



## A CONTEMPORARY APPROACH TO SOLVING SELECTION PROBLEMS: THE ENTROPY-BASED PERFORMANCE MEASUREMENT METHOD

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**Abstract:** In this study, the applicability of the widely used entropy method traditionally employed for calculating criterion weights in the Multi-Criteria Decision-Making (MCDM) literature is investigated as a novel approach for measuring the performance of alternatives. The proposed method, termed Entropy-Based Performance Measurement (EBPM), is grounded in the principle of continuously increasing uncertainty inherent in both natural and social systems. The primary motivation of this approach is to demonstrate, through sensitivity, comparative, and simulation analyses, that the method can produce ideally sensitive, reliable, consistent, stable, and robust results. The study aims to expand the application domain of the entropy method and to contribute to both the MCDM and entropy literature. EBPM is theoretically based on entropy's inherent capability to quantify and enhance informational performance. Without manipulating the original entropy equation, the entropy function is reformulated into a positively increasing structure, enabling it to measure the performance of alternatives. In the methodology section, the characteristics of 15 widely recognized MCDM methods are introduced, the theoretical and mathematical foundations of the proposed approach are explained, and its applicability is demonstrated using the innovation performance data of seven countries selected from the 2024 Global Innovation Index. In the results and discussion section, the quantitative findings and comprehensive explanations of the proposed method are presented in detail. Thus, this study aims to broaden the potential of the entropy method within the field of MCDM and to offer a novel perspective for decision-making processes.

**Keywords:** MCDM, Entropy, EBPM

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### 1. Introduction

The development of new Multi-Criteria Decision-Making (MCDM) methods is of critical importance for overcoming the limitations of existing approaches and offering solutions to a wider range of problem types (Ćirovic and Pamučar, 2022). While traditional methods may be effective under certain criteria, they often fall short when addressing complex and dynamic challenges. Overcoming these limitations enables more accurate and reliable decision-making outcomes. Innovative MCDM approaches enhance the accuracy of decision support processes and strengthen overall decision-making efficiency (Lopez et al., 2023).

Therefore, the discovery and development of novel MCDM methods can provide effective solutions to increasingly complex problems and allow for more refined decisions through the interaction of multiple criteria. This is especially significant in addressing contemporary critical issues such as sustainability, resource management, and risk analysis. One of the core components of MCDM methods characteristic quantitative superiority objectively reveals the relative

dominance of alternatives across multiple criteria (Thakkar, 2021).

Such an approach renders the decision-making process more rational and consistent under prevailing conditions, thus enabling decision-makers to make more reliable and defensible choices. Characteristic quantitative superiority enhances the credibility of decision support systems and clarifies the distinctions between alternatives, thereby contributing to scientifically grounded solutions (Owen, 2023).

In this context, the study proposes a novel method for evaluating the performance of alternatives based on the Entropy method, which is frequently employed in the MCDM literature for calculating the weight values of criteria. This method, referred to as the Entropy-Based Performance Measurement (EBPM), aims to extend the applicability of entropy beyond traditional weight determination, offering a performance evaluation mechanism of alternatives within the broader MCDM framework.

The primary motivation of this research is to demonstrate that the proposed method possesses ideal



sensitivity through sensitivity analyses, yields credible and reliable outcomes in comparative analyses, and proves to be stable and robust under simulation conditions. An additional motivation is to expand the application scope of the entropy method, thereby contributing to both the MCDM literature and entropy-based analytical approaches.

The theoretical foundation of the EBPM method is grounded in the frequently cited notion in the literature that entropy and by extension, uncertainty exhibits a continuously increasing and positively oriented behavior in both natural and social systems (Shankar, 2014). The second theoretical foundation of the method is based on the assumption that the presence of entropy reduces the existing information performance of the systems it influences and consequently increases their information requirements. Accordingly, low levels of entropy imply high information performance, whereas high levels of entropy indicate reduced information performance (Aksakal and Çalışkan, 2020). Within the framework of these two theoretical premises, the entropy function is employed without modifying the original entropy equation, thereby establishing a positively progressive structure that effectively measures the performance of alternatives.

In the methodology section, the study first introduces the characteristics of 15 widely used MCDM methods, each with distinct structural features. Subsequently, the theoretical and mathematical foundations of the proposed EBPM method are comprehensively detailed. Finally, the performance of seven countries selected from the 2024 Global Innovation Index is evaluated using the proposed method based on innovation performance criteria. The discussion section elaborates on the quantitative results.

## **2. Materials and Methods**

### **2.1. Some MCDM Methods and Their Properties**

MCDM methods play a fundamental role in complex decision-making processes, particularly in selecting the most appropriate solution among various alternatives and evaluating the performance of each alternative based on specific criteria (Munier, 2024). In today's decision-making landscape, decision-makers are often faced with a wide array of alternatives possessing diverse attributes, making it essential to identify the optimal choice (Munier, 2021). This process becomes especially crucial in contexts characterized by high uncertainty and complexity, where considering multiple criteria enables more comprehensive and balanced decisions compared to single-criterion evaluations (Zardari et al., 2014).

The literature offers a wide range of MCDM methods, each grounded in different computational techniques. These methods contribute to decision support processes by analyzing alternative performance according to their unique structural frameworks (Thanh, 2021). Such approaches allow decision-makers to assess the

strengths and weaknesses of each alternative while maintaining a balance among criteria. The significance of MCDM lies in its ability to facilitate more effective and informed decisions across various spheres of life. From business and public administration to education and healthcare, MCDM methods serve as valuable tools for solving complex problems and achieving optimized outcomes. Moreover, these methods are critical for the efficient allocation of resources, minimizing risks, and promoting sustainable decision-making practices. As such, MCDM methodologies are indispensable in contemporary decision-making environments where complexity, diversity, and uncertainty are inherent.

As a result, it is commonly observed that researchers make extensive use of methods such as Simple Additive Weighting (SAW) (Azadfallah, 2025), the Weighted Product Method (WPM) (Fan et al., 2025), the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) (Paradhita et al., 2025), the Weighted Aggregated Sum Product Assessment (WASPAS) (Chen et al., 2025), the Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) (Roshanravan et al., 2025), the multi-attributive border approximation area comparison (MABAC) (Mehdiabadi, et al., 2025), CRADIS (Aghamammadli et al., 2024), the Multiple Attribute Utility Theory (MAUT) (Permata et al., 2025), the range of value (ROV) (Andić, 2024), the Complex Proportional Assessment (COPRAS) (Ballamudi, 2024) the ranking of alternatives through functional mapping of criterion sub-intervals into a single interval (RAFSI) (Trung et al., 2022), the combined compromise solution (COCOSO) (Lendvai et al., 2025), the proximity indexed value (PIV) (Ersoy, 2024), the multi attributive ideal-real comparative analysis (MAIRCA) (Öztaş and Öztaş, 2024), and the additive ratio assessment (ARAS) (Aydemir, 2025).

The SAW method, also known as the scoring method, is applicable exclusively to numerical and comparable data sets (Demirci, 2020). The quantitative performances of the alternatives are evaluated based on normalized and weighted values corresponding to the criteria (Sutoyo et al., 2025). The method begins with the construction of a decision matrix. Subsequently, the data are normalized, and the normalized values are multiplied by the respective criterion weights to obtain the weighted normalized decision matrix (Ciardiello and Genovese, 2023). In the final step, the overall score for each alternative is calculated. These scores are then ranked in descending order, thereby facilitating the selection process and concluding the decision-making procedure (Ciardiello and Genovese, 2023).

The WPM evaluates each decision alternative by computing the product of the normalized values corresponding to each criterion, raised to the power of the respective criterion weights (Kaya and Karaşan, 2020). In this context, the quantitative performance of alternatives is based on weighted normalized values

(Chinnasamy et al., 2023). The method involves the following steps: constructing the decision matrix, normalizing the matrix, and then applying exponential weighting to the normalized values using the corresponding criterion weights (Chinnasay et al., 2023). In the final step, the weighted values for each criterion are multiplied for each alternative to obtain the overall performance score. These scores are then ranked in descending order to complete the decision-making process (Alali et al., 2023).

The TOPSIS evaluates decision alternatives based on their proximity to a positive ideal solution and their distance from a negative ideal solution (Başdar, 2019; Çankaya Kurnaz, 2025). The positive ideal solution represents the best values for each criterion, whereas the negative ideal solution represents the worst (Aktaş et al., 2015). In this context, the quantitative superiority of alternatives is associated with being closer to maximum values for benefit-oriented criteria and farther from minimum values (Kaymaz et al., 2020). The TOPSIS method involves several steps: constructing the decision matrix, normalizing the data, and generating the weighted decision matrix by multiplying normalized values with corresponding criterion weights (Çelikkbilek, 2018). Subsequently, the ideal (positive) and anti-ideal (negative) values are determined, and the Euclidean distances of each alternative to these reference points are calculated (Tepe, 2021; Han et al., 2025). In the final step, the relative closeness of each alternative to the positive ideal solution is computed, and the alternatives are ranked in descending order according to these scores (Chaipetch et al., 2025; Han et al., 2025; Alqoud et al., 2025).

The WASPAS method is an integrated multi-criteria decision-making technique that combines the principles of the SAW and WPM approaches (Özdemir, 2018; Chen et al., 2025). The methodology involves the construction of a decision matrix, normalization of the input data, and subsequent calculation of relative importance scores using both SAW and WPM formulations (Arisantoso et al., 2023; Radomska-Zalas, 2023). In the final step, a composite optimality score is computed for each alternative. These scores are then ranked in descending order to determine the most suitable alternative (Zavadskas et al., 2012; Handayani et al., 2023).

The MARCOS method evaluates decision alternatives through a compromise-based approach that considers their proximity to the ideal (AI) and anti-ideal (AAI) solutions (Ecer, 2020). The alternative that is closest to the ideal solution and farthest from the anti-ideal solution is regarded as the most preferable option (El-Araby et al., 2024). The method begins with the normalization of the decision matrix, followed by the application of weights, and then the computation of criterion total for each alternative (Muni et al., 2024). The quantitative superiority of alternatives is associated with their closeness to ideal values and distance from

anti-ideal values, particularly in benefit-oriented criteria (Trung, 2021). Utility degrees are determined by relating these totals to both the ideal and anti-ideal solutions. In the final step, performance scores are calculated using a ratio-based approach that simultaneously considers both reference points (Munier et al., 2024; Andrejic and Vukasin, 2025).

The MABAC method is an evaluation approach based on the distance of each alternative from the boundary approach area of the criterion functions (Ecer, 2020). In the first three steps, a decision matrix is created, normalized, and the weighted normalized decision matrix is obtained (Keleş, 2023). In the fourth step, the boundary approach area matrix is determined, and in the fifth step, the distances of the alternatives to this area are calculated (Akmaludin et al., 2024). The quantitative performance of the alternatives is related to the height of the weighted normalized values and their distance to the boundary approach values of the criteria (Bektaş, 2023). In the final step, the distance values of each alternative across all criteria are summed, and the performance scores are ranked in descending order. (Doković and Doljanica, 2023; Yadav et al., 2025).

The CRADIS method is MCDM approach that evaluates alternatives based on their deviations from the ideal, anti-ideal, and optimal solutions through a utility function (Çilek and Şeyranlioğlu, 2025). The method begins with the creation, normalization, and weighting of the decision matrix. Subsequently, the ideal and anti-ideal solution values are determined, and deviations from these values are calculated (Puška et al., 2023). The utility functions for the alternatives are derived based on these deviation levels. In the final step, both the ideal and anti-ideal solutions are equally weighted, and the average performance of each alternative is determined. In this context, the quantitative superiority of the alternatives depends on the low deviation levels from the ideal and anti-ideal solutions (Özekenci, 2024).

The MAUT method is an approach aimed at maximizing total utility through real-valued utility functions in decision problems involving multiple, conflicting criteria (Atan and Altan, 2020). Preferences are expressed through the utility functions defined for each criterion (Begam, 2024). The method begins with the creation of the decision matrix and the normalization of the data (Çetinkaya et al., 2023). The normalized values are integrated into the exponential form of the base of the natural logarithm,  $e$ , and then the ratio of 1 minus this value to 1.71 is calculated, allowing the marginal utility scores of the alternatives to be determined. The quantitative superiority of the alternatives is related to the magnitude of these marginal utility values based on the exponential values (Ecer, 2020). Finally, the total utility score for each alternative is determined by summing the weighted marginal utilities, and the alternatives are ranked in descending order based on these scores (Özkaya, 2024).

The ROV method begins with the creation of the decision matrix, similar to the SAW method (Turan and Bulak, 2023). In the second step, the matrix values are normalized, and in the third step, the normalized values are weighted, with benefit and cost-oriented criteria summed separately (Madić and Radovanović, 2015). In the final step, the averages of these sums are calculated to determine the performance scores of the alternatives (Madić et al., 2016). In this method, the quantitative superiority of the alternatives is directly related to the magnitude of the weighted normalized criterion values (Ulutaş and Topal, 2020).

The COPRAS method provides a percentage-based analysis by separately considering benefit- and cost-oriented criteria in the evaluation of decision alternatives (Goswami et al., 2021). The method begins with the construction of the decision matrix, followed by normalization of the data and application of the criterion weights. Based on the weighted normalized values, the benefit and cost criteria are aggregated separately (Taherdoost and Mohebi, 2024). The relative significance of each alternative is determined using these values, and performance indices are then calculated. In this context, higher values for benefit criteria and lower values for cost criteria indicate the quantitative superiority of the alternatives (Paksoy, 2017). Finally, the alternatives are ranked in descending order according to their performance indices (Organ and Yalçın, 2016).

The RAFSI method diverges from conventional normalization processes by introducing a distinctive standardization approach capable of transforming data variations within the decision matrix across any subinterval. This feature aims to fulfill the conditions of ideal decision-making (Alossta et al., 2021). The method begins with the construction of the decision matrix. In the second step, the matrix values are matched with their corresponding criterion weights. In the third step, both arithmetic and harmonic means are calculated for each alternative (Žižovic et al., 2020). Subsequently, a normalized decision matrix is derived based on these averages. In the final step, the criterion functions for each alternative are aggregated to determine their overall performance scores (Demir, 2021).

The COCOSO method, developed through the integration of the SAW and WPM techniques, offers a unified compromise decision-making strategy by combining two distinct aggregation logics. Accordingly, the quantitative superiority of alternatives aligns with the dominance structures inherent in both SAW and WPM approaches (Ecer, 2020). The method begins with the construction of the decision matrix, followed by the formation of the normalized decision matrix. In the third step, the sum of the weighted normalized values (S) and the product of the exponential weighted values (P) are calculated (Rasoanaivo et al., 2024). In the fourth step, three distinct evaluation strategies are applied based on the magnitude of the S and P values. In the final step, the arithmetic and

geometric means of these strategies are used to derive the performance scores of the alternatives. In this context, higher values of S and P indicate greater quantitative superiority of the alternatives (Tesić et al., 2023).

The PIV method is based on the principle that the best decision alternatives should be closest to the positive ideal solution. In this method, the proximity index is used to measure the deviations of the normalized values of the alternatives from the ideal values, which vary according to whether the criteria are benefit or cost-oriented (Goswami et al., 2022). These indices are calculated by incorporating the weights of the criteria and are linearly aggregated across all attributes to determine the overall proximity value of each alternative. Within this framework, the alternative with the greatest total weighted normalized proximity is considered the optimal decision alternative (Trung and Tan, 2023). The procedure involves the following steps: construction of the decision matrix, generation of the normalized decision matrix, formation of the weighted normalized decision matrix, calculation of the Weighted Proximity Index for each alternative, and finally, the evaluation of the Overall Proximity Values of the alternatives (Khan et al., 2019).

The MAIRCA method is based on determining the discrepancy between the theoretical solution and the actual outcomes. In this method, the total deviation of each alternative from the expected performance for each criterion is considered (Aksoy, 2021). Accordingly, alternatives with the smallest difference between the theoretical and actual evaluations are deemed to have the greatest quantitative superiority. The procedure begins with the construction of the decision matrix in the first step, followed by the formulation of the preference values for the alternatives in the second step (Zolfani et al., 2020). In the third step, a theoretically derived matrix is developed, while in the fourth step, the actual evaluation matrix is constructed (Işık et al., 2025). Subsequently, a deviation matrix is obtained, and finally, the functional values or performance scores for each alternative are calculated in the last step (Ulutaş, 2019).

In the ARAS method, decision alternatives are evaluated based on their benefit levels, and the optimality value of each alternative is compared with a reference alternative (Altın, 2020). The process begins with the construction of the decision matrix and the normalization of the data. Subsequently, the normalized values are weighted, and the optimality function value for each alternative is calculated accordingly (Arslan, 2017). In the final stage, these values are compared to the reference alternative to determine the performance levels of all alternatives, which are then ranked in descending order (Özbek and Erol, 2017). Therefore, in this method, the quantitative superiority of the alternatives is directly associated with the magnitude of their weighted normalized values (Özbek, 2019).



## 2.2. Proposed Method: ENTROPY-Based Performance Measurement (EBPM)

Shannon entropy, one of the fundamental concepts of information theory, was introduced by Claude E. Shannon in 1948 (Krippendorff, 2019). First defined in his seminal work "A Mathematical Theory of Communication", this concept aims to quantitatively measure the level of uncertainty contained within a system or probability distribution (Nanda, 2020). Moreover, entropy is widely employed to determine the average amount of information conveyed by a message or dataset (Robinson, 2008). In this context, the entropy formula is presented in equation 1 (Cincotta et al., 2021).

$$E = - \sum_{i=1}^m (p_{ij} * \ln(p_{ij})) \quad (1)$$

In the entropy equation presented in Equation 1,  $E$  denotes the total entropy (i.e., the information content or degree of uncertainty);  $p_{ij}$  represents the probability of occurrence of the  $i$ -th event in the  $j$ -th condition;  $\ln$  refers to the natural logarithm (logarithm to the base  $e$ ); and  $m$  indicates the number of data points. Accordingly, the fundamental assumption of Shannon entropy is that events or communication processes occur with specific probabilities (Stevenson, 2021). In this context, low-probability (low entropy) events are considered to carry more information, whereas high-probability (high entropy) events are assumed to provide less information. This characteristic renders the entropy measure an effective indicator for evaluating the overall informational potential of a system by taking into account the probability distribution of events (Bahadır and Türkmençalıkoğlu, 2021).

However, some limitations of Shannon entropy have also been highlighted in the literature. Particularly in systems involving continuous variables, the entropy value may yield negative results or possess units with ambiguous physical interpretations. Such issues complicate the practical applicability of the method (Rudnicki, 2011). Despite these challenges, Shannon entropy remains one of the most fundamental and widely accepted measures for quantitatively assessing information content in the field of information theory (van Stokkum, 2024). In summary, Shannon entropy serves as a critical tool for quantitatively evaluating the uncertainty or unpredictability inherent in a random variable or probability distribution. Within the framework of information theory, it plays a significant role in assessing the informational potential of systems and is extensively applied across various decision-making domains (Zaeemzadeh and Tononi, 2024).

The principal aim of Shannon entropy is to quantitatively measure the "amount of information" conveyed by a random variable. When the probabilities associated with a variable are characterized by high uncertainty meaning that each outcome has an equal likelihood of occurring

the entropy value becomes high. This indicates a low level of existing informational performance and suggests that more information is required to adequately describe the system (Mishra et al., 2019). Conversely, when the outcomes of a variable are more distinct and predictable such that one particular outcome has a much higher probability than the others the entropy value is low. This implies that there is already sufficient informational performance to understand or describe the system, and less additional information is needed (Sharma et al., 2015).

In information theory, entropy is generally associated with concepts such as "uncertainty," "disorder," or "randomness." It is also directly related to "information content," as the realization of an uncertain (i.e., high-entropy) event introduces new information. In cases where entropy is high, the informational performance is low, meaning that each observed event contributes substantially to new knowledge. In contrast, when entropy is low, the information performance per event is considered adequate, or only a limited amount of new information is required. This underscores the notion that enhancing the potential to gain information about an event is only feasible by reducing the uncertainty surrounding that event. High entropy reflects increased complexity or disorder, and the occurrence of low-probability (high-entropy) events is typically associated with a need for greater information acquisition (Aksakal and Çalışkan, 2020).

In the MCDM literature, Shannon entropy is commonly utilized in the criterion weighting process (Ecer, 2020). In this context, entropy emerges as a crucial tool for ensuring a more objective and balanced weighting when evaluating different alternatives (Ayçin, 2019). By considering the uncertainties and diversity among the criteria, entropy serves as a method that contributes to the decision-making process (Dinçer, 2019). The entropy equation used in criterion weighting is detailed in equation 2 (Öztel and Alp, 2020). Subsequently, equation 3 is utilized to measure the importance weights of the criteria within the scope of MCDM (Öztel and Alp, 2020).

$$E_j = - \frac{1}{\ln(m)} \sum_{i=1}^m (p_{ij} * \ln(p_{ij})) \quad (2)$$

$$w_j = 1 - E_j \quad (3)$$

Within the framework of Equation 2, the criterion exhibiting the lowest entropy value corresponds to the one possessing the least uncertainty and, consequently, the highest information capacity (Uludağ and Doğan, 2021). This observation leads to the inference that such a criterion represents the most significant factor, thereby commanding the highest weight. In this context, Shannon entropy, as a quantifier of uncertainty, effectively serves as an indicator of information-carrying potential (Demir

et al., 2021). Accordingly, entropy, or uncertainty, can be conceptualized as an independent variable, while the performance related to information acquisition may be treated as the dependent variable.

In the MCDM literature, the application of entropy is predominantly confined to its role as an independent variable within the criterion weighting process. However, a notable gap exists in the extant literature, as no studies have been identified that mathematically model the influence of entropy itself representing the inherent information potential on the performance evaluation of the alternatives. Consequently, it is postulated that, analogous to the utilization of Shannon entropy as an independent variable for criterion weighting, the information capacity signified by entropy should also be considered a pertinent factor potentially influencing the performance outcomes of the alternatives.

Conventionally within MCDM literature, entropy is employed almost exclusively as an independent variable for the purpose of deriving weights (Bircan, 2020; Baş, 2021). Nevertheless, a mathematical framework that explicitly models the information potential engendered by uncertainty, within the scope of entropy throughout the decision-making process, remains conspicuously absent. It is therefore proposed that, just as entropy serves as an independent variable for criterion weighting in MCDM methodologies, low entropy indicative of high information potential associated with alternatives could be recognized as a factor that positively modulates their information-based performance capabilities. In this regard, the entropy method can be regarded as a potent instrument within decision-making paradigms, contributing significantly to the clarification and refinement of the information presented to the decision-maker (Özcelik and Alp, 2020).

Stated differently, when the decision-making process is conceptualized as an information processing sequence, decision-pertinent information characterized by low uncertainty, which impacts the alternatives, is conveyed, perceived, and processed via the inherent attributes of these alternatives. Within this paradigm, the attributes of the alternatives constitute the fundamental conduits of information. The comprehensiveness and diversity of the information presented through these attributes under conditions of low entropy at the critical decision point directly correlate with the magnitude of their influence on the final decision (Chakraborty et al., 2015).

From an alternative viewpoint, the concept of entropy, or information content, can be defined as the capacity to generate signals possessing communication potential. The principal objective herein is the faithful transmission of the intended information or information content without degradation or loss. Indeed, the necessity for information concerning an event arises only when uncertainty pervades that event. Therefore, if an event exhibits a low probability of occurrence, corresponding to high entropy, it implies that the available information

potential is diminished, necessitating the acquisition of further information (Uludağ and Doğan, 2021). In this context, the information performance of alternatives is amenable to quantification through an entropy-based approach, potentially utilizing the entropy method itself.

It is well-established that the standard Entropy method, particularly when applied using normalized data constrained to the  $[0, 1]$  interval, exhibits a non-monotonic behaviour initially increasing and subsequently decreasing. This characteristic is inconsistent with the inherent expectation within the MCDM context of achieving quantitative superiority when evaluating alternative performance. For instance, in methods such as SAW, WPM, COCOSO, and WASPAS, the quantitative dominance of alternatives is directly proportional to the magnitude of the criterion weights and the normalized performance values; as these values increase, the overall performance scores of the alternatives correspondingly rise (Thakkar, 2021).

Conversely, other MCDM techniques, including TOPSIS, MARCOS, and ARAS, assess alternative performance based on their proximity to ideal solutions (maximum for benefit criteria, minimum for cost criteria) (Munier, 2024). In light of these divergences, it can be asserted that, particularly within the framework of Multi-Criteria Decision-Making (MCDM) utilizing  $[0, 1]$  normalized values, the Entropy method exhibits inconsistent behavior in reflecting the quantitative superiority derived from the magnitudes of criterion weights and normalized data when assessing the performance of alternatives.

Conversely, the monotonically increasing nature of Shannon entropy provides a more robust and widely accepted metric for information measurement. This aligns with the established principle, observed across natural and social-sciences, that entropy tends perpetually towards an increase. A prime exemplification of this is Heisenberg's Uncertainty Principle, which stipulates that the position and momentum of a particle cannot be simultaneously determined with absolute precision. This limitation arises not from an inability to measure the momentum transferred during, for instance, a photon-electron collision, but rather from the inherent constraints of the measurement process itself (Köksal and Köseoğlu, 2010). In quantum mechanics, predicting both the position and momentum of an electron with certainty is impossible; an increase in the uncertainty of a particle's position corresponds to a decrease in the uncertainty (entropy) related to its momentum, and vice versa. Consequently, nature exhibits an inherent tendency towards increasing entropy (Apaydın, 2004; Sakurai and Napolitano, 2012).

Similarly, the Second Law of Thermodynamics defines entropy and dictates its directionality in thermal processes, asserting that the entropy of the universe is constantly increasing (Shankar, 2014). Furthermore, Boltzmann's H-Theorem, which examines the statistical

behavior of gas molecules, mathematically substantiates the monotonic increase of entropy over time (Gressman and Strain, 2010). The Clausius inequality offers another mathematical perspective, asserting that entropy cannot decrease in any cyclic process; rather, it is constrained to increase or remain constant (Narang et al., 2024). From a social science perspective, Gini (2000) posits that human interactions within social systems perpetually augment entropy. Moreover, considering the principle of information conservation alongside the non-additive nature of information and the additive property of entropy collectively underscores the continuity and persistent increase of entropy within isolated systems

(Zhang, 2008). The continuous formation of Shannon entropy can be achieved without manipulating the entropy equation, but by ensuring that the process operates under equal conditions for all values, thereby maintaining the continuity of the entropy function's increase. In this context, the proposed method ensures the continuous increasing position of the entropy function in order to establish quantitative superiority in measuring the performance of alternatives within the MCDM framework. Initially, the weighted normalized values and their original entropy simulation positions are presented in Table 1, while their graphical representation is illustrated in Figure 1.

**Table 1.** Entropy values of the weighted normalized values

| $(wd_{ij}^*)$ | m=2        | m=3        | m=4        | m=5        |
|---------------|------------|------------|------------|------------|
| 0.1           | 0.332193   | 0.209590   | 0.166096   | 0.143068   |
| 0.2           | 0.464386   | 0.292995   | 0.232193   | 0.200000   |
| 0.3           | 0.521090   | 0.328771   | 0.260545   | 0.224421   |
| 0.4           | 0.52877124 | 0.33361751 | 0.26438562 | 0.22772938 |
| 0.400001      | 0.52877112 | 0.33361743 | 0.26438556 | 0.22772932 |
| 0.5           | 0.500000   | 0.315465   | 0.250000   | 0.215338   |
| 0.6           | 0.442179   | 0.278984   | 0.221090   | 0.190436   |
| 0.7           | 0.360201   | 0.227262   | 0.180101   | 0.155130   |
| 0.8           | 0.257542   | 0.162491   | 0.128771   | 0.110918   |
| 0.9           | 0.136803   | 0.086313   | 0.068401   | 0.058918   |
| 0.999999      | 0.0000014  | 0.0000009  | 0.0000007  | 0.0000005  |
| $(wd_{ij}^*)$ | m=6        | m=7        | m=8        | m=9        |
| 0.1           | 0.12851    | 0.11833    | 0.11073    | 0.10480    |
| 0.2           | 0.17965    | 0.16542    | 0.15480    | 0.14650    |
| 0.3           | 0.20159    | 0.18562    | 0.17370    | 0.16439    |
| 0.4           | 0.20455664 | 0.18835212 | 0.17625708 | 0.16680875 |
| 0.400001      | 0.20455659 | 0.18835207 | 0.17625704 | 0.16680872 |
| 0.5           | 0.19343    | 0.17810    | 0.16667    | 0.15773    |
| 0.6           | 0.17106    | 0.15751    | 0.14739    | 0.13949    |
| 0.7           | 0.13934    | 0.12831    | 0.12007    | 0.11363    |
| 0.8           | 0.09963    | 0.09174    | 0.08585    | 0.08125    |
| 0.9           | 0.05292    | 0.04873    | 0.04560    | 0.04316    |
| 0.999999      | 0.0000055  | 0.0000055  | 0.0000055  | 0.0000055  |

m: number of components

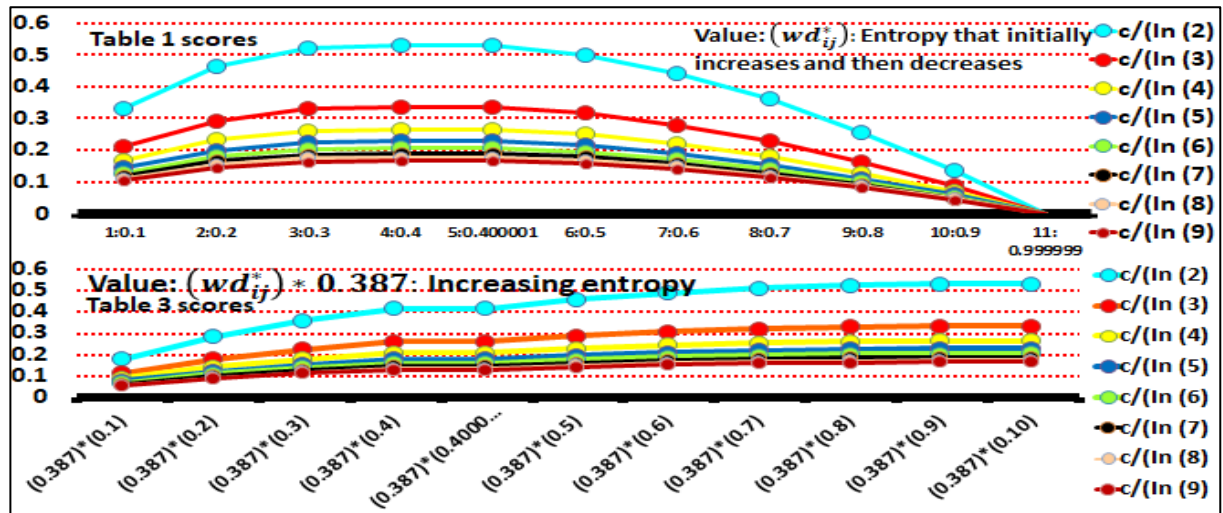


Figure 1. Positions of entropy values.

When Table 1 and Figure 1 are examined together, it is observed that the values of  $wd_{ij}^*$ , representing the weighted normalized scores of each criterion corresponding to each alternative, fall within the range of 0 to 1, as required by the structural nature of MCDM methods. In the simulation analysis, based on Equation 3, it was found that when the  $wd_{ij}^*$  value reached 0.4 in the fourth scenario, the entropy attained its maximum value. However, beyond this point, the entropy began to exhibit a decreasing trend. Accordingly, when the weighted normalized decision matrix contains values exceeding 0.4, the decreasing behavior of the entropy function introduces a contradiction regarding the quantitative superiority of alternatives within the framework of MCDM methodologies.

In contrast, the proposed method, similar to widely used MCDM approaches such as SAW, WPM, COCOSO, and WASPAS, assumes that the quantitative superiority of alternatives is positively correlated with both the magnitude of the criteria weights ( $w$ ) and the normalized values ( $d_{ij}^*$ ). In this context, for the entropy function to demonstrate a monotonically increasing behavior, it is necessary to constrain the weighted normalized values within the interval  $0 < wd_{ij}^* \leq 0.387$ . When each  $wd_{ij}^*$  value is multiplied by the coefficient 0.387, the entropy function becomes strictly increasing, thereby allowing the decision matrix to be standardized in alignment with the proposed approach, as illustrated in Table 2 and Figure 1.

In various simulation experiments, when the  $wd_{ij}^*$  values were standardized using the coefficient 0.4, it was observed also reflected in Table 3 that the  $wd_{ij}^*$  value initially increased up to approximately 0.939, after which it began to decline. Consequently, through extensive simulations, it was determined that the  $wd_{ij}^*$  value that yields a strictly increasing entropy function within the [0,1] interval is approximately 0.387. In each of these scenarios, the weighted normalized values standardized

by the coefficient 0.387 consistently exhibited a monotonically increasing trend (Table 2 and Figure 1). The proposed result has been repeatedly tested and validated across a wide range of scenario sets, including simulations where the number of alternatives ( $m$ ) reached up to 1,000. In each scenario, the entropy value was consistently observed to increase monotonically in a positive direction. This indicates that the method remains stable even under large-scale data conditions and is capable of producing computationally reliable outcomes. Therefore, under such conditions, the proposed method (EBPM) transforms into a continuously increasing entropy function, thereby ensuring consistency in reflecting the quantitative superiority of alternatives.



**Table 2.** Standardization entropy scores of weighted normalized values  $((wd_{ij}^*) * 0.387)$

| $(wd_{ij}^*) * 0.387$       | m=2        | m=3        | m=4        | m=5        |
|-----------------------------|------------|------------|------------|------------|
| 0.03870 (0.1*0.387)         | 0.182      | 0.115      | 0.091      | 0.182      |
| 0.07740 (0.2*0.387)         | 0.286      | 0.180      | 0.143      | 0.286      |
| 0.11610 (0.3*0.387)         | 0.361      | 0.228      | 0.180      | 0.361      |
| 0.15480000 (0.4*0.387)      | 0.4166477  | 0.2628754  | 0.20832385 | 0.4166477  |
| 0.15480004 (0.400001*0.387) | 0.4166478  | 0.2628755  | 0.20832388 | 0.4166478  |
| 0.19350 (0.5*0.387)         | 0.459      | 0.289      | 0.229      | 0.459      |
| 0.23220 (0.6*0.387)         | 0.489      | 0.309      | 0.245      | 0.489      |
| 0.27090 (0.7*0.387)         | 0.510      | 0.322      | 0.255      | 0.510      |
| 0.30960 (0.8*0.387)         | 0.524      | 0.330      | 0.262      | 0.524      |
| 0.34830 (0.9*0.387)         | 0.529      | 0.3343     | 0.264      | 0.529      |
| 0.38700 (0.999999*0.387)    | 0.530      | 0.3344     | 0.265      | 0.530      |
| $(wd_{ij}^*) * 0.387$       | m=6        | m=7        | m=8        | m=9        |
| 0.03870 (0.1*0.387)         | 0.078      | 0.070      | 0.065      | 0.061      |
| 0.07740 (0.2*0.387)         | 0.123      | 0.111      | 0.102      | 0.095      |
| 0.11610 (0.3*0.387)         | 0.155      | 0.140      | 0.128      | 0.120      |
| 0.15480000 (0.4*0.387)      | 0.17944040 | 0.16118133 | 0.14841291 | 0.13888257 |
| 0.15480004 (0.400001*0.387) | 0.17944042 | 0.16118135 | 0.14841292 | 0.13888258 |
| 0.19350 (0.5*0.387)         | 0.197      | 0.177      | 0.163      | 0.153      |
| 0.23220 (0.6*0.387)         | 0.211      | 0.189      | 0.174      | 0.163      |
| 0.27090 (0.7*0.387)         | 0.220      | 0.197      | 0.182      | 0.170      |
| 0.30960 (0.8*0.387)         | 0.226      | 0.203      | 0.187      | 0.175      |
| 0.34830 (0.9*0.387)         | 0.22825    | 0.20502    | 0.18878    | 0.17666    |
| 0.38700 (0.999999*0.387)    | 0.22827    | 0.20504    | 0.18880    | 0.17667    |

m= number of components

**Table 3.** Standardization entropy scores of weighted normalized values  $((wd_{ij}^*) * 0.4)$

| $(wd_{ij}^*) * 0.4$   | m=2        | m=3        | m=4        | m=5        |
|-----------------------|------------|------------|------------|------------|
| 0.04 (0.1*0.4)        | 0.186      | 0.117      | 0.093      | 0.080      |
| 0.08 (0.2*0.4)        | 0.292      | 0.184      | 0.146      | 0.126      |
| 0.12 (0.3*0.4)        | 0.367      | 0.232      | 0.184      | 0.158      |
| 0.16 (0.4*0.4)        | 0.42301699 | 0.26689401 | 0.21150850 | 0.18218350 |
| 0.16000004 (0.41*0.4) | 0.42301704 | 0.26689404 | 0.21150852 | 0.18218352 |
| 0.2 (0.5*0.4)         | 0.464      | 0.293      | 0.232      | 0.200      |
| 0.24 (0.6*0.4)        | 0.494      | 0.312      | 0.247      | 0.213      |
| 0.28 (0.7*0.4)        | 0.51422    | 0.324437   | 0.257110   | 0.221463   |
| 0.32 (0.8*0.4)        | 0.52603    | 0.331890   | 0.263017   | 0.226551   |
| 0.36 (0.9*0.4)        | 0.53061    | 0.334781   | 0.265308   | 0.228524   |
| 0.3756 (0.4*0.9390)   | 0.530622   | 0.334785   | 0.2653109  | 0.228526   |
| 0.37564 (0.4*0.9391)  | 0.530621   | 0.334784   | 0.2653103  | 0.228525   |
| $(wd_{ij}^*) * 0.4$   | m=6        | m=7        | m=8        | m=9        |
| 0.04 (0.1*0.4)        | 0.072      | 0.066      | 0.062      | 0.059      |
| 0.08 (0.2*0.4)        | 0.113      | 0.104      | 0.097      | 0.044      |
| 0.12 (0.3*0.4)        | 0.142      | 0.131      | 0.122      | 0.055      |
| 0.16 (0.4*0.4)        | 0.16364531 | 0.1506816  | 0.14100566 | 0.06380966 |
| 0.16000004 (0.41*0.4) | 0.16364533 | 0.1506817  | 0.14100568 | 0.06380967 |
| 0.2 (0.5*0.4)         | 0.180      | 0.165      | 0.155      | 0.070      |
| 0.24 (0.6*0.4)        | 0.191      | 0.176      | 0.165      | 0.075      |
| 0.28 (0.7*0.4)        | 0.198928   | 0.183169   | 0.171407   | 0.162218   |
| 0.32 (0.8*0.4)        | 0.203498   | 0.187377   | 0.175345   | 0.165945   |
| 0.36 (0.9*0.4)        | 0.205270   | 0.189009   | 0.176872   | 0.167390   |
| 0.3756 (0.4*0.9390)   | 0.2052725  | 0.189011   | 0.1768739  | 0.1673925  |
| 0.37564 (0.4*0.9391)  | 0.2052721  | 0.189010   | 0.1768735  | 0.1673922  |

m= number of components

As illustrated in Table 3 and Figure 1, a noticeable upward trend in entropy values has been observed following the standardization process applied to ensure that the entropy values or the entropy function attain a monotonically increasing structure. Specifically, this standardization involves multiplying the weighted normalized values by a coefficient of 0.387.

Within this context, the Entropy method demonstrates the capability to distinguish between criteria during the weighting phase, and as emphasized in the literature [45], it enhances the discriminative power of the criteria. Similarly, by transforming the entropy function into a monotonically increasing form, it is considered that the performance levels of alternatives can be more clearly differentiated based on their own intrinsic quantitative superiority. In line with this, the implementation steps of the proposed method are systematically presented below.

*ALT*: Alternative

*CRT*: Criteria

*CRT<sub>i</sub>*: *i* – *th* evaluation criterion

*m*: number of criteria

*n*: number of alternative

*d<sub>ij</sub>*: value of the *j* – *th* alternative according to the *i* – *th* evaluation criterion

*w<sub>j</sub>*: weight of the *i* – *th* evaluation criterion (*i* = 1, 2, ..., *m*)

*max(d<sub>ij</sub>)*: maximum value of the alternative according to the *i* – *th* criterion

*min(d<sub>ij</sub>)*: minimum value of the alternative according to the *i* – *th* criterion.

Step 1. Obtaining Decision Matrix (*DM*)

In the first step of the proposed method, the decision matrix is constructed using equation 4.

$$DM = [d_{ij}]_{m \times n}$$

$$= \begin{matrix} ALT \\ CRT_1 \\ CRT_2 \\ \vdots \\ CRT_m \end{matrix} \begin{bmatrix} ALT_1 & ALT_2 & \dots & ALT_n \\ d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \dots & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix} \quad (4)$$

Step 2. Obtaining Normalized Decision Matrix (*DM\**)

In the second phase of the methodology, the decision matrix is normalized by applying Equation 5 for benefit-type criteria and equation 6 for cost-type criteria. Following this step, the normalized decision matrix is constructed in accordance with equation 7, taking into account the nature (i.e., orientation) of each criterion.

For benefit-oriented criteria:

$$d_{ij}^* = \frac{d_{ij}}{\max(d_{ij})} \quad (5)$$

For cost-oriented criteria:

$$d_{ij}^* = \frac{\min(d_{ij})}{d_{ij}} \quad (6)$$

Normalized matrix:

$$DM^* = [d_{ij}^*]_{m \times n}$$

$$= \begin{matrix} ALT \\ CRT_1 \\ CRT_2 \\ \vdots \\ CRT_m \end{matrix} \begin{bmatrix} ALT_1 & ALT_2 & \dots & ALT_n \\ d_{11}^* & d_{12}^* & \dots & d_{1n}^* \\ d_{21}^* & d_{22}^* & \dots & d_{2n}^* \\ \vdots & \vdots & \dots & \vdots \\ d_{m1}^* & d_{m2}^* & \dots & d_{mn}^* \end{bmatrix} \quad (7)$$

Step 3. Obtaining Weighted Normalized Decision Matrix (*wDM\**)

In this step, the normalized values corresponding to each criterion for a given alternative, as presented in equation 8, are multiplied by the respective criterion weights. Subsequently, the weighted normalized decision matrix is obtained using equation 9.

$$wd_{ij}^* = w_j * d_{ij}^* \quad (8)$$

$$wDM^* = [wd_{ij}^*]_{m \times n}$$

$$= \begin{matrix} ALT \\ CRT_1 \\ CRT_2 \\ \vdots \\ CRT_m \end{matrix} \begin{bmatrix} ALT_1 & ALT_2 & \dots & ALT_n \\ wd_{11}^* & wd_{12}^* & \dots & wd_{1n}^* \\ wd_{21}^* & wd_{22}^* & \dots & wd_{2n}^* \\ \vdots & \vdots & \dots & \vdots \\ wd_{m1}^* & wd_{m2}^* & \dots & wd_{mn}^* \end{bmatrix} \quad (9)$$

Step 4. Construction of the Standardized Matrix (*SwDM\**)

In this step, the weighted normalized values are scaled by a factor of 0.387, based on the rationale provided in Table 3, to ensure that none of the values exceed the specified threshold. As a result of this transformation, the entropy function defined in equation 10 is converted into a structure that increases monotonically. Subsequently, the standardized matrix is constructed using equation 11.

$$Swd_{ij}^* = 0.387 * wd_{ij}^* \quad (10)$$

$$SwDM^* = [Swd_{ij}^*]_{m \times n}$$

$$= \begin{matrix} ALT \\ CRT_1 \\ CRT_2 \\ \vdots \\ CRT_m \end{matrix} \begin{bmatrix} ALT_1 & ALT_2 & \dots & ALT_n \\ Swd_{11}^* & Swd_{12}^* & \dots & Swd_{1n}^* \\ Swd_{21}^* & Swd_{22}^* & \dots & Swd_{2n}^* \\ \vdots & \vdots & \dots & \vdots \\ Swd_{m1}^* & Swd_{m2}^* & \dots & Swd_{mn}^* \end{bmatrix} \quad (11)$$

Step 5. Measurement of entropy score of alternatives (*E<sub>j</sub>*)

In this step, based on Equation 1, entropy values of each alternative are measured using Equation 2, within the framework of the increasing entropy function defined in Equation 12. According to the theoretical foundation of entropy in the literature, an increase in entropy implies a decrease in existing information performance and, consequently, a rise in information requirements. Conversely, a lower entropy value indicates higher information performance. Following this step, the

performance values are ranked from the lowest to the highest (equation 12).

$$E_j = -\frac{1}{\ln(m)} * \sum_{i=1}^m (Swd^*_{ij} * \ln(Swd^*_{ij})) \quad (12)$$

Step 6. The knowledge performances of the alternatives ( $KP_j$ )

In this step, in order to achieve a quantitative superiority ranking of the alternatives from highest to lowest, the information performances of the alternatives are calculated as shown in equation 13, by subtracting their entropy values from 1, similar to the approach used for determining criterion weights in Equation 3 of the entropy method. Accordingly, the higher the value obtained by subtracting the entropy from 1, the greater the information performance of the alternative.

$$KP_j = 1 - E_j \quad (13)$$

When the proposed method is examined, it offers several notable advantages from multiple perspectives. First, unlike traditional MCDM approaches, the EBPM method evaluates the information contribution of alternatives to the decision-maker directly through an entropy-based function, thereby providing a more qualified decision support mechanism. By preserving the structural integrity of Shannon entropy, the method integrates scientific rigor into the decision-making process through information generation.

Second, the method emphasizes objectivity in the evaluation process, as it does not rely on subjective weighting and operates based on a predefined threshold value. This feature minimizes decision-maker biases and enables consistent and systematic analysis.

Third, due to its mathematically simple structure and straightforward data processing steps, EBPM is highly applicable to large datasets and across various sectors. Another advantage is its capacity to prevent excessive data dispersion during the standardization phase. As a result, extreme values within the decision matrix are brought under control, and the influence of such values is appropriately considered within the proposed method.

Despite its advantages, the proposed method also has certain limitations. The first limitation arises from the logarithmic computation involved in the method, which makes it sensitive to zero and negative values. In this context, Zhang et al. (2014) emphasized that the decision matrix should be positively oriented and free from zero values, which can be ensured through Z-score standardization. The second limitation pertains to the formation of the standardized matrix, where a significant reduction in values can lead to excessive sensitivity. The inclusion of these highly sensitive values in the computational process may complicate the calculation steps. Moreover, when the original data points are very close to each other, the sensitivity of the standardized

values increases, potentially affecting the overall stability and robustness of the method.

The proposed method, when compared with certain MCDM methods, demonstrates similarities in terms of the computational logic underlying the evaluation of alternatives. Specifically, methods such as SAW (Radulescu and Radulescu, 2024), WPM (Özbek, 2019), WASPAS (Chakraborty et al., 2015), COCOSO (Yazdani et al., 2019), MAUT (Keeney and Raiffa, 1976), ROV (Yakowitz et al., 1993), ARAS (Zavadskas and Turskis, 2010) and COPRAS (Zavadskas et al., 1994) share a common foundation with the proposed approach, in that the quantitative superiority of alternatives is based on the relationship between the weighted normalized values and the numerical magnitude of the criterion weights. This resemblance highlights the fact that these methods adopt a similar calculation framework in determining the performance of alternatives. In contrast, the computational logic of the proposed method significantly differs from that of methods such as TOPSIS (Hwang and Yoon, 1981), MARCOS (Stević et al., 2020), MABAC (Pamućar and Ćirović, 2015) CRADIS (Taşci, 2024), PIV (Goswami et al., 2022), MAIRCA (Pamućar et al., 2018), and RAFSI (Alossta et al., 2021). In these methods, the performance or quantitative dominance of alternatives is determined based on their proximity to an ideal solution point (either maximum or minimum reference values). Therefore, while these methods rely on an evaluation approach grounded in the distance of alternatives from the ideal solution, the proposed method emphasizes the direct quantitative contribution and the effect of weighted normalized score.

When compared to other MCDM methods, the proposed approach offers several notable advantages. Firstly, the EBPM method does not merely evaluate the overall performance of the alternatives; it also quantifies their respective information potentials. This dual functionality allows for a more comprehensive assessment of alternatives beyond conventional performance metrics. Secondly, from the perspective of entropy analysis, the theoretical foundation of the proposed method is inherently associated with both natural and social sciences. This interdisciplinary foundation enhances the applicability of the method in real-world decision-making contexts, particularly when the decision matrix includes criteria drawn from diverse scientific fields. Thirdly, unlike many other MCDM methods, the proposed approach is grounded in the entropy equation, which has previously been employed in both natural and social sciences and is recognized for its validity and reliability in the literature. Accordingly, the theoretical basis of the method is indirectly supported by a broader range of academic disciplines, reinforcing its scientific credibility and cross-disciplinary relevance.

### 2.3. Data Set

In this study, a dataset was constructed within the scope of a sample application to demonstrate that the

performance of alternatives in decision-making problems can be evaluated using the entropy method, and thereby to validate the applicability of the proposed approach. The dataset consists of the 2024 Global Innovation Index (GII) criterion values of seven selected countries exhibiting varying levels of performance (World Intellectual Property Organization, 2024). These countries were deliberately chosen to prevent the criterion values from dominating the overall

performance outcomes and to ensure that the differences among alternatives are not excessively large. Accordingly, there are no dominant values for any alternative within the dataset. Through this approach, the proposed method aims to reveal an ideal differentiation in the performance of alternatives. For the sake of clarity, the abbreviations of the countries and GI criteria are provided in Table 4.

**Table 4.** Data set

| GII Criteria                     | Abbreviations |
|----------------------------------|---------------|
| Institutions                     | CRT1          |
| Human Capital and Research       | CRT2          |
| Infrastructure                   | CRT3          |
| Market Sophistication            | CRT4          |
| Business Sophistication          | CRT5          |
| Knowledge and Technology Outputs | CRT6          |
| Creative Outputs                 | CRT7          |
| Countries/Alternatives           | Abbreviations |
| Saudi Arabia                     | ALT1          |
| Romania                          | ALT2          |
| Qatar                            | ALT3          |
| Brazil                           | ALT4          |
| Chile                            | ALT5          |
| Serbia                           | ALT6          |
| Philippines                      | ALT7          |

### 3. Results

#### 3.1. Computational analysis

In the study, the decision matrix was initially constructed using Equation 4. Subsequently, in the second step of the proposed method, the normalized decision matrix was obtained by applying Equation 5 and Equation 7 to the decision matrix values. In this context, the corresponding values are presented in Table 5.

In the third step of the method, the normalized values were weighted using the Entropy method as defined in

equation 8, and the weighted normalized decision matrix was constructed using equation 9. All procedural steps related to the calculation of criterion weights within the scope of the entropy method are presented in detail in Appendix A in a systematic and transparent manner. This appendix enhances the traceability of the computational process and provides concrete support for the practical applicability of the method. In this context, the weighted normalized values are explained in Table 6.

**Table 5.** Decision and normalized decision matrix

| Decision Matrix            |       |       |       |       |       |       |       |
|----------------------------|-------|-------|-------|-------|-------|-------|-------|
| CRT                        | ALT1  | ALT2  | ALT3  | ALT4  | ALT5  | ALT6  | ALT7  |
| CRT1                       | 64.9  | 42.2  | 73.4  | 31.8  | 56.3  | 46.5  | 47.2  |
| CRT2                       | 43.4  | 30.8  | 36.6  | 33.9  | 33.5  | 35.7  | 26.2  |
| CRT3                       | 46.1  | 51.4  | 50.2  | 45.5  | 45.6  | 52.3  | 34.3  |
| CRT4                       | 48.7  | 32.4  | 34.7  | 38.2  | 38.6  | 42.2  | 29.7  |
| CRT5                       | 23.7  | 31.1  | 25.7  | 36.2  | 30.5  | 22.2  | 36.7  |
| CRT6                       | 20.6  | 29.9  | 17.5  | 24.5  | 21.2  | 29.6  | 28.7  |
| CRT7                       | 24.4  | 28.5  | 25.9  | 32.3  | 27.5  | 17.9  | 26.2  |
| Normalized Decision Matrix |       |       |       |       |       |       |       |
| CRT                        | ALT1  | ALT2  | ALT3  | ALT4  | ALT5  | ALT6  | ALT7  |
| CRT1                       | 1.000 | 0.821 | 1.000 | 0.699 | 1.000 | 0.889 | 1.000 |
| CRT2                       | 0.669 | 0.599 | 0.499 | 0.745 | 0.595 | 0.683 | 0.555 |
| CRT3                       | 0.710 | 1.000 | 0.684 | 1.000 | 0.810 | 1.000 | 0.727 |
| CRT4                       | 0.750 | 0.630 | 0.473 | 0.840 | 0.686 | 0.807 | 0.629 |
| CRT5                       | 0.365 | 0.605 | 0.350 | 0.796 | 0.542 | 0.424 | 0.778 |
| CRT6                       | 0.317 | 0.582 | 0.238 | 0.538 | 0.377 | 0.566 | 0.608 |
| CRT7                       | 0.376 | 0.554 | 0.353 | 0.710 | 0.488 | 0.342 | 0.555 |

**Table 6.** Weighted normalized decision matrix

| CRT     | ALT1  | ALT2  | ALT3  | ALT4  | ALT5  | ALT6  | ALT7  |
|---------|-------|-------|-------|-------|-------|-------|-------|
| C1 *294 | 0.294 | 0.241 | 0.294 | 0.205 | 0.294 | 0.261 | 0.294 |
| C2 *093 | 0.062 | 0.056 | 0.046 | 0.069 | 0.055 | 0.063 | 0.052 |
| C3 *071 | 0.050 | 0.071 | 0.049 | 0.071 | 0.058 | 0.071 | 0.052 |
| C4 *110 | 0.083 | 0.069 | 0.052 | 0.092 | 0.075 | 0.089 | 0.069 |
| C5 *153 | 0.056 | 0.093 | 0.054 | 0.122 | 0.083 | 0.065 | 0.119 |
| C6 *163 | 0.052 | 0.095 | 0.039 | 0.088 | 0.061 | 0.092 | 0.099 |
| C7 *117 | 0.044 | 0.065 | 0.041 | 0.083 | 0.057 | 0.040 | 0.065 |

In the fourth step, the uncertainty values of each decision alternative were ensured to be an increasing function, thereby enhancing their information levels. To achieve this, the matrix was standardized using Equation 10, and the newly standardized matrix was constructed using Equation 11. Consequently, the standardized matrix values are presented in Table 7.

In the fifth step of the proposed method, the ENTROPY

values representing the information capacity of each alternative were calculated using Equation 12. Subsequently, the information performance of the alternatives was determined using Equation 13. The performance rankings of the alternatives were arranged from the highest to the lowest value. In this context, the entropy and information performance values of the alternatives are presented in the Table 8.

**Table 7.** Standardized matrix

| ALT  | ALT1  | ALT2  | ALT3  | ALT4  | ALT5  | ALT6  | ALT7  |
|------|-------|-------|-------|-------|-------|-------|-------|
| CRT1 | 0.114 | 0.093 | 0.114 | 0.080 | 0.114 | 0.101 | 0.114 |
| CRT2 | 0.024 | 0.022 | 0.018 | 0.027 | 0.021 | 0.025 | 0.020 |
| CRT3 | 0.020 | 0.027 | 0.019 | 0.027 | 0.022 | 0.027 | 0.020 |
| CRT4 | 0.032 | 0.027 | 0.020 | 0.036 | 0.029 | 0.034 | 0.027 |
| CRT5 | 0.022 | 0.036 | 0.021 | 0.047 | 0.032 | 0.025 | 0.046 |
| CRT6 | 0.020 | 0.037 | 0.015 | 0.034 | 0.024 | 0.036 | 0.038 |
| CRT7 | 0.017 | 0.025 | 0.016 | 0.032 | 0.022 | 0.015 | 0.025 |

**Table 8.** Performance scores of alternatives

| ALT  | Entropy Score | Performance Score | Rank |
|------|---------------|-------------------|------|
| ALT1 | 0.388         | 0.612             | 2    |
| ALT2 | 0.428         | 0.572             | 5    |
| ALT3 | 0.351         | 0.649             | 1    |
| ALT4 | 0.455         | 0.545             | 7    |
| ALT5 | 0.412         | 0.588             | 3    |
| ALT6 | 0.418         | 0.582             | 4    |
| ALT7 | 0.442         | 0.558             | 6    |

In order to further concretize the proposed method, the mathematical calculation of the performance value of the ALT1 alternative is presented below.

Step 2. Obtaining Normalized Decision Matrix ( $DM^*$ )

$$\text{Equation 5: } d_{CRT1-ALT1}^* = \frac{64.9}{64.9} = 1$$

Step 3. Obtaining Weighted Normalized Decision Matrix ( $wDM^*$ )

$$\text{Equation 8: } wd_{CRT1-ALT1}^* = 0.294 * 1 = 0.294$$

Step 4. Construction of the Standardized Matrix ( $SwDM^*$ )

$$\text{Equation 10: } Swd_{CRT1-ALT1}^* = 0.387 * 0.294 = 0.114$$

Step 5. Meuserement of entropy score of alternatives ( $E_j$ )

$$\begin{aligned} \text{Equation 12: } E_{ALT1} &= (0.114 * -2.174) + (0.024 * -3.727) \\ &+ (0.020 * -3.996) + (0.032 * -3.444) \\ &+ (0.022 * -3.834) + (0.020 * -3.911) \\ &+ (0.017 * -4.073) = -7.5438 \end{aligned}$$

$$E_{ALT1} = \frac{-7.5438}{-1.9469} = 0.3877$$

Step 6. Meuserement of performance score of alternatives ( $KP_j$ )

$$KP_{ALT1} = 1 - 0.388 = 0.612$$

Upon examining Table 8, it can be observed that the obtained ENTROPY values range between 0.649 and 0.545. In this context, the alternative with the highest ENTROPY value, ALT3 (0.649), is the option that provides the most information to the decision-maker. This is followed by ALT1 (0.612), ALT5 (0.588), ALT6 (0.582), ALT2 (0.572), ALT7 (0.558), and ALT4 (0.545). This ranking reflects the contribution of the alternatives to the decision-making process, i.e., their potential for generating information. The results obtained demonstrate that the Entropy-based information



measurement approach objectively reveals the distinctiveness of each alternative within the system and the value of the information it provides to the decision-maker. In this context, a low Entropy value indicates that the alternatives have high information performance.

Consequently, an increase in entropy (uncertainty) suggests high information performance, while a high entropy value indicates low information performance. Therefore, entropy contributes to assisting the decision-maker in making a selection. For instance, the fact that ALT3 has the highest information value indicates that this alternative possesses a stronger and clearer performance profile compared to others under the given alternative, thus providing the decision-maker with more meaningful information. These results demonstrate that the EBPM method yields consistent outcomes both theoretically and mathematically.

### 3.2. Sensitivity Analysis

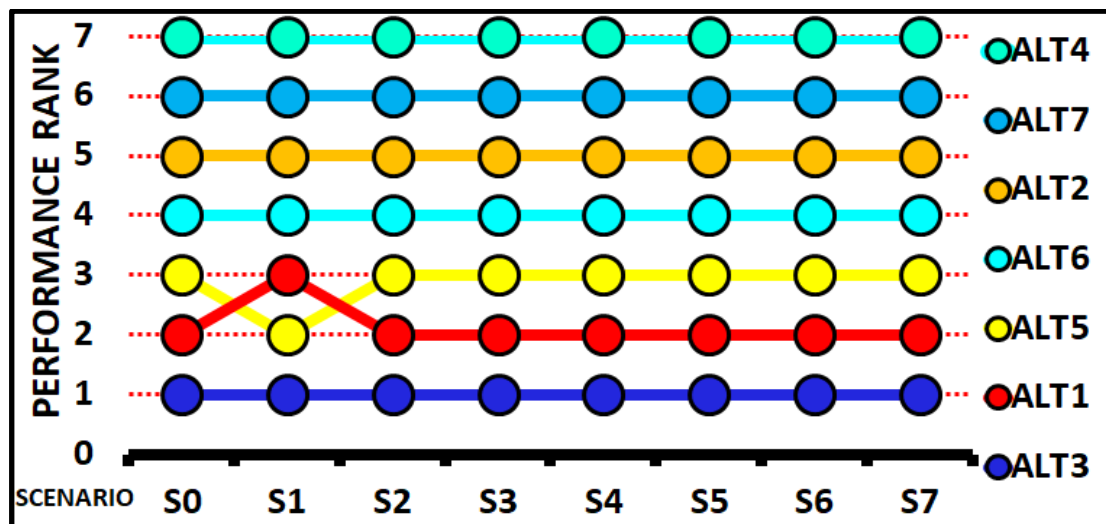
Assessing the robustness of MCDM approaches frequently necessitates the deliberate alteration of the decision environment either through the integration of

additional criteria or by eliminating criteria deemed less competitive within the initial evaluation scope. In such scenarios, it is expected that a resilient MCDM framework will demonstrate a high level of methodological stability, particularly by maintaining a consistent ordinal structure among the ranked entities. This characteristic is vital to ensuring the reliability and validity of the decision outcomes, even in the face of modifications to the input dataset (Demir and Arslan, 2022).

To investigate this dimension of methodological robustness, a comprehensive sensitivity analysis was carried out. The process began with the progressive exclusion of those criteria which, according to the proposed weighting methodology, exhibited the lowest relative significance. By incrementally removing these less influential parameters, the analysis aimed to explore the extent to which the ranking of alternatives remained unaffected or fluctuated under varying model configurations. The corresponding values are presented in Table 9, and the graphical representation of the sensitivity analysis is illustrated in Figure 2.

**Table 9.** Rank reversal score

| Alternatives | S0 | S1 | S2 | S3 | S4 | S5 |
|--------------|----|----|----|----|----|----|
| ALT6         | 7  | 7  | 7  | 7  | 7  | 7  |
| ALT7         | 6  | 6  | 6  | 6  | 6  | 6  |
| ALT4         | 5  | 5  | 5  | 5  | 5  | 5  |
| ALT2         | 4  | 4  | 4  | 4  | 4  | 4  |
| ALT5         | 3  | 2  | 3  | 3  | 3  | 3  |
| ALT3         | 2  | 3  | 2  | 2  | 2  | 2  |
| ALT1         | 1  | 1  | 1  | 1  | 1  | 1  |



**Figure 2.** Rank reversal graph.

A simultaneous examination of Figure 2 and Table 9 clearly reveals that the proposed decision-making method, EBPM, exhibits a high level of structural stability in terms of sensitivity. As part of the sensitivity analysis, eight scenarios—ranging from S0 to S7 were systematically evaluated to assess the model's performance under varying sets of criteria. In each

scenario, the number of criteria included in the model was gradually reduced; specifically, the criterion with the lowest weight was sequentially eliminated from the decision model, and the resulting impact on the ranking of alternatives was meticulously analyzed. While Table 9 provides the numerical representation of alternative rankings under each scenario, Figure 2 offers a visual

depiction of these variations. The base scenario, S0, represents the inclusion of all criteria within the model. Accordingly, the ability to trace changes in rankings holds critical importance for evaluating the model's sensitivity. According to the findings, a limited change in ranking was observed only in the first scenario (S1), during which CRT3 the criterion with the lowest weight based on the ENTROPY method was removed from the model. Specifically, the alternative ALT1 dropped from second to third place, while ALT5 advanced from third to second. Apart from this exceptional case, the rankings of all other alternatives remained unchanged across subsequent scenarios. In the following steps, CRT2 (6th), CRT4 (5th), CRT7 (4th), CRT5 (3rd), CRT6 (2nd), and finally CRT1 (1st) were removed from the model, yet none of these eliminations resulted in any further modifications to the ranking structure.

Particularly notable is the consistent performance of ALT4, which maintained its first-place position throughout all scenarios, thereby underscoring its dominant and stable standing in the decision-making context. Similarly, the rankings of ALT2, ALT3, ALT6, and ALT7 also remained entirely unaffected during the sensitivity analysis, indicating their robustness against structural changes in the set of criteria. This consistency highlights the model's capacity for effectively distinguishing between both dominant and marginal alternatives. The fact that a ranking shift occurred solely between ALT1 and ALT5, and only within a single scenario, demonstrates the strong rank-preserving capability of the proposed method. As depicted in Figure 2, the graphical representation clearly illustrates this singular deviation, while the horizontally stable lines of the remaining alternatives further emphasize the structural resilience of the approach. In conclusion, the EBPM method demonstrates a high level of resistance to variations in the set of decision criteria and is capable of preserving the ranking stability of alternatives under different structural conditions. This characteristic confirms the method's theoretical consistency and practical applicability. Therefore, EBPM can be regarded as a reliable, robust, and methodologically stable decision-support tool with superior rank-preserving capabilities in MCDM problems.

### 3.3. Comparative Analysis

This comparative investigation aims to systematically evaluate the interconnections and relative alignment of the proposed method approach in relation to several well-established techniques within the MCDM domain. The principal objective is to substantiate the effectiveness, dependability, and methodological coherence of the proposed framework by highlighting its alignment with traditional MCDM procedures and its statistically significant and positive correlation with alternative models, as emphasized by Keshavarz-Ghorabae et al. (2021).

To initiate this comparative analysis, a comprehensive

set of benchmark 15 MCDM methods (SAW, WPM, TOPSIS, WASPAS, MARCOS, MABAC, CRADIS, MAUT, ROV, COPRAS, RAFSI, COCOSO, PIV, MAIRCA, ARAS) applied to determine the performance scores of alternatives. These methods were specifically selected due to their widespread adoption and methodological rigor in MCDM literature. The computed scores, along with the corresponding alternative rankings derived from each method, are systematically illustrated in Table 10, Table 11 and visually represented in Figure 3 and Figure 4.

A comprehensive examination of Table 8, Table 10, Table 11, along with Figures 3 and 4, reveals that the proposed method (EBPM) exhibits a high level of consistency and robustness in ranking decision alternatives. According to the EBPM results, ALT3 emerges as the top-performing alternative, followed by ALT1 and ALT5, indicating that the method offers a balanced and discriminative structure from both statistical and decision-making perspectives.

Table 11 presents a comparative ranking analysis, where the performance trends derived from EBPM both increases and decreases closely resemble those produced by widely used MCDM methods such as SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV (adjusted by 180 degrees due to reverse ranking logic), and ARAS. This strong similarity indicates that EBPM not only maintains internal consistency but also generates externally valid rankings that align with conventional methods frequently applied in decision science.

Importantly, a complete rank concordance is observed between EBPM and the MARCOS method. The exact matching of rankings across all alternatives suggests a substantial structural and mathematical alignment between the underlying logic of MARCOS and the formulation of the EBPM model. This harmony not only validates the theoretical foundation of EBPM but also enhances its practical credibility and applicability in real-world decision-making problems. The findings presented in Table 10 further support this assertion. The performance scores generated by EBPM show a high level of correlation with results from other dominant MCDM techniques such as SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV, and ARAS. For example, the top-ranked position of ALT5 is similarly supported by SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV and ARAS.

The findings presented in Table 10 further support this assertion. The performance scores generated by EBPM show a high level of correlation with results from other dominant MCDM techniques such as SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV, and ARAS. For example, the top-ranked position of ALT5 is similarly supported by SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV and ARAS.

**Table 10.** Performance score in scope of methods

| ALT  | SAW    | WPM    | TOPSIS | WASPAS | MARCOS |
|------|--------|--------|--------|--------|--------|
| ALT1 | 0.824  | 0.814  | 0.699  | 0.819  | 0.474  |
| ALT2 | 0.773  | 0.756  | 0.348  | 0.764  | 0.404  |
| ALT3 | 0.815  | 0.800  | 0.743  | 0.807  | 0.480  |
| ALT4 | 0.749  | 0.712  | 0.260  | 0.730  | 0.379  |
| ALT5 | 0.788  | 0.786  | 0.569  | 0.787  | 0.438  |
| ALT6 | 0.747  | 0.730  | 0.392  | 0.738  | 0.406  |
| ALT7 | 0.762  | 0.747  | 0.421  | 0.754  | 0.403  |
| ALT  | MABAC  | CRADIS | MAUT   | ROV    | COPRAS |
| ALT1 | 0.114  | 1.000  | 0.629  | 0.296  | 0.152  |
| ALT2 | 0.045  | 0.929  | 0.586  | 0.262  | 0.140  |
| ALT3 | 0.065  | 0.986  | 0.624  | 0.272  | 0.151  |
| ALT4 | 0.013  | 0.895  | 0.581  | 0.246  | 0.135  |
| ALT5 | 0.044  | 0.949  | 0.519  | 0.261  | 0.145  |
| ALT6 | -0.021 | 0.893  | 0.559  | 0.229  | 0.136  |
| ALT7 | -0.003 | 0.914  | 0.574  | 0.238  | 0.139  |
| ALT  | RAFSI  | COSOSO | PIV    | MAIRCA | ARAS   |
| ALT1 | 6.934  | 3.568  | 0.069  | 0.058  | 0.827  |
| ALT2 | 6.335  | 1.814  | 0.107  | 0.068  | 0.764  |
| ALT3 | 6.504  | 2.023  | 0.075  | 0.065  | 0.820  |
| ALT4 | 6.048  | 2.745  | 0.126  | 0.073  | 0.738  |
| ALT5 | 6.320  | 1.609  | 0.094  | 0.068  | 0.787  |
| ALT6 | 5.753  | 1.382  | 0.099  | 0.078  | 0.742  |
| ALT7 | 5.914  | 2.196  | 0.106  | 0.075  | 0.758  |

**Table 11.** Performance ranks in scope of methods

| ALT  | SAW   | WPM    | TOPSIS | WASPAS | MARCOS |
|------|-------|--------|--------|--------|--------|
| ALT1 | 1     | 1      | 2      | 1      | 2      |
| ALT2 | 4     | 4      | 6      | 4      | 5      |
| ALT3 | 2     | 2      | 1      | 2      | 1      |
| ALT4 | 6     | 7      | 7      | 7      | 7      |
| ALT5 | 3     | 3      | 3      | 3      | 3      |
| ALT6 | 7     | 6      | 5      | 6      | 4      |
| ALT7 | 5     | 5      | 4      | 5      | 6      |
| ALT  | MABAC | CRADIS | MAUT   | ROV    | COPRAS |
| ALT1 | 1     | 1      | 1      | 1      | 1      |
| ALT2 | 3     | 4      | 3      | 3      | 4      |
| ALT3 | 2     | 2      | 2      | 2      | 2      |
| ALT4 | 5     | 6      | 4      | 5      | 7      |
| ALT5 | 4     | 3      | 7      | 4      | 3      |
| ALT6 | 7     | 7      | 6      | 7      | 6      |
| ALT7 | 6     | 5      | 5      | 6      | 5      |
| ALT  | RAFSI | COSOSO | PIV    | MAIRCA | ARAS   |
| ALT1 | 1     | 1      | 1      | 1      | 1      |
| ALT2 | 3     | 5      | 6      | 3      | 4      |
| ALT3 | 2     | 4      | 2      | 2      | 2      |
| ALT4 | 5     | 2      | 7      | 5      | 7      |
| ALT5 | 4     | 6      | 3      | 4      | 3      |
| ALT6 | 7     | 7      | 4      | 7      | 6      |
| ALT7 | 6     | 3      | 5      | 6      | 5      |

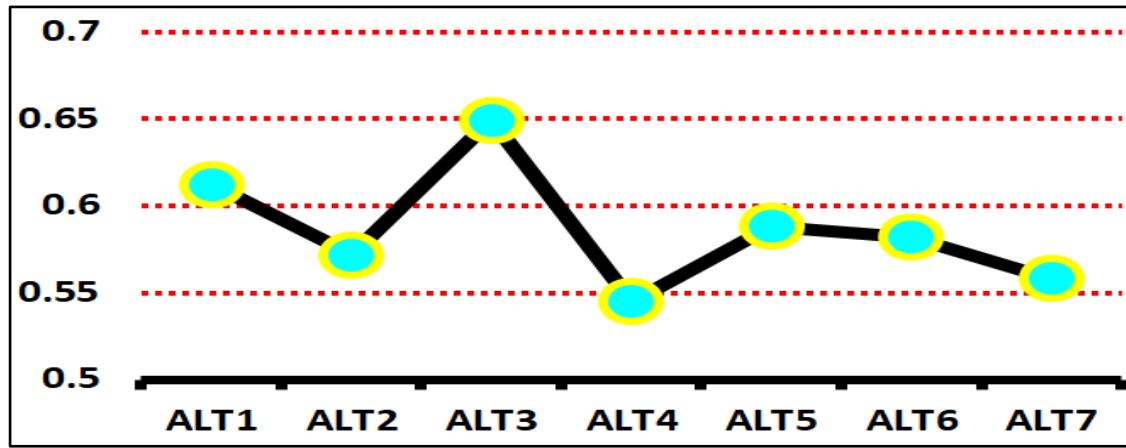


Figure 3. Position of EBPM method.

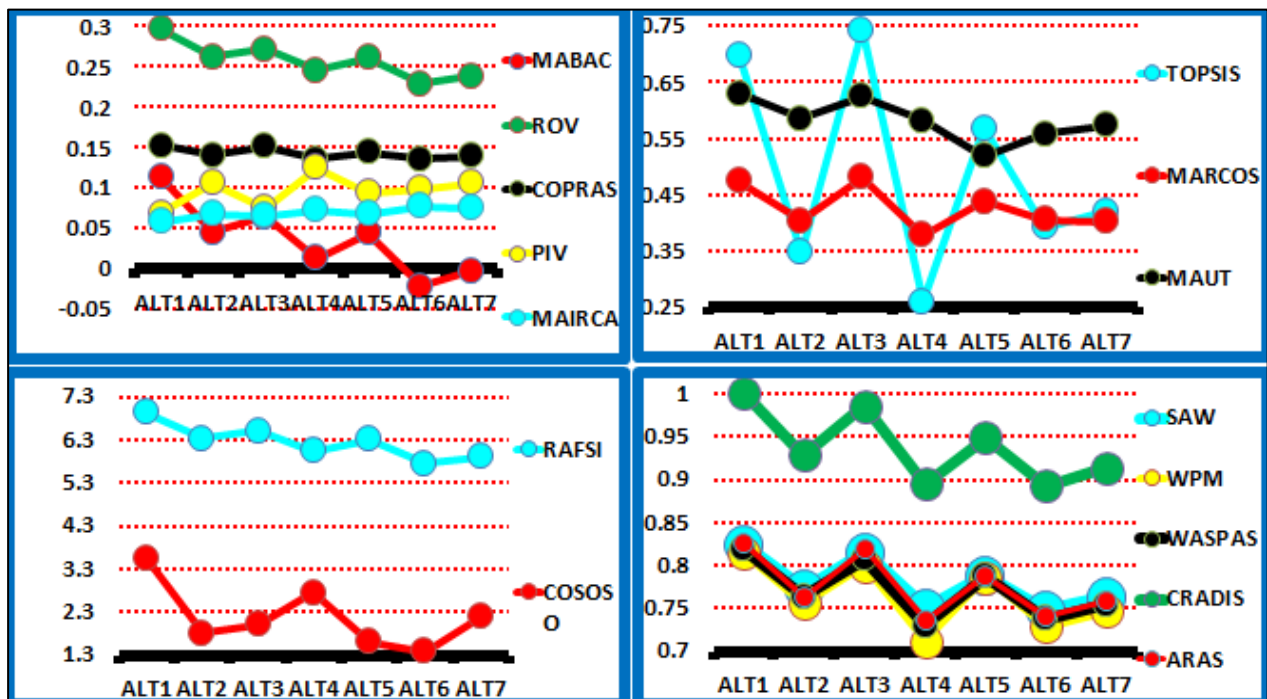


Figure 4. Position of other methods.

A comprehensive examination of Table 8, Table 10, Table 11, along with Figures 3 and 4, reveals that the proposed method (EBPM) exhibits a high level of consistency and robustness in ranking decision alternatives. According to the EBPM results, ALT3 emerges as the top-performing alternative, followed by ALT1 and ALT5, indicating that the method offers a balanced and discriminative structure from both statistical and decision-making perspectives.

Table 11 presents a comparative ranking analysis, where the performance trends derived from EBPM both increases and decreases closely resemble those produced by widely used MCDM methods such as SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV (adjusted by 180 degrees due to reverse ranking logic), and ARAS. This strong similarity indicates that EBPM not only maintains internal consistency but also generates externally valid rankings that align with conventional

methods frequently applied in decision science.

Importantly, a complete rank concordance is observed between EBPM and the MARCOS method. The exact matching of rankings across all alternatives suggests a substantial structural and mathematical alignment between the underlying logic of MARCOS and the formulation of the EBPM model. This harmony not only validates the theoretical foundation of EBPM but also enhances its practical credibility and applicability in real-world decision-making problems.

The findings presented in Table 10 further support this assertion. The performance scores generated by EBPM show a high level of correlation with results from other dominant MCDM techniques such as SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV, and ARAS. For example, the top-ranked position of ALT5 is similarly supported by SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV and ARAS.

Visual interpretations in Figure 3 clearly illustrate the relative distances among alternatives based on EBPM scores, with ALT3 exhibiting a distinctly higher performance level. In contrast, Figure 4, which includes the output distributions of other methods, reveals more pronounced performance fluctuations, suggesting that these conventional approaches may offer less stable or consistent rankings compared to EBPM. In summary, the EBPM method demonstrates a strong capability in producing stable, interpretable, and reliable rankings across decision alternatives. Its close alignment with methods like MARCOS not only confirms its theoretical soundness but also establishes it as a practical, data-driven alternative within the MCDM landscape.

Consequently, the performance rankings obtained

through the EBPM method exhibit a high degree of consistency when compared with both directly proportional and inversely oriented MCDM methods. In particular, a joint evaluation of Figure 3 and Figure 4 reveals that the performance fluctuations of the alternatives are highly aligned with those derived from methods such as SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV and ARAS. This strong alignment indicates that the EBPM method demonstrates a positively strong correlation with these widely recognized MCDM approaches. In support of this conclusion, the correlation coefficients reflecting the degree of association between the EBPM method and the aforementioned MCDM techniques are presented in Table 12.

**Table 12.** Correlation scores

| M | SAW     | WPM     | TOPSIS   | WASPAS   | MARCOS  |
|---|---------|---------|----------|----------|---------|
| S | 0.834** | 0.820** | 0.920**  | 0.832**  | 0.943** |
| M | MABAC   | CRADIS  | MAUT     | ROV      | COPRAS  |
| S | 0.631** | 0.834** | 0.508*   | 0.631**  | 0.869** |
| M | RAFSI   | COSOSO  | PIV      | MAIRCA   | ARAS    |
| S | 0.631** | 0.063*  | -0.904** | -0.631** | 0.866** |

P\*\*<0.01, P\*<0.05, M=method, S= score

As presented in Table 12, the EBPM method exhibits strong and statistically significant correlations with widely recognized and frequently applied multi-criteria decision-making (MCDM) techniques such as SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, and ARAS. This high level of correlation indicates that the performance rankings derived from EBPM are largely consistent with those produced by well-established MCDM approaches. A particularly noteworthy point is that the PIV and MAIRCA methods employ a reverse ranking structure, in which alternatives are ordered from the worst to the best, i.e., in ascending order of performance. Accordingly, the negative but statistically significant correlation coefficients observed between these methods and EBPM are expected and can be interpreted as an indication of methodological consistency. In other words, these inverse correlations reflect the intrinsic ranking logic of the PIV and MAIRCA methods, and despite the opposite direction of the association, they confirm the existence of a strong and meaningful relationship. In addition, the relationships between EBPM and the MABAC, RAFSI, MAIRCA, MAUT, and ROV methods were found to be moderately significant. This suggests that the proposed method achieves an acceptable level of agreement with these techniques, indicating a moderate degree of methodological compatibility.

On the other hand, although the correlation coefficient between EBPM and the COSOSO method is relatively lower than those observed with other methods, it remains statistically significant. This finding implies that, despite some divergence in the computational

frameworks of the two methods, there is limited alignment in terms of decision-making outcomes.

In conclusion, the correlation analysis demonstrates that the EBPM method not only produces stable and consistent rankings but also establishes a methodologically coherent and statistically verifiable relationship with a broad range of mainstream MCDM methods. These findings strongly support the validity and reliability of EBPM in addressing complex decision-making problems.

Overall, the correlation analysis reveals that the EBPM method demonstrates strong associations with both positively and inversely ranked MCDM methods. This not only confirms the statistical robustness of the proposed approach but also underscores its capacity to distinguish between alternatives in alignment with decision-maker preferences. Taken together, the findings suggest that EBPM is a reliable and valid performance assessment tool that yields highly compatible results with prominent methods in the MCDM literature. Hence, considering all comparative analyses, the EBPM method proves to be a trustworthy and effective technique in terms of capturing decision-makers' preferences and discriminating between alternatives.

### 3.4. Simulation analysis

To evaluate the reliability and consistency of the proposed method, a simulation-based study was carried out by constructing alternative decision matrices through the assignment of diverse input values. As the number of simulated scenarios increases, it is anticipated that the discrepancy between the proposed technique and other objective MCDM methods will become more apparent. In



this regard, it is expected that the correlation between the performance scores derived from the proposed method and those obtained from other MCDM techniques will gradually decrease. Such a trend would serve as evidence of the proposed method's enhanced capability to differentiate between criteria based on their relative significance. Moreover, the homogeneity observed in the variance distribution across all scenarios would further substantiate the stability and robustness of the proposed weighting mechanism (Keshavarz-Ghorabae et al., 2021).

As part of this analysis, ten distinct scenarios were developed in the form of decision matrices and subsequently categorized into two separate groups for comparative purposes (Group 1: Scenario 1, Scenario 2, Scenario 3; Group 2: Scenario 4 through Scenario 10). Moreover, although the scenarios utilized in this study were constructed based on randomly generated datasets, particular attention was paid to avoiding excessively dominant values in order to more effectively reveal

performance differences among alternatives within the proposed EBPM framework. Instead, alternatives with relatively close values were deliberately selected to enable a more accurate and meaningful assessment of the method's discriminative capacity. Furthermore, the dataset was designed to exhibit statistical normality, thereby ensuring a balanced distribution of data across criteria. This methodological approach not only provides a sound foundation for conducting sensitivity analyses but also demonstrates that the proposed method does not rely on artificially exaggerated contrasts. Rather, it delivers a performance evaluation based on realistic and substantively meaningful distinctions among alternatives. Following this categorization, correlation coefficients were computed to assess the degree of alignment between the proposed EBPM method and other established weighting approaches across the defined scenarios. The outcomes of these correlation analyses are comprehensively illustrated in Table 13 and Figure 5.

**Table 13.** Correlation scores

| Methods    | SAW     | WPM     | TOPSIS  | WASPAS   | MARCOS   |
|------------|---------|---------|---------|----------|----------|
| Scenario1  | 0.861** | 0.833** | 0.965** | 0.863**  | 0.973**  |
| Scenario2  | 0.933** | 0.888** | 0.981** | 0.901**  | 0.993**  |
| Scenario3  | 0.958** | 0.905** | 0.988** | 0.905**  | 0.996**  |
| Scenario4  | 0.829** | 0.814** | 0.912** | 0.849**  | 0.955**  |
| Scenario5  | 0.817** | 0.803** | 0.905** | 0.831**  | 0.943**  |
| Scenario6  | 0.791** | 0.779** | 0.888** | 0.823**  | 0.932**  |
| Scenario7  | 0.768** | 0.753** | 0.874** | 0.807**  | 0.925**  |
| Scenario8  | 0.744** | 0.729** | 0.869** | 0.800**  | 0.915**  |
| Scenario9  | 0.726** | 0.718** | 0.852** | 0.779**  | 0.907**  |
| Scenario10 | 0.711** | 0.703** | 0.829** | 0.759**  | 0.903**  |
| Methods    | MABAC   | CRADIS  | MAUT    | ROV      | COPRAS   |
| Scenario1  | 0.655** | 0.873** | 0.551*  | 0.654**  | 0.899**  |
| Scenario2  | 0.693** | 0.913** | 0.579*  | 0.693**  | 0.903**  |
| Scenario3  | 0.601** | 0.927** | 0.491*  | 0.604**  | 0.927**  |
| Scenario4  | 0.633** | 0.869** | 0.444*  | 0.631**  | 0.876**  |
| Scenario5  | 0.719** | 0.855** | 0.429*  | 0.616**  | 0.867**  |
| Scenario6  | 0.608** | 0.839** | 0.417*  | 0.612**  | 0.859**  |
| Scenario7  | 0.591*  | 0.826** | 0.404*  | 0.593*   | 0.845**  |
| Scenario8  | 0.582*  | 0.817** | 0.391*  | 0.579*   | 0.839**  |
| Scenario9  | 0.567*  | 0.808** | 0.376*  | 0.569*   | 0.819**  |
| Scenario10 | 0.559*  | 0.800** | 0.359*  | 0.559*   | 0.808**  |
| Methods    | RAFSI   | COSOSO  | ARAS    | PIV      | MAIRCA   |
| Scenario1  | 0.655** | 0.071   | 0.894** | -0.956** | -0.657** |
| Scenario2  | 0.695** | 0.091   | 0.900** | -0.978** | -0.698** |
| Scenario3  | 0.674** | 0.099   | 0.923** | -0.963** | -0.679** |
| Scenario4  | 0.636** | 0.084   | 0.871** | -0.921** | -0.643** |
| Scenario5  | 0.615** | 0.077   | 0.864** | -0.908** | -0.617** |
| Scenario6  | 0.604** | 0.075   | 0.854** | -0.889** | -0.609** |
| Scenario7  | 0.594*  | 0.071   | 0.842** | -0.881** | -0.600** |
| Scenario8  | 0.586*  | 0.067   | 0.833** | -0.876** | -0.589*  |
| Scenario9  | 0.563*  | 0.061   | 0.815** | -0.873** | -0.568*  |
| Scenario10 | 0.555*  | 0.049   | 0.805** | -0.869** | -0.561*  |

P\*\*<0.01, P\*<0.05.

When Table 13 and Figure 5 are examined jointly, it is generally observed that the correlation values between the EBPM method and other MCDM methods tend to decline as the number of scenarios increases. This trend suggests that increasing the number of scenarios reveals greater evaluation differences among the methods. Notably, methods such as TOPSIS, MARCOS, and PIV maintained high correlation levels despite changes in scenario structures, thereby exhibiting consistent and stable performance evaluations. In contrast, methods such as COCOSO demonstrated relatively lower correlation values, indicating a higher sensitivity to scenario variations. Meanwhile, the PIV and MAIRCA methods continued to yield negative correlation coefficients, which is consistent with their reverse ranking logic, wherein lower numerical values indicate better performance. These inverse correlations are not anomalies but rather expected outcomes aligned with the inherent evaluation structures of the respective methods. Additionally, the statistical significance of the correlation coefficients presented in Table 13 is marked at the  $p < .01$  and  $p < .05$  levels. This reinforces the notion that the observed relationships are not coincidental but are statistically valid and meaningful. This analysis offers valuable insights into the sensitivity and consistency of different MCDM methods when subjected to varying decision-making scenarios. The fact that the EBPM method gradually diverges from other methods as the number of scenarios increases, and thereby becomes more distinguishable, highlights its ability to characterize and preserve stability in complex decision environments. Such findings emphasize the robustness and reliability of the proposed EBPM method in multi-scenario decision-

making contexts, further enhancing its value as a dependable and structured performance evaluation tool. In the concluding stage of the simulation analysis, the uniformity of variance in the performance scores determined through the EBPM methodology was rigorously evaluated using Levene's test. This statistical procedure offers a visual and analytical tool for assessing the consistency of variances across different groups. The graphical representation is structured around three essential components: the overall mean Average Decision Metric (ADM), derived from the Analysis of Means (ANOM) for variances based on Levene's test, which acts as the central reference line; and the Upper Decision Limit (UDL) and Lower Decision Limit (LDL), which delineate the acceptable bounds for variance fluctuation. When the variance of a particular group or cluster exceeds these decision thresholds, it indicates a statistically significant deviation from the overall mean ADM, suggesting the presence of variance heterogeneity. Conversely, if the variances of all clusters fall within the UDL and LDL range, this supports the assumption of variance homogeneity. Such consistency reinforces the robustness, reliability, and methodological stability of the proposed methodological framework by confirming the homogeneity of variances under diverse simulation scenarios (Keshavarz-Ghorabae et al., 2021). In this context, Figure 6 presents the graphical results of the ADM-based analysis, offering visual confirmation of these findings, while Table 14 complements and substantiates the interpretation by providing the detailed numerical outcomes underpinning the graphical assessment (Levene Test).

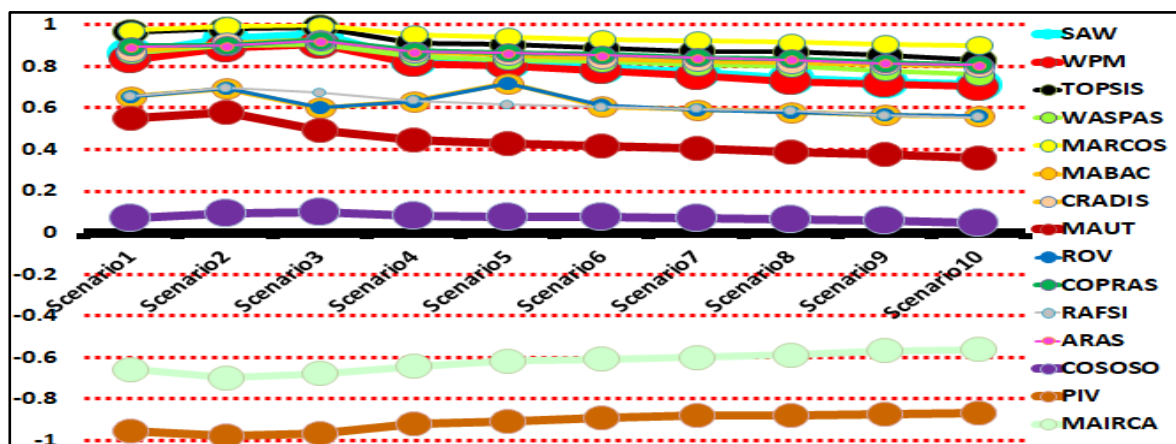
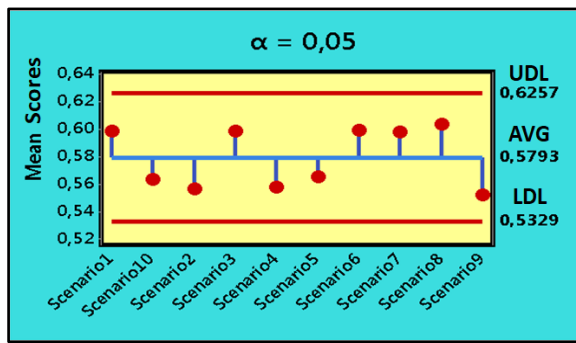


Figure 5. Correlation positions of EBPM with other MCDM methods.



**Figure 6.** ADM graph.

Figure 6 presents a visual summary of the Analysis of Means (ANOM) for the variances of the Average Decision Metric (ADM) weights calculated under different scenarios at a significance level of  $\alpha = 0.05$ . This analysis is based on the Levene's test, which is used to assess the homogeneity of variances. On the graph, the horizontal axis represents the different scenarios (from Scenario 1 to Scenario 10), while the vertical axis displays the Average ADM Weights.

The central blue line (AVG) indicates the overall average of ADM performance scores across all scenarios (0.5793), serving as the main reference point for the variance analysis. The upper red line (0.6257) and the lower red line (0.5329) represent the Upper Decision Limit (UDL) and Lower Decision Limit (LDL), respectively, indicating the boundaries within which the variance is considered acceptable. The yellow dots depict the calculated Average ADM Weights for each individual scenario. As shown in Figure 6, all the scenario-specific ADM scores lie within the range defined by the UDL and LDL. This clearly demonstrates that the variances of ADM scores across different scenarios are homogeneous, and there is no statistically significant deviation from the mean. Such homogeneity validates the robustness, reliability, and methodological consistency of the proposed framework. This finding aligns with the assertion of Keshavarz-Ghorabae et al. (2021), who emphasized that preserving variance homogeneity across simulation scenarios is of critical importance in ensuring methodological consistency.

In conclusion, Figure 6 provides a clear visual depiction of the ANOM analysis based on Levene's test, effectively confirming the homogeneity of variances in ADM performance scores under varying scenarios. This statistical homogeneity reinforces the consistency and credibility of the proposed methodological approach, indicating that the results are built upon a solid foundation. This visual analysis, in conjunction with the numerical findings presented in Table 14, significantly strengthens the validity and reliability of the overall methodological framework. Moreover, based on the results of the ADM diagram and Levene's test, the homogeneity of performance scores generated by the proposed method across random different scenarios has been empirically validated. In this context, the Levene

statistics obtained from scenario datasets exhibiting normal distribution are comprehensively reported in Table 14.

**Table 14.** Correlation scores

| Levene Statistic | df1 | df2 | Sig. (p) |
|------------------|-----|-----|----------|
| 0.167            | 2   | 10  | 0.249    |

$P^* < 0.05$

Upon examining Table 14, it is observed that the significance level ( $p = 0.241$ ) is greater than 0.05. This finding indicates that the variances of the performance scores obtained through the EBPM method across ten different scenarios are homogeneous, thereby supporting the outcomes derived from the ADM analysis. In other words, since there is no statistically significant difference in the variances of the scores obtained under different scenarios, it can be inferred that the model demonstrates consistent performance in terms of variance stability. From a broader perspective, when the quantitative findings of all simulation analyses are considered collectively, it can be concluded that the EBPM method possesses a stable and robust structure. This statistical consistency underscores the method's reliability in multi-scenario decision-making environments and reinforces its potential for practical application in complex decision contexts.

#### 4. Discussion

MCDM methods are systematic and analytical tools developed to solve multidimensional problems in today's increasingly complex decision-making environments [2]. Although existing MCDM methods offer significant advantages, the growing demand for information-based decision-making has exposed certain limitations of these techniques [1]. In this context, the development of novel MCDM approaches not only aims to overcome the constraints of existing models but also paves the way for innovative evaluation techniques grounded in alternative paradigms [4]. In particular, the creation of models that effectively provide informative value to decision-makers and reduce uncertainty highlights a critical, yet unmet, need within the MCDM literature.

Within the scope of this study, the proposed EBPM method introduces a novel evaluation framework based on the informational potential of entropy. The theoretical foundation of the method is built upon two core principles. The first is the continuous tendency of entropy to increase in both natural and social systems [5,107]. The second is the premise that such an increase enhances the information performance of these systems [6]. Without introducing any structural modifications to the Shannon entropy formula, the method transforms the entropy function into a theoretically justified and literature-consistent monotonically increasing structure by rescaling the weighted normalized values based on a predefined threshold. This approach not only offers a

theoretically consistent model but also introduces an original dimension for performance evaluation in decision analysis grounded in information theory.

In the application of the EBPM method to the 2024 Global Innovation Index dataset, the model has been rigorously tested in terms of ranking stability, reliability, and sensitivity. In the sensitivity analysis, even when specific criteria were systematically removed from the decision matrix, no significant changes were observed in the ranking of alternatives. The results of the comparative analysis demonstrate that EBPM exhibits a high degree of correlation with widely used MCDM methods such as SAW, WPM, TOPSIS, WASPAS, MARCOS, CRADIS, COPRAS, PIV, and ARAS, thereby confirming its reliability and credibility as a decision-making tool. On the other hand, the observation that the proposed EBPM method exhibits only moderate correlation with certain MCDM techniques such as MAUT, MABAC, RAFSI, and MAIRCA, and a relatively low correlation with the COCOSO method, can be attributed to the conceptual and computational divergence between these approaches. Fundamentally, this discrepancy arises from the differences in how each method interprets and computes the performance of alternatives. While EBPM directly evaluates the information contribution of each alternative through an entropy-based performance framework, methods like MAUT, MABAC, RAFSI, and MAIRCA adopt diverse structural models based on utility theory, approximation areas, or ideal-theoretical deviations. As a result, the divergence in evaluation paradigms naturally leads to differentiated correlation levels. Specifically, the COCOSO method aggregates performance scores through additive and multiplicative synthesis based on SAW and WPM principles, which conceptually misaligns with the continuously increasing entropy-based formulation of EBPM. Thus, the lower correlation with COCOSO does not indicate a methodological deficiency, but rather reflects the distinctive theoretical foundation and originality of the EBPM approach. These differences underscore EBPM's unique contribution to the MCDM literature, offering an alternative perspective independent of traditional ranking logics.

Furthermore, simulation analyses conducted under various correlation and homogeneity-based scenarios revealed a consistently high level of ranking stability, indicating that EBPM possesses a stable and robust structure.

A key distinguishing advantage of the method lies in its capacity to assess performance not merely based on numerical magnitudes but also on the informational contribution it offers to the decision-maker. Unlike conventional MCDM techniques such as SAW (Radulescu and Radulescu, 2024), WPM (Özbek and Erol, 2017), WASPAS (Zawadskas et al., 2012), COCOSO (Yazdani et al., 2019), MAUT (Keeney and Raiffa, 1976), ROV (Yakowitz et al., 1993), ARAS (Zawadskas et al., 2010), and COPRAS (Zawadskas et al., 1994), which primarily emphasize the magnitude of normalized values and

criterion weights (i.e., quantitative superiority), the EBPM method considers both quantitative dominance and the information-generating capacity of alternatives, thereby enabling a more qualitative and nuanced evaluation.

Moreover, in contrast to proximity-to-ideal-solution-based methods such as TOPSIS (Hwang and Yoon, 1981) MARCOS (Stević et al., 2020), MABAC (Pamućar and Ćirović, 2015), CRADIS (Puška et al., 2023), PIV (Goswami et al., 2022), MAIRCA (Pamucar et al., 2018), and RAFSI (Žižovic et al., 2020), EBPM evaluates each alternative according to its intrinsic information potential, rather than its closeness to an ideal maximum or minimum reference point. Notably, its negative correlation with methods such as MAIRCA and PIV, which operate under a reverse-ranking mechanism, not only reveals the ranking coherence across models but also underlines EBPM's capacity to maintain comparative compatibility with existing methods.

In addition, the entropy-based foundation of EBPM grants it an inherently multi-disciplinary character, making it potentially more usable and insightful for decision-makers across various domains. Nevertheless, the proposed method presents certain limitations when compared to other multi-criteria decision-making (MCDM) techniques. In particular, the EBPM method is sensitive to zero and negative values, which may limit its flexibility in certain application domains. In such cases, the application of Z-standardization scores, as suggested by Zhang et al. (2014), is recommended. In other words, by transforming the values in the decision matrix into Z-standardization scores, all data can be converted into positive numbers, thereby preserving the applicability of the EBPM method. Another significant limitation emerges when the standardized criterion values of alternatives are very close to one another. Under such circumstances, the method's discriminative capacity and computational precision may diminish, making it more challenging to identify meaningful differences between alternatives. To address this issue, it is advisable to employ high-precision numerical operations within the scope of advanced mathematical computation. This would allow for the clearer detection of subtle differences between alternatives, thereby enhancing the method's discriminative performance.

Moreover, this study offers significant contributions to the MCDM literature from several perspectives. Firstly, while the entropy method has traditionally been utilized as a tool for weighting criteria, this research introduces a novel application by employing it directly to measure the performance of alternatives, thus providing a new perspective to the literature. This approach broadens the application potential of the entropy method in decision-making problems.

Furthermore, by integrating information theory and the concept of entropy into MCDM methodology, this study presents an innovative framework that evaluates alternatives not only based on their quantitative



attributes but also on the informational value they provide. The proposed method (EBPM) constitutes an original methodology that assesses the knowledge-generating capacity of alternatives, thereby enabling decision-makers to perform more comprehensive and qualitative analyses. Additionally, the use of entropy as the foundation of the method introduces an interdisciplinary perspective to the MCDM field, facilitating the integration of knowledge from diverse disciplines into decision-making processes.

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Although the present study demonstrates the potential of the proposed EBPM method in the MCDM domain, it also offers several avenues for future research. First, addressing the current limitations of the method may constitute a major focus for subsequent studies. Specifically, solutions can be sought for issues such as the method's sensitivity to zero and negative values, and the diminished discriminatory power when the criterion values of alternatives are closely aligned. In this regard, the adoption of alternative normalization techniques or the development of methodological modifications may be considered. Second, testing the method across various application domains would provide greater insight into its effectiveness and generalizability. Implementing the method with data from different sectors and decision-making problems could help to more clearly identify its strengths and weaknesses. Third, integrating the EBPM method into decision support systems could enable decision-makers to utilize the approach more easily and effectively, thereby enhancing its dissemination and impact on decision-making processes. Fourth, improving visualization techniques to better present the method's outcomes is essential; effective visualization tools can assist decision-makers in interpreting results more intuitively and integrating them into their decision-making processes.

The proposed EBPM is not merely a theoretical tool grounded in the concept of entropy; it also creates a tangible impact on real-world decision-making processes by offering high informational performance to decision-makers. In this context, EBPM reduces the level of uncertainty encountered during the evaluation of alternatives, thereby enabling decisions to be made based on high-quality, information-rich foundations

rather than relying on intuition or subjective judgments. For instance, in the context of policy development, EBPM provides an objective assessment of the informative value of policy alternatives, guiding decision-makers in identifying which option possesses greater strategic impact potential. Similarly, in business strategy formulation, it facilitates the information-based comparison of investment projects or market offerings, allowing organizations to make more rational, data-driven, and sustainable strategic decisions. Therefore, EBPM is not merely an abstract decision-support model but a practical method that enhances the strategic orientation of decision-makers by grounding their choices in measurable, reliable, and information-rich foundations.

## **5. Conclusion**

This study proposes the EBPM method, which provides an information-based alternative performance measurement for MCDM problems. The developed method transforms the classical Shannon Entropy function into a continuously increasing structure through a specific standardization, without manipulating the original entropy function, and measures the potential of alternatives to provide information accordingly. The EBPM method has demonstrated stable and reliable results both in simulation analyses and comparative evaluation studies. Particularly, its high sensitivity, ranking stability, and structural flexibility across various scenarios have led to strong performance from both theoretical and practical perspectives.

The high correlation of the method with different MCDM techniques enhances the validity of EBPM in the current literature and enables integrated analyses between methods. Additionally, its information measurement-based approach provides a multi-dimensional evaluation by considering not only the criterion weights but also the informative value that alternatives present to the decision-maker.

In conclusion, the EBPM method can be considered as an innovative MCDM approach that provides objective, stable, and information-based decision support, contributing both theoretically and methodologically to the literature. Future studies could further increase the method's validity by applying it across different sectors and facilitating its integration into decision support systems.

Although the present study demonstrates the potential of the proposed EBPM method in the MCDM domain, it also offers several avenues for future research. First, addressing the current limitations of the method may constitute a major focus for subsequent studies. Specifically, solutions can be sought for issues such as the method's sensitivity to zero and negative values, and the diminished discriminatory power when the criterion values of alternatives are closely aligned. In this regard, the adoption of alternative normalization techniques or



the development of methodological modifications may be considered. Second, testing the method across various application domains would provide greater insight into its effectiveness and generalizability. Implementing the method with data from different sectors and decision-making problems could help to more clearly identify its strengths and weaknesses. Third, integrating the EBPM method into decision support systems could enable decision-makers to utilize the approach more easily and effectively, thereby enhancing its dissemination and impact on decision-making processes. Fourth, improving visualization techniques to better present the method's outcomes is essential; effective visualization tools can assist decision-makers in interpreting results more intuitively and integrating them into their decision-making processes. Finally, exploring the potential integration of the EBPM method with other MCDM approaches may lead to the development of more comprehensive and robust decision-making frameworks. The scope of the EBPM method can be further expanded through future research endeavors. For instance, applying the EBPM approach to decision-making problems in various domains such as healthcare, energy, environmental management, supply chain optimization, and sustainable development could provide valuable insights into its interdisciplinary applicability. Moreover, integrating EBPM with uncertainty-based MCDM approaches—such as fuzzy logic, grey system theory, rough set theory, or D-numbers—has the potential to enhance its methodological flexibility in decision environments characterized by ambiguity. Another promising research direction involves adapting the method to group decision-making processes or multi-layered (hierarchical) decision models. Additionally, evaluating the method's computational efficiency, processing time, and algorithmic performance when applied to large-scale datasets is crucial for assessing its practical scalability. Finally, conducting parameter sensitivity analyses on components such as normalization techniques, entropy coefficients, and weighting strategies will contribute to a deeper understanding of the method's behavior across different data structures and decision contexts.

## Author Contributions

The percentages of the author' contributions are presented below. The author reviewed and approved the final version of the manuscript.

|     | F.F.A. |
|-----|--------|
| C   | 100    |
| D   | 100    |
| S   | 100    |
| DCP | 100    |
| DAI | 100    |
| L   | 100    |
| W   | 100    |
| CR  | 100    |
| SR  | 100    |
| PM  | 100    |

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management.

## Conflict of Interest

The author declared that there is no conflict of interest.

## Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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