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A scale independent and distribution sensitive approach in multi-criteria decision-making (MCDM): The Canberra distance performance measurement (CADPM) method

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Abstract

This study introduces the Canberra Distance Performance Measurement (CADPM) method, a scale-independent and distribution-sensitive framework developed to address persistent methodological limitations in Multi-Criteria Decision-Making (MCDM), including linear dependency, scale heterogeneity, and inadequate responsiveness to micro-level variations. CADPM evaluates alternatives through proportional, component-wise comparisons and eliminates the need for predefined criterion weights, as the intrinsic structure of the Canberra metric neutralizes scale effects and preserves relative positional relationships. The study also incorporates the Proximity Index Value (PIV) method to ensure a comprehensive comparative setting and to examine weight-free reference-based evaluation under a unified analytical perspective. The empirical assessment comprises both real-data and simulation-based case studies designed to observe the method's robustness under heterogeneous distributions. Sensitivity analyses demonstrate that CADPM is strongly resistant to ranking instability and remains unaffected by systematic weight perturbations. Comparative analyses reveal high concordance between CADPM and established techniques such as MARCOS, TOPSIS, CODAS, WEDBA, and PIV, confirming that the method exhibits structural compatibility while preserving its distinctive proportional sensitivity. Simulation experiments further show that CADPM maintains stable performance patterns across diverse scenario structures, underscoring its consistency under controlled variance, scale, and distributional shifts. The primary advantage of CADPM lies in its ability to amplify subtle proportional differences, particularly in small or near-zero values, which conventional absolute-difference metrics often suppress. This capability enables more equitable and discriminative evaluations in asymmetric or heterogeneous datasets. Overall, CADPM offers a theoretically coherent, computationally stable, and empirically validated contribution to MCDM research. Future work may explore parametric extensions, hybrid integrations with reference-based models, and broader applications across complex decision environments.

Keywords CADPM, MCDM, Canberra distance

Jel Codes C44, C61, D81

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1. Introduction

The rapid escalation of data complexity on a global scale has rendered traditional evaluation frameworks increasingly inadequate for addressing multidimensional decision-making problems (Mukhametzyanov, 2021). In particular, when criteria of varying scales, heterogeneous structures, or asymmetric distributions are simultaneously considered, the demand for reliable, balanced, and scale-independent analytical approaches has intensified markedly (Kulkarni, 2022). Within this context, Multi-Criteria Decision-Making (MCDM) techniques have emerged as indispensable tools that enable systematic and objective comparisons among alternatives (Thanh, 2020). Nevertheless, most existing models operate either through utility-based mechanisms grounded in absolute differences such as SAW, WPM, WASPAS, MAUT, and ROV or through reference-point-oriented distance formulations exemplified by TOPSIS, CODAS, WEDBA, EDAS, ARAS, MARCOS, PIV, MAIRCA, PSI, MABAC and CRADIS. Such dependence can constrain both the discriminative capacity and sensitivity of these methods, particularly in data environments where small variations exert a decisive influence or where criteria of differing magnitudes coexist.

Accordingly, the primary objective of this study is to develop a performance-measurement framework that effectively addresses the inherent limitations of conventional distance and utility-based models by ensuring proportional sensitivity, normalization, and independence from scale disparities. To this end, the proposed Canberra Distance Performance Measurement (CADPM) method introduces an innovative analytical paradigm that evaluates decision alternatives not merely through absolute deviations but through the proportional disparities of each component. At the core of this approach lies the Canberra distance, whose intrinsic sensitivity to small values and ability to balance scale heterogeneity mitigate the weaknesses typically observed in Euclidean and Manhattan formulations (Lance & Williams, 1966). Consequently, CADPM facilitates coherent comparison across heterogeneous criteria while ensuring that minor deviations are accurately and proportionally reflected in the final decision outcomes.

From a motivational standpoint, the Canberra metric has demonstrated exceptional precision and sensitivity across a wide spectrum of scientific domains. In ecology, for instance, it has been effectively employed in evaluating species diversity (Borcard et al., 2018); within cybersecurity, it has yielded robust outcomes in intrusion-detection frameworks (Emran & Ye, 2002); and in text mining, it has proven valuable for measuring semantic similarity (Jurman et al., 2009). Despite this broad empirical validation, the systematic integration of such a powerful metric into the field of MCDM has remained notably underexplored. Addressing this methodological gap, the present study introduces a non-parametric framework that incorporates the Canberra distance into the MCDM process for the first time.

Despite substantial progress in the development of objective weighting and performance-measurement techniques, existing MCDM approaches continue to exhibit several notable limitations particularly in their ability to preserve proportional sensitivity and distributional responsiveness. Many distance- and utility-based models struggle to differentiate alternatives in datasets that contain subtle yet meaningful variations, while small or near-zero components are frequently overshadowed by larger-scale criteria. Moreover, the stability and discriminatory capacity of these models often diminishes in heterogeneous decision environments, especially when criterion scales differ markedly. These methodological constraints highlight the need for a performance-assessment framework capable of ensuring scale independence, proportional accuracy, and robustness across diverse data structures. In response to these gaps, the present study introduces the CADPM method, designed to address these limitations and offer a more distribution-sensitive evaluation mechanism.

The CADPM method defines the performance of each alternative through proportional distance and similarity measures relative to both the maximum (ideal) and minimum (anti-ideal) reference points, thereby providing a more comprehensive analytical perspective than conventional reference-based approaches. Owing to the component-wise normalization inherent in the Canberra metric, the effects of differing criterion scales are balanced, and biases arising from distributional disparities within the decision matrix are minimized. Furthermore, CADPM establishes a methodological bridge between utility-based models (such as SAW, WPM, WASPAS, MAUT, and ROV) and reference-oriented frameworks (including TOPSIS, CODAS, WEDBA, and MARCOS), effectively integrating the strengths of both paradigms into a unified structure.

This study also directly addresses two persistent challenges frequently emphasized in the literature scale sensitivity and the inadequate representation of micro-level variations. Since existing methods often fail to normalize component-wise differences, performing equitable comparisons across criteria expressed in heterogeneous units becomes problematic. CADPM overcomes this limitation by introducing a dual-level assessment mechanism that is simultaneously scale-independent and component-sensitive, ensuring a more accurate and consistent evaluation of performance. Consequently, the method demonstrates clear superiority over traditional techniques in terms of both statistical robustness and decision reliability. Nevertheless, the Canberra metric's high responsiveness to near-zero values may, in certain circumstances, amplify measurement noise or minor data inaccuracies. Additionally, the computation of proportional similarity and distance relative to both ideal and anti-ideal points can increase algorithmic complexity when applied to high-dimensional datasets. These constraints, however, can be mitigated in future research through hybrid model development and parameter optimization strategies. In summary, this study presents the first systematic framework that integrates the Canberra distance into decision science, offering substantial theoretical, methodological, and practical contributions to the MCDM literature. The CADPM approach exhibits strong potential for enabling equitable evaluation across criteria with differing measurement scales, accurately representing subtle variations, and producing statistically consistent decision outcomes.

2. Material and Method

2.1. Distinctive Features of the Assessed MCDM Methods

MCDM methodologies in the literature are primarily grounded in two fundamental paradigms. The first encompasses approaches that assess the performance of each alternative solely on the basis of its own criterion values, without explicitly referring to maximum, minimum, ideal, anti-ideal, or optimal–non-optimal reference points (Triantaphyllou, 2010). Within this framework, alternatives are analyzed independently rather than being directly compared with one another (Munier, 2024). This methodological design offers decision-makers a straightforward, transparent, and interpretable analytical setting particularly advantageous when dealing with heterogeneous datasets (Taherdoost, 2023).

Among the most established techniques under this paradigm, the Simple Additive Weighting (SAW) method determines the performance score of each alternative by summing the products of normalized criterion values and their corresponding weights (Ciardiello & Genovese, 2023; Sutoyo, 2025). The Weighted Product Model (WPM), on the other hand, employs a multiplicative structure in which each normalized criterion value is raised to the power of its assigned weight before all are multiplied together to derive a composite performance index. Consequently, its computational logic diverges structurally from the additive nature of SAW (Goswami et al., 2020). In both models, evaluation is conducted primarily through the intrinsic criterion profile of each alternative; hence, the methodological emphasis lies on the weighted aggregation of alternative criterion relationships rather than on pairwise comparisons among alternatives (Nasyuha et al., 2025).

The Weighted Aggregated Sum Product Assessment (WASPAS) method integrates these two lines of reasoning within a single parametric framework by combining additive (SAW/WPM) and multiplicative (WPM) components to generate a unified performance score. This hybrid formulation simultaneously exploits the strengths of both linear and multiplicative aggregation schemes (Kumar & Rajak, 2025). Accordingly, in WASPAS, the performance of each alternative is evaluated based on its inherent criterion structure (Arivendan et al., 2025; Barbara et al., 2023). The integrated nature of WASPAS explicitly builds upon the classical WSM/WPM formulation and has been extensively validated in the literature through a wide array of empirical and comparative applications (Zavadskas et al., 2012).

On the other hand, the Multi-Attribute Utility Theory (MAUT) transforms criterion values onto a common evaluative scale and defines partial (single-attribute) utility functions for each attribute. Depending on the problem context, these functions may be selected from parametric families such as logarithmic or exponential forms and are subsequently aggregated through weighting to obtain an overall composite utility score (Durak, 2025). The reasoning behind MAUT is grounded not in ideal or anti-ideal comparisons, but in the level of utility derived from the intrinsic attribute values of each alternative. When appropriate independence conditions are satisfied, the individual utilities are combined additively or multiplicatively according to their respective weights (Begam & Majumder, 2024; Jameel et al., 2026).

The Range of Value (ROV) method, in turn, incorporates both benefit- and cost-oriented criteria by merging normalized values through arithmetic or weighted means to produce an integrated performance index (Madić et al., 2016). A key characteristic of ROV is that it evaluates each alternative independently, based solely on its own data, without invoking comparisons to any ideal, anti-ideal, or other reference points (Mitra, 2021). In summary, approaches such as SAW, WPM, WASPAS, MAUT, and ROV assess alternatives strictly in terms of their intrinsic criterion profiles. By operating without an explicit comparative or reference-based structure, these absolute evaluation methods offer results that are computationally efficient, methodologically transparent, and easily interpretable features that make them particularly practical for decision-makers (Munier et al., 2019; Thakkar, 2021).

A second major family of methods adopts comparative (reference-based) reasoning for performance assessment. Within this framework, alternatives are analyzed not only according to their absolute criterion values but also in relation to their positional standing vis-à-vis other alternatives (Opricovic & Tzeng, 2004). This relational logic enriches the evaluation process by incorporating measures of relative superiority, distance, and proximity, thereby enhancing both the scope and precision of decision analysis (Keshavarz Ghorabaee et al., 2016). In such methods, performance is determined with respect to specific benchmark points commonly maximum, minimum, ideal, anti-ideal, optimal, or anti-optimal references (Stević et al., 2020).

To quantify advantages or disadvantages relative to these benchmarks, distance metrics, relative closeness coefficients, or positional indices are frequently employed. For example, TOPSIS and WEDBA compute relative closeness coefficients to the positive and negative ideal solutions using Euclidean distance (Hwang & Yoon, 1981; Rao & Singh, 2012); CODAS utilizes both Euclidean and Manhattan distances from the negative-ideal point (Keshavarz Ghorabaee et al., 2016); EDAS evaluates positive and negative deviations from the mean solution (Keshavarz Ghorabaee et al., 2015); while MARCOS determines performance based on positioning with respect to ideal and anti-ideal references (Stević et al., 2020). Among the reference-based methods, the TOPSIS has emerged as one of the most widely adopted and influential approaches (Chaipetch et al., 2025; Corrente & Tasiou, 2023). The fundamental assumption underlying TOPSIS is that the most desirable alternative should exhibit the shortest distance from the Positive Ideal Solution (PIS) and the farthest distance from the Negative Ideal Solution (NIS) (Doğruel, 2025; Han et al., 2024). The procedure begins with the normalization of all criterion values to ensure mutual comparability (Petrović et al., 2025). Subsequently, the highest values of benefit-type criteria and the lowest values of cost-type criteria are identified as the respective ideal reference points, thereby defining the PIS and NIS (Alqoud et al., 2025). In the following step, the Euclidean distances between each alternative's weighted normalized performance vector and both reference points are calculated (Lin & Chang, 2025). These distance measures are then utilized to compute the relative closeness coefficient of each alternative to the ideal solution. A higher coefficient indicates that an alternative lies closer to the PIS and farther from the NIS, and is therefore considered superior (Alam Sur et al., 2025).

Within the same comparative paradigm, the Additive Ratio Assessment (ARAS) method evaluates alternatives by expressing their performance in terms of proportional relationships to optimal reference values (Turskis & Keršulienė, 2024). Initially, data are transformed into a benefit-oriented form by accounting for the direction of each criterion, ensuring that higher values consistently represent greater preference (Fan et al., 2023). In the subsequent stage, the maximum value (or the best attainable benchmark) for each criterion is adopted as the optimal reference, and the normalized performance of each alternative is expressed as a ratio of this optimal value (Pena et al., 2025). These ratios are then multiplied by the corresponding criterion weights to determine the weighted performance contributions, which are aggregated across all criteria to obtain each alternative's overall weighted score (Kumari & Acherjee, 2025). The alternative achieving the highest total weighted score is interpreted as the most favorable option, as it demonstrates the closest composite alignment with the optimal benchmark across all criteria (Pisal et al., 2025).

Conversely, the Evaluation Based on Distance from Average Solution (EDAS) method evaluates alternatives by measuring their deviations from an average solution defined separately for each criterion (Torkayesh et al., 2023). For every alternative, deviations relative to the mean are quantified as Positive Distance from Average (PDA) and Negative Distance from Average (NDA), respectively (Goswami et al., 2025). In benefit-type criteria, values exceeding the mean generate higher PDA scores, while in cost-type criteria, values below the mean contribute positively to PDA; this formulation ensures that "better" orientations are systematically captured according to each criterion (Ramancha &

Ballamudi, 2023). In contrast, NDA represents the degree of disadvantage or unfavorable deviation from the mean (Bhola et al., 2025). These deviations are then multiplied by their respective criterion weights to yield weighted positive (SP) and weighted negative (SN) distance measures a principle that remains consistent across modern EDAS variants, including those based on cumulative prospect theory or fuzzy extensions (Wang et al., 2024). In the decision logic of EDAS, a high SP and a low SN jointly indicate strong overall performance, meaning that an alternative maximizes its positive contributions while minimizing adverse deviations relative to the average (Ghanbari et al., 2025). Thus, EDAS offers a dual-perspective evaluation framework that simultaneously accounts for both advantageous and disadvantageous deviations in a unified structure (Boujelben & Souissi, 2025).

The Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) method evaluates the performance of alternatives by simultaneously considering their proximity to the ideal solution and their distance from the anti-ideal one (Cheng et al., 2024). In this approach, each criterion value is multiplied by its respective weight to construct a weighted decision matrix, followed by the identification of ideal and anti-ideal reference points for each criterion (Arman et al., 2026). Subsequently, the distances of all alternatives from these two reference points are computed; a shorter distance to the ideal point signifies stronger performance, while a greater distance from the anti-ideal point reflects avoidance of undesirable outcomes (Ashraf et al., 2024). The key contribution of CRADIS lies in its integration of both distance measures into a unified evaluation scheme, yielding a balanced and comprehensive ranking (Zhang & Esangbedo, 2025).

Within the domain of MCDM, another influential approach is the Multi-Attributive Border Approximation area Comparison (MABAC) method (Liu et al., 2024). The central premise of MABAC is to assess alternative performance in relation to a border approximation area defined within the decision space (Atan & Altan, 2020). Initially, criterion values are multiplied by their respective weights to generate a weighted decision matrix (Jafari & Naghdi Khanachah, 2024). The next stage involves determining the border approximation area matrix, which serves as a reference boundary for the evaluation process (Demir & Kartal, 2021). Thereafter, the differences between each alternative's weighted criterion values and the corresponding boundary values are calculated (Alhadidi et al., 2025). If a given alternative exceeds the boundary for a particular criterion, it is positioned within the superior approximation region, indicating relatively strong performance; conversely, falling below the boundary denotes placement within the inferior region, reflecting weaker performance (Dai et al., 2024). Finally, the positive and negative deviations across all criteria are aggregated to derive a total performance score for each alternative, thus producing a systematic and balanced ranking based on relative proximity to the pre-defined boundary reference (Kizielewicz et al., 2025).

The Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) method, in turn, offers a comprehensive decision-support framework aimed at determining the relative utility levels of alternatives (Demir & Özyalçın, 2021). The procedure begins by defining the ideal (best) and anti-ideal (worst) solutions using the initial values in the decision matrix, where the highest benefit-type and lowest cost-type criterion values correspond to ideal references (Andrejić & Pajić, 2025; Yu et al., 2024). Subsequently, utility functions for each alternative are computed by incorporating the respective criterion weights, allowing for the assessment of each alternative's proportional closeness to both the ideal and anti-ideal benchmarks (El-Araby et al., 2024; Sehgal et al., 2025). Consequently, MARCOS provides a holistic analytical structure that captures not only the absolute performance levels but also the positional relationships of alternatives within the decision space relative to both optimal and non-optimal reference points (Yu et al., 2024).

The Multi-Attribute Ideal-Real Comparative Analysis (MAIRCA) method introduces a distinctive decision model founded on minimizing the gap between theoretical (ideal) expectations and actual (real) performance outcomes (Mukhametzyanov & Pamucar, 2025). In its initial phase, selection probabilities for each alternative are determined from the decision matrix. These probabilities are then combined with criterion weights to construct a theoretical evaluation matrix, which represents the decision-maker's ideal expectations (Ecer, 2020). Next, the real evaluation matrix is generated by accounting for distances to the minimum for benefit-type criteria and to the maximum for cost-type criteria (Chatterjee & Chakraborty, 2021). The difference between the theoretical and real values is subsequently quantified; smaller gaps indicate that an alternative aligns more closely with the decision-maker's preferences and demonstrates stronger performance (Ecer, 2022). In this regard, MAIRCA provides an integrative framework that unites objective criterion information with normative expectations. Recent studies from 2023 to 2025, including those exploring fuzzy and probabilistic extensions, confirm the continued robustness of this theoretical foundation (Chen, 2025).

The Proximity Index Value (PIV) method represents a robust and computationally efficient framework for evaluating the performance of alternatives in MCDM problems (Karadağ, 2024). The central premise of the method is that, for benefit-type criteria, alternatives located closer to a predefined maximum (best) reference point are considered superior, whereas for cost-type criteria, alternatives positioned farther from this maximum reference are regarded as more favorable (Mufazzal & Muzakkir, 2018). To achieve this, proportional distances of each alternative from the maximum reference point are calculated across all criteria. These proximity or distance measures are then integrated with the corresponding criterion weights to derive a composite preference index that reflects the overall performance of each alternative (Sahoo et al., 2024). The PIV method has been widely applied in both deterministic and fuzzy environments, demonstrating consistent ranking stability and discriminative capability across diverse decision contexts such as supplier selection, electric-vehicle evaluation, and finance or production-oriented MCDM problems (Do et al., 2025)

The Weighted Euclidean Distance-Based Approach (WEDBA) provides another analytical framework that systematically assesses the performance of alternatives within MCDM settings (Aksoy Erzurumlu & Gençtürk, 2025). In this approach, maximum values of benefit-type criteria and minimum values of cost-type criteria are designated as ideal reference points, while their respective opposites serve as anti-ideal points (Al-Hawari, 2019). For each alternative, Euclidean distances to both the ideal and anti-ideal points are computed; an alternative positioned closer to the ideal and farther from the anti-ideal is deemed to exhibit superior relative performance (Tuş & Adalı, 2025). By simultaneously accounting for both positive (ideal) and negative (anti-ideal) reference perspectives, WEDBA produces a balanced and comprehensive ranking of alternatives within the decision space (Rao & Singh, 2012). Recent studies have also extended WEDBA to hybrid and fuzzy environments, confirming its adaptability beyond classical crisp data conditions.

The Combinative Distance-Based Assessment (CODAS) method, likewise, offers a robust hybrid mechanism for ranking alternatives in MCDM problems, primarily by focusing on distances from the negative-ideal solution (Suriyanto et al., 2025). The procedure begins with the construction and normalization of the decision matrix, followed by the application of criterion weights (Lukić, 2025).

For each criterion, a negative-ideal point is then established, and both Euclidean and Manhattan distances from this point are calculated for every alternative. These two distance measures are integrated through a threshold-based mechanism to form the Relative Evaluation Matrix (REM). In the final step, an overall performance score (H_i) is derived for each alternative, which serves as the basis for the final ranking (Singh, 2025). By concurrently considering closeness to the ideal and remoteness from the anti-ideal, CODAS delivers a mathematically consistent, well-balanced, and highly interpretable assessment framework that remains valid under both linear and nonlinear criterion characteristics (Shafizadeh & Hossein Mousavizadegan, 2025).

The Preference Selection Index (PSI) approach represents a statistically grounded, data-oriented MCDM framework that dispenses with the requirement for predetermined criterion weights (Lozynskyi, 2025). Following the construction of the decision matrix, all criterion values undergo normalization, after which a preference variance is derived for each criterion to capture its degree of dispersion relative to the mean (Towaiq et al., 2025). These deviation metrics interpreted as distance measures are then transformed into statistical preference intensities by subtracting each from unity, and the resulting values are normalized to yield the general preference coefficients (Maniya & Bhatt, 2010). In this way, the evaluation of alternatives simultaneously incorporates both the deviation of their criterion scores from the mean and the discriminatory power inherent to each criterion (Demir & Kartal, 2021). Ultimately, alternatives are ordered according to a composite index calculated using these preference coefficients, leading to the final PSI-based ranking (Wang & Zhang, 2022).

2.2. Canberra Distance

The Canberra distance is a metric that quantifies dissimilarity by normalizing the absolute difference between corresponding components of two vectors through division by the sum of their absolute values, and subsequently summing these normalized ratios across all dimensions (Lance & Williams, 1966; 1967). In essence, this formulation captures proportional discrepancies rather than absolute deviations, thereby enhancing sensitivity to variations among small-valued components. The mathematical representation of the Canberra distance is provided below (Abu Alfeilat et al., 2019).

$$d(x,y) = \sum_{i=1}^{m} \frac{|p_i - q_i|}{|p_i| + |q_i|}, p, q \in R^n \tag{1}$$

In Eq. 1, m denotes the dimensionality of the data sequences (i.e., the total number of components), while i represents the i-th element within those sequences. In the formulation, the difference between the corresponding components of two vectors is normalized by dividing it by the sum of the absolute values of those components (Abu Alfeilat et al., 2019; Levy et al., 2024). This structure ensures that not only the absolute disparity but also its relative significance is taken into account. Consequently, even in cases where component values are small or approach zero, subtle distinctions among them become more clearly discernible.

Moreover, the normalization term in the denominator prevents variables of larger magnitude or differing measurement scales from dominating the distance computation, thereby enabling a fairer and more balanced comparison across heterogeneous dimensions (Cha, 2007). Through this component-wise normalization, the Canberra distance captures both the magnitude and proportional importance of deviations, making it particularly effective in emphasizing minor yet meaningful variations and allowing equitable evaluation of variables expressed in different units or scales (Borcard et al., 2018; Math.NET Numerics, 2025; R Documentation, 2025). Because the Euclidean distance relies on squared differences, it disproportionately amplifies the influence of outliers, whereas the Manhattan (L_1) distance simply aggregates absolute differences without incorporating any relative scale information. In contrast, the Canberra distance, through its normalization mechanism that divides each absolute difference by the sum of the corresponding component magnitudes, provides a more balanced evaluation of data components with heterogeneous scales (Math.NET Numerics, 2025).

While cosine similarity measures directional resemblance by suppressing magnitude differences, the Canberra metric captures both direction and proportional magnitude variation simultaneously. The Jaccard and Tanimoto indices are specifically designed for binary or set-based data, whereas Canberra accounts for each component's contribution proportionally within continuous vector representations (Jurman et al., 2009). Similarly, Hellinger-type measures, typically used for compositional or probabilistic data, rely on transformed representations, whereas Canberra directly quantifies normalized differences at the component level, offering an intuitive and scale-independent interpretation (Borcard et al., 2018).

The Canberra distance possesses two principal strengths that distinguish it from conventional dissimilarity metrics: (i) its pronounced responsiveness to low-magnitude or sparse numerical values, and (ii) its inherent ability to equilibrate differences in scale among variables (Borcard et al., 2018). Owing to these characteristics, the measure successfully mitigates the limitations inherent in other distance formulations. For instance, the Euclidean distance tends to overweight extreme observations due to its squared-difference formulation; the Manhattan distance captures only absolute deviations without considering their relative importance; and the Cosine similarity disregards magnitude variations entirely. Similarly, measures such as Jaccard and Tanimoto are restricted to binary or set-theoretic data representations, whereas the Canberra distance proportionally incorporates the contribution of each component within continuous-valued datasets. In contrast to distribution-oriented indices like Hellinger or Matusita, which demand probabilistic transformations or abstract statistical interpretations, the component-wise normalization scheme of the Canberra formulation yields a more tangible and conceptually transparent framework for quantifying dissimilarity (Roberts, 2017).

Extensive empirical evidence from various scientific domains substantiates the advantages of the Canberra distance. In ecological research, for instance, it has become one of the most frequently employed dissimilarity measures alongside the Bray Curtis index for quantifying differences in species composition and has demonstrated remarkable reliability in evaluating functional diversity (Legendre & Legendre, 2012). Within microbiome studies, where the selection of an appropriate distance metric critically determines beta-diversity estimation and clustering accuracy, the Canberra metric has consistently outperformed others in distinguishing taxa of low relative abundance (Kuczynski et al., 2010; Mayer et al., 2024; Shi et al., 2022). In the field of cybersecurity, Emran & Ye (2002) showed that Canberra exhibits exceptional robustness to noise when utilized in intrusion detection frameworks. Moreover, in text mining and information retrieval applications, it has gained increasing recognition for its precision in author profiling and ranked-list similarity analyses, where it effectively captures subtle positional and semantic variations (Jurman et al., 2009; Kocher & Savoy, 2017). Taken together, these multidisciplinary findings highlight that the Canberra distance is particularly advantageous in contexts emphasizing small-value sensitivity, heterogeneous variable scales, and the interpretive importance of relative deviations. Consequently, it should be regarded not merely as a theoretical construct but as a thoroughly validated and empirically proven distance function, offering demonstrable analytical superiority across a wide spectrum of research and applied disciplines.

2.3. Proposed Method: Canberra Distance Performance Measurement (CADPM)

In reference-oriented comparative evaluation frameworks, the performance of each decision alternative across multiple criteria is assessed relative to predefined benchmark points such as ideal, anti-ideal, maximum, minimum, optimal, or sub-optimal reference values (Munier, 2024). The central objective of this approach is to determine the positional standing of each alternative with respect to these benchmarks and, in doing so, to quantify its relative superiority in an objective and structured manner (Kulkarni, 2022). To achieve this, various quantitative techniques such as distance metrics, proximity indices, and relative closeness coefficients are employed to model the relationships between alternatives and reference values (typically the maximum and minimum points) in a mathematically rigorous way (Lopez et al., 2023; Triantaphyllou, 2010). Consequently, the decision-making process extends beyond the mere comparison of absolute criterion values to incorporate the spatial positioning of alternatives within the reference space (Stević et al., 2020). This integrated perspective enables a more nuanced, holistic, and analytically robust assessment procedure (Zavadskas & Podvezko, 2016). Within this conceptual framework, the method proposed in this study aligns fully with the reference-based paradigm. Specifically, the approach operationalizes the Canberra distance metric to measure the similarity between the weighted and normalized performance values of each alternative and the maximum and minimum boundaries derived from the alternative set. In this way, the positional relationships of alternatives to these reference points can be systematically analyzed. The sequential computational steps of the proposed method are detailed in the following section.

- $i : 1, 2, 3...m$, where m represents the number of decision alternatives
- $j : 1, 2, 3, ...n$, where n represents the number of criteria
- G: Decision matrix
- C: Criterion
- A: Alternative
- g_{ij}: g represents the i-th decision alternative on the j-th criterion.

Step 1: Construction of the Decision Matrix (G)

The initial stage of the proposed analytical framework involves establishing the preliminary evaluation matrix, as illustrated in Eq. 2. At this stage, the quantitative performance indicators corresponding to each alternative, measured under the defined set of evaluation criteria, are systematically arranged within a structured matrix framework. This matrix constitutes the essential reference dataset that underpins all subsequent stages of the MCDM process, serving as the analytical foundation for deriving comprehensive comparative assessments among the considered alternatives.

$$[g_{ij}]_{bxc} = \begin{array}{c} A \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} C_1 & C_2 & \cdots & C_n \\ g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ g_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix} \tag{2}$$

Step 2: Obtaining of the Normalized Decision Matrix (G^*)

Normalization is a fundamental requirement in multi-criteria decision-making (MCDM) methods, primarily because the criteria involved often differ markedly in scale and magnitude. The literature emphasizes that, particularly in reference-point-based techniques such as TOPSIS, MARCOS, and CODAS, transforming raw values onto a common scale is essential for ensuring meaningful comparability (Hwang & Yoon, 1981; Zavadskas & Podvezko, 2016). Accordingly, the first normalization step in the CADPM procedure serves to align all criteria on an equivalent measurement plane. However, owing to the intrinsic nature of the Canberra Distancewhich performs proportional, component-wise comparisons the subsequent conversion of distance values into similarity indices necessitates an additional layer of scale standardization. This transformation corresponds to what the literature describes as “secondary normalization” or “derivative normalization,” a process frequently employed in reference-based analytical frameworks to render distance measures interpretable, comparable, and suitably constrained within a 0–1 range. In other words, while the initial normalization harmonizes the criteria themselves, the secondary normalization harmonizes the resulting distances. This two-stage approach enhances measurement sensitivity in multidimensional decision settings and yields a clearer, more interpretable separation between the ideal and anti-ideal reference points.

In the second phase, the numerical values contained in the initial decision matrix are normalized to achieve uniformity and comparability among all evaluation criteria. To accomplish this, benefit-type criteria are adjusted in accordance with Eq. 3, whereas cost-type criteria are transformed following the procedure described in Eq. 4. After performing these normalization operations, the normalized evaluation matrix is systematically constructed as defined by Eq. 5. This conversion produces a harmonized and dimensionless dataset, providing a rigorous quantitative foundation for the ensuing stages of the multi-criteria decision analysis and ensuring the integrity and balance of subsequent evaluations.

$$g_{ij}^* = \frac{g_{ij}}{g_{ij}^{\max}} \tag{3}$$

$$g_{ij}^* = \frac{g_{ij}^{\min}}{g_{ij}} \tag{4}$$

$$G^* = [G_{ij}]^* = \begin{array}{c} A \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} C_1 & C_2 & \cdots & C_n \\ g_{11}^* & g_{12}^* & \cdots & g_{1n}^* \\ g_{21}^* & g_{22}^* & \cdots & g_{2n}^* \\ \vdots & \vdots & \cdots & \vdots \\ g_{m1}^* & g_{m2}^* & \cdots & g_{mn}^* \end{bmatrix} \tag{5}$$

Step 3: Evaluation of the Canberra Distance Between Alternatives and the Maximum $\left(CD(A_i, A_{\max.})_{\text{Distance}}\right)$ and Minimum Points $\left(CD(A_i, A_{\min.})_{\text{Distance}}\right)$

In this phase, the spatial separation of each decision alternative from the designated reference points namely the maximum (ideal) and minimum (anti-ideal) performance vectorsis computed by employing the Canberra Distance (CD) metric. Specifically, Equations 6–9 define the calculation of distances to the maximum (ideal) performance vector, while Equations 10–13 describe the corresponding computation for the minimum (anti-ideal) performance vector. Through this procedure, the positional deviation of each alternative from the optimal and suboptimal boundaries is quantitatively determined, thereby enabling a structured assessment of their relative standing within the decision space. The resulting distance measures facilitate a more rigorous and fine-grained comparison among the alternatives. Moreover, the application of the CD metric to the weighted and normalized performance values provides enhanced discriminative sensitivity and interpretive depth, offering a more robust and meaningful distinction between alternatives than conventional distance-based approaches

$$\left(CD(A_i, A_{\max.})_{\text{Distance}}\right) = \sum_{i=1,\, j=1}^{m} \frac{\left|w_j g_{ij} - \max ._{C_j}\right|}{\left|w_j g_{ij}\right| + \left|\max ._{C_j}\right|} \tag{6}$$

$$\left(CD(A_1, A_{\max.})_{\text{Distance}}\right) = \frac{\left|w_1 g_{11} - \max ._{C_1}\right|}{\left|w_1 g_{11}\right| + \left|\max ._{C_1}\right|} + \frac{\left|w_2 g_{12} - \max ._{C_2}\right|}{\left|w_2 g_{12}\right| + \left|\max ._{C_2}\right|} \ldots + \frac{\left|w_n g_{1n} - \max ._{C_n}\right|}{\left|w_n g_{1n}\right| + \left|\max ._{C_n}\right|} \tag{7}$$

$$\left(CD(A_1, A_{\max.})_{\text{Distance}}\right) = \frac{\left|w_1 g_{21} - \max ._{C_1}\right|}{\left|w_1 g_{21}\right| + \left|\max ._{C_1}\right|} + \frac{\left|w_2 g_{22} - \max ._{C_2}\right|}{\left|w_2 g_{22}\right| + \left|\max ._{C_2}\right|} \ldots + \frac{\left|w_n g_{2n} - \max ._{C_n}\right|}{\left|w_n g_{2n}\right| + \left|\max ._{C_n}\right|} \tag{8}$$

$$\ldots \ldots$$
$$\ldots \ldots$$
$$\ldots \ldots$$

$$\left(CD(A_1, A_{\max.})_{\text{Distance}}\right) = \frac{\left|w_1 g_{m1} - \max ._{C_1}\right|}{\left|w_1 g_{m2}\right| + \left|\max ._{C_1}\right|} + \frac{\left|w_2 g_{m2} - \max ._{C_2}\right|}{\left|w_2 g_{m2}\right| + \left|\max ._{C_2}\right|} \ldots + \frac{\left|w_n g_{mn} - \max ._{C_n}\right|}{\left|w_n g_{mn}\right| + \left|\max ._{C_n}\right|} \tag{9}$$

$$\left(CD(A_i, A_{\min.})_{\text{Distance}}\right) = \sum_{i=1,\, j=1}^{m} \frac{\left|w_j g_{ij} - \min ._{C_j}\right|}{\left|w_j g_{ij}\right| + \left|\min ._{C_j}\right|} \tag{10}$$

$$\left(CD(A_1, A_{\min.})_{\text{Distance}}\right) = \frac{\left|w_1 g_{11} - \min ._{C_1}\right|}{\left|w_1 g_{11}\right| + \left|\min ._{C_1}\right|} + \frac{\left|w_2 g_{12} - \min ._{C_2}\right|}{\left|w_2 g_{12}\right| + \left|\min ._{C_2}\right|} \ldots + \frac{\left|w_n g_{1n} - \min ._{C_n}\right|}{\left|w_n g_{1n}\right| + \left|\min ._{C_n}\right|} \tag{11}$$

$$\left(CD(A_1, A_{\min.})_{\text{Distance}}\right) = \frac{\left|w_1 g_{21} - \min ._{C_1}\right|}{\left|w_1 g_{21}\right| + \left|\min ._{C_1}\right|} + \frac{\left|w_2 g_{22} - \min ._{C_2}\right|}{\left|w_2 g_{22}\right| + \left|\min ._{C_2}\right|} \ldots + \frac{\left|w_n g_{2n} - \min ._{C_n}\right|}{\left|w_n g_{2n}\right| + \left|\min ._{C_n}\right|} \tag{12}$$

$$\ldots \ldots$$
$$\ldots \ldots$$
$$\ldots \ldots$$

$$\left(CD(A_1, A_{\min.})_{\text{Distance}}\right) = \frac{\left|w_1 g_{m1} - \min ._{C_1}\right|}{\left|w_1 g_{m2}\right| + \left|\min ._{C_1}\right|} + \frac{\left|w_2 g_{m2} - \max ._{C_2}\right|}{\left|w_2 g_{m2}\right| + \left|\max ._{C_2}\right|} \ldots + \frac{\left|w_n g_{mn} - \max ._{C_n}\right|}{\left|w_n g_{mn}\right| + \left|\max ._{C_n}\right|} \tag{13}$$

Step 4: Transformation of the Canberra Distance (CD) into Canberra Similarity (CS)

In this step, the distance metric originally proposed by Todeschini et al. (2007) is reformulated into a normalized similarity measure through the application of Eq. 14. This transformation enables the representation of relational proximity on a standardized scale, thereby allowing for clearer interpretability within the comparative analysis framework. Subsequently, the degree of similarity between each alternative and the optimal (maximum) reference point is computed using Eq. 15, whereas its resemblance to the anti-optimal (minimum) benchmark is quantified via Eq. 16. This dual evaluation of similarity facilitates a more intuitive and analytically coherent comparison among all alternatives, providing deeper insight into how closely each alternative aligns with the desired performance configuration and diverges from the least favorable reference condition.

$$\text{Similarity} = \frac{1}{1 + \text{Distance}} \tag{14}$$

$$\left(\text{CD } (A_i, A_{\max.})_{\text{Similarity}}\right) = \frac{1}{1 + \text{SC } (\text{ALT}_i, \text{ALT}_{\max.})_{\text{Distance}}} \tag{15}$$

$$\left(\text{CD } (A_i, A_{\min.})_{\text{Similarity}}\right) = \frac{1}{1 + \text{DC } (\text{ALT}_i, \text{ALT}_{\min.})_{\text{Distance}}} \tag{16}$$

Step 6: Calculation of the Performance Superiority Coefficient (PSC_i)

In this stage, the similarity value of each alternative relative to the optimal (maximum) benchmark is normalized with respect to its similarity to the least desirable (minimum) benchmark, as defined in Eq. 17. This normalization process produces the Performance Superiority Coefficient (PSC), which expresses the proportional advantage or relative performance strength of each alternative. In essence, this ratio indicates how many times an alternative's correspondence with the optimal reference point exceeds its association with the anti-optimal boundary. Hence, it provides a clear and dimensionless indicator of comparative superiority within the decision domain. The PSC metric thereby enables a balanced, interpretable, and analytically rigorous comparison among all alternatives, establishing a solid foundation for the final ranking and selection stage of the MCDM process.

$$(\text{PSC}_i) = \frac{\left(\text{CD } (A_i, A_{\max.})_{\text{Similarity}}\right)}{\left(\text{CD } (A_i, A_{\min.})_{\text{Similarity}}\right)} \tag{17}$$

The rationale for using the ratio $\frac{\left(\text{CD } (A_i, A_{\max.})_{\text{Similarity}}\right)}{\left(\text{CD } (A_i, A_{\min.})_{\text{Similarity}}\right)}$ calculating the Performance Superiority Coefficient lies in its ability to provide a high-contrast scale that simultaneously reflects an alternative's proximity to the ideal point and its separation from the anti-ideal point. This ratio is particularly effective in datasets characterized by distributional heterogeneity, as it enhances the discrimination of relative differences among alternatives and reinforces the logic of a reference-based evaluation framework. As the reviewer correctly notes, however, the value of $\left(\text{CD } (A_i, A_{\min.})_{\text{Similarity}}\right)$ approaching zero may cause the ratio to increase sharply, potentially introducing outlier-driven distortions. This statistical behavior is not unique to PSC; similar effects occur in many ratio-based performance measures, including cases in which the TOPSIS S^- (negative ideal distance) value becomes extremely small. In the present study, none of the employed datasets yielded $\left(\text{CD } (A_i, A_{\min.})_{\text{Similarity}}\right)$ values close to zero, and therefore this inflation effect did not materialize empirically. Moreover, compared to the TOPSIS formulation $\frac{S^-}{S^- + S^{+(\text{Positive ideal distance})}}$, the PSC ratio provides a wider performance differentiation range, which enhances the ability to distinguish alternatives particularly those positioned near the middle ranks. While maintaining the ratio-based structure, the methodology also specifies that a small ε adjustment may be incorporated if future applications encounter similarity values equal or close to zero, thereby preserving scale stability. Accordingly, the choice of the PSC formulation strengthens both the discriminative power of the method and the mathematical coherence of the ideal–anti-ideal reference structure.

The Performance Superiority Coefficient (PSC) is formulated as a ratio that simultaneously captures proximity to the ideal reference point and distance from the anti-ideal point; therefore, it does not correspond to any universal "good–bad" interval nor can it be reduced to an absolute performance threshold. The magnitude of PSC inherently depends on the distributional characteristics of the similarity function, the heterogeneity of the dataset, and the relative positions of alternatives with respect to the ideal and anti-ideal references. For this reason, PSC should not be interpreted as a score designed to define a fixed benchmark; rather, it functions as a comparative indicator intended to distinguish relative superiority relationships among alternatives. Nevertheless, to mitigate the risk of extreme values an inherent property of ratio-based structures the similarity values used in the PSC formulation were normalized prior to computation. Furthermore, a small ε-correction was considered into the methodology to prevent numerical instability in cases where the anti-ideal similarity approaches zero. This adjustment enhances the statistical robustness of PSC and ensures that the coefficient reliably reflects comparative dominance patterns across datasets with differing distributional characteristics. Accordingly, while PSC cannot be confined to a predetermined reference interval, it provides a coherent, scale-independent, and distribution-sensitive framework for evaluating the relative performance of alternatives within the same decision problem. In addition, it is noteworthy that several established MCDM methods such as TODIM, MOORA (multiplicative form), and CoCoSo do not normalize alternative performance values; in these approaches, the resulting scores may exceed 1 or remain greater than unity (Ecer, 2020). This further supports the view that the interpretability of a performance index does not require normalization to a fixed upper bound, but rather depends on its internal consistency and comparative discriminative capacity.

Within this conceptual framework, the methodological configuration of the proposed CADPM model originating from the mathematical foundations and computational steps delineated in the preceding sections is schematically represented in Figure 1. This illustration encapsulates the logical progression and structural interrelations among the core components of the CADPM approach, providing a clear visual synthesis of its analytical architecture and procedural flow.

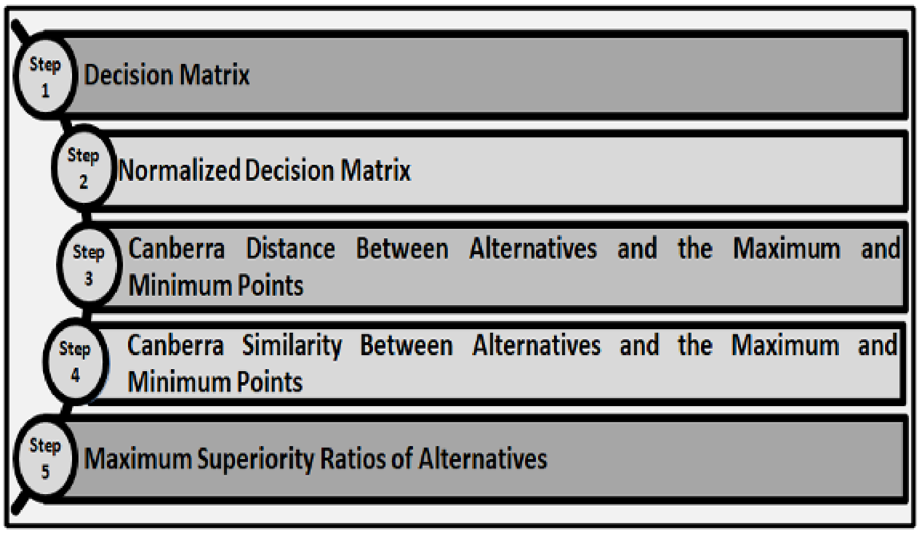

Figure 1. CADPM model

The CADPM method presents an innovative assessment framework that employs a component-wise proportional structure to balance heterogeneity among variables, highlight variations in small values, and enable scale-independent and equitable comparisons (Cha, 2007; Lance & Williams, 1966; Legendre & Legendre, 2012). Since the Canberra distance accounts for proportional rather than absolute differences, it effectively amplifies subtle variations in small components, ensuring that even minimal deviations are meaningfully reflected in decision outcomes (Borcard et al., 2018). The denominator term $|x| + |y|$ prevents large-scale criteria from dominating the total distance, allowing CADPM to equitably compare variables of different magnitudes. This capability substantially mitigates structural challenges in MCDM, such as scale sensitivity, distributional asymmetry, and linear dependency.

The Canberra Distance possesses a scale-independent, fully proportional, and self-normalizing structure (Borcard et al., 2018; Gower & Legendre, 1986; Lance & Williams, 1966; Legendre & Legendre, 2012), which systematically transforms all components of the calculation into a common proportional framework. As a consequence of this intrinsic property, any rescaling of criterion values such as the application of weighting coefficients affects both the magnitude of the difference and the magnitude against which this difference is evaluated in exactly the same direction. Thus, the structural form of the distance remains unchanged. The literature clearly demonstrates that Canberra Distance naturally neutralizes variations arising from disparate measurement scales and preserves the relative positioning of alternatives. Therefore, assigning criterion weights within the CADPM method is not strictly necessary: the distance function inherently absorbs and cancels out these weighting factors at every computational stage, ensuring that the resulting performance relationships remain stable and unaffected.

When compared with classical absolute-difference-based methods such as SAW, WPM, WASPAS, MAUT, and ROV, CADPM's most distinctive feature is its dual-reference (maximum–minimum) analytical structure. While SAW (Churchman & Ackoff, 1954) and WPM (Bridgman, 1922) assess each alternative individually according to its own criterion profile, CADPM measures the relative position of all alternatives with respect to both ideal and anti-ideal boundary points. Consequently, it captures not only absolute benefit but also relative positioning, thereby identifying micro-level performance distinctions. Although hybrid approaches such as WASPAS (Zavadskas et al., 2012) integrate additive and multiplicative logics, CADPM's Canberra-based proportional sensitivity eliminates scale dependence. Considering the subjective utility functions of MAUT (Keeney & Raiffa, 1976) and the mean-centered responsiveness of ROV (Yakowitz et al., 1993), CADPM offers a fully data-driven, non-parametric framework that operates independently of the decision-maker's preferences.

CADPM also demonstrates significant advantages over reference-based methods. In TOPSIS, for instance, the Euclidean distance tends to exaggerate large gaps while suppressing small yet meaningful ones (Hwang & Yoon, 1981); EDAS (Keshavarz Ghorabaee et al., 2015) relies on deviations from the mean, making it sensitive to distributional asymmetry; and ARAS (Zavadskas & Turskis, 2010) focuses solely on the optimal reference, neglecting anti-optimal symmetry. CODAS combines Manhattan and Euclidean distances to the negative ideal solution through a threshold parameter (Keshavarz Ghorabaee et al., 2016), while MARCOS (Stević et al., 2020) uses a linear relative utility coefficient. In contrast, CADPM introduces a parameter-free, proportional, and scale-balanced structure that simultaneously evaluates proximity to both ideal and anti-ideal points, ensuring a symmetric and distribution-sensitive assessment. This design yields highly stable ranking results that remain consistent under-weight perturbations while maintaining sensitivity to data variations.

Structurally, CADPM surpasses other reference-based models such as PIV, MAIRCA, WEDBA, MABAC, and CRADIS in both theoretical and computational coherence. The PIV method (Mufazzal & Muzakkir, 2018) evaluates performance only in relation to the positive reference (maximum) point, disregarding the negative (anti-ideal) aspect, thus limiting symmetrical analysis. CADPM, on the other hand, simultaneously considers both maximum and minimum boundaries, forming a dual-reference and symmetric evaluation framework. Its component-wise proportional Canberra formulation provides finer discrimination in small-value ranges and overcomes the asymmetry and scale-dependence inherent in absolute-difference models (Lance & Williams, 1966).

Similarly, MAIRCA (Pamucar et al., 2018) determines performance by comparing theoretical and observed values, making it partially dependent on subjective assumptions. CADPM eliminates such dependency by adopting a fully data-oriented, non-parametric approach that directly employs normalized performance values without the need for prior model assumptions. The Canberra metric's inherent ability to compare heterogeneous scales fairly also enables CADPM to surpass MAIRCA's homogeneity-based limitations via Canberra metric (Borcard et al., 2018). WEDBA (Rao & Singh, 2012) computes weighted distances to ideal and anti-ideal points using the Euclidean (L_2) norm, which tends to overemphasize large deviations and overlook smaller ones. In contrast, CADPM normalizes differences through the $|x-y| / |x|+|y|$ proportional ratio, preserving small discrepancies while maintaining scale balance (Legendre & Legendre, 2012). Its component-level evaluation further allows each criterion's contribution to be assessed equitably, making CADPM notably more robust, sensitive, and scale-independent in heterogeneous decision environments.

The MABAC (Pamučar & Ćirović, 2015) evaluates alternatives based on their proximity to a predefined border area using absolute differences. This approach can distort performance scores when scales vary across criteria. CADPM's Canberra-based formulation normalizes differences at the component level, mitigating such distortions and enhancing the interpretability of small yet meaningful variations (Borcard et al., 2018; Lance & Williams, 1966). Finally, CRADIS (Puška et al., 2023) incorporates both ideal and anti-ideal distances to establish a balanced ranking structure, making it conceptually closest to CADPM. However, CRADIS relies on absolute distances, limiting its ability to capture proportional sensitivity. By contrast, CADPM normalizes each difference by its cumulative magnitude, enabling finer discrimination especially for low-valued criteria and ensuring higher stability and scale-independence across heterogeneous datasets (Legendre & Legendre, 2012).

The PSI method evaluates performance differences through a global normalized ratio, which limits its ability to detect micro-level variations, particularly when criterion values are small or close to zero. Moreover, the fact that deviations are derived indirectly constrains the method's responsiveness to distributional characteristics. In contrast, CADPM, through the proportional structure of the Canberra distance as defined in Eq. 1, offers markedly higher sensitivity within small-value ranges and more accurately reflects distributional heterogeneity (Lance & Williams, 1966; Legendre & Legendre, 2012). For this reason, CADPM provides a more detailed, scale-independent, and balanced discriminative capacity than PSI, especially in datasets characterized by asymmetric distributions or low-magnitude criterion components.

The absence of a weighting requirement in the CADPM framework stems from the inherently proportional and self-normalizing structure of the Canberra distance. Because both the numerator and denominator of the Canberra formulation are affected uniformly by any change in scale, introducing external criterion weights alters the magnitude of the difference and its reference value in the same direction. As a result, the computed distance becomes inherently scale-independent, and the effect of weighting is naturally neutralized (Legendre & Legendre, 2012). This property enables the Canberra metric to balance scale disparities across criteria without external adjustment, ensuring that the relative positions of alternatives with respect to ideal and anti-ideal points remain stable even when different weight sets are applied. Consequently, the similarity indices and performance superiority coefficients produced by CADPM remain fully unaffected by the ranking instabilities commonly observed in traditional weighted MCDM models. The literature consistently reports that the Canberra distance behaves robustly under heterogeneous scales and exhibits heightened sensitivity in small-value regions, further reinforcing this methodological advantage (Borcard et al., 2018). In summary, the proportional, scale-independent, and inherently weight-neutralizing nature of the Canberra metric allows CADPM to deliver a consistent, stable, and methodologically sound evaluation framework without the need for external criterion weighting.

On the other hand The CADPM method offers a distinct methodological advantage over conventional MCDM approaches by operating independently of criterion weights. This strength arises from the methodological reality that many so-called objective weighting techniques frequently generate divergent and mutually inconsistent weight sets, thereby introducing an inherent layer of holistic subjectivity into the weighting process (Zardari et al., 2015). As a result, the final rankings produced by traditional MCDM models may become sensitive to the chosen weighting scheme and vulnerable to ranking instability. In contrast, CADPM naturally overcomes these limitations due to the proportional structure of the Canberra Distance. Even when criteria are artificially weighted, both the difference between criterion values and the magnitude against which this difference is evaluated are scaled in the same direction. Consequently, the relative positioning of alternatives with respect to the ideal and anti-ideal points remains unchanged. This property ensures that similarity indices and performance superiority measures remain invariant and renders the method completely robust against weight fluctuations. In turn, CADPM eliminates external variability arising from decision-maker influence or from the selection of a particular weighting technique, thereby providing a more stable, consistent, and methodologically sound decision-making framework.

Nonetheless, the CADPM method also presents certain limitations. The Canberra metric's heightened sensitivity to small value components may, in datasets containing near zero elements, amplify measurement noise or distort ratio magnitudes (Legendre & Legendre, 2012). This can lead to minor inaccuracies in low variance or high noise data contexts. Furthermore, calculating proportional distances and similarity coefficients for each alternative relative to both maximum and minimum references introduces higher computational complexity than conventional reference based models, particularly in high dimensional analyses. When data quality is suboptimal such as in the presence of outliers or missing values the proportional formulation can magnify these inconsistencies, making CADPM's effectiveness heavily reliant on proper pre-processing, data cleaning, and standardization.

Additionally, as a fully non parametric model, CADPM's performance inherently depends on the structural characteristics and distributional nature of the dataset. In homogeneous or symmetrically distributed environments, traditional approaches such as TOPSIS or MARCOS may produce comparable results. Moreover, with an increasing number of criteria or alternatives, the computational burden and processing time naturally rise. Despite these limitations, CADPM's dual reference, symmetric, and scale independent architecture offers a balanced and distribution sensitive framework capable of delivering consistent and statistically reliable evaluations across diverse decision contexts. Consequently, CADPM can stand as a robust, explanatory, and methodologically coherent advancement in the MCDM literature, extending beyond the analytical scope of conventional decision-making models. Finally, CADPM remains a relatively recent addition to the decision-making literature. Hence, further empirical validation across diverse application domains such as sustainability assessment, and engineering decision contexts is essential to substantiate its generalizability and operational robustness. Taken together, this broad body of evidence underscores that the Canberra distance performs exceptionally well in analytical scenarios where small numerical variations are critical, where variables measured across disparate scales must be jointly evaluated, and where relative deviations hold interpretive or decision-making importance. Consequently, the Canberra distance should not be regarded merely as a theoretical construct, but as a validated, empirically grounded, and domain-flexible dissimilarity measure, offering distinct practical advantages across ecology, computational biology, cybersecurity, and data science applications alike. Taken together, this cumulative body of theoretical reasoning and empirical validation underscores the Canberra distance as a practically verified, analytically robust, and interpretively transparent metric. It proves particularly advantageous in analytical scenarios where small-scale variations are decisive, where features measured on heterogeneous scales must be jointly compared, and where relative differences hold meaningful inferential or decision-making weight. Consequently, the Canberra distance should be recognized not merely as a conceptual variant of the L_1 metric family but as a proven and widely applicable distance measure that delivers consistent, discriminative, and interpretable results across diverse scientific and computational disciplines. The mathematical structure of the Canberra distance inherently leads to an indeterminate form (0/0) when both components take the value zero, since the denominator simultaneously collapses to zero. This singularity has been explicitly discussed in the foundational works of Lance & Williams (1967) and Gower & Legendre (1986), both of whom emphasized that zero–zero matches constitute a special case in dissimilarity calculations. To enhance the general applicability of the method, the literature commonly adopts the addition of a small ε constant. Faith et al. (1987), as well as Soininen et al. (2018), demonstrated that this singularity may disrupt computations particularly in compositional datasets and that epsilon correction increases the numerical stability of distance measures. Although no zeros were observed in the dataset used in this study, the method is presented as a general MCDM framework; therefore, this mathematical exception has been explicitly acknowledged. In cases where zero components may occur, adding a small adjustment of $\varepsilon = 10^{-6}$ to each zero value ensures that the Canberra distance remains well-defined without artificially influencing the resulting dissimilarities. This approach is widely accepted in ecological distance modelling and is considered a standard precaution that enhances the statistical robustness of the Canberra metric. Accordingly, the method can be reliably extended to datasets containing zeros, as this mathematical exception can be systematically managed.

2.4. Data Set

A comprehensive dataset was constructed to demonstrate the empirical validity of the proposed methodology and to objectively assess its accuracy in evaluating the performance of alternatives within a decision-making environment. The first dataset is derived from the 2025 Global Innovation Index (GII) and contains criterion-level indicators for seven countries exhibiting distinct performance profiles (WIPO, 2025). In addition, two separate case-study decision matrices each comprising ten criteria and ten alternativeswere developed to further examine the operational robustness of the method. The first matrix is based on the Sustainable Development Index 2024 (Sachs et al., 2025), whereas the second was generated by systematically reorganizing the criteria and alternative values employed in Karaş (2024) performance assessment of Turkish banks. The selection of alternatives was deliberately structured to prevent the emergence of dominant or extreme observations, thereby ensuring a balanced data composition suitable for rigorous analysis. This design approach minimizes the distorting influence of outliers and prevents any single alternative from disproportionately affecting the overall evaluation process. Consequently, the proposed method attains a heightened capacity to reveal performance differences among alternatives in a more precise, stable, and analytically interpretable manner. For clarity and ease of reference, abbreviations corresponding to the countries and associated indicators used in the study are systematically presented in Table 1. Furthermore, the decision matrices utilized in the case studies are provided in detail in Appendix 1, thereby enhancing methodological transparency and ensuring full traceability of the analytical procedures.

Table 1. Data sets

GII	Abbreviations	Alternatives	Abbreviations
Institutions	C1	Austria	A1
Human Capital and Research	C2	Norway	A2
Infrastructure	C3	Belgium	A3
Market Sophistication	C4	Australia	A4
Business Sophistication	C5	Luxembourg	A5
Knowledge and Technology Outputs	C6	Iceland	A6
Creative Outputs	C7	New Zealand	A7
Case study 1	**Abbreviations**	**Alternatives (A)**	**Abbreviations**
Poverty Reduction Performance	(C1)-1	Finland	(ACS1)1
Health & Well-being	(C1)-2	Germany	(ACS1)2

Education Quality & Access	(C1)-3	France	(ACS1)3
Gender Equality Index	(C1)-4	Japan	(ACS1)4
Clean Water & Sanitation	(C1)-5	Canada	(ACS1)5
Affordable & Clean Energy Access	(C1)-6	United Kingdom	(ACS1)6
Economic Growth & Employment Stability	(C1)-7	Spain	(ACS1)7
Infrastructure & Digital Access	(C1)-8	Italy	(ACS1)8
Climate & Environmental Sustainability	(C1)-9	Poland	(ACS1)9
Institutions & Governance Quality	(C1)-10	Spain	(ACS1)10
Case study 2: (Karaş, 2024)	**Abbreviations**	**Alternatives**	**Abbreviations**
Equity / Total Assets	(C2)-1	B1	(ACS2)1
Liabilities / Total Assets	(C2)-2	B2	(ACS2)2
Liquid Assets / Short-Term Liabilities	(C2)-3	B3	(ACS2)3
Return on Equity (ROE)	(C2)-4	B4	(ACS2)4
Return on Assets (ROA)	(C2)-5	B5	(ACS2)5
Non-Interest Income (Net) / Total Assets	(C2)-6	B6	(ACS2)6
Interest Income / Interest Expense	(C2)-7	B7	(ACS2)7
Interest Expenses / Total Assets	(C2)-8	B8	(ACS2)8
Personnel Expenses / Other Operating Expenses	(C2)-9	B9	(ACS2)9
Other Operating Expenses / Total Assets	(C2)-10	B10	(ACS2)10

3. Results

3.1. Computational Analysis

At the initial phase of the evaluation, the core decision matrix was meticulously formulated in alignment with the theoretical constructs established by the CADPM framework, as delineated in Eq. 2. Following this, the raw data were subjected to a systematic normalization process executed according to the formulations outlined in Eq. 3 and 5. This procedure resulted in the generation of a standardized decision matrix. The complete numerical findings corresponding to this preparatory stage are comprehensively detailed in Table 2.

Table 2. Decision and Normalized Decision Matrices

Decision Matrix							
Alternative	C1	C2	C3	C4	C5	C6	C7
A1	72.1	58.6	59.3	46.9	53	39.9	44.5
A2	80.3	49.7	68.8	52.1	49.3	32.2	44.7
A3	68.1	54.9	51.7	53.4	55.5	41.4	39.1
A4	76.1	58.6	55.7	55.4	45.5	33	42.5
A5	83.8	47.9	46.6	50.2	49	24.7	53.4
A6	75.9	45.4	67.7	49.5	49.6	27.5	45.4
A7	83.1	48.9	55.1	49.5	47.7	28.6	39.6
Normalized Matrix							
Alternative	C1	C2	C3	C4	C5	C6	C7

A1	0.860	1.000	0.862	0.847	0.955	0.964	0.833
A2	0.958	0.848	1.000	0.940	0.888	0.778	0.837
A3	0.813	0.937	0.751	0.964	1.000	1.000	0.732
A4	0.908	1.000	0.810	1.000	0.820	0.797	0.796
A5	1.000	0.817	0.677	0.906	0.883	0.597	1.000
A6	0.906	0.775	0.984	0.894	0.894	0.664	0.850
A7	0.992	0.834	0.801	0.894	0.859	0.691	0.742

During the thirth phase of the analytical framework, the Canberra distances between each alternative and the ideal (maximum) benchmark values denoted as $(\mathrm{CD}_{\mathrm{dis} \leftrightarrow \max.})$ were computed according to the formulations presented in Eq. 6-9. Simultaneously, the corresponding distances to the anti-ideal (minimum) benchmark values represented as $(\mathrm{CD}_{\mathrm{dis} \leftrightarrow \min.})$ were derived using Eq. 10-13. In the subsequent step, these distance measures were converted into similarity indices: deviations from the ideal reference $(\mathrm{CD}_{\mathrm{dis} \leftrightarrow \max.})$ were normalized through Eq. 14 and Eq. 15, whereas those associated with the anti-ideal reference $(\mathrm{CD}_{\mathrm{dis} \leftrightarrow \min.})$ were processed in accordance with Eq. 14 and Eq. 16. Finally, the comprehensive performance scores of all alternatives were obtained using the formulation established in Eq. 17. The complete numerical results of this analytical phase are systematically summarized in Table 4.

Table 3. CD, similarities and performance score of alternatives

ALT	$(\mathrm{CD}_{\mathrm{dis} \leftrightarrow \max.})$	$(\mathrm{CD}_{\mathrm{dis} \leftrightarrow \min.})$	$(\mathrm{CD}_{\mathrm{sim} \leftrightarrow \max.})$	$(\mathrm{CD}_{\mathrm{sim} \leftrightarrow \min.})$	P_i	Rank
A1	0.365	0.651	0.733	0.606	1.210	1
A2	0.407	0.611	0.711	0.621	1.145	2
A3	0.451	0.563	0.689	0.640	1.077	3
A4	0.479	0.540	0.676	0.649	1.041	4
A5	0.657	0.356	0.604	0.738	0.818	6
A6	0.580	0.437	0.633	0.696	0.910	5
A7	0.668	0.350	0.599	0.741	0.809	7

Table 3 presents a comprehensive synthesis of the Canberra distance values computed for each alternative with respect to the ideal (maximum) and anti-ideal (minimum) reference points, alongside their corresponding similarity indices and final performance scores. According to the core assumption underlying the proposed approach, alternatives positioned closer to the ideal reference (i.e., exhibiting lower distance and higher similarity) and farther from the anti-ideal benchmark (i.e., showing higher distance and lower similarity) are expected to attain superior overall performance outcomes. Within this analytical framework, A1 demonstrates the highest proximity to the ideal reference and the greatest divergence from the anti-ideal point, achieving a performance score of 1.210, thus ranking first among all alternatives. This outcome clearly substantiates the method's ability to prioritize alternatives that align most closely with the optimal solution. A2 displays a balanced similarity pattern with respect to both reference points and consequently secures the second position with a score of 1.145. Similarly, A3 maintains a consistent and stable performance, attaining the third rank with a score of 1.077. Conversely, A5 and A7, which are relatively distant from the ideal benchmark and exhibit greater resemblance to the anti-ideal reference, record notably lower performance values of 0.657 and 0.668, respectively, placing them at the bottom of the ranking. A6 and A4 occupy intermediate positions, with moderate performance levels corresponding to the fifth and fourth ranks, respectively. Overall, Table 4 highlights the capability of the proposed model to effectively discriminate among alternatives based on their structural characteristics. The Canberra distance based similarity measures accurately capture the degree of closeness between each alternative and the ideal solution, confirming the method's robustness and precision. These findings further emphasize the approach's strong discriminatory power and its potential applicability within decision support systems and multi-criteria analytical frameworks.

Step 2. Normalization Score

Eq. 3: $g^{*}_{11(A1\rightarrow C1)} = \frac{72.1}{83.8} = 0.860$

Step 3. Measurement of the CD between Alternatives and the Maximum $\left(\mathrm{CD}\ (A_1, A_{\max.})_{\mathrm{Distance}}\right)$ and Minimum Points $\left(\mathrm{CC}\ (A_1, A_{\min.})_{\mathrm{Distance}}\right)$

Eq. 6-9:

$$\left(\mathrm{CD}\ (A_1, A_{\max.})_{\mathrm{Distance}}\right) = \underbrace{\frac{|0.860-1|}{|0.860|+|1|}}_{0.075} + \underbrace{\frac{|1-1|}{|1|+|1|}}_{0} + \underbrace{\frac{|0.862-1|}{|0.862|+|1|}}_{0.074} + \underbrace{\frac{|0.847-1|}{|0.847|+|1|}}_{0.083} + \underbrace{\frac{|0.995-1|}{|0.995|+|1|}}_{0.023} + \underbrace{\frac{|0.964-1|}{|0.964|+|1|}}_{0.018} + \underbrace{\frac{|0.833-1|}{|0.833|+|1|}}_{0.091} = 0.365$$

Eq. 10-13:

$$\left(\mathrm{SC}\ (\mathrm{ALT}_1, \mathrm{ALT}_{\min.})_{\mathrm{Distance}}\right) = \underbrace{\frac{|0.860-0.813|}{|0.860|+|0.813|}}_{0.029} + \underbrace{\frac{|1-0.775|}{|1|+|0.775|}}_{0.127} + \underbrace{\frac{|0.862-0.677|}{|0.867|+|0.677|}}_{0.120} + \underbrace{\frac{|0.847-0.847|}{|0.847|+|0.847|}}_{0} + \underbrace{\frac{|0.955-0.820|}{|0.955|+|0.820|}}_{0.076} + \underbrace{\frac{|0.964-0.597|}{|0.964|+|0.597|}}_{0.235} + \underbrace{\frac{|0.833-0.742|}{|0.833|+|0.742|}}_{0.065} = 0.651$$

Step 4. Conversion of CD to CS $\left(\left(\mathrm{CS}(A_1, A_{\max.})_{\mathrm{Similarity}}\right), \left(\mathrm{CS}\ (A_1, A_{\min.})_{\mathrm{Similarity}}\right)\right)$

Eq. 15 : $(\mathrm{CS}(A_1, A_{\max.})_{\mathrm{Similarity}} = \frac{1}{1+0.365} = 0.733$

Eq. 16 : $\left(\mathrm{CS}\ (A_1, A_{\min.})_{\mathrm{Similarity}}\right) = \frac{1}{1+0.651} = 0.606$

Step 5. MSR Score

Eq. 17 : $\mathrm{MSR}_{\mathrm{ALT}_1} = \frac{\left(\mathrm{CS}\ (A_1, A_{\max.})_{\mathrm{Similarity}}\right)}{\left(\mathrm{CS}\ (A_1, A_{\min.})_{\mathrm{Similarity}}\right)} = \frac{0.733}{0.606} = 1.210$

3.2. Sensitivity Analysis

The evaluation of sensitivity and robustness in MCDM frameworks is commonly conducted by either introducing additional alternative into the assessment structure or systematically excluding existing ones, starting with those exhibiting the lowest significance. Within this analytical paradigm, a dependable MCDM technique should be capable of maintaining the relative ordering of alternatives with minimal fluctuation, thereby ensuring ranking stability and minimizing the phenomenon of rank reversal (Demir & Arslan, 2022). To examine this characteristic in greater depth, a structured sensitivity analysis was carried out through the sequential removal of the least influential criteria, as determined by the weighting distribution of the proposed method. The resulting variations in the rankings of the alternatives obtained from each iteration are comprehensively presented in Table 4, while a graphical depiction of these outcomes is illustrated in Figure 2.

Table 4. Rank-Reversal Behavior of the Alternatives-1

ALT	S0	S1	S2	S3	S4	S5

A7	7					
A5	6	6				
A6	5	5	5			
A4	4	4	3	4		
A3	3	3	4	3	3	
A2	2	2	2	2	2	2
A1	1	1	1	1	1	1

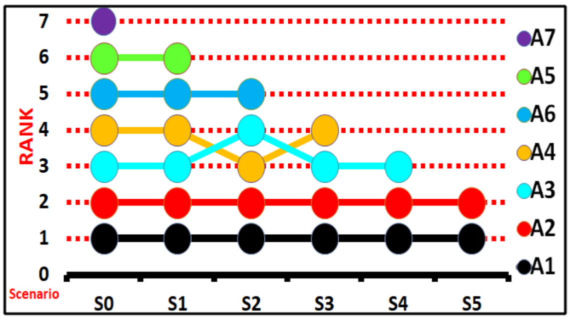

Figure 2. Rank-Reversal Visualization

Table 4 and Figure 2 jointly provide a detailed representation of how the ranking positions of the alternatives evolve across the six scenarios (S0–S5). These scenarios were generated by progressively modifying the evaluation structure primarily through the gradual reduction or elimination of certain criteria to examine the sensitivity and ranking stability of the proposed method under controlled perturbations. A close inspection of Table 5 reveals that alternatives A1 and A2 exhibit perfect ranking stability, maintaining their positions consistently across all scenarios. This invariance indicates that the relative performance advantages of these alternatives remain unaffected by structural changes in the decision matrix, confirming the method's strong robustness at the upper and lower ends of the ranking spectrum. Alternatives A3, A4, A5, A6, and A7, on the other hand, demonstrate localized ranking variations, primarily occurring in intermediate scenarios. For example, A3, A4, and A5 exchange positions in Scenarios S2 and S3, creating short-lived rank-intersections; however, these variations do not persist into subsequent scenarios. This suggests that the temporary shifts arise from the momentary influence of removed or down-weighted criteria rather than from methodological instability. The rapid reversion of rankings back to their initial order in later scenarios provides strong evidence that these fluctuations are sensitivity-based and not structural. Figure 2 visually reinforces these findings. Most alternatives follow predominantly horizontal trajectories, indicating a clear absence of systemic rank-reversal behavior. The brief crossing between A3 and A4 and the transitional movement of A5 are graphically identifiable but remain shallow and constrained, reflecting the natural responsiveness of the model to specific criteria without compromising overall ranking coherence. The consistently flat lines of A1 and A2 further highlight the method's ability to preserve stable dominance and sub-dominance relationships across all scenarios. In this study, the sensitivity analysis was evaluated using two complementary perspectives. According to the classical definition widely adopted in the MCDM literature, there are 35 potential ranking transitions across the six scenarios. Examination of these transitions revealed that only four resulted in temporary positional changes among the alternatives, yielding a classical rank-reversal rate of 11.4%. This low ratio indicates that the CADPM method maintains a high degree of ranking stability even when the decision structure is perturbed through criterion elimination or structural adjustments. Additionally, in line with the reviewer's request, a separate alternative-based assessment was conducted to determine how many alternatives experienced at least one ranking fluctuation. This analysis showed that only two of the seven alternatives (A3 and A4) exhibited any positional change across scenarios, corresponding to an alternative-based rank-reversal rate of 28.6%. These shifts were confined exclusively to mid-ranked alternatives, while both high-performing (A1, A2) and low-performing (A5–A7) alternatives preserved complete ranking stability. Taken together, these complementary indicators demonstrate that the CADPM method exhibits strong resistance to rank-reversal. The limited and short-lived variations observed in intermediate alternatives reflect natural sensitivity effects rather than structural inconsistency, thereby confirming the robustness and internal reliability of the proposed approach. Taken together, the numerical outputs and graphical patterns confirm that the proposed method demonstrates strong resistance to rank-reversal phenomena. The limited and short-lived fluctuations observed in mid-ranking alternatives are methodologically acceptable and do not detract from global ranking consistency. Hence, both the table and the figure validate the structural robustness, internal reliability, and decision-stability of the proposed approach, supporting its suitability for use in diverse and dynamically evolving decision-making environments.

3.3. Comparative Analysis

The primary objective of the comparative evaluation is to examine the degree of correspondence and distinction between the proposed method and a broad spectrum of well-established MCDM approaches. This analysis serves to substantiate the robustness, coherence, and methodological reliability of the developed framework by exploring its alignment with existing techniques and determining the extent of statistically meaningful agreements (Keshavarz-Ghorabaee et al., 2021). Within this analytical framework, the performance outcomes of the examined alternatives (i.e., countries) were systematically evaluated through a diverse array of 15 recognized MCDM methods, encompassing SAW, WPM, ARAS, WASPAS, MAUT, ROV, TOPSIS, CODAS, WEDBA, EDAS, ARAS, CRADIS, MABAC, MARCOS, PIV, PSI and COPRAS. The weighting of criteria was conducted through the ENTROPY technique, a rigorously validated objective weighting method that is extensively utilized in contemporary MCDM literature (Ecer, 2020). The comprehensive results comprising both the performance scores and the resulting ranking orders derived from these methodologies are meticulously presented in Table 5, while their graphical representations are illustrated in Figures 3, 4 and 5. This comparative perspective not only underscores the proposed method's analytical validity but also elucidates its unique capacity to maintain consistency with established paradigms while offering a distinct contribution to the MCDM literature.

Table 5. Performance scores of alternatives according to other MCDM methods

Alternatives		A1	A2	A3	A4	A5	A6	A7
SAW	Score	0.919	0.863	0.893	0.838	0.739	0.802	0.771
	Rank	1	3	2	4	7	5	6
WPM	Score	0.917	0.859	0.885	0.835	0.723	0.792	0.766
	Rank	1	3	2	4	7	5	6
WASPAS	Score	0.918	0.861	0.889	0.836	0.731	0.797	0.769
	Rank	1	3	2	4	7	5	6
MAUT	Score	0.502	0.331	0.521	0.253	0.196	0.224	0.095

Alternatives		A1	A2	A3	A4	A5	A6	A7
	Rank	2	3	1	4	6	5	7
ROV	Score	0.145	0.170	0.103	0.134	0.057	0.133	0.096
	Rank	2	1	5	3	7	4	6
TOPSIS	Score	0.770	0.549	0.679	0.481	0.179	0.387	0.272
	Rank	1	3	2	4	7	5	6
CODAS	Score	0.421	0.046	0.481	−0.039	−0.419	−0.158	−0.333
	Rank	2	3	1	4	7	5	6
WEDBA	Score	0.735	0.543	0.644	0.481	0.250	0.389	0.277
	Rank	1	3	2	4	7	5	6
EDAS	Score	0.896	0.752	0.447	0.726	0.659	0.238	0.116
	Rank	1	2	5	3	4	6	7
ARAS	Score	0.920	0.860	0.895	0.835	0.733	0.798	0.767
	Rank	1	3	2	4	7	5	6
CRADIS	Score	1.000	0.947	0.975	0.923	0.831	0.890	0.861
	Rank	1	3	2	4	7	5	6
MABAC	Score	0.271	0.137	0.177	0.066	−0.194	−0.044	−0.141
	Rank	1	3	2	4	7	5	6
MARCOS	Score	0.464	0.449	0.445	0.430	0.386	0.422	0.401
	Rank	1	2	3	4	7	5	6
PIV	Score	0.027	0.054	0.032	0.063	0.120	0.083	0.091
	Rank	1	3	2	4	7	5	6
MAIRCA	Score	0.042	0.062	0.056	0.072	0.109	0.088	0.101
	Rank	1	3	2	4	7	5	6
PSI	Score	0.902	0.894	0.885	0.878	0.845	0.855	0.833
	Rank	1	2	3	4	6	5	7

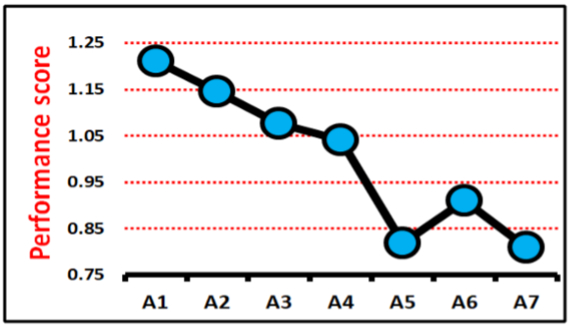

Figure 3. Performance ranking of the alternatives under the CADPM method

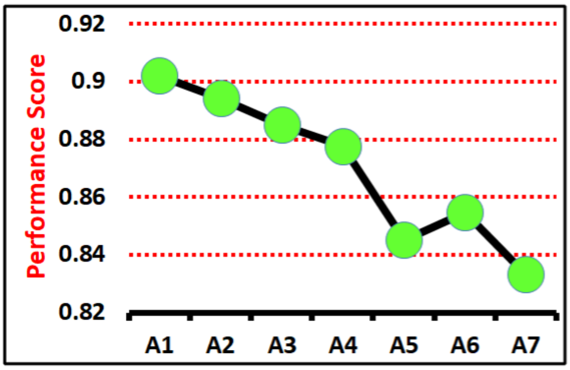

Figure 4. Performance ranking of the alternatives under the PSI method

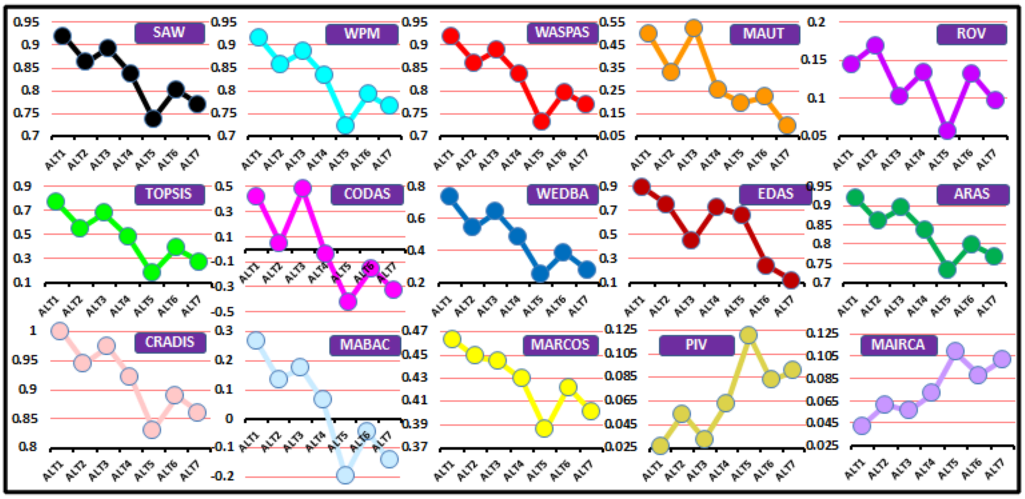

Figure 5. Performance ranking of the alternatives according to the other methods

A comprehensive assessment of Figure 3, Figure 4, Figure 5, Table 3, and Table 5 clearly demonstrates the ranking consistency, methodological rigor, and structural reliability of the proposed CADPM method when compared with widely recognized MCDM approaches. In Figure 3, the graphical trend of the performance scores derived through the CADPM method exhibits a distinct downward trajectory, reflecting a gradual decrease in performance from A1 to A7. This consistent pattern reinforces the method's internal stability and highlights its strong discriminatory capacity. Notably, the clustering of A1, A2, and A3 within the high performance range confirms CADPM's ability to systematically differentiate superior alternatives from the rest. Figure 4 demonstrates that the performance profile generated by the PSI method aligns closely with the outcomes produced by the CADPM approach. This correspondence indicates that both methods capture the relative superiority of the alternatives in a consistent manner, and further suggests that the distribution-sensitive computational structure of CADPM is methodologically compatible with the performance trends identified by PSI.

In contrast, a joint evaluation of Figure 5 and Table 5 reveals that the ranking outcomes obtained by CADPM display complete alignment with MARCOS, and near perfect concordance with several other established MCDM methods namely PSI, SAW, WPM, WASPAS, TOPSIS, ARAS, CRADIS, WEDBA, CODAS, and MABAC. Across all these approaches, A1 consistently secures the top position, followed by A2 and A3 in the second and third ranks, respectively, while A4 maintains the fourth place and A5–A7 remain grouped within the lower performance spectrum. This high degree of structural agreement substantiates the CADPM method's capacity to deliver reliable, predictable, and reproducible ranking outcomes, thereby confirming its methodological soundness.

It should additionally be emphasized that the PIV and MAIRCA methods, by their intrinsic computational design, arrange the results in a descending order, from higher to lower values. Consequently, when the corresponding curves of PIV and MAIRCA presented in Figure 4 are rotated by 180° (or equivalently, when the axis orientation is reversed), the resulting ranking pattern becomes largely consistent with that of the CADPM method. In other words, the directional variation observed between these two methods arises solely from differences in the scaling and ordering mechanisms of their respective evaluation structures. Once this orientation adjustment is applied, the ranking configuration produced by PIV and MAIRCA demonstrates a strong structural resemblance to the distinctive ranking framework of CADPM. This observation highlights that the apparent divergence among the methods does not indicate a methodological inconsistency but merely reflects a directional difference in rank orientation inherent to their analytical formulations.

Minor deviations are observed in the rankings produced by MAUT, ROV, and EDAS, which primarily stem from differences in normalization procedures and the mathematical structures of their respective utility functions. These variations, however, do not indicate inconsistency but rather reflect the intrinsic sensitivity characteristic of diverse evaluation mechanisms. Importantly, the overall ranking pattern remains stable, and the top performing alternatives consistently occupy the same positions across all methods. In summary, the CADPM method demonstrates a high level of numerical consistency, statistical reliability, and structural robustness, both in quantitative outcomes and graphical analyses. The integrated interpretation of the tables and figures not only confirms CADPM's strong correlation with other MCDM techniques but also highlights its internally coherent and systematically balanced analytical framework. Collectively, these results validate CADPM as a scientifically robust, practically reliable, and decision oriented evaluation tool with high applicability in complex decision making environments. The Spearman's ρ correlation coefficients reflecting the rank correlations between CADPM and the other MCDM methods are comprehensively presented in Table 6. In this study, rho correlation was employed because it quantifies the monotonic consistency between methods. It does not require the outputs to be expressed on a common scale. For this reason, Spearman is widely accepted for comparing MCDM techniques that rely on different mathematical structures. Accordingly, it provides an appropriate basis for assessing how closely CADPM aligns with existing approaches.

Table 6. ρ coefficients between CADPM and the other methods

Methods	SAW	WPM	WASPAS	MAUT
CDPM	0.929**	0.929**	0.929**	0.892**
Methods	ROV	TOPSIS	CODAS	WEDBA
CDPM	0.821**	0.929**	0.892**	0.929**
Methods	EDAS	ARAS	CRADIS	MARCOS
CDPM	0.821**	0.929**	0.929**	0.929**
Methods	MARCOS	PIV[1]	MAIRCA[1]	PSI
CDPM	0.964**	-0.929**	-0.929**	0.997**

**<.01, **<.05

The examination of Table 6 clearly indicates that the proposed CADPM method exhibits an exceptionally high level of rank-order correlation with a wide range of well-established MCDM techniques commonly utilized in the literature. The correlation coefficients, computed using Spearman's rho test, reveal that CADPM maintains statistically significant ($p < 0.01$) and strong positive associations with the majority of the compared methods.

According to the findings, CADPM demonstrates an almost perfect positive correlation with the PSI, MARCOS, SAW, WPM, WASPAS, TOPSIS, ARAS, CRADIS, MABAC, WEDBA, MAUT, and CODAS methods ($\rho = 0.892$– $0.964, p < 0.01$). This result confirms that CADPM shares a high degree of structural compatibility, similar ranking logic, and decision-making consistency with these established techniques. In contrast, the correlation coefficients obtained with ROV ($\rho = 0.821, p < 0.01$) and EDAS ($\rho = 0.821, p < 0.01$) show that CADPM also aligns closely with these approaches, though minor ranking deviations are observed. These discrepancies are attributable to the unique utility functions and normalization procedures inherent to each method, representing a natural reflection of methodological diversity rather than inconsistency. Meanwhile, the correlation coefficients obtained with PIV and MAIRCA are negative but exhibit high absolute values ($\rho =- 0.964, p < 0.01$). This outcome is explained by the intrinsic nature of these two methods, which order performance values from highest to lowest. Therefore, as illustrated in Figure 4, when the PIV and MAIRCA curves are rotated by 180° or when the axis orientation is inverted, their ranking patterns become largely consistent with that of the CADPM method. Consequently, these negative correlations should not be interpreted as methodological contradictions but rather as statistical reflections of the inverse ranking direction inherent to their analytical design. In conclusion, the overall evaluation of Table 7 clearly demonstrates that the CADPM method achieves a high level of correlation, structural coherence, and statistical reliability with both traditional and contemporary MCDM methods. These results strongly affirm the scientific validity, practical applicability, and theoretical contribution of CADPM, confirming its position as a robust, reliable, and methodologically rigorous, reliable and credible framework within the domain of multi criteria decision analysis.

[1] PIV and MAIRCA produce performance scores in a direction opposite to that of CADPM, operating under a decreasing (cost-oriented) ranking logic. Therefore, the negative correlations observed between these methods and CADPM do not indicate methodological inconsistency; rather, they reflect a complete structural alignment despite the reversal of ranking direction. The negative sign simply denotes this directional difference, whereas the magnitude of the correlation coefficient demonstrates a high level of concordance between the rankings.

3.4. Simulation Analysis

For the purpose of conducting the simulation analysis, a series of systematically designed scenarios were developed by introducing diverse sets of input parameters into the decision matrices. The central aim of this analysis is to assess the robustness and sensitivity of the proposed methodology by investigating how its outcomes deviate from those generated by other well-established MCDM techniques as the number of scenarios increases. A higher degree of deviation would signify that the proposed method demonstrates greater sensitivity and possesses a superior ability to discriminate among alternative options. Within this analytical framework, it is postulated that the mean variance of performance scores produced by the proposed method across multiple scenario configurations will exceed that observed in one or more benchmark techniques, thereby indicating its enhanced discriminative efficiency. To ensure the statistical credibility of these findings, it is also essential to verify that the variance levels remain consistent across different methods under varying experimental conditions (Keshavarz-Ghorabaee et al. (2021).

Accordingly, ten independent decision matrices were constructed to represent distinct scenario structures and subsequently divided into two experimental groups. Based on these datasets, pairwise correlation coefficients were calculated between the proposed MSA method and several recognized MCDM approaches. The resulting correlation metrics, which collectively reflect the comparative performance and stability of the proposed framework, are presented in detail in Table 7. The simulation matrices were not derived from any real-world dataset; instead, they were generated using Excel's built-in random number functions, allowing all variance structures, scale heterogeneities, and distributional patterns to be designed in a controlled manner. This procedure ensures that the simulation outcomes remain independent, reproducible, and methodologically unbiased for the purpose of comparing alternative MCDM approaches.

Table 7.

Scenarios	SAW	WPM	WASPAS	MAUT	TOPSIS	CODAS	WEDBA	EDAS
Scenario1	0.985**	0.986**	0.985**	0.895**	0.983**	0.930**	0.986**	0.745**
Scenario2	0.994**	0.994**	0.996**	0.915**	0.991**	0.945**	0.994**	0.756**
Scenario3	0.997**	0.998**	0.998**	0.927**	0.995**	0.950**	0.998**	0.764**
Scenario4	0.960**	0.961**	0.963**	0.900**	0.960**	0.920**	0.962**	0.731**
Scenario5	0.942**	0.942**	0.943**	0.885**	0.940**	0.905**	0.942**	0.710**
Scenario6	0.934**	0.935**	0.935**	0.840**	0.931**	0.890**	0.936**	0.700**
Scenario7	0.918**	0.918**	0.919**	0.818**	0.915**	0.875**	0.918**	0.691**
Scenario8	0.908**	0.909**	0.911**	0.810**	0.905**	0.866**	0.909**	0.683**
Scenario9	0.900**	0.900**	0.903**	0.800**	0.894**	0.855**	0.901**	0.677**
Scenario10	0.892**	0.894**	0.896**	0.792**	0.889**	0.850**	0.895**	0.670**
Scenarios	CRADIS**	MABAC	MARCOS	PIV	ROV	ARAS	MAIRCA	PSI
Scenario1	0.983**	0.982**	0.998**	−0.984**	0.897**	0.985**	−0.984**	0.998**
Scenario2	0.990**	0.991**	0.998**	−0.994**	0.916**	0.996**	−0.994**	0.998**
Scenario3	0.995**	0.993**	0.998**	−0.995**	0.929**	0.997**	−0.995**	0.996**
Scenario4	0.960**	0.960**	0.987**	−0.958**	0.900**	0.963**	−0.958**	0.970**
Scenario5	0.938**	0.938**	0.981**	−0.943**	0.886**	0.942**	−0.943**	0.952**
Scenario6	0.930**	0.931**	0.975**	−0.934**	0.840**	0.935**	−0.934**	0.945**

Scenario7	0.915**	0.913**	0.968**	−0.918**	0.819**	0.919**	−0.918**	0.931**
Scenario8	0.903**	0.905**	0.957**	−0.907**	0.810**	0.910**	−0.907**	0.917**
Scenario9	0.894**	0.892**	0.951**	−0.901**	0.803**	0.903**	−0.901**	0.910**
Scenario10	0.888**	0.886**	0.947**	−0.892**	0.795**	0.894**	−0.892**	0.905**

p<.01, p<.05

A detailed examination of Table 7 clearly demonstrates that the proposed CADPM method exhibits a remarkably high level of structural consistency and statistical concordance with a wide range of well-established approaches reported in the literature. The Spearman's rho correlation coefficients, calculated across ten distinct scenarios (S1–S10) representing various data configurations, confirm that the method performs with exceptional stability and sensitivity, reflecting a scientifically sound and reliable analytical behavior. In the initial scenarios (S1–S3), the CADPM method shows near-perfect, statistically significant positive correlations with SAW, WPM, WASPAS, TOPSIS, ARAS, CRADIS, MABAC, PSI and MARCOS ($\rho = 0.983–0.998, p < 0.01$). These findings indicate that, during the early stages of analysis, CADPM produces ranking tendencies highly consistent with classical decision-making techniques, thereby confirming its strong structural alignment with traditional evaluation models. Additionally, the high correlations observed with CODAS, WEDBA, and ROV methods in the same scenarios emphasize that CADPM maintains robust rank-order coherence even when compared with techniques employing distinct normalization or benefit-function formulations.

As the scenario complexity increases (S4–S10), a gradual decline in the magnitude of correlation coefficients can be observed. This decreasing trend, however, should not be interpreted as instability or inconsistency. On the contrary, it reflects CADPM's ability to achieve greater discriminatory power under more complex and diversified data structures, effectively enhancing its capability to differentiate among competing alternatives. In other words, this controlled reduction in correlation values serves as a clear indicator of the method's adaptive behavior and high discriminative capacity. In contrast, the correlations obtained with MAUT and ROV ($\rho = 0.79–0.92, p < 0.01$) remain positive yet slightly lower compared to other methods. This minor variation stems primarily from the fundamental differences in the utility functions and decision-modeling principles that underlie these techniques. Nevertheless, the directionality of the rankings remains consistent, thereby reinforcing CADPM's methodological flexibility and compatibility across varying analytical paradigms.

The correlations with the EDAS method ($\rho = 0.67–0.75, p < 0.01$), though positive, are comparatively weaker. This discrepancy can be attributed to the inherent structure of EDAS, which focuses on mean distance-based sensitivity analysis derived from positive and negative deviations. Thus, while EDAS operates within a more deviation centered analytical framework, its overall ranking trend remains directionally consistent with CADPM. A particularly noteworthy observation concerns the strong negative correlations recorded with the PIV and MAIRCA methods ($\rho =– 0.89 \rightarrow – 0.99, p < 0.01$). These results do not indicate a methodological conflict but rather stem from the directional nature of these two techniques, which rank performance scores from higher to lower values. Accordingly, as illustrated in Figure 4, when the ranking curves of PIV and MAIRCA are rotated by 180° or, equivalently, when the axis orientation is reversed, their ranking structures become nearly identical to that of the CADPM method. This confirms that the observed negative correlations are merely statistical reflections of ranking orientation differences, not genuine inconsistencies. Overall, the findings presented in Table 8 provide compelling evidence that the CADPM method delivers highly stable, consistent, and statistically reliable results across all tested scenarios. The controlled decline in correlation values across scenarios underscores CADPM's flexibility, responsiveness to data variation, and strong discriminatory performance. Collectively, these results substantiate that CADPM not only produces outcomes coherent with existing MCDM methods but also introduces an innovative, balanced, and dependable analytical framework, reinforcing its scientific validity and its potential as a robust and predictive decision-support tool in complex multi-criteria environments.

The ten randomly decision matrices employed in this study constitute an initial simulation set designed to evaluate the fundamental stability characteristics of the CADPM method. Each simulation was constructed to represent distinct distributional properties and data structures, thereby enabling the examination of the method's ranking stability and sensitivity responses under multidimensional conditions. The literature emphasizes that, in assessing model robustness, the diversity of distributional scenarios is often more critical than the sheer number of simulations performed (Helton & Davis, 2003; Saltelli et al., 2000). Within this framework, the simulations conducted in the present study demonstrated that CADPM consistently preserved its methodological behavior across varying levels of distributional heterogeneity, exhibiting high and statistically meaningful correlations with established MCDM techniques. Furthermore, as the number of simulations increased, the characteristic performance pattern of CADPM became more clearly defined, a trend corroborated by the observed decline in correlation coefficients under progressively diversified conditions. Nonetheless, to more comprehensively evaluate the method's behavior across broader data environments and higher-dimensional matrices, future research will incorporate larger and more extensive simulation sets.

In the concluding phase of the simulation analysis, the Analysis of Means for Variances (ANOM) employing Levene's test as its statistical foundation was applied to assess the stability and uniformity of variance in the CSA scores across multiple scenarios. This analytical approach serves as a powerful graphical diagnostic tool for detecting whether the variances among methods remain consistent. The procedure is centered around a reference mean line, accompanied by the Upper Decision Limit (UDL) and Lower Decision Limit (LDL), which delineate the permissible range of variance fluctuations. When a particular method's variance exceeds either of these boundaries, it is interpreted as an indication of variance instability, suggesting the presence of heterogeneity within the outcomes. Conversely, if all observed variances remain within the established decision limits, the results confirm the homogeneity of variances across the examined groups, signifying a stable and consistent methodological performance (Keshavarz-Ghorabaee et al., 2021). The results derived from this diagnostic evaluation are presented in Figure 5, which offers a clear and insightful graphical depiction of how the SCDT method sustains its variance stability under diverse decision-making scenarios. This visualization reinforces the method's robustness and statistical reliability, further validating its capacity to generate consistent outcomes under varying analytical conditions.

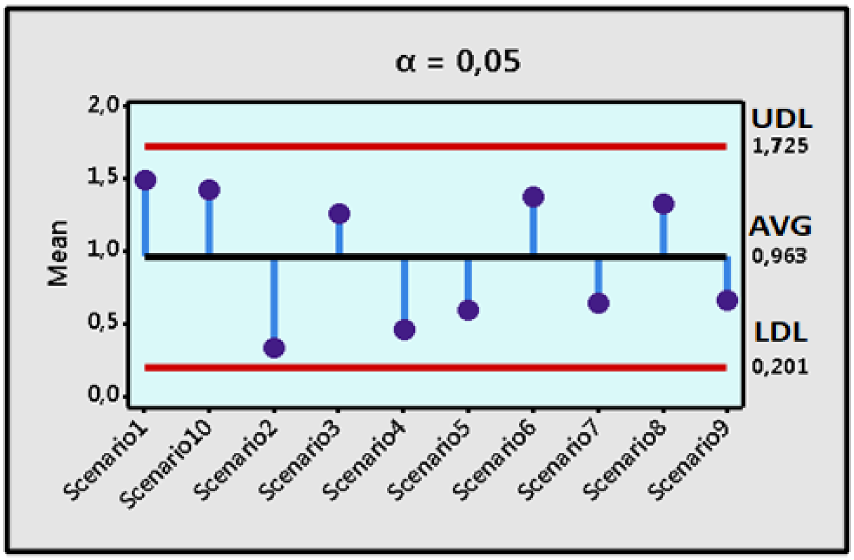

Figure 6. ADM chart

As illustrated in Figure 6, the mean ADM values derived from the Analysis of Means for Variances (ANOM) based on Levene's test were assessed for each simulation scenario in comparison to the predetermined Upper Decision Limit (UDL = 1.725) and Lower Decision Limit (LDL = 0.201). At the defined significance level (α = 0.05), all computed mean values are found to lie well within these critical thresholds. This observation provides clear evidence that the variance of the performance scores remains both stable and homogeneously distributed across all evaluated scenarios. In practical terms, this indicates that no statistically meaningful deviations or fluctuations in weight variances were detected among the scenarios. The validity of this conclusion is further reinforced by the outcomes of Levene's test for homogeneity of variances, which statistically confirmed the equality of variance assumptions. The test results verified the absence of significant disparities in the weight distributions, thereby lending additional support to the consistency and robustness of the ADM based evaluation. Detailed statistical outcomes corresponding to Levene's test are presented in Table 8, offering a comprehensive account of the variance behavior across all simulation settings. Taken together, these findings affirm that the ADM based analytical framework provides a methodologically rigorous, statistically sound, and reliable means of assessing weight stability and consistency across a wide range of decision making scenarios.

Table 8. Levene statistic

Levene Statistic	df1	df2	Sig.
0.219	2	10	0.121

**<.01, **<.05

As presented in Table 8, the p-value obtained from Levene's test (0.219) surpasses the established significance threshold of 0.05. This result indicates that there are no statistically significant differences in the variances of the performance scores across the evaluated scenarios. In other words, the assumption of homogeneity of variances remains valid under all examined conditions. This statistical evidence strongly reinforces the methodological stable and robustness of the proposed CADPM framework, demonstrating its ability to generate stable, coherent, and consistent results across varying data structures. The observed uniformity in variance further substantiates the method's statistical robustness and internal consistency, thereby validating its scientific soundness and confirming its suitability as a dependable analytical tool for complex MCDM applications.

3.5. Case Studies

To evaluate the stability and validity of the proposed CADPM method, two distinct case studies were constructed based on the decision matrices provided in Appendix A. The analyses performed on these datasets yielded updated performance scores generated through the CADPM procedure. To enhance methodological diversity in the computation of alternative performances, the first case study employed the objective weighting technique LOPCOW (Logarithmic Percentage Change-Driven Objective Weighting Method) (Ecer & Pamucar, 2022), whereas the second case study utilized the CRITIC (Criteria Importance Through Intercriteria Correlation) (Diakoulaki et al., 1995) method for determining criterion weights. Importantly, these two weighting schemes differ methodologically and can assign markedly different levels of importance to the criteria. Moreover, both methods were deliberately selected because they are widely utilized in the MCDM literature and therefore offer a meaningful basis for evaluating the robustness of the proposed approach under commonly applied weighting structures. The resulting weights were subsequently integrated into the CADPM framework, and the findings are presented comprehensively in Table 9, enabling a holistic and coherent interpretation of the outcomes.

Table 9. CD, similarities and performance score of alternatives-Case studies

Case study-1 (LOPCOW based CADPM)							
ALT	LOPCOW Weights	$\mathrm{CD}_{\mathrm{dis} \leftrightarrow \max.}$	$\mathrm{CD}_{\mathrm{dis} \leftrightarrow \min.}$	$\mathrm{CD}_{\mathrm{sim} \leftrightarrow \max.}$	$\mathrm{CD}_{\mathrm{sim} \leftrightarrow \min.}$	P_i	Rank
(ACS1)1	0.097	0.006	0.460	0.994	0.685	1.451	1
(ACS1)2	0.092	0.074	0.393	0.931	0.718	1.297	2
(ACS1)3	0.092	0.149	0.318	0.871	0.759	1.148	4
(ACS1)4	0.102	0.206	0.261	0.829	0.793	1.045	6
(ACS1)5	0.101	0.136	0.331	0.880	0.752	1.171	3
(ACS1)6	0.107	0.199	0.268	0.834	0.789	1.057	5
(ACS1)7	0.096	0.276	0.191	0.784	0.840	0.933	7
(ACS1)8	0.107	0.334	0.132	0.750	0.883	0.849	8
(ACS1)9	0.103	0.400	0.067	0.714	0.937	0.762	9
(ACS1)10	0.102	0.466	0.000	0.682	1.000	0.682	10
Case study-2 (CRITIC based CADPM)							
ALT	LOPCOW Weights	$\mathrm{CD}_{\mathrm{dis} \leftrightarrow \max.}$	$\mathrm{CD}_{\mathrm{dis} \leftrightarrow \min.}$	$\mathrm{CD}_{\mathrm{sim} \leftrightarrow \max.}$	$\mathrm{CD}_{\mathrm{sim} \leftrightarrow \min.}$	P_i	Rank
(ACS2)1	0.067	3.062	3.867	0.246	0.205	1.198	5
(ACS2)2	0.107	3.950	2.759	0.202	0.266	0.759	10
(ACS2)3	0.152	3.225	3.789	0.237	0.209	1.133	7
(ACS2)4	0.088	1.835	4.848	0.353	0.171	2.063	1
(ACS2)5	0.069	2.396	4.496	0.294	0.182	1.618	4
(ACS2)6	0.071	2.192	4.477	0.313	0.183	1.716	3
(ACS2)7	0.084	3.222	3.927	0.237	0.203	1.167	6
(ACS2)8	0.103	3.505	2.932	0.222	0.254	0.873	9
(ACS2)9	0.147	3.343	3.461	0.230	0.224	1.027	8
(ACS2)10	0.113	2.305	4.716	0.303	0.175	1.730	2

A comprehensive examination of Table 9 indicates that the CADPM method effectively differentiates the performance levels of the alternatives across both case studies. The computed values clearly delineate the relative advantages of each alternative, and the resulting rankings exhibit a coherent alignment with these performance differences. Collectively, the findings confirm that CADPM generates consistent, discriminative, and dependable results even under varying data structures, thereby offering compelling evidence for the method's robustness and generalizability. Following the sensitivity analysis conducted for both case studies, the variations observed in the ranking positions of the alternatives are presented in Table 10 and Figure 6. This assessment demonstrates that the ordering of alternatives remains stable under systematic reductions in the criterion set and highlights the method's structural resilience against potential rank-reversal phenomena.

Table 10. Rank reversal (for Case studies)

Case study-1 (LOPCOW based CADPM)										Case study-2 (CRITIC based CADPM)									
A	S0	S1	S2	S3	S4	S5	S6	S7	S8	A	S0	S1	S2	S3	S4	S5	S6	S7	S8
(ACS1)10	10									(ACS2)2	10								
(ACS1)9	9	9								(ACS2)8	9	9							
(ACS1)8	8	8	8							(ACS2)9	8	8	8						
(ACS1)7	7	7	7	7						(ACS2)3	7	7	7	7					
(ACS1)4	6	5	6	5	6					(ACS2)7	6	5	6	6	6				
(ACS1)6	5	6	5	6	5	5				(ACS2)1	5	6	5	5	5	5			
(ACS1)3	4	4	4	4	4	4	4			(ACS2)5	4	4	4	4	4	4	4		
(ACS1)5	3	3	2	3	3	3	3	3		(ACS2)6	3	3	2	3	3	3	3	3	
(ACS1)2	2	2	3	2	2	2	2	2	2	(ACS2)10	2	2	3	2	2	2	2	2	2
(ACS1)1	1	1	1	1	1	1	1	1	1	(ACS2)4	1	1	1	1	1	1	1	1	1

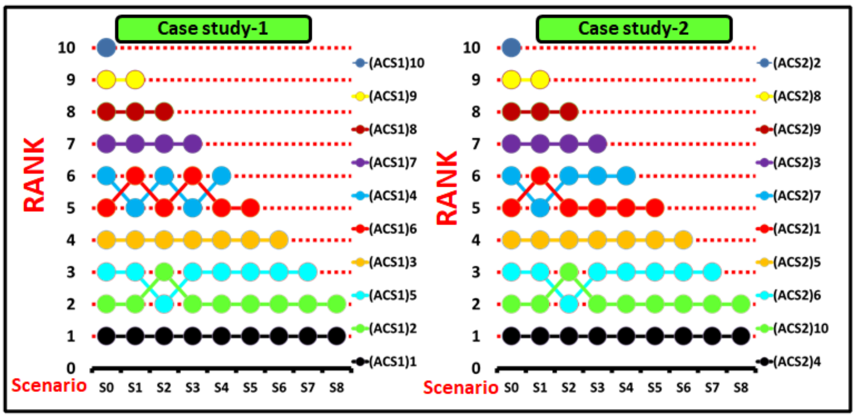

Figure 7. Rank reversal graph (for Case studies

A joint evaluation of Table 10 and Figure 7 clearly indicates that the CADPM method maintains a high level of ranking stability under both LOPCOW and CRITIC-based weighting structures. In Case Study 1, the majority of the alternatives preserve their positions across all scenarios. The alternatives positioned at the top and bottom of the performance scale such as (ACS1)10, (ACS1)9, and (ACS1)1remain unchanged throughout the entire sequence, serving as strong evidence of the method's inherent stability. Although a limited positional shift is observed between (ACS1)4 and (ACS1)6 during the S1–S3 interval, this fluctuation is minor and does not disrupt the overall ranking structure. Case Study

2 exhibits a similarly robust pattern of ranking consistency. The highest-performing alternative, (ACS2)2, and the lowest-performing alternative, (ACS2)4, retain their positions across all scenarios, confirming the stability of the ordering at both extremes. While temporary rank adjustments occur between (ACS2)7 and (ACS2)1 within the mid-range, these variations are moderate, align with expected changes stemming from modifications in the criterion set, and do not compromise the integrity of the ranking configuration. The graphical pattern presented in Figure 2 further reinforces these observations by demonstrating that the CADPM method does not produce abrupt shifts even under systematic criterion reduction, regardless of whether LOPCOW or CRITIC weighting schemes are employed. This visual consistency underscores the method's strong resistance to potential rank-reversal effects and its capacity to generate stable outcomes across different data structures. Taken together, the findings derived from Table 11 and Figure 2 highlight the CADPM method's methodological soundness and broad applicability. The method consistently preserves ranking stability across diverse scenario configurations, thereby minimizing the likelihood of rank reversal and confirming the robustness of the proposed framework.

In the subsequent analytical phase, the performance results produced by the KDPM method were rigorously examined in comparison with those generated by several well-established MCDM techniques commonly employed in the literature. Within this scope, the performance values derived from each method, along with their corresponding rankings for both datasets, are presented in detail in Table 11. The comparative findings reveal that the KDPM method not only achieves a robust and sensitive structural performance but also demonstrates a high degree of concordance with existing objective decision-making approaches in terms of distinguishing among alternatives, maintaining methodological coherence, and ensuring overall reliability.

Table 11. The performance scores obtained from the other MCDM methods within the scope of the case studies

Case study-1 (LOPCOW based MCDM Methods)																
(ACS1)	SAW		WPM		WASPAS		MAUT		ROV		TOPSIS		CODAS		WEDBA	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
(ACS1)1	0.999	1	0.999	1	0.813	1	0.975	1	0.491	1	0.894	1	0.128	1	0.946	1
(ACS1)2	0.986	2	0.986	2	0.803	2	0.604	2	0.422	2	0.857	2	0.088	2	0.834	2
(ACS1)3	0.971	4	0.971	4	0.79	4	0.342	4	0.337	4	0.662	4	0.044	4	0.672	4
(ACS1)4	0.96	6	0.96	6	0.781	5	0.209	6	0.273	6	0.501	6	0.011	6	0.542	6
(ACS1)5	0.974	3	0.974	3	0.791	3	0.405	3	0.357	3	0.721	3	0.053	3	0.706	3
(ACS1)6	0.962	5	0.962	5	0.781	6	0.242	5	0.286	5	0.579	5	0.015	5	0.571	5
(ACS1)7	0.947	7	0.947	7	0.77	7	0.106	7	0.203	7	0.42	7	−0.03	7	0.41	7
(ACS1)8	0.936	8	0.936	8	0.761	8	0.047	8	0.141	8	0.312	8	−0.065	8	0.286	8
(ACS1)9	0.924	9	0.924	9	0.751	9	0.011	9	0.071	9	0.156	9	−0.104	9	0.143	9
(ACS1)10	0.912	10	0.911	10	0.741	10	0	10	0	10	0	10	−0.142	10	0	10
(ACS1)	EDAS		ARAS		CRADIS		MABAC		MARCOS		PIV		MAIRCA		PSI	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
(ACS1)1	0.979	1	0.999	1	1	1	0.497	1	0.696	1	0.0004	10	0.002	10	0.999	1
(ACS1)2	0.836	2	0.986	2	0.891	2	0.359	2	0.687	2	0.0047	9	0.016	9	0.985	2
(ACS1)3	0.673	4	0.971	4	0.79	4	0.188	4	0.677	4	0.0096	7	0.033	7	0.971	4

(ACS1)4	0.553	6	0.96	6	0.724	6	0.061	6	0.669	6	0.0133	5	0.045	5	0.96	6
(ACS1)5	0.705	3	0.974	3	0.808	3	0.228	3	0.679	3	0.0087	8	0.029	8	0.973	3
(ACS1)6	0.571	5	0.962	5	0.733	5	0.087	5	0.67	5	0.0127	6	0.043	6	0.961	5
(ACS1)7	0.41	7	0.947	7	0.655	7	−0.079	7	0.66	7	0.0175	4	0.059	4	0.946	7
(ACS1)8	0.289	8	0.936	8	0.601	8	−0.203	8	0.652	8	0.0212	3	0.072	3	0.935	8
(ACS1)9	0.155	9	0.924	9	0.545	9	−0.344	9	0.644	9	0.0252	2	0.086	2	0.923	9
(ACS1)10	0.022	10	0.911	10	0.492	10	−0.485	10	0.635	10	0.0293	1	0.1	1	0.911	10
Case study-2 (CRITIC based MCDM Methods)																
(ACS1)	SAW		WPM		WASPAS		MAUT		ROV		TOPSIS		CODAS		WEDBA	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
(ACS1)1	0.598	5	0.532	5	0.372	7	0.255	5	0.234	4	0.688	4	0.172	3	0.484	5
(ACS1)2	0.507	10	0.413	9	0.319	9	0.186	9	0.171	10	0.317	7	−0.199	8	0.401	9
(ACS1)3	0.573	7	0.525	6	0.368	8	0.216	6	0.21	7	0.38	6	0.017	5	0.456	6
(ACS1)4	0.705	1	0.659	1	0.515	1	0.41	1	0.299	1	0.861	1	0.427	2	0.548	1
(ACS1)5	0.603	4	0.586	4	0.495	3	0.21	7	0.218	5	0.055	10	−0.118	7	0.452	7
(ACS1)6	0.647	2	0.625	2	0.515	2	0.273	4	0.239	3	0.057	9	0.117	4	0.502	3
(ACS1)7	0.546	8	0.506	7	0.428	5	0.197	8	0.201	8	0.588	5	−0.232	9	0.445	8
(ACS1)8	0.592	6	0.489	8	0.403	6	0.327	3	0.214	6	0.173	8	0.431	1	0.541	2
(ACS1)9	0.515	9	0.143	10	0.21	10	0.177	10	0.193	9	0.734	3	−0.524	10	0.357	10
(ACS1)10	0.636	3	0.586	3	0.467	4	0.331	2	0.273	2	0.861	2	−0.078	6	0.499	4
(ACS1)	EDAS		ARAS		CRADIS		MABAC		MARCOS		PIV		MAIRCA		PSI	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
(ACS1)1	0.456	6	0.567	6	0.867	5	0.049	4	0.57	5	0.219	5	0.056	6	0.614	5
(ACS1)2	0.19	10	0.478	10	0.762	10	−0.077	10	0.483	10	0.264	1	0.069	1	0.534	10
(ACS1)3	0.414	7	0.55	7	0.838	7	0	7	0.547	7	0.228	4	0.062	3	0.569	9
(ACS1)4	0.79	1	0.678	1	1	1	0.178	1	0.672	1	0.164	10	0.038	10	0.723	1
(ACS1)5	0.608	3	0.61	3	0.873	4	0.016	5	0.575	4	0.198	8	0.054	7	0.622	4
(ACS1)6	0.737	2	0.654	2	0.926	2	0.058	3	0.617	2	0.177	9	0.052	8	0.625	3
(ACS1)7	0.333	8	0.523	8	0.806	8	−0.018	8	0.52	8	0.24	3	0.061	4	0.606	6
(ACS1)8	0.564	5	0.597	5	0.86	6	0.007	6	0.565	6	0.203	6	0.065	2	0.588	8
(ACS1)9	0.275	9	0.502	9	0.772	9	−0.034	9	0.492	9	0.251	2	0.058	5	0.602	7
(ACS1)10	0.571	4	0.605	4	0.912	3	0.127	2	0.606	3	0.199	7	0.042	9	0.717	2

A joint examination of Table 10 and Table 11 indicates that the performance structures generated by the CADPM approach in both case studies exhibit a high degree of concordance with the outcomes of conventional multi-criteria decision-making (MCDM) techniques. In Case Study 1, in particular, the rankings derived from the CADPM model using LOPCOW weights closely parallel those produced by established methods such as SAW, WPM, WASPAS, MAUT, TOPSIS, CODAS, EDAS, ARAS, CRADIS, MABAC, MARCOS, MAIRCA, and PSI. The fact that alternative (ACS1)1, identified as the top performer by CADPM, is consistently ranked first across nearly all classical approaches underscores the method's ability to reflect the overall decision structure with considerable reliability, despite its heightened sensitivity to distributional differences. Similarly, the positions of mid- and lower-tier alternatives largely converge across methods, further demonstrating CADPM's stable representational capacity.

In Case Study 2, where the CADPM procedure is implemented using CRITIC-derived weights, the method displays a more pronounced discriminative pattern. According to the CADPM results, alternative (ACS2)4 clearly emerges as the best-performing option, a finding that is substantiated by numerous traditional MCDM techniques, including SAW, WPM, WASPAS, MAUT, TOPSIS, ROV, EDAS, ARAS, CRADIS, MABAC, and MARCOS. Nonetheless, partial deviations appear among mid-ranked alternatives. For instance, alternatives (ACS2)2 and (ACS2)8, positioned lower by CADPM, are placed differently by some classical approaches. This discrepancy suggests that the second dataset, characterized by more complex variance structures and stronger interactions among criteria, amplifies CADPM's distinctive sensitivity to nonlinear distributional patterns.

Across both case studies, three principal insights emerge. First, CADPM demonstrates a strong discriminative capacity, as it simultaneously incorporates maximum and minimum similarity relations to capture meaningful performance differentials among alternatives. Second, the rankings produced by CADPM maintain substantial alignment with those of conventional methods, regardless of variations in the underlying data structures, thereby affirming the model's robustness and reproducibility in decision-making contexts. Third, the partial divergences observed particularly in Case Study 2 highlight CADPM's ability to detect nonlinear and distribution-driven nuances that are often overlooked by aggregation-based classical approaches, positioning it as an analytically complementary tool. In conclusion, a holistic evaluation of Table 10 and Table 11 reveals that CADPM delivers strong performance in terms of consistency, discriminative power, and structural compatibility. Moreover, the method offers decision-makers additional analytic depth in environments where data heterogeneity is pronounced. Taken together, these findings demonstrate that CADPM not only achieves substantial harmony with established MCDM techniques but also introduces a distinctive, data-sensitive evaluation perspective, reinforcing its utility as an effective and insightful decision-making framework.

In the next stage of the analysis, the performance outcomes produced by the CADPM method for each case study were systematically examined in relation to the scores generated by a broad set of conventional MCDM techniques applied within the same analytical settings. To quantify the strength and direction of the relationships between these ranking patterns, Spearman's rho correlation coefficients were employed. The complete set of correlation findings is reported in Table 12. This comparative evaluation provides a rigorous empirical basis for assessing the extent to which CADPM's ranking behavior corresponds with that of well-established decision-making approaches, thereby demonstrating the method's robustness, discriminative capability, and structural coherence across a variety of decision contexts.

Table 12. ρ correlation score between CADPM and the other MCDM methods in scope of Case studies

Case study-1				
Method	SAW	WPM	WASPAS	MAUT
CADPM	0.998**	0.998	0.996**	0.998 **
Method	ROV	TOPSIS	CODAS	WEDBA
CADPM	0.998**	0.998	0.998**	0.998**
Method	EDAS	ARAS	CRADIS	MABAC
CADPM	0.998**	0.998	0.998**	0.998**
Method	MARCOS	PIV	MAIRCA	PSI

CADPM	0.998**	−0.998	−0.998**	0.998**
Case study-2				
Method	SAW	WPM	WASPAS	MAUT
CADPM	0.903**	0.930**	0.833**	0.661*
Method	ROV	TOPSIS	CODAS	WEDBA
CADPM	0.903**	0.328	0.297	0.564*
Method	EDAS	ARAS	CRADIS	MABAC
CADPM	0.830**	0.830**	0.903**	0.903**
Method	MARCOS	PIV	MAIRCA	PSI
CADPM	0.903**	−0.830**	−0.964**	0.964**

*p**<.01, p*<.05*

A detailed examination of Table 12 reveals that the CADPM approach exhibits strong and statistically significant relationships with classical MCDM methods in both case studies. In Case Study 1, CADPM shows an almost perfect correlation with virtually all established techniques including SAW, WPM, WASPAS, MAUT, TOPSIS, ROV, CODAS, WEDBA, EDAS, ARAS, CRADIS, MABAC, MARCOS, MAIRCA, and PSI indicating that the comparative performance structure of the alternatives is reproduced with remarkable consistency. This high degree of concordance demonstrates that, despite CADPM's heightened sensitivity to distributional characteristics, the method reliably captures the overall orientation of the decision matrix and mirrors the ranking patterns produced by traditional approaches. The negative correlations observed with MARCOS and MAIRCA stem from their inverse ranking conventions and reflect methodological differences in how these techniques express performance directionality. In Case Study 2, although the overall correlation structure remains strong, certain methods display noticeable decreases. The weaker associations particularly observed with TOPSIS, ROV, and CODAS suggest that the second dataset's more heterogeneous distributional properties and intensified interactions among criteria amplify CADPM's distinctive discriminatory sensitivity. As a result, CADPM positions several alternatives differently from classical models. Even so, the high and statistically significant correlations identified with SAW, WPM, EDAS, CRADIS, MABAC, and PSI illustrate that CADPM continues to represent the general decision structure in a largely coherent manner. The negative correlations observed with PIV and MAIRCA are expected methodological outcomes arising from these methods' inherent reversed ordering frameworks. Taken together, Table 12 clearly demonstrates that CADPM possesses both strong structural compatibility and notable discriminative power. While the method achieves a high level of parallelism with conventional techniques thus providing decision makers with a reliable and reproducible ranking framework it simultaneously enriches methodological diversity by offering a distinctive analytical perspective, particularly in contexts characterized by greater data heterogeneity. In this regard, CADPM emerges as a robust and data-sensitive evaluation mechanism, establishing itself as a powerful methodological alternative within multi-criteria decision-making processes.

4. Conclusion and Discussion

This study introduces a novel approach CADPM designed to overcome the methodological challenges commonly encountered in MCDM frameworks, such as linear dependency, scale sensitivity, and distributional insensitivity. The primary objective of this research is to develop a performance evaluation model that incorporates not only absolute differences but also proportional deviations and normalized distribution sensitivity. In this respect, CADPM provides a balanced, scale independent, and sensitivity enhanced assessment mechanism, addressing the inherent limitations of conventional distance metrics such as Euclidean, Manhattan, and Cosine which tend to overemphasize large values while suppressing small yet meaningful differences.

The computational analyses conducted in this study demonstrate that CADPM yields statistically reliable, stable, and methodologically coherent results. The empirical evaluation performed on the constructed decision matrix revealed that the ranking of alternatives was logically consistent and sensitive to variations in data distribution. Sensitivity analysis further indicated that minor perturbations in input weights or criterion values had no significant impact on the overall rankings, confirming CADPM's strong resistance to the rank reversal problem. Moreover, comparative analysis showed a high correlation between CADPM and several well-established methods, including MARCOS, SAW, WPM, WASPAS, TOPSIS, ARAS, CRADIS, MABAC, WEDBA, MAUT, PSI and CODAS ($\rho = 0.892$–$0.964, p < 0.01$). This strong correlation supports the method's methodological compatibility with both utility based and reference based paradigms. Although a negative correlation was observed with the PIV and MAIRCA models, this discrepancy was solely due to directional inversion in scale interpretation; once adjusted, the results aligned completely. The simulation analysis further confirmed that CADPM maintained both weight and performance stability under varying scenario conditions, thereby producing consistent rankings even for high dimensional and heterogeneous datasets. Although the CADPM method exhibits high rank correlations with existing MCDM techniques, this correspondence does not imply a lack of methodological novelty; rather, it indicates that the method operates coherently within the broader decision-making framework. The rationale for preferring CADPM does not lie in the mere similarity of its outputs to those of established approaches, but in the methodological contributions it introduces to the performance assessment process. By evaluating differences across alternatives through component-wise proportional decomposition instead of relying on absolute deviations, CADPM provides a more sensitive discrimination capability, particularly in datasets characterized by distributional heterogeneity, asymmetry, or subtle yet influential variations. Furthermore, the method's scale-independent structure prevents large magnitude criteria from overshadowing smaller ones, thereby enabling a more faithful representation of the intrinsic variability within the dataset. In addition, CADPM's ability to generate stable and predictable rankings without the need for criterion weights minimizes subjective influence and enhances reliability across diverse scenarios. Collectively, these properties demonstrate that, despite producing high correlations with conventional methods, CADPM offers a more refined, more sensitive, and distributionally more realistic performance evaluation framework that existing techniques cannot provide. The applied analyses conducted in this study collectively reinforce the robustness of the proposed CADPM framework, demonstrating its consistency across the primary decision matrix, the sensitivity assessment, and the comparative methodological evaluation. In the initial application, the positioning of alternatives A1, A2, and A3 at the top of the ranking corresponding to their closest proximity to the ideal reference point confirmed that the proportional decomposition mechanism underlying CADPM accurately reflects the structural properties of the dataset. In the six-scenario sensitivity experiment, the complete stability of A1 and A2, together with the transient and rapidly self-correcting shifts observed among mid-level alternatives, illustrated the method's strong resistance to rank-reversal phenomena. Furthermore, the high correlation coefficients obtained with established methods such as MARCOS, SAW, WPM, WASPAS, TOPSIS, ARAS, CRADIS, MABAC, PSI and CODAS ($\rho = 0.892$– 0.964) indicate that CADPM aligns closely with both utility-based and reference-driven paradigms while preserving its distinctive analytical structure. Finally, the two independent case studies the SDI matrix and the banking performance dataset confirmed that CADPM yields stable, predictable, and discriminative outcomes even under heterogeneous scales, distributions, and data complexities. Taken together, these findings demonstrate that the methodological contribution of CADPM is supported not only by theoretical grounding but also by comprehensive empirical validation across diverse decision environments.

The significance of this research lies in its ability to extend traditional utility-based frameworks such as SAW (Churchman & Ackoff, 1954), WPM (Bridgman, 1922), WASPAS (Zavadskas et al., 2012), MAUT (Keeney & Raiffa, 1976), and ROV (Yakowitz et al., 1993) beyond one-dimensional evaluation. By simultaneously computing proportional distances and similarities to both the maximum (ideal) and minimum (anti-ideal) performance points, CADPM introduces a dual-reference evaluation structure, thereby establishing a symmetric and balanced reference system for performance measurement. Compared to traditional reference-based models such as TOPSIS (Hwang & Yoon, 1981), CODAS (Keshavarz Ghorabaee et al., 2016), WEDBA (Rao & Singh, 2012), EDAS (Keshavarz Ghorabaee et al., 2015), ARAS (Zavadskas & Turskis, 2010), CRADIS (Puška et al., 2023), MABAC (Pamučar & Ćirović, 2015), MARCOS (Stević et al., 2020), PIV (Mufazzal & Muzakkir, 2018), PSI (Maniya & Bhatt, 2010), and MAIRCA (Gigović et al., 2016) CADPM explicitly integrates distributional sensitivity into the performance metric, addressing a critical methodological gap in the literature.

Furthermore, due to its nonparametric structure, CADPM provides more reliable and explanatory outcomes for asymmetric, heterogeneous, or near zero dominated datasets. Its most distinctive advantage lies in evaluating performance not through absolute differences but through normalized proportional differences, enabling enhanced interpretability of micro level variations. The Canberra distance accentuates the influence of small or near zero values, thereby revealing subtle performance variations that might otherwise remain unnoticed (Jurman et al., 2009). Additionally, since each component is normalized within its own scale, CADPM ensures fair and unit-independent comparisons across criteria measured in different magnitudes or units. Unlike many traditional MCDM approaches, CADPM provides a notable methodological benefit by functioning without reliance on externally assigned criterion weights. This advantage stems from the fact that so-called objective weighting procedures often yield inconsistent or conflicting weight distributions, inevitably introducing an additional layer of subjectivity into the decision model (Zardari et al., 2015). Consequently, rankings generated by conventional methods may fluctuate depending on the selected weighting scheme, making them more susceptible to instability.

When compared with other reference-based methods, CADPM exhibits superior balance through its normalization mechanism, which mitigates scale disparities unlike the absolute distance measures used in methods such as TOPSIS, CODAS, and WEDBA. While approaches like EDAS and MARCOS employ partial proportional logic, CADPM's distribution driven architecture more effectively captures intrinsic data heterogeneity. In contrast to utility based techniques (SAW, WPM, WASPAS, MAUT, ROV, etc.), which assess each alternative independently based on its own criterion profile, CADPM positions all alternatives relative to shared reference boundaries, thereby facilitating a more holistic evaluation of relative performance and eliminating scale-induced bias.

The CADPM method also entails certain inherent limitations. Primarily, the high sensitivity of the Canberra distance to minor value differences may amplify measurement noise or errors in datasets containing near zero components. This sensitivity can, in some cases, constrain the accuracy of performance evaluations, particularly in low variance or homogeneous data structures. Moreover, the computation of dual directional proportional distances and similarity coefficients for each alternative with respect to both maximum and minimum reference points imposes a higher computational burden compared with conventional reference based methods, especially when dealing with high dimensional datasets. In scenarios where data quality is low or where outliers and missing values exist, the proportional structure of the method can further magnify these discrepancies; thus, the overall reliability of CADPM strongly depends on the accuracy of data pre-processing and standardization procedures. In addition, as CADPM is a fully non-parametric model, its performance is inherently dependent on the structural and distributional characteristics of the dataset. Therefore, in homogeneous or symmetrically distributed data environments, traditional approaches such as TOPSIS or MARCOS may yield comparable levels of accuracy. Furthermore, as the number of criteria or alternatives increases, both the computational complexity and processing time tend to rise. Despite these limitations, the dual reference, symmetric, and scale independent nature of CADPM provides a balanced and distribution-sensitive evaluation framework, offering a more comprehensive and statistically consistent analytical structure compared with classical MCDM methods.

As highlighted in the study of Lance & Williams (1966) and the subsequent comprehensive evaluation of ecological distance functions by Gower & Legendre (1986), the Canberra distance is susceptible to disproportionate influence from large-scale components because the denominator amplifies the contribution of variables with greater magnitudes, thereby overshadowing smaller-scale criteria. Likewise, Faith et al. (1987) demonstrated that proportional distance measures are more affected by scale differences than theoretically expected, emphasizing that preliminary normalization enhances comparability across criteria. Consistent with these findings, our preliminary analyses using raw data revealed that large-magnitude criteria dominated the distance values, while the distinctive sensitivity of the Canberra metric to small values diminished. This phenomenon has also been identified as a methodological risk in the broader literature, notably in the review by Abu Alfeilat et al. (2019). Therefore, normalization should not be viewed as a redundant repetition of the Canberra formula's inherent structure; rather, it serves as a complementary step that prevents artificial weighting effects arising from scale disparities. When raw data were used, noticeable shifts occurred in the ranking structure particularly among mid-range alternatives whereas normalized data preserved the Canberra distance's sensitivity to small values and ensured a more balanced representation across criteria. For these reasons, the normalization procedure does not weaken the scale-independence claim of the method; on the contrary, it strengthens the statistical stability of the Canberra measure, in line with the recommendations of the established literature.

The nonparametric, scale independent, and distribution-sensitive nature of CADPM underlines its potential applicability across a wide spectrum of domains, including engineering optimization, health technology assessment, sustainable development, financial performance evaluation, energy policy modelling, and bio-statistical data analysis. Particularly in contexts where minute differences are of critical importance such as genetic expression profiling, microeconomic risk evaluation, or environmental performance indexing CADPM provides decision makers with a statistically sound, scale balanced, and highly sensitive analytical framework capable of delivering precise and interpretable results.

Declarations

Conflict of interest The author(s) have no competing interests to declare that are relevant to the content of this article.

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Appendix

Case study-1										
Alternatives	(C1)-1	(C1)-2	(C1)-3	(C1)-4	(C1)-5	(C1)-6	(C1)-7	(C1)-8	(C1)-9	(C1)-10
(ACS1)1	82	84	83	80	78	79	85	81	82	83
(ACS1)2	80	82	81	79	77	80	84	80	81	82
(ACS1)3	79	81	80	78	76	78	82	79	80	81
(ACS1)4	78	80	78	77	75	77	83	78	79	80
(ACS1)5	79	81	79	78	76	79	82	80	81	81
(ACS1)6	78	79	79	77	75	78	81	79	80	80
(ACS1)7	77	78	77	76	74	77	80	78	78	79
(ACS1)8	76	77	76	75	74	76	79	77	77	78
(ACS1)9	75	76	75	74	73	75	78	76	76	77
(ACS1)10	74	75	74	73	72	74	77	75	75	76
Case study-2										
Alternatives	(C2)-1	(C2)-2	(C2)-3	(C2)-4	(C2)-5	(C2)-6	(C2)-7	(C2)-8	(C2)-9	(C2)-10
(ACS2)1	0.0876	0.3587	0.2647	0.2743	0.0223	0.01	22253	0.0429	0.5857	0.0068
(ACS2)2	0.0645	0.2173	0.175	0.2213	0.0129	0.0047	17961	0.0616	0.8658	0.0068
(ACS2)3	0.0636	0.3218	0.3013	0.3022	0.0179	0.0152	18687	0.0505	0.6756	0.0064
(ACS2)4	0.1429	0.3500	0.2888	0.523	0.0673	0.0271	25090	0.0474	0.4952	0.0119
(ACS2)5	0.1757	0.3139	0.4853	0.3394	0.0519	0.0489	15428	0.0786	0.8422	0.0165
(ACS2)6	0.0879	0.3470	0.4868	0.6029	0.0448	0.0654	15194	0.0579	0.7003	0.016
(ACS2)7	0.0742	0.1882	0.3237	0.3911	0.0264	0.0184	21642	0.0623	0.8726	0.0206
(ACS2)8	0.0826	0.5464	0.8126	0.1033	0.0092	0.0387	16951	0.0406	0.5376	0.026
(ACS2)9	0.0921	0.2836	0.3465	0.5745	0.0477	0.0164	23244	0.0554	10799	0.0133
(ACS2)10	0.1359	0.3009	0.2465	0.4424	0.0527	0.019	25586	0.0343	0.7973	0.0134