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# NEW GROUP DECISION SUPPORT METHOD BASED ON A HYBRID OF THE EVAMIX, CRITIC AND VIKOR METHODS

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Abstract. Decision support is a field that has proven its importance in several sectors. Indeed, decision support methods are increasingly used in various organizations and have contributed to solving complex decision problems. Most of these methods were developed within a multi-criteria framework with a single decision-maker. However, these have shown their limitations. In fact, a decision made by one decision-maker does not necessarily lead to the best decision. To address these problems, collective decision-making methods have been developed. In order to contribute to better decision-making, we have developed a new collective decision support method based on the EVAMIX, CRITIC, and VIKOR methods. This hybrid approach has allowed us to obtain a collective decision-making method that combines both qualitative and quantitative criteria and provides a compromise solution that respects everyone's priorities. To test this new method, we created applications and then conducted a comparative study with existing methods in the literature; this gave us acceptable results.

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## 1. Introduction

Decision-making is a crucial aspect that can negatively or positively impact a person's life, the functioning of an organization, and international relations. Given its importance, several methods have been developed to improve decision-making [15]. In the literature, most of these methods are developed within a multi-criteria framework involving a single decision-maker. However, according to decision-making specialists, this approach does not necessarily reflect reality. Indeed, a decision made by a single decision-maker can be easily influenced by personal factors [13]. This has led specialists to focus their attention on collective decision-making to address the shortcomings of single-decision-making. In the literature, the EVAMIX method, developed in [1] , is a method with good properties because it allows for the aggregation of quantitative and qualitative criteria. The CRITIC method

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developed in [7], which is an objective method, allows for the objective determination of the weight of decision-makers. In [2], the VIKOR method has demonstrated good properties because it provides a compromise solution. Given the good properties of these three methods, wouldn't a combination yield a result closer to the ideal in a multi-criteria, multi-decision-maker framework? This leads us to propose a hybrid approach with the aim of contributing to better collective decision-making. Indeed, many multi-criteria, multi-decision-maker methods exist in the literature with good properties, but these are not without flaws. To construct our method, we adopt the following approach: We will first use the EVAMIX method to aggregate the quantitative and qualitative criteria of the decision-makers and assign a partial score to each action for each decision-maker. Next, we will use the CRITIC method to determine the overall weight of each decision-maker, and finally, the VIKOR method to determine the overall score and ranking of each action for all decision-makers. For the proper execution of our work, we will: First, conduct a literature review on various decision-support methods. Second, present the main results of the new MADG-ECV group decision-support method. Furthermore, perform a numerical application of the MADG-ECV method. In addition, conduct a comparative study of this method with MACBEV [12] and LON-ZO, both developed in [12] [17]. Moreover, determine the advantages and limitations of MADG-ECV. Finally, propose avenues for future research.

## 2. Literature review

Table 1. Decision Matrix

| Critères | $C_1$ | $\cdots$ | $C_n$ |
|---|---|---|---|
| Poids | $W_1$ | $\cdots$ | $W_n$ |
| $A_1$ | $t_{11}$ | $\cdots$ | $t_{1n}$ |
| $A_2$ | $t_{21}$ | $\cdots$ | $t_{2n}$ |
| $\vdots$ | $\vdots$ | $\ddots$ | $\vdots$ |
| $A_m$ | $t_{m1}$ | $\cdots$ | $t_{mn}$ |

### 2.1. **The EVAMIX method.**

In the literature there are several decision support methods which combine qualitative and quantitative criteria [12]. The EVAMIX method (EVAluation of MIXed data) is a multi-criteria decision support method which was developed in 1982 by Voogd [1] [12]. It is a method which combines both quantitative and qualitative criteria without converting them directly into quantitative criteria. This specificity gives it a great advantage over other methods. According to [12] it develops in four stages.

Step 1: Calculation of the dominance index $\alpha_{ii'}$ and $\beta_{ii'}$ respectively, for the ordinal (O) and cardinal (C) criteria. With system 1.

$$\begin{cases} \alpha_{ii'} &= \left[\sum_{j\in o}\{W_j \times sgn(e_{ij}-e_{i'j})\}^c\right]^{\frac{1}{c}}, i', i \in \{1;..;m\}, j \in \{1;...;n\} \\ \beta_{ii'} &= \left[\sum_{j\in c}\{W_j \times (e_{ij}-e_{i'j})\}^c\right]^{\frac{1}{c}}, i', i \in \{1;..;m\}, j \in \{1;...;n\} \end{cases} \quad (1)$$

With

$$sgn(e_{ij}-e_{i'j}) = \begin{cases} 1, & e_{ij} < e_{i'j} \\ 0, & e_{ij} = e_{i'j} \\ -1, & e_{ij} > e_{i'j} \end{cases} \quad (2)$$

Step 2: Calculation of the normalized dominance index $\delta_{ii'}$ et $d_{ii'}$ respectively, for the ordinal and cardinal criteria using system 3.

$$\begin{cases} \delta_{ii'} &= \frac{(\alpha_{ii'}-\alpha^-)}{(\alpha^+-\alpha^-)}, i', i \in 1;...;m; \\ d_{ii'} &= \frac{(\beta_{ii'}-\beta^-)}{(\beta^+-\beta^-)}, i', i \in 1;...;m. \end{cases} \quad (3)$$

With $\alpha^+$ and $\alpha^-$ respectively the maximum and the minimum of the $\alpha_{ii'}$ of the ordinal criteria. $\beta^+$ and $\beta^-$ respectively the maximum and the minimum of the $\beta_{ii'}$ of the cardinal criteria.

Step 3: Calculation of the total dominance of the action through equation 4.

$$D_{ii'} = W_o\delta_{ii'} + W_c d_{ii'} \quad (4)$$

with $W_o = \sum_{j\in o} W_j$ and $W_c = \sum_{j\in c} W_j$.

Step 4: Calculation of the score of each action. This is obtained with formula 5.

$$S_i = \left[\sum_{i'} \frac{D_{i'i}}{D_{ii'}}\right]^{-1}; i, i' \in \{1, ..., m\} \quad (5)$$

Step 5: Ranking of actions.

With EVAMIX, the best action is the one with the highest score.

2.2. **The CRITIC method.** The CRiteria Importance Through Intercriteria Correlation (CRITIC) method was proposed by Diakoulaki, Mavrotas and Papayannakis in 1995 [1]. It is a method that is part of the objective method categories. According to [7] it makes it possible to objectively determine the weight of the alternatives. This characteristic allows it to give a result closer to the ideal. It is developed from the correlation coefficient. It develops in four stages.

Step 1: Normalization of the decision matrix 1. Equation 6 7.

$$x_{ij} = \frac{t_{ij} - t_i^-}{t_i^+ - t_i^-}; i = 1, ..., m \quad j = 1, ...n \quad (6)$$

$$x_{ik} = \frac{t_{ik} - t_i^-}{t_i^+ - t_i^-}; i = 1, ..., m \quad k = 1, ...n \tag{7}$$

Step 2: Calculation of the correlation coefficient using equation 8.

$$\rho_{jk} = \frac{\sum_{i=1}^{m}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)}{\sqrt{\sum_{i=1}^{m}(x_{ij} - \bar{x}_j)^2 \sum_{i=1}^{m}(x_{ik} - \bar{x}_k)^2}} \tag{8}$$

With $\bar{x}_j = \frac{1}{n}\sum_{j=1}^{n} x_{ij}$ et $\bar{x}_k = \frac{1}{n}\sum_{k=1}^{n} x_{ik}$

Step 3: Calculating the index $C$ using 9.

$$C_j = \sigma_j \sum_{k=1}^{n}(1 - \rho_{jk}); j = 1, ..., n \tag{9}$$

With $\sigma_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{m}(x_{ij} - \bar{x}_j)^2}; i = 1, ..., m$

Step 4: Calculating the weight through 10.

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{10}$$

2.3. **The VIKOR method.** The VIšekriterijumska Optimizacija KOpromisno Rangiranje (VIKOR) method, which means Multi-Criteria Optimization and Compromise Solution in Serbian, is a method developed by Opricovic in 1998 [9] . It is a compensatory method that provides compromise solutions [1]. It is developed in five (5) steps, namely:

Step 1: The normalization of the decision matrix by equation 11.

$$f_{ij} = \frac{t_{ij}}{\sqrt{\sum_{i=1}^{m} t_{ij}^2}}; j = 1, ..., n \tag{11}$$

Step 2: The choice of: $f^-$ and $f^*$.

The indices $f^-$ and $f^*$ are calculated for the positive criteria using equation 12.

$$\begin{aligned} f_j^* &= \max_i f_{ij} \\ f_j^- &= \min_i f_{ij}; i = 1, ..., m; j = 1, ..., n \end{aligned} \tag{12}$$

The indices $f^-$ and $f^*$ and are calculated for the negative criteria using equation 13.

$$\begin{aligned} f_j^* &= \min_i f_{ij} \\ f_j^- &= \max_i f_{ij}; i = 1, ..., m; j = 1, ..., n \end{aligned} \tag{13}$$

Step 3: Calculation of $S$ and $R$.

The indices $S$ and $R$ are obtained for each action using the following equations 14 and 15.

$$S_i = \sum_{j=1}^{n} w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}; i = 1, ..., m \tag{14}$$

$$R_i = \max_j \left( w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \right); i = 1, ..., m, j = 1, ..., n \tag{15}$$

Step 4: Calculation of the final $Q_i$ score.

The final score is determined by equation 16.

$$\begin{aligned} Q_i &= v \times [(S_i - S^*)/(S^- - S^*)] + (1 - v) \times [(R_i - R^*)/(R^- - R^*)] \\ S^* &= \min_i S_i, S^- = \max_i S_i, R^* = \min_i R_i, R^* = \max_i R_i. \end{aligned} \tag{16}$$

Where $v$ indicates the strategic weight, often considered to be equal to $0.5$.

Step 5: Stock ranking. During this step, the stocks are ranked in descending order according to the values of $(S)$, $(R)$ and $(Q)$. The stock with the lowest score is the best stock.

2.4. **The LON-ZO method.** The Longin-Zoinabo (LON-ZO) method is a group decision-making aid method that is developed in two parts [12] [17]. First, there is aggregation at the level of each decision-maker in equation 17.

$$G_k(a_i) = \sum_{j=1}^{m} w_j^k . g_j^k(a_i) \tag{17}$$

where:

$G_k(a_i)$ is the overall score of alternative $a_i$ with respect to decision-maker $k$;

$w_j^k$ is the weight assigned to criterion $j$ by decision-maker $k$;

$g_j^k(a_i)$ is the score assigned to alternative $a_i$ on criterion $j$ by decision-maker $k$.

Finally, the determination of the final score based on the harmonic mean is done by equation 18.

$$U(a_i) = \frac{n}{\sum_{i=1}^{n} \frac{1}{G_k(a_i)}} \tag{18}$$

where:

$U(a_i)$ is the final numerical value of the alternative $a_i$;

$G_k(a_i)$ is the overall value of the alternative $a_i$ as determined by decision-maker $k$.

2.5. **The MACBEV method.** The Collective Aggregation Method Based on the EVAMIX and VMAVA+ Methods (MACBEV) is a voting method derived from a hybrid of the EVAMIX and VMAVA+ methods [12] [19] [10] and is developed in two parts. The first part consists of determining an overall score for each action in relation to each decision-maker, following the steps of the EVAMIX method. The second part is the determination of the best action based on the VMAVA+ method.

## 3. Main results

3.1. **Presentation of the new Group Decision Support Method based on the EVAMIX, CRITIC and VIKOR methods (MADG-ECV).** This new method is a hybrid of the EVAMIX, CRITIC, and VIKOR methods, used in group analysis that aggregates both quantitative and qualitative criteria, resulting in a compromise solution with objective weightings. It is developed in three main parts. The first part determines the partial score using the EVAMIX method, the second part calculates the weights of each decision-maker based on the CRITIC method, and the third part determines the overall score of each alternative using the VIKOR method.

3.1.1. *Articulation and modeling of individual preferences.* Let's take an example with $k$ decision-makers, where {decision-maker 1,...,decision-maker $k$ } is the set of decision-makers, $m$ criteria, where {criteria 1,..., criteria $m$} is the set of criteria, and $n$ actions, where $\{A_1,...,A_k\}$ is the set of actions. The problem can be modeled as follows: Table 2.

Table 2. Decision-maker's preference $k$

| | criteria 1 | $\cdots$ | criteria $m$ |
|---|---|---|---|
| $W_j^k$ | $W_1^k$ | $\cdots$ | $W_m^k$ |
| $A_1$ | $f_1^k(a_1)$ | $\cdots$ | $f_m^k(a_1)$ |
| $A_2$ | $f_1^k(a_2)$ | $\cdots$ | $f_m^k(a_2)$ |
| $\vdots$ | $\vdots$ | $\ddots$ | $\vdots$ |
| $A_n$ | $f_1^k(a_n)$ | $\cdots$ | $f_m^k(a_n)$ |

$f_m^k(a_n)$ is the score assigned to action $a_i$ on criteria $m$ by decision-maker $k$;
$W_j^k$: is th weight assigned to criteria $j$ by decision-maker $k$.

3.1.2. *Part One: Determining the partial score.*

Step 1: Calculation of the dominance index $\alpha_{il}^k$ and $\beta_{il}^k$ respectively, for the ordinal $(O)$ and cardinal $(C)$ criteria. With system 19.

$$\begin{cases} \alpha_{il}^k &= \left[\sum_{j\in o}\{W_j^k \times sgn(f_j^k(a_i)-f_j^k(a_l))\}^c\right]^{\frac{1}{c}}, l,i\in\{1;..;n\}, j\in\{1;...;m\} \\ \beta_{il}^k &= \left[\sum_{j\in c}\{W_j^k \times (f_j^k(a_i)-f_j^k(a_l))\}^c\right]^{\frac{1}{c}}, l,i\in\{1;..;n\}, j\in\{1;...;m\} \end{cases} \tag{19}$$

With

$$sgn(f_j^k(a_i)-f_j^k(a_l)) = \begin{cases} 1, & f_j^k(a_i) < f_j^k(a_l) \\ 0, & f_j^k(a_i) = f_j^k(a_l) \\ -1, & f_j^k(a_i) > f_j^k(a_l) \end{cases} \tag{20}$$

And $c$ is any real number. In our case, we will consider that $c = 1$

Step 2: Calculation of the normalized dominance index $\delta_{il}^k$ and $d_{il}^k$ respectively, for the ordinal and cardinal criteria using system 21.

$$\begin{cases} \delta_{il}^k &= \frac{(\alpha_{il}^k-\alpha^-)}{(\alpha^+-\alpha^-)}, l,i\in 1;...;n; \\ d_{il}^k &= \frac{(\beta_{il}^k-\beta^-)}{(\beta^+-\beta^-)}, l,i\in 1;...;n. \end{cases} \tag{21}$$

With $\alpha^+$ and $\alpha^-$ respectively the maximum and minimum of the $\alpha_{il}^k$ of the ordinal criteria. $\beta^+$ and $\beta^-$ respectively the maximum and minimum of the $\beta_{il}^k$ of the cardinal criteria.

Step 3: Determination of the total dominance of action $a_i$ over action $a_l$ through equation 22.

$$D_{il}^k = W_o^k\delta_{il}^k + W_c^k d_{il}^k \tag{22}$$

With $W_o^k = \sum_{j\in o} W_j^k$ et $W_c^k = \sum_{j\in c} W_j^k$

Step 4: Calculation of the partial score of action $a_i$ of decision-maker $k$. This is obtained with formula 23.

$$S^k(a_i) = \left[\sum_l \frac{D_{li}^k}{D_{il}^k}\right]^{-1}; i,l\in\{1,...,m\} \tag{23}$$

With $k$ decision-makers, $m$ criteria and $n$ alternatives we will have the following partial score table: 3.

TABLE 3. Partial score

| | decision-maker 1 | $\cdots$ | decision-maker $k$ |
|---|---|---|---|
| $A_1$ | $S^1(a_1)$ | $\cdots$ | $S^k(a_1)$ |
| $A_2$ | $S^1(a_2)$ | $\cdots$ | $S^k(a_2)$ |
| $\vdots$ | $\vdots$ | $\ddots$ | $\vdots$ |
| $A_n$ | $S^1(a_n)$ | $\cdots$ | $S^k(a_n)$ |

3.1.3. *Part Two: Calculating the overall influence of decision-makers.*

Step 1: Calculation of the correlation coefficient based on the proposed standard deviation Diakoulaki and Al hence equation 24.

$$V_{kk'} = \frac{\sum_{i=1}^{m} \left(S^k(a_i) - \overline{S^k(a_i)}\right)\left(S^{k'}(a_i) - \overline{S^{k'}(a_i)}\right)}{\sum_{i=1}^{m} \left(S^k(a_i) - \overline{S^k(a_i)}\right)^2 \sum_{i=1}^{m} \left(S^{k'}(a_i) - \overline{S^{k'}(a_i)}\right)^2} \tag{24}$$

With:

$V_{kk'}$: The correlation coefficient between decision-maker $k$ and decision-maker $k'$;

$\overline{S^k(a_i)}$: The average of all actions with respect to decision-maker $k$;

$\overline{S^{k'}(a_i)}$: The average of all actions with respect to decision-maker $k'$.

Step 2: The overall weight of each decision-maker with equation 25.

$$P^k = \frac{\beta_k}{\sum_{j=1}^{k} \beta_j} \tag{25}$$

With $\beta_j$ given by 26.

$$\beta_j = \sigma_j \sum_{j'=1}^{k} (1 - V_{jj'}); j = 1; ...; k \tag{26}$$

$\sigma_j$: The standard deviation of decision-maker $f$ for all actions;

$P^k$: The weight of decision-maker $k$;

$k$: The number of decision-makers.

With $k$ decision-makers, $m$ criteria and $n$ alternatives we will have the following decision-maker weight table: Table 4.

TABLE 4. Overall weight of each decision-maker

| | decision-maker 1 | $\cdots$ | decision-maker $k$ |
|---|---|---|---|
| weight | $P^1$ | $\cdots$ | $P^k$ |

### 3.2. **Part Three: Determining the overall score of each alternative.**

TABLE 5. Partial score and overall weight

| | decision-maker 1 | $\cdots$ | decision-maker $k$ |
|---|---|---|---|
| weight | $P^1$ | $\cdots$ | $P^k$ |
| $A_1$ | $S^1(a_1)$ | $\cdots$ | $S^k(a_1)$ |
| $A_2$ | $S^1(a_2)$ | $\cdots$ | $S^k(a_2)$ |
| $\vdots$ | $\vdots$ | $\ddots$ | $\vdots$ |
| $A_n$ | $S^1(a_n)$ | $\cdots$ | $S^k(a_n)$ |

Step 1: Determining the maximum partial score and the minimum partial score for each decision-maker.

$S^k_-$ is the minimum partial score for each decision-maker;

$S^k_*$ is the maximum partial score for each decision-maker.

Step 2: Calculation of the maximum utility $G(a_i)$ with 27 and the minimum regret $R(a_i)$ with 28 of each action.

$$G(a_i) = \sum_{j=1}^{k} P^j \frac{(S^j_* - S^j(a_i))}{(S^j_* - S^j_-)}; i = 1, ..., n \tag{27}$$

$$R(a_i) = \max_j \left( P^j \frac{(S^j_* - S^j(a_i))}{(S^j_* - S^j_-)} \right); i = 1, ..., n, j = 1, ..., k \tag{28}$$

$P^j$: Weight of each decision-maker;

$S^j(a_i)$: The partial score of each decision-maker with respect to action $a_i$;

$S^j_*$: The maximum score of each decision-maker;

$S^j_-$: The minimum score of each decision-maker;

$k$: The number of decision-makers.

Step 3: Determining the overall score of each action by 29.

$$\begin{cases} Q(a_i) &=& v\left[\frac{\left(G(a_i)-g^*(a_i)\right)}{\left(G(a_i)^- - G^*(a_i)\right)}\right] + (1-v)\left[\frac{\left(R(a_i)-R^*(a_i)\right)}{\left(R^-(a_i)-R^*(a_i)\right)}\right] \\ G^*(a_i) &=& \min_i G(a_i); \quad G^-(a_i) = \max_i G(a_i); \\ R^*(a_i) &=& \min_i R(a_i); \quad R^-(a_i) = \max_i R(a_i). \end{cases} \tag{29}$$

$v$ indicates the strategic weight, often considered to be equal to $0.5$.

Action $a_l$ is better compared to action $a_i, i = 1, .., n$ si $Q(a_l) < Q(a_i), i \neq l$.

### 3.3. Algorithmic complexity study of the MADG-ECV method.

**Part One: Determining the Partial Score.** In this part we were inspired by [3].

Separation of cardinal and ordinal criteria.

For cardinal criteria with $k$ decision-makers, its complexity will be $O(k)$;

For ordinal criteria with $k$ decision-makers, its complexity will be $O(k)$;

Total complexity is $O(k)$.

Dominance index.

For cardinal criteria with $k$ decision-makers, its complexity will be $O(m^2.n.k)$;

For ordinal criteria with $k$ decision-makers, its complexity will be $O(m^2.n.k)$;

Total complexity: $O(m^2.n.k)$.

Total dominance has a complexity of $O(n.k)$.

Partial scoring has a complexity of $O(n.k)$.

In summary, the overall complexity of this part is:

$$O\big(\max\{k; n.k; m^2.n.k\}\big) = O(m^2.n.k) \tag{30}$$

**Part Two: Determining the Overall Weight.**

For determining the standard deviation, we have: $O(1)$;

For the correlation matrix, we have: $O(1)$;

For calculating $\beta_k$, we have: $O(1)$;

For the weight, we have: $O(1)$.

We then have an overall complexity for the second part which is:

$$O\big(\max\{1; k\}\big) = O(k)\} \tag{31}$$

**Part Three: Determining the Overall Score.**

For the calculation of $S_-^k$ and $S_+^k$, we have: $O(k)$.

For the calculation of maximum utility $G(a_i)$ and minimum regret $R(a_i)$, we have: $O(n)$.

For the calculation of $Q(a_i)$, we have: $O(1)$..

Therefore, the overall complexity of this part is equal to:

$$O\big(\max\{1; k; n\}\big) = O(k; n) \tag{32}$$

**Conclusion.** According to the results of equations 30 31 and 32, the complexity of the MADG-ECV method will therefore be: $O\big(\max\{k; n.k; m^2.n.k\}\big) = O(m^2.n.k)$.

3.4. **Properties of the MADG-ECV method.** This section is inspired by [6] [8].

Let $A = \{A_1; A_2; ...; A_n\}$: the set of alternatives, $C = \{c_1; c_2; ...; c_m\}$: the set of criteria, $D = \{D_1; D_2; ...; D_k\}$: the set of decision-makers, and $Q(A) = \{Q(A_1); Q(A_2); ...; Q(A_n)\}$: the set of overall scores.

**Property 1.** *Transitivity*

***Principle:***

*Let $A_1$, $A_2$ and $A_3 \in A$ be three alternatives. If $A_1$ is preferred to $A_2$ and $A_2$ is preferred to $A_3$, then $A_1$ is preferred to $A_3$.*

*Let $Q(A_1)$ be the overall score of action $A_1$, $Q(A_2)$ the overall score of alternative $A_2$ and $Q(A_3)$ that of alternative $A_3$. If $Q(A_1) < Q(A_2)$ then $A_1$ is preferred to $A_2$ and if $Q(A_2) < Q(A_3)$ then $A_2$ is preferred to $A_3$ therefore $Q(A_1) < Q(A_3)$ hence $A_1$ is preferred to $A_3$.*

***Proof:***

*By definition:*

$$Q(A_1) < Q(A_2) \Rightarrow Q(A_2) - Q(A_1) > 0 \tag{33}$$

*By definition:*

$$Q(A_2) < Q(A_3) \Rightarrow Q(A_3) - Q(A_2) > 0 \tag{34}$$

*By summing 33 and 34, we have:*

$Q(A_2) - Q(A_1) + Q(A_3) - Q(A_2) > 0 \Rightarrow -Q(A_1) + Q(A_3) > 0$, *hence* $Q(A_1) < Q(A_3)$

***Conclusion:***

*Since we have shown that if $Q(A_1) < Q(A_2)$ and $Q(A_2) < Q(A_3)$ then $Q(A_1) < Q(A_3)$, we can therefore conclude that MADG-ECV is transitive.*

**Property 2.** *Unanimous*

***Principle:***

*Let $<_k$: be the preference relation of each decision-maker and $<_*$ the overall preference relation, $A = \{A_x; A_{y_1}; ...; A_{y_n}\}$: be the set of alternatives with $A_x$ being the best action, $D = \{D_1; D_2; ...; D_k\}$: be the set of decision-makers, and $Q(A) = \{Q(A_x); Q(A_{y_1}); ...; Q(A_{y_n})\}$: be the set of overall scores and $Q(A_x)$ the smallest score. If $Q(A_x) <_k \{Q(A_{y_1}); ...; Q(A_{y_n})\}$ then $A_x$ is the action judged most appropriate by all decision-makers, therefore $Q(A_x) <_* \{Q(A_{y_1}); ...; Q(A_{y_n})\}$ , consequently $A_x$ is unanimously the best action.*

***Proof:***

*By definition, $Q(A_x) <_1 \{Q(A_{y_1}); ...; Q(A_{y_n})\}$ means that $Q_(A_x)$ is the lowest score according to decision-maker 1;*

*By definition,* $Q(A_x) <_2 \{Q(A_{y_1}); ...; Q(A_{y_n})\}$ *means that* $Q_(A_x)$ *is the lowest score according to decision-maker* 2*;*

$\vdots$

*By definition,* $Q(A_x) <_k \{Q(A_{y_1}); ...; Q(A_{y_n})\}$ *means that* $Q_(A_x)$ *is the lowest score according to decision-maker* $k$*;*

*By intersection,* $Q(A_x) <_* \{Q(A_{y_1}); ...; Q(A_{y_n})\}$.

***Conclusion:***

*Since we have shown that* $Q(A_x) <_* \{Q(A_{y_1}); ...; Q(A_{y_n})\}$ *then MADG-ECV is Unanimous.*

**Property 3.** *Anonymity*

***Principle:***

*A method is said to be anonymous if and only if the preferences of the decision-makers remain invariant for any permutation of the data. Mathematically, we say that the MADG-ECV method is anonymous if, for any permutation* $\sigma$ *of the decision-makers, we have:* $Q(A) = Q(A_\sigma) \Rightarrow Q\{A_1, .., An\} = Q\{A_{\sigma 1}, .., A\sigma n\}$ *with* $A = \{A_1, .., An\}$ *the set of actions,* $Q(A) = Q\{A_1, .., An\}$ *the final scores of the initial data, and* $Q(A_\sigma) = Q\{A_{\sigma 1}, .., A\sigma n\}$ *the final scores of the permuted data.*

***Proof:***

*By definition,* $S^k_-$ *is the minimum partial score of each decision-maker in the unpermuted decision matrix.* $S^k_{\sigma-}$ *is the minimum partial score of each decision-maker in the permuted decision matrix. If* $S^k_-$ *is the minimum partial score of a decision-maker k after permutation, we can observe that decision-maker k has moved to a different column, but the partial score that decision-maker* $k$ *assigned to each action remains the same. Hence,* $S^k_- = S^k_{\sigma-}$*; consequently,* $S^k_-$ *is anonymous because its determination of a decision-maker* $k$ *does not depend on the other decision-makers.*

*By definition,* $S^k_*$ *is the maximum partial score of each decision-maker in the unpermuted decision matrix.* $S^k_{\sigma*}$ *is the maximum partial score of each decision-maker in the permuted decision matrix. If* $S^k_*$ *is the minimum partial score of a decision-maker* $k$ *after permutation, we can observe that decision-maker* $k$ *has moved to a different column, but the partial score that decision-maker* $k$ *assigned to each action will remain the same. Hence,* $S^k_* = S^k_{\sigma*}$*; consequently,* $S^k_* = S^k_{\sigma*}$ *is anonymous because its determination of a decision-maker* $k$ *does not depend on the other decision-makers.*

*By definition,* $G(A_i) = \sum_{j=1}^{k} P^j \frac{(S^j_* - S^j(a_i))}{(S^j_* - S^j_-)}; i = 1, ..., n$ *is the maximum utility of the normal matrix and* $G_\sigma(A_i) = \sum_{j=1}^{k} P^j_\sigma \frac{(S^j_{\sigma*} - S^j_\sigma(a_i))}{(S^j_{\sigma*} - S^j_{\sigma-})}; i = 1, ..., n$ *is the maximum utility of the matrix that has undergone a permutation of the decision-makers.* $G(A_i) = G_\sigma(A_i)$ *Because, in fact, it had been shown that for any permutation of the decision-makers, their partial scores did not change. This means that the maximum and minimum partial scores also remain invariant under the permutation, as do the overall* *weights. We can therefore deduce that the calculation of maximum utility $G(A_i)$ does not depend on the position of the new column to which decision-maker $k$ has been assigned. Hence, the anonymity of the calculation of $G(A_i)$.*

*By definition, $R(A_i) = \max_j \left( P^j \frac{(S_*^j - S^j(a_i))}{(S_*^j - S_-^j)} \right); i = 1, ..., n, j = 1, ..., k$ is the minimum regret of the normal matrix and $R_\sigma(A_i) = \max_j \left( P_\sigma^j \frac{(S_{\sigma*}^j - S_\sigma^j(a_i))}{(S_{\sigma*}^j - S_{\sigma-}^j)} \right); i = 1, ..., n, j = 1, ..., k$ is the minimum regret of the matrix that has undergone a permutation of the decision-makers. $R(A_i) = R_\sigma(A_i)$ indeed, based on the unanimity of $G(A_i)$ we can conclude that $\max_j \left( P^j \frac{(S_*^j - S^j(a_i))}{(S_*^j - S_-^j)} \right); i = 1, ..., n, j = 1, ..., k$ is independent of the column to which decision-maker $k$ is newly assigned. Hence the anonymity of the calculation of $R(A_i)$.*

*By definition, $Q(A_i) = v\left[\frac{(G(A_i) - g^*(A_i))}{(G(A_i)^- - G^*(A_i))}\right] + (1 - v)\left[\frac{(R(A_i) - R^*(A_i))}{(R^-(A_i) - R^*(A_i))}\right]$ is the overall score of each action for the normal matrix. With $G^*(A_i) = \min_i G(A_i)$; $G^-(A_i) = \max_i G(A_i)$; $R^*(A_i) = \min_i R(A_i)$; $R^-(A_i) = \max_i R(A_i)$ and $Q_\sigma(A_i) = v\left[\frac{(G_\sigma(A_i) - g_\sigma^*(A_i))}{(G_\sigma(A_i)^- - G_\sigma^*(A_i))}\right] + (1 - v)\left[\frac{(R_\sigma(A_i) - R_\sigma^*(A_i))}{(R_\sigma^-(A_i) - R_\sigma^*(A_i))}\right]$ is the overall score for each action in the normal matrix. With $G^*(A_i) = \min_i G_\sigma(A_i)$; $G_\sigma^-(A_i) = \max_i G_\sigma(A_i)$; $R_\sigma^*(A_i) = \min_i R_\sigma(A_i)$; $R_\sigma^-(A_i) = \max_i R_\sigma(A_i)$ the overall score of each action in the matrix that underwent a permutation of decision-makers. $Q(A_i) = Q_\sigma(A_i)$ because $R(A_i)$ and $G(A_i)$ are unanimous, and since $v$ is a constant, it does not depend on the decision-maker's position in the matrix. Consequently, the decision-maker's position in the new decision matrix that has undergone the permutation does not impact the value of $Q(Ai)$, therefore it is unanimous.*

***Conclusion:***

*Since we have shown that $Q(A_i) = Q_\sigma(A_i)$ then MADG-ECV is anonymous.*

**Property 4.** *Neutrality*

***Principle:***

*Let $D_{nm}^k$ be the initial matrix of $k$ decision-makers with $Q(A_i)$ the score of their best action, $S_{nk}^k$ their partial score matrix, and $D_{nm}^k\{\pi\}$ the matrix of $k$ decision-makers whose scores have been modified with $Q(A_i)\{\pi\}$ the score of their best action, and $S_{nk}^k\{\pi\}$ their partial score matrix. A method is said to be neutral if, when each decision-maker changes their score, the best action also changes. We say that the MADG-ECV method is neutral if, for any change $\pi$ in the scores of each decision-maker, we have: $D_{nm}^k \neq D_{nm}^k\{\pi\} \Rightarrow Q(A_i) \neq Q(A_i)\{\pi\}$.*

***Proof:***

*By definition, the MADG-ECV method is designed to solve group decision problems. Each decision-maker has a decision matrix $D_{nm}^k$. Applying the EVAMIX method to each decision matrix yields a unique partial score $S_{nk}^k$ for each decision-maker. If one or more decision-makers change their scores, a new matrix $D_{nm}^k\{\pi\}$ is obtained. Applying the EVAMIX method to each decision matrix whose scores have*

*been modified yields a unique partial score* $S^k_{nk}\{\pi\}$ *for each decision-maker. Since* $D^k_{nm} \neq D^k_{nm}\{\pi\}$, *then* $S^k \neq S^k\{\pi\}$*. This is true because the EVAMIX method is neutral.*
*If* $D^k_{nm} \neq D^k_{nm}\{\pi\}$ *and* $S^k \neq S^k\{\pi\}$ *then* $P^k \neq P^k\{\pi\}$*. Indeed, the CRITIC method is neutral.*
*If* $D^k_{nm} \neq D^k_{nm}\{\pi\}$, $S^k \neq S^k\{\pi\}$ *and* $P^k \neq P^k\{\pi\}$ *then since the calculation of* $Q(A_i)$ *depends on* $D^k_{nm}$, $S^k_{nk}$ *and* $P^k$ *and* $Q(A_i)\{\pi\}$ *depends on* $D^k_{nm}\{\pi\}$, $S^k_{nk}\{\pi\}$ *and* $P^k\{\pi\}$ *then necessarily* $Q(A_i) \neq Q(A_i)\{\pi\}$.

***conclusion:***
*Since we have shown that Dnm* $D^k_{nm} \neq D^k_{nm}\{\pi\} \Rightarrow Q(A_i) \neq Q(A_i)\{\pi\}$ *then MADG-ECV is therefore neutral.*

**Theorem 1.** *The MADG-ECV method is a group decision-making aid method that is transitive, unanimous, anonymous, and neutral.*

## 4. Digital application of the MADG-ECV

This example is taken from [12]. For the development of the MADG-ECV method we considered the preferences of three decision-makers, which are presented in Tables 6 7 and 8 respectively for decision-maker 1, decision-maker 2, and decision-maker 3.

Table 6. Decision-maker preference 1

| | criteria 1 | criteria 2 | criteria 3 | criteria 4 |
|---|---|---|---|---|
| $W$ | 6 | 5 | 4 | 7 |
| $A_1$ | Good | 5 | Not very important | 7 |
| $A_2$ | Quite good | 6 | Important | 7 |
| $A_3$ | Fair | 7 | Very important | 1 |
| $A_4$ | Fair | 4 | Less important | 2 |

Table 7. Decision-maker preference 2

| | criteria 1 | criteria 2 | criteria 3 | criteria 4 |
|---|---|---|---|---|
| $W$ | 4 | 5 | 7 | 5 |
| $A_1$ | Fairly good | 8 | Very important | 4 |
| $A_2$ | Fair | 4 | Very important | 3 |
| $A_3$ | Good | 1 | Not very important | 1 |
| $A_4$ | Fairly good | 1 | Not very important | 2 |

TABLE 8. Decision-maker preference 3

| | criteria 1 | criteria 2 | criteria 3 | criteria 4 |
|---|---|---|---|---|
| $W$ | 1 | 5 | 2 | 4 |
| $A_1$ | Good | 2 | Not very important | 6 |
| $A_2$ | Very good | 8 | Less important | 3 |
| $A_3$ | Fair | 4 | Very important | 7 |
| $A_4$ | Good | 3 | Less important | 4 |

TABLE 9. Table for converting qualitative criteria into quantitative criteria using the SAARTY scale

| | | |
|---|---|---|
| Fair | Note very important | 3 |
| Quite good | Less important | 5 |
| Good | Important | 7 |
| Very good | Very important | 9 |

In this section, we use the steps of the EVAMIX method to calculate the partial score of Decision-Maker 1 in Table 15 . First, we determined the dominance index of the ordinal criteria 10 and the cardinal criteria 11 . Next, we calculated the normalized dominance index of the ordinal and cardinal criteria, respectively, using Tables 12 and 13. Finally, we calculated the total dominance of the actions according to Decision-Maker 1 table 15.

TABLE 10. Dominance index of ordinal criteria decision-maker 1

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0 | 2 | 2 | 2 |
| $A_2$ | −2 | 0 | 2 | 10 |
| $A_3$ | −2 | −2 | 0 | 4 |
| $A_4$ | −2 | −10 | −4 | 0 |

TABLE 11. Dominance index of cardinal criteria decision-maker 1

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0 | −5 | 32 | 40 |
| $A_2$ | 5 | 0 | 37 | 45 |
| $A_3$ | −32 | −37 | 0 | 8 |
| $A_4$ | −40 | −45 | −8 | 0 |

Table 12. Normalized dominance index of the ordinal criteria of decision-maker 1

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.5 | 0.6 | 0.6 | 0.6 |
| $A_2$ | 0.4 | 0.5 | 0.6 | 1 |
| $A_3$ | 0.4 | 0.4 | 0.5 | 0.7 |
| $A_4$ | 0.4 | 0 | 0.3 | 0.5 |

Table 13. Normalized dominance index of the cardinal criteria of decision-maker 1

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.5 | 0.44 | 0.85 | 0.94 |
| $A_2$ | 0.55 | 0.5 | 0.91 | 1 |
| $A_3$ | 0.14 | 0.08 | 0.5 | 0.58 |
| $A_4$ | 0.05 | 0 | 0.41 | 0.5 |

Table 14. The total control of the decision-maker's actions 1

| $D_{11}$ | $D_{12}$ | $D_{13}$ | $D_{14}$ | $D_{21}$ | $D_{22}$ | $D_{23}$ | $D_{24}$ | $D_{31}$ | $D_{32}$ | $D_{33}$ | $D_{34}$ | $D_{41}$ | $D_{42}$ | $D_{43}$ | $D_{44}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 11 | 11.33 | 16.33 | 17.33 | 10.66 | 11 | 16.93 | 22 | 5.73 | 5.06 | 11 | 14.06 | 4.66 | 0.00 | 7.93 | 11 |

Table 15. Partial score of decision-maker 1

| | decision-maker 1 |
|---|---|
| $A_1$ | 0.39 |
| $A_2$ | 0.42 |
| $A_3$ | 0.12 |
| $A_4$ | 0.15 |

In this section, we will also use the steps of the EVAMIX method to calculate the partial score of Decision-Maker 2, table 21. To do this, we will first determine the dominance index of the ordinal criteria table 16 and the cardinal criteria table 17. Then, we will calculate the normalized dominance index of the ordinal and cardinal criteria, respectively, using tables 18 and 18. Finally, we will calculate the total dominance of the actions according to Decision-Maker 2, represented by table 20.

Table 16. Dominance index of cardinal criteria decision-maker 2

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0 | 4 | 3 | 7 |
| $A_2$ | −4 | 0 | 3 | 3 |
| $A_3$ | −3 | −3 | 0 | 4 |
| $A_4$ | −7 | −3 | −4 | 0 |

Table 18. Normalized dominance index of the ordinal criteria of decision-maker 2

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.5 | 0.78 | 0.71 | 1 |
| $A_2$ | 0.2 | 0.5 | 0.71 | 0.71 |
| $A_3$ | 0.28 | 0.28 | 0.5 | 0.78 |
| $A_4$ | 0 | 0.28 | 0.21 | 0.5 |

Table 17. Dominance index of cardinal criteria decision-maker 2

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0 | 25 | 50 | 45 |
| $A_2$ | −25 | 0 | 25 | 20 |
| $A_3$ | −50 | −20 | 0 | −5 |
| $A_4$ | −45 | −20 | 5 | 0 |

Table 19. Normalized dominance index of the cardinal criteria of decision-maker 2

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.5 | 0.75 | 1 | 0.95 |
| $A_2$ | 0.25 | 0.5 | 0.75 | 0.7 |
| $A_3$ | 0 | 0.25 | 0.5 | 0.45 |
| $A_4$ | 0.05 | 0.3 | 0.45 | 0.5 |

Table 20. The total control of the decision-maker's action 2

| $D_{11}$ | $D_{12}$ | $D_{13}$ | $D_{14}$ | $D_{21}$ | $D_{22}$ | $D_{23}$ | $D_{24}$ | $D_{31}$ | $D_{32}$ | $D_{33}$ | $D_{34}$ | $D_{41}$ | $D_{42}$ | $D_{43}$ | $D_{44}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 10.5 | 16.14 | 17.85 | 20.5 | 4.85 | 10.5 | 15.35 | 14.85 | 3.14 | 5.64 | 10.5 | 13.14 | 0.5 | 6.14 | 7.85 | 10.5 |

Table 21. Partial score of decision-maker 2

| | decision-maker 2 |
|---|---|
| $A_1$ | 0.66 |
| $A_2$ | 0.19 |
| $A_3$ | 0.09 |
| $A_4$ | 0.02 |

To determine the partial score of Decision-Maker 3 in table 27 using the EVAMIX method, we first determine the dominance index of the ordinal criteria table 22 and cardinal criteria table 23. Next, we calculate the normalized dominance index of the ordinal and cardinal criteria, respectively, using tables 24 and 25. Finally, we calculate the total dominance of the actions according to decision-Maker 1 in table 26.

TABLE 22. Dominance index of ordinal criteria decision-maker 3

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0 | −3 | −1 | −2 |
| $A_2$ | 3 | 0 | −1 | 1 |
| $A_3$ | 1 | 1 | 2 | 2 |
| $A_4$ | 2 | −1 | 0 | 0 |

TABLE 24. Normalized dominance index of the ordinal criteria of decision-maker 3

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.5 | 0 | 0.33 | 0.16 |
| $A_2$ | 1 | 0.5 | 0.33 | 0.66 |
| $A_3$ | 0.66 | 0.66 | 0.5 | 0.83 |
| $A_4$ | 0.83 | 0.33 | 0.16 | 0.5 |

TABLE 23. Dominance index of cardinal criteria decision-maker 3

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0 | −18 | −14 | 3 |
| $A_2$ | 18 | 0 | 4 | 21 |
| $A_3$ | 14 | −4 | 0 | 17 |
| $A_4$ | −3 | −21 | −17 | 0 |

TABLE 25. Normalized dominance index of the cardinal criteria of decision-maker 3

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ |
|---|---|---|---|---|
| $A_1$ | 0.5 | 0.07 | 0.16 | 0.57 |
| $A_2$ | 0.92 | 0.5 | 0.59 | 1 |
| $A_3$ | 0.83 | 0.40 | 0.5 | 0.90 |
| $A_4$ | 0.42 | 0 | 0.09 | 0.5 |

TABLE 26. The total control of the decision-maker's action 3

| $D_{11}$ | $D_{12}$ | $D_{13}$ | $D_{14}$ | $D_{21}$ | $D_{22}$ | $D_{23}$ | $D_{24}$ | $D_{31}$ | $D_{32}$ | $D_{33}$ | $D_{34}$ | $D_{41}$ | $D_{42}$ | $D_{43}$ | $D_{44}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | 0.64 | 2.5 | 5.64 | 11.35 | 6 | 6.35 | 11 | 9.5 | 5.64 | 6 | 10.64 | 6.35 | 1 | 1.35 | 6 |

TABLE 27. Partial score of decision-maker 3

| | decision-maker 3 |
|---|---|
| $A_1$ | 0.04 |
| $A_2$ | 0.49 |
| $A_3$ | 0.39 |
| $A_4$ | 0.04 |

At this stage of the work, we proceed to calculate the weight by the CRITIC method in table 32 via table 31. To do this we first grouped the partial scores of the three decision-makers in table 28. Then, calculate the standard deviation of the partial score of each decision-maker on all the actions in table 29. Finally, determine the correlation coefficient through table 30..

TABLE 28. Partial score of decision-makers

| | decision-maker 1 | decision-maker 2 | decision-maker 3 |
|---|---|---|---|
| $A_1$ | 0.39 | 0.66 | 0.04 |
| $A_2$ | 0.42 | 0.19 | 0.49 |
| $A_3$ | 0.12 | 0.09 | 0.39 |
| $A_4$ | 0.15 | 0.02 | 0.04 |

TABLE 29. The standard deviation

| | decision-maker 1 | decision-maker 2 | decision-maker 3 |
|---|---|---|---|
| $\sigma_j$ | 0.156 | 0.288 | 0.234 |

TABLE 30. The correlation coefficient

| | decision-maker 1 | decision-maker 2 | decision-maker 3 |
|---|---|---|---|
| decision-maker 1 | 1.000 | 0.676 | $-0.369$ |
| decision-maker 2 | 0.676 | 1.000 | $-0.369$ |
| decision-maker 3 | $-0.369$ | $-0.369$ | 1.000 |

TABLE 31. Calculation of $\sum_{j'=1}^{k}(1 - V_{jj'})$

| | decision-maker 1 | decision-maker 2 | decision-maker 3 | $\sum_{j'=1}^{k}(1 - V_{jj'})$ |
|---|---|---|---|---|
| decision-maker 1 | 0.000 | 0.323 | 1.369 | 1.693 |
| decision-maker 2 | 0.323 | 0.000 | 1.369 | 1.693 |
| decision-maker 3 | 1.369 | 1.369 | 0.000 | 2.738 |

TABLE 32. Overall weight of each decision-maker

| | $\sum_{j'=1}^{k}(1 - V_{jj'})$ | $\beta_j = \sigma_j \sum_{j'=1}^{k}(1 - V_{jj'})$ | $P^k = \frac{\beta_k}{\sum_{j=1}^{k} \beta_j}$ |
|---|---|---|---|
| decision-maker 1 | 1.693 | 0.265 | 0.190 |
| decision-maker 2 | 1.693 | 0.488 | 0.349 |
| decision-maker 3 | 2.738 | 0.642 | 0.459 |

In this final part of the MADG-ECV method, we will determine the overall score for each action by applying the different steps of the VIKOR method. To do this, we first used table 33, which summarizes the partial scores and overall weights of the actions relative to the decision-makers, to determine the maximum and minimum partial scores for each decision-maker in table 34. Finally, table 35 explains the calculation of the overall score for each action.

TABLE 33. Partial score and overall weight of decision-makers

| | decision-maker 1 | decision-maker 2 | decision-maker 3 |
|---|---|---|---|
| $P^k$ | 0.19 | 0.34 | 0.45 |
| $A_1$ | 0.39 | 0.66 | 0.04 |
| $A_2$ | 0.42 | 0.19 | 0.49 |
| $A_3$ | 0.12 | 0.09 | 0.39 |
| $A_4$ | 0.15 | 0.02 | 0.04 |

TABLE 34. Maximum partial score $S_*^k$ and minimum partial score $S_-^k$ of each decision-maker

| | decision-maker 1 | decision-maker 2 | decision-maker 3 |
|---|---|---|---|
| $P^k$ | 0.19 | 0.34 | 0.45 |
| $A_1$ | 0.39 | 0.66 | 0.04 |
| $A_2$ | 0.42 | 0.19 | 0.49 |
| $A_3$ | 0.12 | 0.09 | 0.39 |
| $A_4$ | 0.15 | 0.02 | 0.04 |
| $S_*^k$ | 0.49 | 0.66 | 0.49 |
| $S_-^k$ | 0.12 | 0.02 | 0.04 |

TABLE 35. Overall stock scores and stock ranking

| | decision-maker 1 | decision-maker 2 | decision-maker 3 | $G(a_i)$ | $R(a_i)$ | $Q(a_i)$ | Rank |
|---|---|---|---|---|---|---|---|
| $A_1$ | 0.01 | 0.00 | 0.45 | 0.46 | 0.45 | 0.65 | $3^{th}$ |
| $A_2$ | 0.00 | 0.24 | 0.00 | 0.24 | 0.24 | 0.00 | $1^{st}$ |
| $A_3$ | 0.19 | 0.30 | 0.10 | 0.59 | 0.30 | 0.37 | $2^{nd}$ |
| $A_4$ | 0.17 | 0.34 | 0.45 | 0.96 | 0.45 | 1.00 | $4^{th}$ |

According to the results of the MADG-ECV method, action $A_2$ is the best action compared to the other actions.

4.1. **Resolution with the MACBEV method.** According to [12], the MACBEV method determines action $A_2$ as the best action from the perspective of all decision-makers. This result is presented in table 36.

TABLE 36. Results obtained using the MACBEV method

| Actions | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $m_{dk} = \sqrt[n]{\prod_{k=1}^{p}} S_k(a_i)$ |
|---|---|---|---|---|---|
| $d_1$ | 3 | 4 | 1 | 2 | 2.21 |
| $d_2$ | 4 | 3 | 1 | 1 | 2.21 |
| $d_3$ | 1 | 4 | 2 | 2 | 2.21 |
| $m_{dk} = \sqrt[p]{\prod_{k=1}^{p}} = S_k(a_i)$ | 228 | 3.63 | 3 | 1.58 | |
| Rank | $3^{rd}$ | $1^{st}$ | $2^{nd}$ | $4^{th}$ | |

4.2. **Resolution with the LON-ZO Method.** According to [17], the LON-ZO method is a decision-making aid that aggregates only quantitative criteria. For its application in our example from [12], the goal was to convert the qualitative criteria into quantitative criteria using the SAARTY scale from table [15]. After this conversion, we used the steps of the LON-ZO method to obtain the results shown in table 37. According to this method, action $A_2$ is the best compared to the other actions.

TABLE 37. Results obtained using the LON-ZO method

| Actions | $\sum_{j=1}^{5} W_j^1 g_j^1$ | $\sum_{j=1}^{5} W_j^2 g_j^2$ | $\sum_{j=1}^{5} W_j^3 g_j^3$ | $U(a_i) = \frac{3}{\sum_{k=1}^{3} \frac{1}{G_k(a_i)}}$ | Rank |
|---|---|---|---|---|---|
| $A_1$ | 128 | 143 | 47 | 83.14 | $2^{nd}$ |
| $A_2$ | 137 | 110 | 71 | 98.44 | $1^{st}$ |
| $A_3$ | 96 | 59 | 69 | 71.66 | $3^{rd}$ |
| $A_4$ | 72 | 56 | 48 | 57.05 | $4^{th}$ |

## 5. Comparative study of MADG-ECV with LON-ZO and MACBEV

5.1. **Theoretical comparison.** According to the theoretical results of our example, the LON-ZO method and the MACBEV method gave the action $A_2$ as the best action. The new MADG-ECV method à confirms that the action $A_2$ is the best of all actions. We note that the MADG-ECV method can contribute to good collective decision-making.

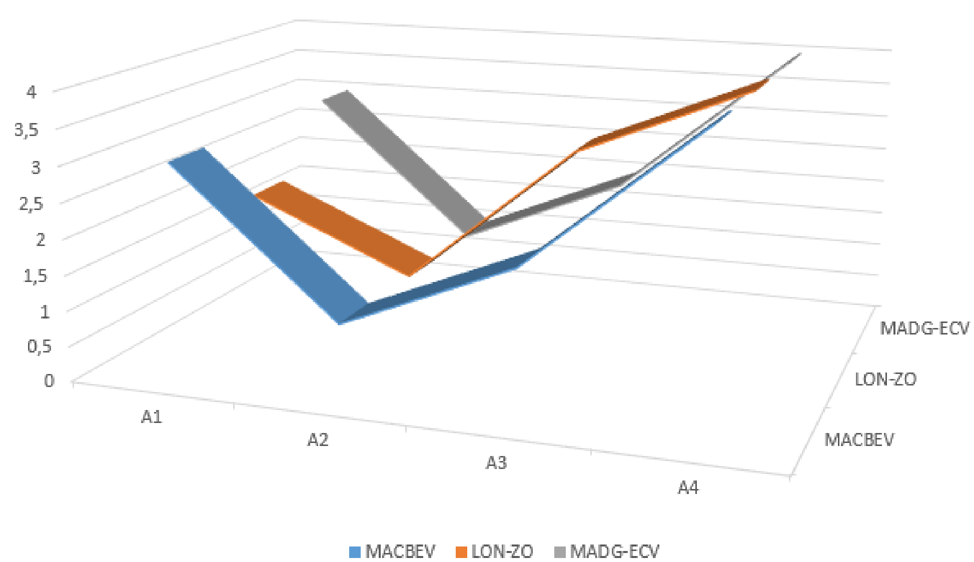


FIGURE 1. Graphical comparison of the MACBEV method, LON-ZO method and MADG-ECV method

5.2. **Graphical comparison of MACBEV method, LON-ZO method and MADG-ECV method.** According to the results in Figure 1, all three methods confirmed that stock $A_2$ is the best stock and stock $A_4$ is the worst. However, the MACBEV and MADG-ECV methods ranked $A_3$ second and $A_1$ third, respectively. The LON-ZO method, however, ranked $A_1$ second and $A_3$ third. These results demonstrate that the MADG-ECV method provides a clear ranking of the stocks.

## 6. Advantages and limitations of MADV-ECV

6.1. **Advantages of MADG-ECV.** The MADG-ECV method is a method that aggregates conflicting qualitative and quantitative criteria without converting the qualitative ones into quantitative ones. It objectively generates the overall weights of each decision maker, which allows it to give results closer to the ideal. This quality allows it to provide a better compromise solution. This allows it to give a clear classification of actions. All these qualities give it a considerable advantage over à the LON-ZO method, MACUQ [15] and CHEMATRE [16] whose applications require a conversion of qualitative criteria into quantitative criteria. It can be used in several domains unlike the MACBEV method which is developed in the voting framework. The MADG-ECV method being transitive, unanimous, anonymous and neutral, this is an advantage because these properties allow us to conclude that MADG-ECV is coherent. It is also very easy à to apply.

6.2. **MADG-ECV Limits.** The MADG-ECV method has not yet been implemented with computer software, this is a limitation for aggregating large amounts of data. This method has not been developed in the group decision framework with data in interval form. This once again weakens this method.

## 7. Conclusion

In this work, we developed a new method called MADG-ECV, a group decision-making aid that aggregates both qualitative and quantitative criteria. It also objectively generates the weights of each decision-maker and provides a compromise solution with a clear ranking of actions. After conducting a practical study, we showed that the MADG-ECV method gives satisfactory results, similar to the LON-ZO and MACBEV methods. Despite its advantages, the lack of implementation limits its application. Given that it is very difficult to find a completely perfect decision-making aid in the literature, in order to improve the MADG-ECV method, we will develop a computer code in our future work that will take into account a significant amount of data with an acceptable execution time.

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**Conflicts of Interest.** The authors declare that there are no conflicts of interest regarding the publication of this paper.

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