K., Pamučar, D., Stević, Ž., & Mardani, A. (2020). Multi-Criteria Decision-Making Techniques for Improvement Sustainability Engineering Processes. Symmetry, 12(6), 986. https://doi.org/10.3390/SYM12060986

[16] Kaspar, K., & Kaliyaperumal, P. (2024). Optimizing Automotive Logistics Using MCGDM: A Data-Driven Approach to the Selection of Warehouse Location With Octagonal Neutrosophic Application. Advances in Fuzzy Systems, 2024(1). https://doi.org/10.1155/ADFS/7672845

[17] Zhang, M., & Duan, J. (2024). Literature Review: Application of MCDM Methodology to Logistics Location Problems. Frontiers in Sustainable Development, 4(4), 205–212. https://doi.org/10.54691/FHJMB632

[18] Costa, J., & Silva, M. (2024). Multicriteria Decision-Making in Public Security: A Systematic Review. Mathematics, 12(11). https://doi.org/10.3390/MATH12111754

[19] Chellappa, V., & Ginda, G. (2023). Application of multiple criteria decision making (MCDM) methods for construction safety research. Proceedings of the Institution of Civil Engineers, 177(3), 127–136. https://doi.org/10.1680/JMAPL.23.00006

[20] Li, Y., Ding, Y., Guo, Y., Cui, H., Gao, H., Zhou, Z., ... & Chen, F. (2023). An integrated decision model with reliability to support transport safety system analysis. Reliability Engineering & System Safety, 239, 109540.. https://doi.org/10.1016/J.RESS.2023.109540

[21] Karavidic, Z., & Projovic, D. (2018). A multi-criteria decision-making (MCDM) model in the security forces operations based on rough sets. Decision Making: Applications in Management and Engineering, 1(1), 97–120. https://doi.org/10.31181/DMAME180197K

[22] Kumar, R. (2024). A Comprehensive Review of MCDM Methods, Applications, and Emerging Trends. Decision Making Advances, 3(1), 185–199. https://doi.org/10.31181/DMA31202569

[23] Alamoodi, A. H., Zaidan, B. B., Albahri, O. S., Garfan, S., Ahmaro, I. Y., Mohammed, R. T., ... & Malik, R. Q. (2023). Systematic review of MCDM approach applied to the medical case studies of COVID-19: trends, bibliographic analysis, challenges, motivations, recommendations, and future directions. Complex & intelligent systems, 9(4), 4705-4731. https://doi.org/10.1007/S40747-023-00972-1

[24] Akram, M., Ali, G., Butt, M. A., & Alcantud, J. C. R. (2021). Novel MCGDM analysis under m-polar fuzzy soft expert sets. Neural Computing and Applications, 33(18), 12051–12071. https://doi.org/10.1007/S00521-021-05850-W

[25] Penadés-Plà, V., García-Segura, T., Martí, J. V., & Yepes, V. (2016). A review of multi-criteria decision-making methods applied to the sustainable bridge design. Sustainability, 8(12). https://doi.org/10.3390/SU8121295

[26] Podvezko, V. (2011). The comparative analysis of MCDA methods SAW and COPRAS. Engineering Economics, 22(2), 134–146. https://doi.org/10.5755/J01.EE.22.2.310

[27] Fishburn, P. C. (1967). Letter to the Editor—Additive Utilities with Incomplete Product Sets: Application to Priorities and Assignments. Operations Research, 15(3), 537–542. https://doi.org/10.1287/OPRE.15.3.537

[28] Zavadskas, E. K., Turskis, Z., Antucheviciene, J., & Zakarevicius, A. (2012). Optimization of Weighted Aggregated Sum Product Assessment. Elektronika ir Elektrotechnika, 122(6), 3–6. https://doi.org/10.5755/J01.EEE.122.6.1810

[29] Hwang, C.-L., & Yoon, K. (1981). Multiple Attribute Decision Making (Vol. 186). https://doi.org/10.1007/978-3-642-48318-9

[30] Mardani, A., Zavadskas, E. K., Govindan, K., Senin, A. A., & Jusoh, A. (2016). VIKOR Technique: A Systematic Review of the State of the Art Literature on Methodologies and Applications. Sustainability, 8(1), 37. https://doi.org/10.3390/SU8010037
[31] Brauers, W. K. M., Ginevičius, R., & Podvezko, V. (2010). Regional development in Lithuania considering multiple objectives by the MOORA method. Technological and Economic Development of Economy, 16(4), 613–640. https://doi.org/10.3846/TEDE.2010.38
[32] Krstić, M., Agnusdei, G. P., Miglietta, P. P., Tadić, S., & Roso, V. (2022). Applicability of Industry 4.0 Technologies in the Reverse Logistics: A Circular Economy Approach Based on COmprehensive Distance Based RAnking (COBRA) Method. Sustainability, 14(9). https://doi.org/10.3390/su14095632
[33] Saaty, R. W. (1987). The analytic hierarchy process—what it is and how it is used. Mathematical Modelling, 9(3–5), 161–176. https://doi.org/10.1016/0270-0255(87)90473-8
[34] Saaty, T. L. (2006). The analytic network process. International Series in Operations Research and Management Science, 95, 1–26. https://doi.org/10.1007/0-387-33987-6_1
[35] Costa, C. A. B. E., & Vansnick, J.-C. (1994). MACBETH — An Interactive Path Towards the Construction of Cardinal Value Functions. International Transactions in Operational Research, 1(4), 489–500. https://doi.org/10.1111/J.1475-3995.1994.00325.X
[36] Pamučar, D., Stević, Ž., & Sremac, S. (2018). A New Model for Determining Weight Coefficients of Criteria in MCDM Models: Full Consistency Method (FUCOM). Symmetry, 10(9), 393. https://doi.org/10.3390/SYM10090393
[37] Mareschal, B. (2005). PROMETHEE methods. International Series in Operations Research and Management Science, 78, 163–195. https://doi.org/10.1007/0-387-23081-5_5
[38] Roy, B. (1968). Classement et choix en présence de points de vue multiples. Revue française d'informatique et de recherche opérationnelle, 2(8), 57–75. https://doi.org/10.1051/RO/196802V100571
[39] Pamučar, D., & Ćirović, G. (2015). The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). Expert Systems with Applications, 42(6), 3016–3028. https://doi.org/10.1016/J.ESWA.2014.11.057
[40] Hatefi, M. A. (2019). Indifference threshold-based attribute ratio analysis: A method for assigning the weights to the attributes in multiple attribute decision making. Applied Soft Computing, 74, 643–651. https://doi.org/10.1016/J.ASOC.2018.10.050
[41] Sarabando, P., & Dias, L. C. (2010). Simple procedures of choice in multicriteria problems without precise information about the alternatives' values. Computers & Operations Research, 37(12), 2239–2247. https://doi.org/10.1016/J.COR.2010.03.014
[42] Chan, L. K., & Wu, M. L. (2002). Quality function deployment: A comprehensive review of its concepts and methods. Quality Engineering, 15(1), 23–35. https://doi.org/10.1081/QEN-120006708
[43] Hiremani, V., Devadas, R. M., Gujjar, J. P., Johar, S., & Sapna, R. (2024). Ranking of Institutes Using MCDM SAW Method Under Uncertainty. 2024 5th International Conference for Emerging Technology (INCET 2024). https://doi.org/10.1109/INCET61516.2024.10593015
[44] Purohit, N., Srivastava, P., & Pandey, P. (2023). An Integrated Framework of RNN and MCDM SAW Method for Efficient Resource Provisioning in Cloud Computing. *IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, 30–36. https://doi.org/10.1109/R10-HTC57504.2023.10461779
[45] Biswas, T. K., & Chaki, S. (2022). Applications of Modified Simple Additive Weighting Method in Manufacturing Environment. International Journal of Engineering, Transactions A: Basics, 35(4), 830–836. https://doi.org/10.5829/IJE.2022.35.04A.23
[46] Wang, Y. J. (2020). Combining quality function deployment with simple additive weighting for interval-valued fuzzy multi-criteria decision-making with dependent evaluation criteria. Soft Computing, 24(10), 7757–7767. https://doi.org/10.1007/S00500-019-04394-5
[47] Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445–455. https://doi.org/10.1016/S0377-2217(03)00020-1
[48] Çalık, A. (2021). A novel Pythagorean fuzzy AHP and fuzzy TOPSIS methodology for green supplier selection in the Industry 4.0 era. Soft Computing, 25(3), 2253–2265. https://doi.org/10.1007/S00500-020-05294-9
[49] Alao, M. A., Popoola, O. M., & Ayodele, T. R. (2021). Selection of waste-to-energy technology for distributed generation using IDOCRIW-Weighted TOPSIS method: A case study of the City of Johannesburg, South Africa. Renewable Energy, 178, 162–183. https://doi.org/10.1016/J.RENENE.2021.06.031
[50] Micale, R., Marannano, G., Giallanza, A., Miglietta, P. P., Agnusdei, G. P., & La Scalia, G. (2019). Sustainable vehicle routing based on firefly algorithm and TOPSIS methodology. Sustainable Futures, 1, 100001. https://doi.org/10.1016/J.SFTR.2019.100001

[51] Zeng, J., Lin, G., & Huang, G. (2021). Evaluation of the cost-effectiveness of Green Infrastructure in climate change scenarios using TOPSIS. Urban Forestry & Urban Greening, 64, 127287. https://doi.org/10.1016/J.UFUG.2021.127287
[52] Opricovic, S., & Tzeng, G. H. (2007). Extended VIKOR method in comparison with outranking methods. European Journal of Operational Research, 178(2), 514–529. https://doi.org/10.1016/J.EJOR.2006.01.020
[53] Purwanto, H., & Susilawati, I. (2024). Web-Based Expert System Chatbot Determines The Best Cheap Camera For New Users Using The Vikor Method. International Journal of Informatics Engineering and Computing, 1(1), 29–39. https://doi.org/10.70687/IJIMATIC.V1.I1.27
[54] Nivedita, Agrawal, S., Sharma, M. K., Rathour, L., & Mishra, V. N. (2024). Type-2 Gaussian neuro-fuzzy VIKOR technique in multi-criteria decision-making for medical diagnostic. Optimization and Computing using Intelligent Data-Driven Approaches for Decision-Making, 128–151. https://doi.org/10.1201/9781003503057-9
[55] Xu, W., Qian, J., Wu, Y., Yan, S., Ni, Y., & Yang, G. (2024). A VIKOR-Based Sequential Three-Way Classification Ranking Method. Algorithms, 17(11), 530. https://doi.org/10.3390/A17110530
[56] Chakraborty, S. (2011). Applications of the MOORA method for decision making in manufacturing environment. International Journal of Advanced Manufacturing Technology, 54(9–12), 1155–1166. https://doi.org/10.1007/S00170-010-2972-0
[57] Attri, R., & Grover, S. (2014). Decision making over the production system life cycle: MOORA method. International Journal of System Assurance Engineering and Management, 5(3), 320–328. https://doi.org/10.1007/S13198-013-0169-2
[58] Petrov, I. (2021). Renewable energies projects selection: block criteria systematization with AHP and Entropy-MOORA methods in MCDM. E3S Web of Conferences, 327, 02004. https://doi.org/10.1051/E3SCONF/202132702004
[59] Sitorus, Z., Karim, A., Nasyuha, A. H., & Aly, M. H. (2024). Implementation of MOORA and MOORSA Methods in Supporting Computer Lecturer Selection Decisions. Jurnal Infotel, 16(3). https://doi.org/10.20895/INFOTEL.V16I3.1184
[60] Simamora, W. S., Harahap, S. S., Idaman, A., & Simatupang, S. (2024). Analysis of the Multi Objective Optimization by Ratio Analysis (MOORA) Method in Determining Pilot Areas at PT. XYZ. Journal of Computer Networks, Architecture and High Performance Computing, 6(3), 1098–1106. https://doi.org/10.47709/CNAHPC.V6I3.4149
[61] Chakraborty, S., Bhattacharyya, O., Zavadskas, E. K., & Antucheviciene, J. (2015). Application of WASPAS Method as an Optimization Tool in Non-traditional Machining Processes. Information Technology and Control, 44(1), 77–88. https://doi.org/10.5755/J01.ITC.44.1.7124
[62] Ramadani, R., Fadillah, R., & Fitriyani, I. N. (2024). Selection of Head of Study Program using Weighted Aggregated Sum Product Assessment (WASPAS) method. Internet of Things and Artificial Intelligence Journal, 4(3), 481–491. https://doi.org/10.31763/IOTA.V4I3.803
[63] Suendri, & Wardani, A. (2024). Implementation of the WASPAS Method in Selection Librarian FST UIN Sumatera Utara. Jurnal Sistem Cerdas, 7(1), 38–44. https://doi.org/10.37396/JSC.V7I1.385
[64] Wayahdi, M. R., & Ruziq, F. (2024). Designing an Used Goods Donation System to Reduce Waste Accumulation Using the WASPAS Method. Sinkron: Jurnal dan Penelitian Teknik Informatika, 8(4), 2325–2334. https://doi.org/10.33395/SINKRON.V8I4.14115
[65] Popović, G., Pucar, Đ., & Smarandache, F. (2022). MEREC-COBRA approach in e-commerce development strategy selection. Journal of Process Management and New Technologies, 10(3–4), 66–74. https://doi.org/10.5937/JOUPROMAN2203066P
[66] Razak, S. A., Rodzi, Z. M., Al-Sharqi, F., & Ramli, N. (2025). Revolutionizing Decision-Making in E-Commerce and IT Procurement: An IVPNS-COBRA Linguistic Variable Framework for Enhanced Multi-Criteria Analysis. International Journal of Economic Sciences, 14(1), 1–31. https://doi.org/10.31181/IJES1412025176