



Research article

A novel composite ratio and Euclidean aggregation (CREA) multi-criteria decision-making method for decision support in cross-country biomedical and biotechnology research system evaluation

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Abstract: This paper proposes the composite ratio and Euclidean aggregation (CREA) method, a new multi-criteria decision-making approach for biotechnology country evaluation. CREA assesses national biotechnology performance by integrating heterogeneous criteria related to regulation, innovation, research productivity, market size, clinical-trial activity, human capital, and intellectual-property protection. The method applies a common fixed-reference normalization expression to both criterion types while preserving their different preference directions. The benefit-performance and non-benefit-burden components are then aggregated separately and integrated through a hybrid Euclidean–ratio index. Objective criterion weights were determined using the SITDE method. Biotech patents received the highest weight of 0.126, while the IP protection index received the lowest weight of 0.048. The empirical application evaluated 13 countries using 10 criteria. The United States ranked first with a CREA score of 3.575, followed by Israel with 3.297 and China with 3.279, whereas Canada ranked last with a score of 1.058. Comparative analysis with RAM, COPRAS, MOORA, MOOSRA, and MULTI-MOORA produced Spearman correlations ranging from 0.962 to 0.995. Under the tested Ct5 weight-perturbation scenarios, the maximum absolute changes in CREA scores ranged from 0.17% to 4.45%, while the ranking positions of all 13 countries remained unchanged. In one rank-reversal experiment involving the addition of Denmark, the rankings of the original countries remained unchanged under CREA, whereas TOPSIS produced rank changes for 11 countries. These findings provide preliminary evidence of ranking stability and practical usefulness in the present biotechnology

benchmarking application. Broader validation using larger samples, multiple datasets, and additional rank-reversal scenarios is required before general conclusions regarding the stability of CREA can be drawn.

Keywords: composite ratio and Euclidean aggregation; multi-criteria decision-making; biotechnology country evaluation; SITDE; rank reversal

Mathematics Subject Classification: 90B50, 90C29

1. Introduction

1.1. Strategic importance of biotechnology country evaluation

In recent years, biotechnology has emerged as one of the most strategically important areas of economic and scientific development, influencing not only its traditional area of scientific jobs but also affecting other important economic sectors like health care, agriculture, pharmaceuticals, environmental sustainability, and manufacturing. The increasing importance of biotechnology is demonstrated in its role in providing food security, using resources more efficiently, reducing emissions, and being part of the circular economy and its impact on diagnostic, vaccine, and therapy development Tyczewska et al. [1], Wei et al. [2]. These developments indicate that biotechnology has evolved from a specialized area of research into a cross-sectoral platform technology that supports economic development and improves quality of life.

Recent developments in biotechnology have strengthened its close association with bioeconomy and knowledge-based development systems. In this way, biotechnology is not only a technology; it is a structural change, with science and technology innovation, industrial systems, and policy systems becoming increasingly connected Wei et al. [2], Losacker et al. [3]. Furthermore, biotechnology is now a source of international competition, with countries seeking to improve their scientific leadership, the efficiency of regulations, innovation ecosystems, and intellectual property. Consequently, the capacity for a nation to compete in biotechnology is determined by many factors, including institutional investments, innovation policy, stakeholder coordination, and governance Bettanti et al. [4], Aghmiuni et al. [5], Han et al. [6].

Although biotechnology has gained global significance, national performance in biotechnology development and application varies considerably across countries due to differences in underlying structural conditions, such as research and development (R&D) capabilities, productivity of R&D, regulatory conditions, market conditions, and human capital. Empirical evidence indicates that innovation performance is not evenly distributed among economies due to very different levels of knowledge created, disseminated, and absorbed Furman et al. [7], and country competitiveness is linked to differences in R&D expenditures, patenting activity, and technological outputs Raghupathi and Raghupathi [8]. Clearly, there is a significant need for systematic evaluation of biotechnology at the country level to provide policymakers, investors, and researchers with the tools to determine relative competitiveness, diagnose structural gaps, and develop strategic directions for increasing biotechnology research and production.

1.2. Multi-criteria complexity in biotechnology performance assessment

One of the main challenges in evaluating national biotechnology performance is its multidimensional nature, which cannot be adequately captured by a single measure. Each country has different levels of performance in biotechnology, but the variables used to assess national performance also fall into multiple heterogeneous categories that impact the overall performance of each country. Variables such as patent production, research capacity, number of publications, regulatory efficiency, market size, number of clinical trials, and ability to protect intellectual property are heterogeneous in nature in that some of these variables provide benefits and should be maximized, whereas some variables provide no benefits and should be minimized. This adds significant complexity to evaluating these at the country level because there is performance variation across countries within several of these categories.

A key issue in biotechnology country evaluation is that strong performance in one dimension may be accompanied by weaker performance in another. For instance, some countries will have good performance for innovation-related metrics such as patent production and number of publications; however, they may have poor performance as it relates to regulatory efficiency (i.e., barriers to commercialization). Therefore, equal comparisons across nations using a simple linear methodology will result in misleading assessments. Previous research has indicated that there are multiple interacting or overlapping determinants influencing how biotechnology is valued; thus, decision-making in these situations requires a multi-criteria approach that provides a structured framework for weighing the complex trade-offs that can occur between the different determinants Belton and Stewart [9], Mardani et al. [10]. In addition, the existing MCDA literature supports that the evaluation of complex technologies or healthcare does, in fact, consist of multiple dimensions of performance and involves competing criteria that require systematic integration Thokala et al. [11], Angelis and Kanavos [12].

As such, evaluating biotechnological performance at the country's level should not be treated solely as a descriptive comparison measurement but as a structured multi-criteria decision-making (MCDM) issue that requires proper modeling of the heterogeneity existing within and between the many competing criteria.

1.3. Ranking instability and rank-reversal challenges in MCDM

Although multi-criteria methods provide a suitable framework for biotechnology evaluation, questions remain regarding the stability and reliability of the rankings produced by a multi-criteria approach. It is important to note that most existing ranking methodologies rely on heavy use of normalization techniques, weighting schemes, and aggregation techniques. Therefore, a ranking resulting from these methodologies is likely to be affected by the choices made regarding methodology and the characteristics of the dataset being ranked.

A major concern in country-level ranking systems is that relative rankings may change even when a country's individual performance is unchanged Nardo et al. [13]. Recent examinations of composite indicators and ranking systems demonstrate the influence of scaling choices and threshold definitions on resulting rankings Kelemen et al. [14], raising additional concerns about robustness and interpretability Greco et al. [15]. In addition, the stability of a ranking is influenced by the mathematical transformation of the heterogeneous dataset used to create the ranking and is sensitive to extreme values as well as normalization techniques Centre [16].

A closely related issue is rank reversal, where the relative order of alternatives in a ranking is modified by the introduction of new alternatives, removal of existing alternatives, or modification of

the normalization base. This phenomenon has been widely acknowledged as one of the most significant limitations of many MCDM models Liu et al. [17]. For this reason, resistance to rank reversal is considered a significant determinant of a reliable decision-making model Žižović et al. [18]. Additional recent research indicates that improving ranking robustness and decreasing ranking instability should remain as key methodological objectives in MCDM Paradowski et al. [19].

Given the use of rankings for making strategic and policy decisions in biotechnology benchmarking between countries, ranking instability can greatly reduce the ability to correctly interpret and rely on the rankings generated using a multi-criteria approach.

1.4. Research gap

Therefore, the methodological gap is not the absence of methods addressing normalization, compensation, or ranking robustness. Rather, the reviewed literature does not appear to provide a unified framework that simultaneously uses criterion-specific fixed-reference normalization, preserves benefit-performance and non-benefit-burden aggregates separately, and integrates the magnitudes of these two components with a benefit-to-burden ratio within a single ranking index.

To address this gap, CREA retains the weighted benefit-performance and non-benefit-burden components separately until the final evaluation stage. These components are denoted by AS_{i+} and AS_{i-} , respectively. A higher AS_{i+} indicates stronger performance on the benefit criteria, whereas a lower AS_{i-} indicates a smaller non-benefit burden.

The two aggregate components are subsequently integrated through the following hybrid Euclidean–ratio index: $CREA_i = \sqrt{AS_{i+}^2 + AS_{i-}^2} + \frac{AS_{i+}}{AS_{i-}}$. The Euclidean component captures the combined magnitude of the separately retained benefit-performance and non-benefit-burden aggregates, while the ratio component evaluates beneficial performance relative to the corresponding non-benefit burden. Thus, a higher benefit aggregate increases the ratio component, whereas a greater non-benefit burden increases the denominator and reduces the ratio component.

This structure differs from TOPSIS's ideal-distance calculation, VIKOR's utility–regret compromise index, RAFSI's reference-interval scoring, RAM's root-based assessment, and DNMA's integration of multiple subordinate normalization and aggregation models. Therefore, the methodological contribution of CREA lies not in any individual element considered separately but in the ordered integration of fixed-reference normalization, separate benefit-performance and non-benefit-burden aggregation, and hybrid Euclidean–ratio evaluation.

1.5. Motivation for the proposed CREA method

The methodological limitations identified in the preceding section motivate the development of CREA as a structured framework for biotechnology country evaluation. The method is designed to integrate heterogeneous criteria while preserving the different preference directions of benefit and non-benefit criteria. CREA applies a common criterion-specific fixed-reference normalization expression, under which higher normalized values are preferred for benefit criteria and lower normalized values are preferred for non-benefit criteria.

CREA retains the benefit-performance aggregate and the non-benefit-burden aggregate separately until the final evaluation stage. The benefit-performance aggregate represents the weighted contribution of desirable criteria, whereas the non-benefit-burden aggregate represents the weighted magnitude of undesirable criteria such as cost, delay, and rejection rate. This separation improves

group-level interpretability and prevents the two criterion groups from being prematurely reduced to a single additive score.

The final CREA operator combines the Euclidean magnitude of the two aggregate components with a benefit-to-burden ratio. The Euclidean component represents the joint magnitude of the separately retained aggregates, whereas the ratio component evaluates beneficial performance relative to the corresponding non-benefit burden. This structure differs from the ideal-distance logic of TOPSIS, the utility–regret structure of VIKOR, the reference-interval scoring of RAFSI, the root-based assessment of RAM, and the multiple-model aggregation of DNMA.

CREA also uses predetermined criterion-specific reference bounds that remain fixed during the addition or removal of alternatives. This design reduces alternative-set dependence caused by recalculating normalization references. However, the resulting ranking-stability property is conditional on the maintenance of the specified reference bounds, criterion weights, preference directions, original data, and aggregation rule.

1.6. Research objectives

The key objectives of this research are:

- To propose the Composite Ratio and Euclidean Aggregation (CREA) method as a structured multi-criteria decision-making framework for biotechnology country evaluation.
- To comprehensively evaluate biotechnology performance across countries by integrating multiple heterogeneous indicators within a unified decision-making structure.
- To preserve the distinct roles of benefit performance and non-benefit burden throughout the evaluation process, thereby improving the interpretability of the country assessment.
- To reduce alternative-set dependence caused by recalculating normalization references and to examine ranking stability under fixed model parameters.
- To evaluate the comparative ranking consistency and application-specific stability of the proposed CREA framework using established MCDM methods, sensitivity analysis, and rank-reversal analysis.
- To provide practical benchmarking support for policymakers, investors, and researchers in identifying competitive environments, structural differences, and strategic directions in biotechnology development.

1.7. Main contributions of the study

This study proposes an integrated MCDM framework for evaluating national biotechnology performance across heterogeneous criteria. The framework applies the same criterion-specific fixed-reference normalization expression to both benefit and non-benefit criteria while preserving their different preference directions: higher normalized values are preferred for benefit criteria, whereas lower normalized values are preferred for non-benefit criteria.

A further methodological contribution of this study lies in the introduction of a hybrid MCDM framework designed to enhance ranking robustness by reducing normalization dependence and the risk of rank reversal Więckowski and Sałabun [20], Sotoudeh-Anvari [21]. The hybrid nature of the proposed framework combines the benefits of Euclidean aggregation with those of ratio-based evaluation, improving interpretability while supporting ranking consistency under the stated conditions D'Agostino et al. [22], Jiang et al. [23]. These findings are consistent with current research

efforts aimed at creating robust MCDM models that account for the variability associated with comparing the performance of multiple alternatives.

From a practical perspective, this study offers practitioners a systematic and structured approach for comparing biotechnology performance across different countries, enabling policymakers, investors, and researchers to identify competitively advantageous locations and structural differences and to make informed strategic choices.

2. Literature review

2.1. *Biotechnology country evaluation and benchmarking*

Although biotechnology has traditionally been examined at the laboratory or firm level, it is increasingly recognized as a national strategic capability shaped by research systems, industry actors, regulatory institutions, public policy, and intellectual property frameworks. Previous research regarding national innovation systems established that biotechnology's development is heavily influenced by the scope of institutional coordination and the design of public policy. This is especially true of nations trying to establish long-term competitiveness in the biotechnology sector Kaiser and Prange [24]. Related research has also suggested that the management of intellectual property significantly influences how biotechnology firms engage in innovation and commercialization activities Thumm [25].

This broader view of biotechnology is supported by several empirical and policy-oriented studies. Aghmiani et al. [5] studied how biotechnology innovation is influenced by policy, institutional, and environmental factors, while Bettanti et al. [4] demonstrated that the success of biopharmaceutical innovative ecosystems is determined by the level of coordination between various stakeholders rather than by simply the scientific output produced independently. Previous studies Van Beuzekom [26], Arundel [27], Friedrichs and van Beuzekom [28] considered biotechnology to be a sector that needs specific indicators for tracking the innovation activity of firms and measuring their economic contribution to the economy, reinforcing the importance of biotechnology to national policymakers. Collectively, these studies indicate that the degree to which biotechnology competes internationally varies according to the varying levels of research capacity, quality of governance, support from the market, and protection of intellectual property within the different countries' systems.

Country-level biotechnology benchmarking is important for identifying national strengths and weaknesses, guiding policy priorities, supporting investment decisions, and strengthening international collaboration. However, the methodology that has been used to benchmark biotechnology is fragmented in nature. Many studies have utilized indicators that are based on patents, which are useful for capturing trends related to innovation but may not adequately reflect the quality of regulation, the capability to translate research results into products, or the level of maturity of the ecosystem surrounding biotechnology Arundel [27]. Other studies have used indicators based on publications, which capture the visibility and reach of the research being conducted but not necessarily how ready the research findings are for commercialization. Regardless of the approach, studies that are driven by broad-ranging sets of indicators are likely to be influenced by both the selection of the variables and the logical process used to aggregate the data to form a comprehensive view of biotechnology. As such, much of the existing literature may continue to view countries through a partial lens as opposed to viewing them through an integrated framework of comparison.

2.2. Biotechnology evaluation as a multi-criteria decision-making problem

This fragmentation reflects a broader methodological problem: the absence of a comprehensive and systematic framework for evaluating the relative biotechnology performance of countries. To assess the overall performance of a country within the biotechnology field, it is necessary to consider multiple metrics. For example, one country may be performing well in scientific publications while performing poorly within the regulatory framework, the ability to commercialize a product or service, or the extent to which it has a supportive marketplace. Furthermore, the criteria used are characterized not only by differences in the magnitude of the metrics (i.e., the scale of measurement) but also in the direction of their interpretation (i.e., some criteria are “positive” and should be maximized; other criteria are “negative” and should be minimized).

Given this multidimensional structure, biotechnology benchmarking is well-suited to a multi-criteria decision-making (MCDM) framework. MCDM is a systematic process for evaluating a set of alternative options based on a variety of criteria, frequently having opposing interests or goals. Therefore, MCDM methods can be effectively applied in the assessment of biotechnology benchmarking across multiple variables Triantaphyllou [29]. Several methods exist for the implementation of the MCDM process to support assessments in a variety of settings, e.g., AHP, TOPSIS, VIKOR, PROMETHEE, ELECTRE, COPRAS and many others Alvarez et al. [30], Cinelli et al. [31]. This broad spectrum of methods not only provides an opportunity to apply various methods to a variety of situations but demonstrates that there is no single best method for all types of evaluations.

A variety of MCDM methods have been used to evaluate biotechnology, health care, and innovation. Several examples are provided in Table 1.

Table 1. Selected MCDM studies in biotechnology, healthcare, R&D, innovation, and country-level evaluation.

Author(s)	MCDM method/approach	Application context
Chang et al. [32]	Hybrid MCDM	Evaluation of strategic alliance partners in the green biopharmaceutical industry
Oliveira et al. [33]	Critical review of MCDA	Review of the methodological quality and challenges of MCDA studies in health technology assessment
de Souza et al. [34]	Systematic review of MCDM approaches	Review of MCDM methods and criteria used in R&D project portfolio selection
Garcia-Bernabeu et al. [35]	Multi-criteria reference-point-based approach	Assessment of regional innovation performance in Spain
Liu et al. [17]	Hybrid MCDM	Evaluation of regional intellectual capital and innovation capacity
Ozkaya et al. [36]	Hybrid data mining and MCDM	Cross-country comparison using innovation indicators
Ersoy [37]	Entropy, PIV, ROV, COPRAS, and comparative MCDM analysis	Assessment of ICT development in G7 countries

As shown in Table 1, the verified studies include biotechnology-industry partner evaluation, methodological reviews of MCDA in health technology assessment and R&D project selection,

regional intellectual-capital and innovation-performance assessment, and cross-country comparisons of innovation and ICT development. However, limited attention has been given to an integrated country-level biotechnology benchmarking framework that simultaneously incorporates regulatory, scientific, technological, market, clinical, human-capital, and intellectual-property dimensions. This limitation supports the need for the comprehensive evaluation structure developed in the present study.

Despite the growing application of MCDM methods in recent years, most existing studies have focused on domains such as energy systems, sustainability, and supply chain management, with relatively limited attention given to biotechnology country evaluation. The gap indicates the need for further exploration of robust, structural, and stable MCDM frameworks for comprehensive biotechnology country benchmarking.

In biotechnology and related sectors, the use of MCDM has proved useful. For example, Chang et al. [32] developed a hybrid MCDM model for strategic alliance partner evaluation in the green biopharmaceutical industry, which illustrated that biotechnology-related decision-making often requires the systematic integration of multiple criteria. Beyond biotechnology, MCDM has been applied extensively in health technology assessments, where Oliveira et al. [33] and Baltussen et al. [38] have demonstrated that multi-criteria frameworks are highly beneficial when simultaneously assessing the technical, economic, social, and policy components of health technologies. Similar conclusions were reached in the areas of innovation and R&D evaluation, where de Souza et al. [34] identified the use of MCDM as an effective tool for selecting R&D projects with complex and conflicting objectives. Hence, benchmarking biotechnology countries is consistent with the logic of MCDM and is an application area that requires multi-criteria thinking.

2.3. Normalization dependence, ranking instability, and rank reversal in MCDM

MCDM is an appropriate tool for evaluating complex decision problems, but its application is also associated with significant methodological issues. The most well-known methodological issue related to MCDM is the need to normalize the criteria to allow for comparison. This need for normalization is because different criteria will typically have different units and scales, making it necessary to create a normalized set of values. In practice, however, normalization is not a purely neutral procedure, as the results of using different normalization techniques will frequently differ, even when all other variables (alternatives, criteria, and weights) are the same. Liao and Wu [39] and Wen et al. [40] have demonstrated this in their studies, indicating that when different transformation rules are used, the rankings of alternatives may differ substantially.

This issue becomes particularly evident when examining methods such as TOPSIS and VIKOR. Ploskas and Papathanasiou [41] demonstrated that by using different normalization procedures in either of these methods, there is an opportunity for the rankings to differ and, in some cases, alter the selection of the best alternative. Consequently, the final rankings will depend not only on how well an alternative performs but also on how the data were scaled using the mathematical technique employed. Therefore, normalization is a critical concern in MCDM and is not merely a technical issue.

Another issue regarding MCDM methods is that the validity of the ranking of alternatives may be difficult to assess. In many real-world cases, there is no way to know the true ranking of alternatives, which makes it difficult to establish the reliability of any method used to obtain a ranking of alternatives. This has been discussed by Chang and Yeh [42] and Triantaphyllou and Baig [43] in earlier works, both highlighting that there is no consistently objective benchmark available for most decision scenarios. There have been several suggestions regarding how to evaluate the credibility of

MCDM methods. Some examples of the research on this topic include Wang and Triantaphyllou [44], Saaty and Ergu [45], and Brans and De Smet [46], but to date, there has not been an extensive application of these criteria. Gilliams et al. [47] noted similarly that when attempting to compare different methods, it is common for the conclusion reached about a method's credibility to depend on the context in which it was analyzed, as opposed to any universally applicable criteria.

One of the most significant methodological concerns is the phenomenon known as rank reversal. Rank reversal is defined as a change in the relative ranking of an established set of alternatives due to the introduction of a new alternative, removal of an alternative, or any alteration of the decision structure that does not fundamentally affect the original performance data. Rank reversal was first presented in the context of AHP by Belton and Gear [48], but more recent research has shown that rank reversal is a general problem, not just limited to AHP. Wang and Luo [49] illustrated that rank reversal can occur within the SAW and TOPSIS decision models and thus classified it as a more general problem across MCDM methods. García-Cascales and Lamata [50] further indicated that the calculation of normalized distance in TOPSIS models upon the change in the set of alternatives is the reason behind rank reversal. Furthermore, Mousavi-Nasab and Sotoudeh-Anvari [51] argued that the potential of rank reversal to induce a greater concern regarding the credibility of decisions has particular importance in the case of material selections. These studies indicate that ranking instability is one of the major methodological issues of concern in MCDM.

2.4. Robustness-oriented MCDM methods

Conventional methods such as TOPSIS and VIKOR provide important benchmark structures for alternative ranking. TOPSIS evaluates alternatives according to their relative proximity to positive-ideal and negative-ideal solutions, whereas VIKOR identifies a compromise alternative using measures of group utility and maximum individual regret. Although both methods are widely applied, their ranking outcomes may be influenced by the selected normalization procedure and changes in the available alternative set, because their reference values are generally derived from the current decision matrix. These limitations have motivated the development of robustness-oriented methods such as RAFSI, RAM, and DNMA.

The growing body of MCDM research aimed at improving ranking methods is due, in part, to issues raised with respect to rank reversal and normalization dependence. The development of methods that explicitly address rank reversal has become an active direction of MCDM method development. An example of this kind of method is the RAFSI method developed by Žižović et al. [18], which was designed to accommodate the irregularities in rankings that may occur through modified normalization and aggregation structures. These examples show that robustness is now a central focus of MCDM development rather than a secondary concern.

Recent efforts to improve MCDM robustness have also focused on normalization and aggregation procedures. An example of such a method is the DNMA (duo normalization with multiple aggregation) method developed by Liao and Wu [39], which integrates double normalization with various aggregation methods to reduce distortions that may arise from using one form of transformation rule only. Simultaneously, research is increasing on robustness via the use of sensitivity analysis and formal diagnostics for stability tests. A comprehensive review of sensitivity analysis methods used in MCDA can be found in Więckowski and Sałabun [20]. In addition, the introduction of novel coefficients by Paradowski et al. [19] provides further opportunities for quantifying robustness quantitatively across various forms of perturbation, thereby expanding the use of such assessments to assess ranking stability.

Despite these methodological developments, the selected MCDM methods address different aspects of evaluation and robustness. TOPSIS uses distances from positive-ideal and negative-ideal solutions, while VIKOR employs a compromise-ranking structure based on group utility and maximum individual regret. RAFSI emphasizes reference-interval transformation to reduce alternative-set dependence, RAM applies a root-based and partially compensatory assessment structure, and DNMA integrates multiple normalization and aggregation models to reduce reliance on a single transformation and ranking procedure. These approaches provide important methodological advances, but they use different intermediate representations and final aggregation mechanisms.

None of these methods, in their original formulations, constructs a paired intermediate representation consisting of a separately aggregated benefit-performance component and a separately aggregated non-benefit-burden component, subsequently combining their Euclidean magnitude with a benefit-to-burden ratio. This structure is relevant to biotechnology country evaluation because the assessment simultaneously involves regulatory burdens and desirable dimensions related to innovation, research, markets, clinical activity, human capital, and intellectual-property protection. Therefore, the need remains for an interpretable framework that preserves benefit performance and non-benefit burden separately until the final stage and integrates their joint magnitude and relative benefit-to-burden relationship within one ranking index.

Recent developments also indicate increasing research interest in advanced and hybrid MCDM frameworks that integrate different weighting, normalization, aggregation, and uncertainty-handling procedures. Basilio et al. [52] provided a recent contextual overview of such developments in operational research. This reference is used to position CREA within the broader development of advanced and hybrid MCDM approaches; it is not used as direct mathematical support for the CREA normalization procedure, aggregation operator, monotonicity condition, or ranking-stability proposition.

Recent fuzzy MCDM research has extended decision-support models to situations characterized by uncertainty, ambiguity, and imprecise expert assessments. Liu et al. [53] integrated cubic Fermatean fuzzy sets with SWARA, vector-similarity measures, and an extended VIKOR method for selecting industrial wastewater-treatment technologies. Liu et al. [54] proposed an interval-valued Fermatean fuzzy framework combining divergence- and entropy-based measures, an improved PIPRECIA weighting procedure, and an extended CRADIS method for green-building-material selection. Liu et al. [55] integrated a generalized Hellinger-type distance measure, AHP, and an extended MAIRCA method within an interval-valued Fermatean fuzzy environment for assessing sustainable energy systems. Similarly, Liu et al. [56] developed a linear Diophantine fuzzy hybrid model combining entropy–divergence measures, SWARA, and OCRA for evaluating renewable-energy resources. These studies demonstrate the growing importance of fuzzy representations in handling uncertain, linguistic, and interval-valued decision information. In contrast, the present CREA framework is developed for crisp secondary numerical data and focuses primarily on aggregation structure and ranking stability. Therefore, the current CREA formulation complements rather than replaces fuzzy MCDM models, while its extension to fuzzy and interval-valued decision environments represents an important future research direction.

2.5. Methodological positioning of CREA

The reviewed literature reveals a dual gap, one related to application and the other to methodology. From an application perspective, the current state of biotechnology country assessments remains

fragmented. Most of the literature that has been published uses individual elements, such as patents Thumm [25], publications Lowe et al. [57], ecosystem structure Bettanti et al. [4], or policy indicators Aghmiuni et al. [5], Arundel [27]; however, limited integration exists across multiple relevant criteria to create a comprehensive country ranking framework. This fragmentation is evident in both the foundational biotechnology research and policy documents reviewed, which mainly emphasize separate innovation, policy, scientific output, and ecosystem-related dimensions rather than an integrated country-level MCDM ranking framework.

From a methodological perspective, the MCDM literature repeatedly demonstrates that rankings are sensitive to data normalization, aggregation structure, and changes in the set of alternatives. Ploskas and Papathanasiou [41], Liao and Wu [39], and Wen et al. [40] have emphasized this issue in their research on the impact of normalization, as did Belton and Gear [48], Wang and Luo [49], García-Cascales and Lamata [50], and Mousavi-Nasab and Sotoudeh-Anvari [51] in their studies on rank reversibility and instability. While recent robustness-oriented methods and analytical frameworks have moved the field forward, research works such as Žižović et al. [18], Więckowski and Sałabun [20], and Paradowski et al. [19] are all concerned with both rank instability and rank reversal susceptibility.

Thus, there remains a need for a comprehensive MCDM framework for biotechnology country evaluation that integrates benefit criteria and non-benefit burdens within a coherent comparative structure. To address this application and methodological gap, the present study proposes the Composite Ratio and Euclidean Aggregation (CREA) method. CREA aims to improve group-level interpretability through separate benefit-performance and non-benefit-burden aggregation and to reduce alternative-set dependence through fixed-reference normalization.

3. Proposed CREA method

3.1. Conceptual philosophy of CREA

The CREA method is an MCDM approach designed for decision problems containing both benefit and non-benefit criteria. CREA recognizes two distinct aggregate dimensions: the benefit-performance aggregate, denoted by AS_{i+} , and the non-benefit-burden aggregate, denoted by AS_{i-} . A higher AS_{i+} is preferred, whereas a lower AS_{i-} is preferred Cinelli et al. [31], Guitouni and Martel [58].

Through its separate aggregation structure, CREA recognizes that the evaluation of alternatives with mixed criteria involves two different dimensions: the positive contribution of benefit criteria and the undesirable burden associated with non-benefit criteria. Accordingly, CREA does not pool all criteria into a single composite score at an early stage. Instead, it retains the benefit-performance aggregate AS_{i+} and the non-benefit-burden aggregate AS_{i-} separately until the final evaluation stage. This structural design preserves group-level interpretability and reduces the information loss that may occur when conflicting criterion groups are prematurely combined Cinelli et al. [31], Guitouni and Martel [58].

CREA is based on the premise that benefit performance and non-benefit burden should not be treated as fully symmetric and that compensation between them should be controlled rather than unrestricted. In many additive methods, poor performance in one dimension may be completely offset by strong performance in another dimension. CREA, by contrast, is designed as a partially compensatory method in which some trade-off is permitted, but the required compensation is neither constant nor one-to-one. This approach is consistent with the distinction between full and partial compensation discussed in the MCDM literature Cinelli et al. [31], Guitouni and Martel [58].

More specifically, CREA combines two evaluation logics within a single final index. The Euclidean component, $\sqrt{AS_{i+}^2 + AS_{i-}^2}$, captures the joint magnitude of the separately aggregated benefit-performance and non-benefit-burden dimensions. The ratio component, $\frac{AS_{i+}}{AS_{i-}}$, evaluates beneficial performance relative to the corresponding non-benefit burden. Thus, a larger benefit aggregate increases the ratio, whereas a larger non-benefit burden increases the denominator and reduces the ratio. Rather than relying only on additive, distance-based, magnitude-based, or ratio-based logic, CREA combines these perspectives within a hybrid geometric-relational structure Cinelli et al. [31], Guitouni and Martel [58].

The proposed aggregation formula is motivated by two distinct information requirements. A magnitude-based measure can represent the joint size of the two aggregate components, but may not adequately indicate whether beneficial performance is strong relative to the corresponding burden. Conversely, a ratio-based measure can represent the benefit-to-burden relationship but may assign the same value to alternatives having proportionally similar benefit and burden aggregates, even when their aggregate magnitudes differ substantially. Therefore, neither magnitude nor the benefit-to-burden ratio alone provides a complete representation of the paired aggregate structure.

CREA combines these two complementary forms of information within one operator. The Euclidean component retains information about the joint magnitude of the benefit-performance and non-benefit-burden aggregates, while the ratio component captures their relative benefit-to-burden relationship. This purpose differs from the core objectives of ideal-distance, compromise-ranking, reference-interval, root-assessment, and multiple-model aggregation methods. Reproducing the same paired representation and dual evaluation within an established method would require replacing its central aggregation rule. CREA is therefore proposed as a distinct aggregation structure rather than as a minor modification of an existing method.

A key implication of this design is that CREA is intended to assign greater preference to alternatives that demonstrate strong benefit performance while maintaining a comparatively low non-benefit burden. Conversely, alternatives that appear favorable mainly because of a low burden but remain weak on the benefit criteria should not necessarily be treated as equally desirable. Thus, weak benefit performance is not intended to be compensated to the same extent by a favorable non-benefit position. A related principle is reflected in the philosophy of the root assessment method, in which compensation between beneficial and non-beneficial dimensions is treated as unequal Sotoudeh-Anvari [21].

It is important to recognize that the Euclidean component increases with both AS_{i+} and AS_{i-} , whereas a larger AS_{i-} represents a greater non-benefit burden. Therefore, the Euclidean term should be interpreted as a magnitude component rather than as an independent desirability measure. The complete CREA score decreases with increasing non-benefit burden only within the admissible decision domain established mathematically in Section 3.3.7. Within this domain, the ratio penalty dominates the positive effect of the burden aggregate in the Euclidean component, and the method exhibits conditional, state-dependent, and asymmetric compensation.

Another important methodological feature of CREA is its normalization strategy. The method uses criterion-specific lower and upper reference bounds, L_j and U_j , which form a fixed-reference normalization structure. The same normalization expression is applied to both benefit and non-benefit criteria, while their preference directions remain different: higher normalized values are preferred for benefit criteria, whereas lower normalized values are preferred for non-benefit criteria. This structure is important because the rank-reversal literature has shown that rankings may change when alternatives

are added or removed, particularly when normalization depends on the observed alternative set. Methods such as RAFSI also employ fixed-reference normalization to address this concern Žižović et al. [18]. In this context, CREA is designed to reduce alternative-set dependence, although its ranking stability must be evaluated empirically and interpreted under the stated validity assumptions.

Taken together, CREA is conceptually grounded in preserving the dual structure of multi-criteria performance, applying controlled and asymmetric compensation between benefit performance and non-benefit burden, and combining aggregate magnitude with a benefit-to-burden relationship within a hybrid operator. These features distinguish CREA from purely additive methods and provide the conceptual basis for assessing it as a potentially interpretable and stability-oriented MCDM framework.

It is important to clarify that the present CREA formulation assumes crisp and directly measurable criterion values. Unlike recent fuzzy MCDM frameworks, it does not explicitly model linguistic assessments, interval-valued membership information, hesitancy, or ambiguity in expert judgments. Its present methodological focus is the structured aggregation of benefit-performance and non-benefit-burden criteria and the stability of the resulting rankings. Extending the CREA aggregation operator to fuzzy decision matrices would require suitable fuzzy normalization, aggregation, comparison, and defuzzification procedures

3.2. Methodological positioning of CREA against existing MCDM methods

The methodological contribution of CREA can be clarified by comparing its computational structure with conventional and robustness-oriented MCDM methods, particularly TOPSIS, VIKOR, RAFSI, RAM, and DNMA. Although these methods are designed to evaluate and rank alternatives under multiple criteria, they differ substantially in their normalization structures, intermediate representations, compensation mechanisms, and final aggregation rules.

TOPSIS ranks alternatives based on their closeness to positive-ideal and distance from negative-ideal solutions. Since these reference points depend on the available alternatives, adding or removing alternatives may change the final ranking. CREA avoids ideal-point distances by using criterion-specific reference bounds and separately aggregating benefit and non-benefit criteria.

VIKOR ranks alternatives through a compromise approach based on group utility, individual regret, and a balancing parameter. CREA differs by avoiding utility–regret indices and instead combining the Euclidean magnitude of separately aggregated benefit and non-benefit-burden components with their relative benefit-to-burden ratio.

RAFSI uses criterion-specific reference intervals to reduce dependence on the alternative set. CREA has the same objective but differs by preserving separate benefit and non-benefit aggregates and combining them through Euclidean magnitude and a benefit-to-burden ratio.

RAM applies a root-based, partially compensatory structure to control benefit performance and non-benefit burden. CREA also limits unrestricted compensation but instead evaluates the paired components AS_{i+} and AS_{i-} using their combined magnitude and relative benefit-to-burden relationship.

DNMA combines linear and vector normalization with multiple aggregation models to reduce dependence on a single procedure. CREA differs by using one criterion-specific reference-bound normalization method and one transparent Euclidean–ratio index.

Therefore, CREA does not claim that fixed-reference normalization, separate treatment of criterion directions, Euclidean aggregation, or ratio evaluation is individually new. Its methodological contribution lies in the ordered integration of criterion-specific fixed-reference normalization, separate aggregation into the benefit-performance component AS_{i+} and the non-benefit-burden component

AS_{i-} , and their final integration through the hybrid Euclidean–ratio index. The resulting operator jointly represents aggregate magnitude and the benefit-to-burden relationship.

3.2.1. Formal methodological limitations addressed by CREA and validity assumptions

A specific methodological limitation addressed by CREA is the alternative-set dependence that arises when normalization bounds, ideal solutions, or other reference values are recalculated after an alternative is added or removed. Under such procedures, the normalized values and final scores of the original alternatives may change even though their criterion performances remain unchanged. CREA is designed to reduce this source of instability by using criterion-specific reference bounds that remain fixed during alternative-set modification.

CREA also addresses the loss of group-level interpretability caused by the premature pooling of benefit and non-benefit criteria. Instead of combining all criteria into a single aggregate at the initial stage, CREA retains the benefit-performance aggregate and the non-benefit-burden aggregate separately until the final aggregation stage. These components are denoted by $B_i = AS_{i+}$ and $N_i = AS_{i-}$, respectively. Here, a higher B_i indicates better beneficial performance, whereas a lower N_i indicates a smaller non-benefit burden. Therefore, the contributions of the two criterion groups remain observable before the final CREA index is calculated.

The formal ranking-stability property of CREA is conditional on the following assumptions:

A1. For every criterion j , the lower and upper reference bounds L_j and U_j are specified before the ranking analysis, satisfy $L_j < U_j$, and remain unchanged when alternatives are added or removed.

A2. The criterion values of the original alternatives remain unchanged, and every newly added alternative is evaluated using the same fixed reference bounds. If a new criterion value lies outside the established interval, the bounded-normalization rule in Section 3.3.2 is applied by clipping the normalized value to 0 or 1, without recalibrating the reference bounds.

A3. The criterion weights w_j remain fixed during the alternative-set modification and are not re-estimated after a new alternative is introduced.

A4. The classification and preference direction of the criteria remain unchanged during alternative-set modification. The benefit set is denoted by J_B , and the non-benefit set is denoted by J_N , where $J_B \cap J_N = \emptyset$ and $J_B \cup J_N = J$. Higher normalized values are preferred for criteria in J_B , whereas lower normalized values are preferred for criteria in J_N .

A5. The criterion weights are nonnegative and normalized, such that $w_j \geq 0$ and $\sum_{j=1}^n w_j = 1$.

A6. The aggregate non-benefit burden is strictly positive for every evaluated alternative, including any newly added alternative: $N_i = AS_{i-} > 0$. This condition ensures that the ratio component of the CREA index is mathematically defined.

A7. For each evaluated alternative, the benefit-performance aggregate and non-benefit-burden aggregate satisfy $N_i^3 < B_i \sqrt{B_i^2 + N_i^2}$, where $B_i = AS_{i+}$ and $N_i = AS_{i-}$. This condition ensures that an increase in the non-benefit burden decreases the final CREA score within the evaluated decision domain.

Proposition 1: Conditional invariance under alternative-set expansion

Let A be the original set of alternatives, and let $A' = A \cup (a_{\text{new}})$ be the expanded alternative set. Under Assumptions A1–A7, the normalized values, weighted normalized values, benefit aggregates,

non-benefit-burden aggregates, and final CREA scores of every original alternative remain unchanged after the addition of a_{new} . Consequently, the relative ranking of the original alternatives is preserved.

Proof

For any original alternative i , its criterion value x_{ij} remains unchanged. Since the reference bounds and bounded-normalization rule remain unchanged, the normalized values of the original alternatives remain identical before and after alternative-set expansion, regardless of whether the newly added alternative lies within or outside the specified bounds:

$$r_{ij}^{A'} = r_{ij}^A.$$

Because the criterion weights remain unchanged,

$$v_{ij}^{A'} = w_j r_{ij}^{A'} = w_j r_{ij}^A = v_{ij}^A.$$

Therefore, the separately calculated benefit-performance and non-benefit-burden aggregates also remain unchanged:

$$B_i^{A'} = B_i^A, N_i^{A'} = N_i^A.$$

Substituting these unchanged components into the CREA aggregation formula gives:

$$CREA_i^{A'} = CREA_i^A.$$

Hence, the scores and relative order of all original alternatives remain unchanged.

The proposition establishes conditional resistance to alternative-set dependence caused by the recalculation of normalization references. It does not imply universal immunity to rank reversal. The property may not hold when the reference bounds, bounded-normalization rule, criterion weights, criterion directions, original performance values, or aggregation rule are changed.

The preservation of benefit and non-benefit information can also be stated formally. If the two criterion groups are prematurely reduced to a single net additive score, $S_i = B_i - N_i$, different benefit-burden structures can produce the same scalar value. For example, the pairs $(B_i, N_i) = (0.60, 0.20)$ and $(B_i, N_i) = (0.50, 0.10)$ both produce $S_i = 0.40$, although their benefit-performance and non-benefit-burden compositions differ. Thus, early aggregation is a many-to-one mapping, and the original group-level composition cannot be recovered from the resulting scalar score. CREA avoids this intermediate information loss by retaining (B_i, N_i) separately until the final evaluation stage. This property improves group-level interpretability, although the final CREA index remains a scalar ranking measure.

Overall, as summarized in Table 2, the methodological contribution of CREA lies in combining criterion-specific fixed-reference normalization, separate benefit-performance and non-benefit-burden aggregation, and a hybrid Euclidean-ratio evaluation within a single framework.

Table 2. Structural comparison of CREA with selected MCDM methods.

Feature	TOPSIS	VIKOR	RAFSI	RAM	DNMA	CREA
Primary ranking logic	Distance from ideal and anti-ideal solutions	Compromise between group utility and individual regret	Reference-interval assessment	Root-based partially compensatory assessment	Integration of multiple normalization and aggregation models	Euclidean magnitude and benefit-to-burden ratio
Normalization basis	Usually alternative-set dependent	Usually alternative-set dependent	Criterion-specific reference intervals	Method-specific normalization	Target-based linear and vector normalization	Common criterion-specific fixed-reference normalization
Reference structure	Positive and negative ideal solutions	Best and worst criterion values	Fixed/reference intervals	Root-assessment reference structure	Multiple normalized decision structures	Fixed criterion bounds
Benefit/non-benefit treatment	Converted and pooled before distance calculation	Converted and pooled within utility and regret measures	Transformed before final aggregation	Asymmetric/root-based treatment	Handled within subordinate models	Benefit performance and non-benefit burden are aggregated separately as AS_{i+} and AS_{i-}
Intermediate representation	Separation distances	Utility and regret indices	Transformed criterion scores	Root-assessment components	Multiple subordinate utilities/ranks	Paired benefit-performance and non-benefit-burden aggregates (AS_{i+} , AS_{i-})
Final ranking mechanism	Relative closeness coefficient	VIKOR compromise index	RAFSI score	RAM score	Combined subordinate rankings	Hybrid Euclidean magnitude and benefit-to-burden index $\sqrt{AS_{i+}^2 + AS_{i-}^2} + \frac{AS_{i+}}{AS_{i-}}$
Main methodological distinction	Does not use separate benefit/non-benefit Euclidean-ratio integration	Does not use paired magnitude-dominance integration	Does not use CREA's paired Euclidean-ratio operator	Does not use CREA's fixed-bound paired operator	Does not use one paired Euclidean-ratio index	Combines criterion-specific fixed-reference normalization, separate benefit-performance and non-benefit-burden aggregates, and a hybrid Euclidean-ratio evaluation within a single framework

3.3. Computational procedure of the CREA method

This study proposes a systematic MCDM framework for evaluating biotechnology performance across countries using diverse criteria within a single decision structure. Since country-level biotechnology evaluation involves both benefit and non-benefit criteria, the evaluation process must account for criteria with different directions of preference while producing consistent cross-country rankings. The present research adopts the composite ratio and Euclidean aggregation (CREA) as the overall method of evaluation. The first step of the CREA methodology is the development of a decision matrix and then the normalization of criteria scores based on their individual minimum and maximum values, which reduces the dependency upon the set of alternatives under consideration. Next, the normalized scores are multiplied by their respective weights, resulting in the weighted decision matrix. At this point, the benefit-performance and non-benefit-burden components of each alternative are aggregated separately and subsequently integrated through the hybrid CREA operator to form a final composite index that incorporates both Euclidean magnitude and ratio-based evaluations. As such, the framework maintains the dual nature of a multi-criteria assessment and results in rankings of countries for biotechnology purposes with clearer and more stable outcomes.

3.3.1. Construction of the decision matrix

Consider a multi-criteria decision-making (MCDM) problem consisting of a finite set of m alternatives, denoted as $A_i (i = 1, 2, \dots, m)$, which are evaluated against a set of n decision criteria, represented as $C_j (j = 1, 2, \dots, n)$. These criteria can be broadly categorized into two distinct types. The first category includes benefit (desirable) criteria, such as productivity, efficiency, and profitability, where higher values indicate better performance. The second category consists of non-benefit (undesirable) criteria, such as cost, risk, or processing time, where lower values are preferred.

Let x_{ij} denote the performance rating of alternative A_i with respect to criterion C_j . Based on these evaluations, the decision problem can be represented in the form of a matrix:

$$M(A, C) = [X_{ij}]_{m \times n} = \begin{bmatrix} A/C & C_1 & C_2 & \cdots & C_j \\ A_1 & M_{11} & M_{12} & \cdots & M_{1j} \\ A_2 & M_{21} & M_{22} & \cdots & M_{2j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_i & M_{i1} & M_{i2} & \cdots & M_{ij} \end{bmatrix} \quad (1)$$

where each element x_{ij} captures the performance level of the i -th alternative under the j -th criterion. In addition, each criterion C_j is associated with a corresponding importance weight w_j , forming the weight vector $W = [w_1, w_2, \dots, w_n]$, subject to the normalization condition $\sum_{j=1}^n w_j = 1, w_j > 0$. It

is important to note that the determination of criterion weights is assumed to be conducted using appropriate weighting techniques and is not explicitly addressed within the scope of this study. Based on the defined decision matrix and weight structure, the proposed CREA method is applied to evaluate and rank the available alternatives through a systematic sequence of computational steps.

3.3.2. Fixed-reference normalization

Since criteria in an MCDM problem are generally expressed in different measurement units and scales, the original criterion values cannot be compared directly. Accordingly, the CREA method

transforms the original performance values into dimensionless normalized scores using predetermined lower and upper reference bounds, denoted by L_j and U_j , respectively. This transformation ensures comparability across criteria and reduces the possibility that criteria with larger numerical scales will dominate the evaluation.

The same fixed-reference normalization expression is applied to both benefit and non-benefit criteria:

$$z_{ij} = \frac{x_{ij} - L_j}{U_j - L_j}, i = 1, 2, \dots, m, j = 1, 2, \dots, n, \quad (2)$$

where x_{ij} denotes the performance value of alternative A_i with respect to criterion C_j , and L_j and U_j denote the predetermined lower and upper reference bounds of criterion C_j .

Although the same mathematical transformation is applied to all criteria, the direction of preference depends on the criterion type. For a benefit criterion, a higher normalized value indicates better performance. For a non-benefit criterion, a lower normalized value indicates better performance, whereas a higher normalized value represents a greater undesirable burden, such as higher cost, longer approval time, or a higher rejection rate. Therefore,

$$\begin{cases} \text{Higher } z_{ij} \text{ is preferred,} & j \in B, \\ \text{Lower } z_{ij} \text{ is preferred,} & j \in NB, \end{cases}$$

where B and NB denote the sets of benefit and non-benefit criteria, respectively.

The reference bounds used in CREA are treated as calibration parameters rather than values that are recalculated whenever the set of alternatives changes. Once L_j and U_j have been specified, they are retained during the addition or removal of alternatives. Consequently, the normalized values of the original alternatives remain unchanged, provided that the same reference bounds and bounded-normalization rule are maintained. If the reference bounds are recalculated after modifying the alternative set, the conditional invariance property described in Section 3.2.1 no longer applies.

The standard fixed-reference transformation produces normalized values within the interval $[0, 1]$ when the observed criterion value satisfies

$$L_j \leq x_{ij} \leq U_j.$$

However, a newly introduced alternative may contain a criterion value below the predetermined lower bound or above the predetermined upper bound. In such cases, the direct transformation may generate a normalized value below 0 or above 1. To preserve the common $[0, 1]$ scale, CREA applies the following bounded-normalization rule:

$$r_{ij} = \min \{1, \max\{0, z_{ij}\}\},$$

where z_{ij} is the initially calculated normalized value obtained from Equation (2).

Accordingly, an observation below L_j is assigned a normalized value of 0, whereas an observation above U_j is assigned a normalized value of 1. This clipping rule is applied uniformly to both benefit and non-benefit criteria. However, the preference interpretation remains criterion specific. For benefit criteria, 0 represents the least desirable reference-level performance, and 1 represents the most desirable reference-level performance. For non-benefit criteria, 0 represents the lowest undesirable burden and is therefore preferred, whereas 1 represents the highest undesirable burden and is therefore least preferred.

Observations lying within the specified reference interval are normalized using Equation (2) without modification. The lower and upper reference bounds are not recalculated during the same

ranking exercise because recalibration would change the normalized values of the existing alternatives and weaken the fixed-reference property of the method.

If out-of-range observations occur frequently or substantially exceed the specified bounds, the reference intervals should be reviewed before conducting a new evaluation. In such a case, the revised bounds must be applied consistently to all alternatives, and the complete analysis must be recalculated.

This bounded-normalization procedure ensures that all final normalized values remain within the interval $[0, 1]$, while allowing newly introduced alternatives to be evaluated without automatically changing the normalized values of the existing alternatives. Under this formulation, benefit criteria retain a higher-is-better orientation, whereas non-benefit criteria retain a lower-is-better orientation throughout the subsequent aggregation process.

3.3.3. Objective criteria weighting using SITDE

The criteria included in the present study were first selected based on their established relevance to biotechnology performance, including regulatory efficiency, research and development, patent activity, scientific publications, market size, clinical-trial activity, human capital, and intellectual-property protection. Therefore, the substantive relevance of the criteria is determined by the biotechnology literature and the application context, rather than by their statistical distributions.

After the relevant criteria were selected, the skewness impact through distributional evaluation (SITDE) method was used to derive objective, data-driven weights from the observed decision matrix. In SITDE, skewness is interpreted as a measure of distributional asymmetry and discriminatory information among the evaluated alternatives. A strongly skewed criterion indicates that the performances of the countries are unevenly distributed, with some countries differing substantially from the remaining alternatives. Such a criterion may provide greater statistical differentiation within the present dataset.

However, a higher level of skewness does not necessarily imply that a criterion is inherently more important to biotechnology development, policy, or national competitiveness. Skewness may also arise from an extreme observation, sample composition, or a naturally uneven distribution. Therefore, SITDE weights should be interpreted as measures of the relative distributional influence of the criteria within the observed dataset, rather than as direct measures of their causal, strategic, or normative importance.

This distinction is important because objective statistical weighting and substantive domain importance represent different concepts. A criterion with a relatively low SITDE weight may still be strategically important to biotechnology performance, even when it contributes less statistical discrimination among the countries in the current sample. Conversely, a criterion with a high SITDE weight provides greater differentiation in the observed decision matrix, but it should not automatically be interpreted as the most important criterion from a policy or expert perspective.

Accordingly, the normalized SITDE weights used in CREA quantify the sample-specific distributional contribution of each criterion and satisfy:

$$W_j \geq 0, \quad \sum_{j=1}^n W_j = 1, j = 1, 2, \dots, n$$

3.3.4. Construction of the weighted normalized matrix

After obtaining the normalized decision matrix, the relative importance of each criterion is incorporated by multiplying the normalized values by their corresponding weights. This step is essential because not all criteria contribute equally to the decision-making process, and their influence

should therefore be reflected according to their assigned importance. Accordingly, the weighted normalized value of alternative A_i under criterion C_j is computed as

$$R_{ij} = w_j \times Z_{ij}, i = 1, 2, \dots, m, j = 1, 2, \dots, n \quad (3)$$

where w_j denotes the weight of criterion C_j , and Z_{ij} represents the normalized value obtained in Step 1. This transformation is justified because it adjusts the normalized scores in accordance with the relative significance of the criteria, thereby ensuring that more important criteria exert greater influence on the final evaluation. As a result, the weighted normalized matrix provides a more realistic and decision-relevant basis for the aggregation process in the subsequent step.

3.3.5. Separate aggregation of benefit performance and non-benefit burden

In this step, the weighted normalized values are aggregated separately for benefit and non-benefit criteria to preserve their distinct contributions to the overall evaluation. This separation is important because benefit and non-benefit criteria represent different directions of preference and combining them prematurely may lead to loss of interpretability and distortion in the ranking process.

The aggregate benefit score for alternative A_i is computed as

$$AS_{i+} = \sum_{j \in B} R_{ij}, \quad i = 1, 2, \dots, m \quad (4)$$

Similarly, the aggregate non-benefit score for alternative A_i is obtained as

$$AS_{i-} = \sum_{j \in NB} R_{ij}, \quad i = 1, 2, \dots, m \quad (5)$$

where B and NB denote the sets of benefit and non-benefit criteria, respectively. Here, AS_{i+} represents the weighted contribution of the benefit criteria, for which a higher value is preferred. In contrast, AS_{i-} represents the weighted magnitude of the non-benefit burden, for which a lower value is preferred. Retaining these components separately preserves the different preference directions and improves group-level interpretability before final aggregation.

This step is justified because it maintains the dual structure of the decision problem by evaluating positive and negative contributions independently. Such a separation allows for a more balanced and meaningful assessment of alternatives and forms the foundation for the hybrid aggregation used in the final ranking stage.

3.3.6. Final CREA index and ranking rule

In the final step, the overall performance of each alternative is evaluated by combining the aggregated benefit and non-benefit scores through a composite ranking index. This index integrates both the magnitude of performance and the relative balance between desirable and undesirable contributions. The composite score for each alternative A_i is computed as

$$Z_i = \sqrt{AS_{i+}^2 + AS_{i-}^2} + \frac{AS_{i+}}{AS_{i-}}, \quad i = 1, 2, \dots, m \quad (6)$$

In Equation (6), AS_{i+} denotes the aggregate benefit performance, whereas AS_{i-} denotes the aggregate non-benefit burden. The first component, $\sqrt{AS_{i+}^2 + AS_{i-}^2}$, represents the joint Euclidean magnitude of the two aggregate dimensions. This component is interpreted as a magnitude measure and not

independently as a desirability score. The second component, $\frac{AS_{i+}}{AS_{i-}}$, represents the benefit-to-burden ratio. A higher benefit aggregate increases the ratio, whereas a greater non-benefit burden increases the denominator and reduces the ratio. The formulation requires $AS_{i-} > 0$. Therefore, alternatives with a zero non-benefit burden fall outside the present formulation. Due to the joint magnitude of the separately retained benefit-performance and non-benefit-burden aggregates, the monotonic decrease of the complete CREA score with respect to burden is conditional on the mathematical requirement established in Section 3.3.7 and Assumption A7.

The two components capture different but complementary aspects of the alternative's aggregate structure. A ratio-only measure may assign the same score to proportional benefit–burden pairs even when their aggregate magnitudes differ substantially. In contrast, a Euclidean-magnitude measure may produce similar values for alternatives having different benefit-to-burden relationships. Therefore, neither component alone fully represents both aggregate magnitude and the relative relationship between beneficial performance and undesirable burden.

By combining the two components, CREA jointly evaluates the magnitude of the separately retained aggregates and the benefit-to-burden relationship. The formula is therefore not introduced merely as an alternative mathematical expression. It is designed to retain information that may be lost when only additive, distance-based, magnitude-based, or ratio-based aggregation is used. This provides the methodological justification for introducing a distinct aggregation operator rather than adapting an established method whose original ranking logic addresses a different evaluation objective.

The alternatives are ranked in descending order of $CREA_i$. A higher CREA score indicates a preferable alternative within the admissible decision domain defined by Assumption A7.

3.3.7. Mathematical demonstration of partial and asymmetric compensation

To formally examine the compensatory structure of CREA, let

$$B = AS_{i+}, N = AS_{i-},$$

where $B > 0$ represents the aggregate benefit component, and $N > 0$ represents the aggregate non-benefit burden. Equation (6) can therefore be written as

$$F(B, N) = \sqrt{B^2 + N^2} + \frac{B}{N}.$$

The marginal effect of the aggregate benefit component is obtained by differentiating $F(B, N)$ with respect to B :

$$\frac{\partial F}{\partial B} = \frac{B}{\sqrt{B^2 + N^2}} + \frac{1}{N}.$$

Since $B > 0$ and $N > 0$,

$$\frac{\partial F}{\partial B} > 0.$$

Therefore, an increase in the aggregate benefit component always increases the CREA score.

The marginal effect of the aggregate non-benefit-burden component is:

$$\frac{\partial F}{\partial N} = \frac{N}{\sqrt{B^2 + N^2}} - \frac{B}{N^2}.$$

When N represents an undesirable burden, an increase in N reduces the CREA score whenever

$$\frac{\partial F}{\partial N} < 0.$$

This condition is equivalent to

$$N^3 < B\sqrt{B^2 + N^2}.$$

This inequality defines the admissible decision domain within which the CREA score decreases as the non-benefit burden increases. Outside this domain, the Euclidean component may dominate the ratio penalty, and monotonicity with respect to burden is not guaranteed.

$$dF = \frac{\partial F}{\partial B} dB + \frac{\partial F}{\partial N} dN = 0.$$

Therefore, the local compensation rate is

$$\frac{dB}{dN} \Big|_F = - \frac{\frac{\partial F}{\partial N}}{\frac{\partial F}{\partial B}},$$

or, after substituting the partial derivatives,

$$\frac{dB}{dN} \Big|_F = - \frac{\frac{N}{\sqrt{B^2 + N^2}} - \frac{B}{N^2}}{\frac{B}{\sqrt{B^2 + N^2}} + \frac{1}{N}}.$$

This compensation rate depends on the existing values of both B and N . Consequently, the amount of benefit improvement required to offset a deterioration in the non-benefit-burden component varies across alternatives. CREA therefore permits compensation, but the compensation is partial and state-dependent rather than unrestricted or uniformly one-to-one.

The asymmetric nature of the CREA operator can also be demonstrated by interchanging the two aggregate components. The original CREA function is

$$F(B, N) = \sqrt{B^2 + N^2} + \frac{B}{N},$$

whereas interchanging the components gives

$$F(N, B) = \sqrt{B^2 + N^2} + \frac{N}{B}.$$

The difference between the two expressions is

$$F(B, N) - F(N, B) = \frac{B}{N} - \frac{N}{B} = \frac{B^2 - N^2}{BN}.$$

Except when $B = N$, this difference is non-zero. Therefore, benefit and non-benefit-burden components are not treated symmetrically. The benefit component appears in the numerator of the ratio term, whereas the non-benefit-burden component appears in the denominator. This establishes the asymmetric compensatory structure of CREA mathematically.

For example, using the aggregate values reported for the USA,

$$B = AS_{i+} = 0.601, N = AS_{i-} = 0.204.$$

The corresponding marginal effects are

$$\frac{\partial F}{\partial B} = \frac{0.601}{\sqrt{0.601^2 + 0.204^2}} + \frac{1}{0.204} \approx 5.849,$$

and

$$\frac{\partial F}{\partial N} = \frac{0.101}{\sqrt{0.601^2 + 0.204^2}} - \frac{0.601}{0.204^2} \approx -14.120.$$

Therefore, the local compensation rate is

$$\frac{dB}{dN} \Big|_F = -\frac{-14.120}{5.849} \approx 2.414.$$

Thus, near the USA's observed aggregate position, an increase of 0.01 in the non-benefit burden would require an approximate increase of 0.024 in the benefit aggregate to keep the CREA score unchanged.

The proposed CREA for solving the MCDM problem is carried out as illustrated in Figure 1.

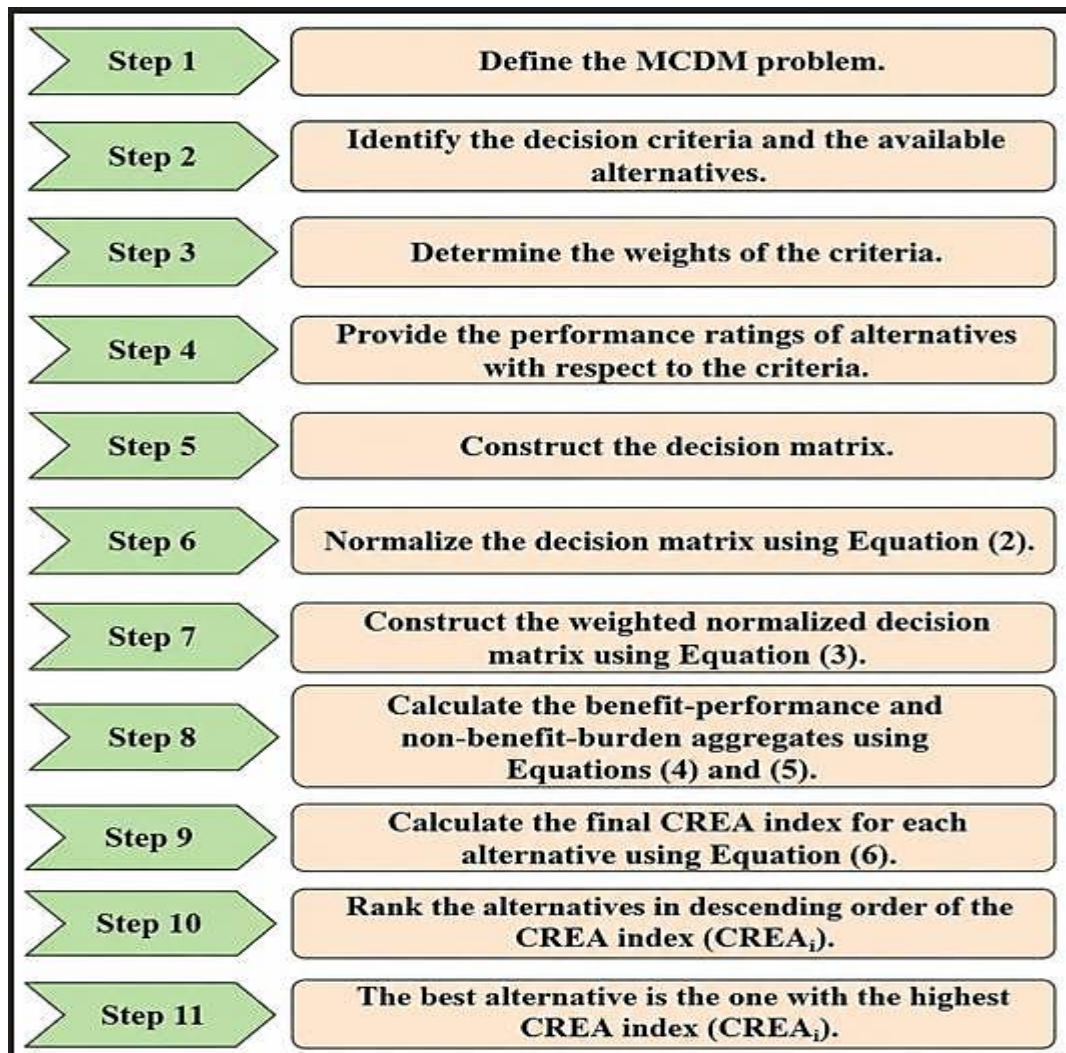


Figure 1. Procedural framework of the proposed composite ratio and Euclidean aggregation (CREA) method.

The following methodological framework outlines how the CREA method can be applied to biotechnology country evaluations in a multi-criteria decision-making context. To ensure consistency across all evaluations, CREA uses fixed reference normalization with lower and upper bounds for each criterion, objective weighting through SITDE methodology, weighted normalization, and the separate aggregation of benefit and non-benefit criteria before integrating them into an overall composite index for ranking each country.

The CREA method combines ratio-based evaluation with Euclidean aggregation to preserve the structural distinction between benefit and non-benefit criteria. This integrated design provides a balanced, interpretable, and potentially robust ranking mechanism for biotechnology country evaluation compared with conventional MCDM approaches.

To determine the relative effectiveness and reliability of the CREA method, the resulting rankings generated using the CREA method will be compared with results generated through RAM, COPRAS, MOORA, and MOOSRA. Additionally, Spearman's rank correlation coefficient will be computed to determine the level of agreement across all rankings. Sensitivity analysis will also be performed to understand how variations in weights will impact the ordering of alternatives, as well as performing a rank reversal test to examine whether the rankings of existing alternatives remain stable under changes to the alternatives set. Collectively, these analyses will provide insight into the robustness, stability, and practical applicability of the CREA method for benchmarking country biotechnology.

4. Empirical application and results

4.1. Data preparation and cross-country comparability

The dataset was compiled from secondary sources using the most recent comparable values available. The final decision matrix contained no missing values; therefore, no statistical imputation was required. No author-generated interpolation, extrapolation, model-based estimation, or substitution of values was performed. Where an original secondary source reported an estimated indicator, such as biotechnology market size, the published estimate was used directly without independent re-estimation by the authors. Monetary indicators were retained in the US-dollar values reported by the original sources; therefore, no additional currency conversion or separate inflation adjustment was performed. Common indicator definitions were used wherever possible. However, differences in observation years, data coverage, source methodologies, indicator definitions, and national reporting standards may still affect cross-country comparability.

4.2. Construction of the decision matrix and evaluation criteria

The initial decision matrix was constructed using the criteria identified earlier for evaluating biotechnology countries and the data from secondary data for each criterion, as reported in Table 3. The initial decision matrix outlines the performance of the biotechnology sector within each country based on each of the defined criteria.

Table 3. Initial decision matrix of the selected biotechnology countries with respect to the evaluation criteria.

ID	Alternative	Ct1 (min)	Ct2 (min)	Ct3 (min)	Ct4 (max)	Ct5 (max)	Ct6 (max)	Ct7 (max)	Ct8 (max)	Ct9 (max)	Ct10 (max)
A1	USA	8	74	13	3.5	3052	22,000	433	197,090	4825.18	8.007
A2	Germany	2.4	19	19	3.5	814	6523	54.8	59,190	5787.44	7.57
A3	UK	2.4	48	19	2.8	348	5010	31	53,240	4472.69	7.538
A4	China	1.5	19	20	2.8	644	5282	274	136,980	1849.24	6.451
A5	Japan	12	22.5	10	3.45	500	8957	32.2	68,760	5629.80	7.149
A6	South Korea	9.8	60	12	5.25	314	7200	25.5	30,091	9434.76	6.635
A7	India	9	20	18	0.65	1300	23,325	150	78,456	259.26	5.236
A8	Singapore	9	22.8	12	2.2	153	1021	12	5821	7917.00	7.513
A9	Switzerland	14	60	9	3.35	432	1224	8.5	14,654	6021.40	6.597
A10	France	12.9	19	19	2.2	441	4232	15.13	50,132	5181.85	7.542
A11	Russia	12	32.5	29	2.3	40	7345	440	13,541	2683.95	4.41
A12	Canada	15	60	15	1.6	241	3645	65	39,871	5411.83	6.866
A13	Israel	2.3	10.15	10	6.3	278	1076	28	15,023	2213.65	6.906

Table 4. Description and classification of the evaluation criteria used in biotechnology country assessment.

Criterion Code	Criterion	Description	Unit	Type
C1	Drug approval time	Average time required for regulatory approval of drugs	Months	Non-benefit
C2	Clinical trial cost	Average cost incurred per clinical trial	USD million per trial	Non-benefit
C3	Regulatory approval of rejection rate	Percentage of regulatory submissions rejected	%	Non-benefit
C4	R&D expenditure	National expenditure on research and development	% of GDP	Benefit
C5	Biotech patents	Annual number of biotechnology patents	Annual count	Benefit
C6	Biotech publications	Annual number of biotechnology-related publications	Annual count	Benefit
C7	Biotech market size	Estimated size of the biotechnology market	USD billion	Benefit
C8	Clinical trials	Number of registered clinical trials	Registered count	Benefit
C9	Life science researchers per million	Number of life science researchers per million population	Per million	Benefit
C10	IP protection index	Strength of intellectual property protection	0–10 scale	Benefit

For clarity in the evaluation framework, each criterion included in the study is briefly described in terms of its meaning, measurement unit, and decision orientation. Since biotechnology country performance is inherently multidimensional, the selected criteria reflect regulatory efficiency,

innovation capability, scientific output, market strength, research capacity, and institutional support. In addition, the criteria are classified as either benefit or non-benefit based on their contribution to overall biotechnology performance. The summary description of the criteria considered in this study is presented in Table 4.

The absolute indicators for biotech patents, publications, market size, and clinical trials primarily capture the overall scale and capacity of a national biotechnology system rather than size-adjusted efficiency. Larger countries may naturally report higher values because of their greater population, economy, research base, and healthcare infrastructure. Therefore, the resulting rankings should be interpreted as measures of overall biotechnology capacity, not as pure measures of efficiency or productivity. This scale effect is partially balanced by the inclusion of relative indicators such as R&D expenditure as a percentage of GDP and life-science researchers per million population, together with regulatory and institutional criteria.

Table 5. Normalized decision matrix of the selected biotechnology countries based on the CREA normalization procedure.

Alternative	Ct1 (min)	Ct2 (min)	Ct3 (min)	Ct4 (max)	Ct5 (max)	Ct6 (max)	Ct7 (max)	Ct8 (max)	Ct9 (max)	Ct10 (max)
USA	0.533	1.000	0.448	0.556	1.000	0.943	0.984	1.000	0.511	1.000
Germany	0.160	0.257	0.655	0.556	0.267	0.280	0.125	0.300	0.613	0.945
UK	0.160	0.649	0.655	0.444	0.114	0.215	0.070	0.270	0.474	0.941
China	0.100	0.257	0.690	0.444	0.211	0.226	0.623	0.695	0.196	0.806
Japan	0.800	0.304	0.345	0.548	0.164	0.384	0.073	0.349	0.597	0.893
South Korea	0.653	0.811	0.414	0.833	0.103	0.309	0.058	0.153	1.000	0.829
India	0.600	0.270	0.621	0.103	0.426	1.000	0.341	0.398	0.027	0.654
Singapore	0.600	0.308	0.414	0.349	0.050	0.044	0.027	0.030	0.839	0.938
Switzerland	0.933	0.811	0.310	0.532	0.142	0.052	0.019	0.074	0.638	0.824
France	0.860	0.257	0.655	0.349	0.144	0.181	0.034	0.254	0.549	0.942
Russia	0.800	0.439	1.000	0.365	0.013	0.315	1.000	0.069	0.284	0.551
Canada	1.000	0.811	0.517	0.254	0.079	0.156	0.148	0.202	0.574	0.857
Israel	0.153	0.137	0.345	1.000	0.091	0.046	0.064	0.076	0.235	0.862

To ensure comparability among criteria measured in different units and scales, the original decision matrix is transformed into a normalized decision matrix using the predetermined lower and upper reference bounds specified for each criterion. In the proposed CREA method, the normalization procedure is performed according to Equation (2), using the same fixed-reference normalization expression for both benefit and non-benefit criteria. However, the direction of preference differs according to the criterion type: higher normalized values indicate better performance for benefit criteria, whereas lower normalized values indicate better performance for non-benefit criteria. Accordingly, the normalized values of the non-benefit criteria represent undesirable burdens, while those of the benefit criteria represent desirable performance. The use of criterion-specific fixed reference bounds reduces alternative-set dependence caused by recalculating normalization references when alternatives are added or removed. This conditional stability property applies when the same

reference bounds, criterion weights, criterion directions, original performance values, bounded-normalization rule, and aggregation procedure are retained. The resulting normalized decision matrix is presented in Table 5.

The criteria were selected based on their relevance to biotechnology-system evaluation, while their objective statistical weights were estimated using the SITDE method Gopisetty and Sama [59]. In this application, a higher SITDE weight indicates that a criterion contributes greater distributional asymmetry and discrimination among the 13 evaluated countries. It does not necessarily indicate that the criterion is more important from a causal, strategic, or policy perspective. Therefore, the weight of each criterion should be interpreted as its relative data-driven influence within the present decision matrix. On this basis, biotech patents received the highest SITDE weight, indicating the strongest distributional contribution in the current sample, whereas the IP protection index received the lowest weight, indicating lower statistical differentiation among the evaluated countries. This result should not be interpreted as evidence that intellectual-property protection is substantively unimportant to biotechnology development. The resulting objective weights are presented in Table 6 and illustrated in Figure 2.

Table 6. Criteria weight estimation through the SITDE method.

ID	Ct1 (min)	Ct2 (min)	Ct3 (min)	Ct4 (max)	Ct5 (max)	Ct6 (max)	Ct7 (max)	Ct8 (max)	Ct9 (max)	Ct10 (max)
W_{ij}	0.108	0.106	0.091	0.100	0.126	0.113	0.110	0.113	0.085	0.048

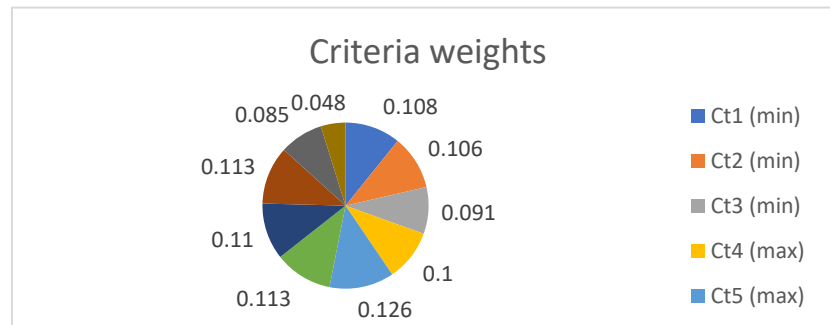


Figure 2. Distribution of criterion weights obtained using the SITDE method.

The normalized values were multiplied by the corresponding SITDE weights using Equation (3). The resulting weighted normalized matrix reflects the normalized performance of each alternative together with the sample-specific distributional influence assigned to each criterion. The weighted values of Ct1–Ct3 represent non-benefit burdens, whereas those of Ct4–Ct10 represent benefit performance. The resulting weighted normalized decision matrix is presented in Table 7.

Table 7. Weighted normalized decision matrix.

Alternative	Ct1 (min)	Ct2 (min)	Ct3 (min)	Ct4 (max)	Ct5 (max)	Ct6 (max)	Ct7 (max)	Ct8 (max)	Ct9 (max)	Ct10 (max)
USA	0.058	0.106	0.041	0.055	0.126	0.106	0.109	0.113	0.043	0.048
Germany	0.017	0.027	0.060	0.055	0.034	0.032	0.014	0.034	0.052	0.046
UK	0.017	0.069	0.060	0.044	0.014	0.024	0.008	0.030	0.040	0.046
China	0.011	0.027	0.063	0.044	0.027	0.026	0.069	0.078	0.017	0.039
Japan	0.086	0.032	0.032	0.054	0.021	0.043	0.008	0.039	0.051	0.043
South Korea	0.071	0.086	0.038	0.083	0.013	0.035	0.006	0.017	0.085	0.040
India	0.065	0.029	0.057	0.010	0.054	0.113	0.038	0.045	0.002	0.032
Singapore	0.065	0.033	0.038	0.035	0.006	0.005	0.003	0.003	0.071	0.046
Switzerland	0.101	0.086	0.028	0.053	0.018	0.006	0.002	0.008	0.054	0.040
France	0.093	0.027	0.060	0.035	0.018	0.020	0.004	0.029	0.047	0.046
Russia	0.086	0.046	0.091	0.036	0.002	0.035	0.110	0.008	0.024	0.027
Canada	0.108	0.086	0.047	0.025	0.010	0.018	0.016	0.023	0.049	0.042
Israel	0.017	0.014	0.032	0.100	0.011	0.005	0.007	0.009	0.020	0.042

Table 8. Final ranking results of the selected biotechnology countries based on CREA.

Alternative	AS_{i-}	AS_{i+}	$\sqrt{AS_{i+}^2 + AS_{i-}^2} + \frac{AS_{i+}}{AS_{i-}}$	Rank
USA	0.204	0.601	3.575	1
Germany	0.104	0.266	2.836	4
UK	0.146	0.207	1.674	8
China	0.101	0.299	3.279	3
Japan	0.150	0.260	2.031	6
South Korea	0.194	0.279	1.780	7
India	0.150	0.293	2.282	5
Singapore	0.135	0.169	1.467	9
Switzerland	0.215	0.181	1.125	12
France	0.180	0.198	1.369	11
Russia	0.224	0.242	1.411	10
Canada	0.241	0.182	1.058	13
Israel	0.063	0.194	3.297	2

Note: The benefit-performance aggregates, non-benefit-burden aggregates, and CREA scores were calculated using the full-precision normalized values and criterion weights. The aggregate values displayed in Table 8 are rounded to three decimal places for presentation. Therefore, direct recalculation using only the displayed rounded aggregates may produce small numerical differences.

The weighted normalized values were aggregated separately into the benefit-performance component AS_{i+} and the non-benefit-burden component AS_{i-} . These two components were subsequently integrated using Equation (6). The resulting aggregate components, CREA scores, and country rankings are presented in Table 8 and illustrated in Figure 3.

Table 8 shows that the proposed CREA framework produces a clear ranking among the selected biotechnology countries. The United States achieves the highest CREA score of 3.575 and ranks first, followed by Israel with a score of 3.297 and China with a score of 3.279. At the lower end of the ranking, France ranks eleventh, Switzerland ranks twelfth, and Canada ranks thirteenth with the lowest CREA score of 1.058. These results indicate that CREA differentiates the alternatives by jointly considering benefit performance, non-benefit burden, aggregate magnitude, and the benefit-to-burden relationship. The ranking distribution is further illustrated in Figure 3.

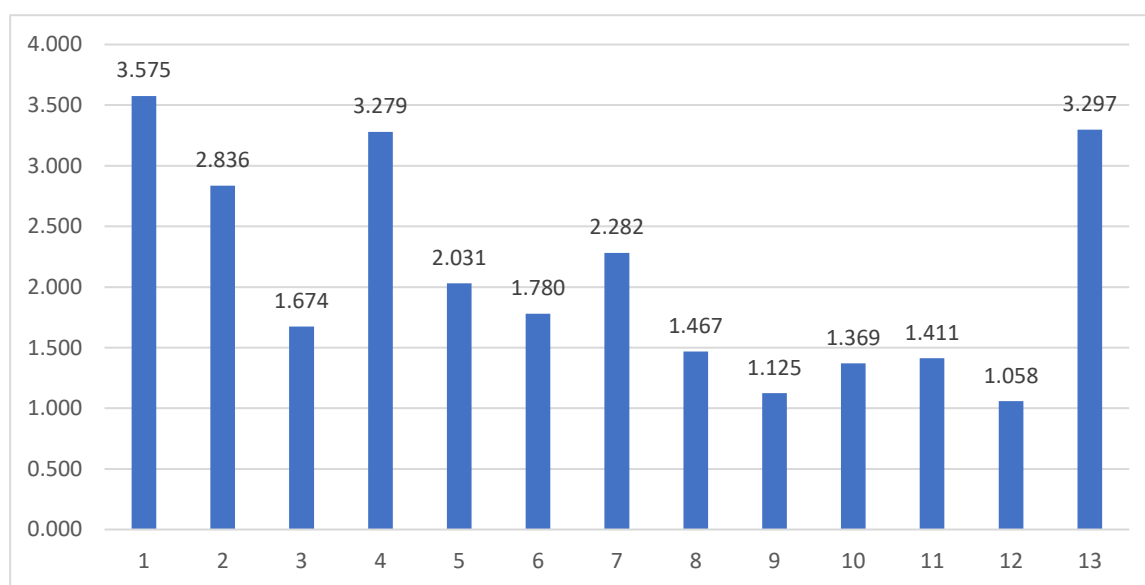


Figure 3. Final CREA scores of the selected biotechnology countries.

5. Comparative and robustness analysis

5.1. Comparative evaluation with established MCDM methods

The ranking outcomes from the proposed CREA approach were then benchmarked against five commonly used MCDM approaches (RAM, COPRAS, MOORA, MOOSRA, and MULTI-MOORA), each based on different ranking logics and aggregation structures, allowing for the proposed framework to be compared across a broad range of evaluative criteria, which is useful for assessing the comparative consistency of the ranking results Li et al. [60]. Spearman's rank correlation coefficient was computed to assess how closely CREA agrees with each of the other MCDM methodologies. The results of the comparative rankings and the Spearman's correlation coefficients for each of the approaches are shown in Table 9.

Table 9. Comparative analysis of CREA with existing MCDM methods.

Alternative	CREA	RAM	COPRAS	MOORA	MOOSRA	MULTI-MOORA
USA	1	1	1	1	3	1
Germany	4	3	4	3	4	3
UK	8	8	8	8	8	8
China	3	2	3	2	2	2
Japan	6	6	6	6	6	6
South Korea	7	7	7	7	7	7
India	5	4	5	4	5	4
Singapore	9	10	10	9	9	9
Switzerland	12	12	12	12	12	12
France	11	11	11	10	10	10
Russia	10	9	9	11	11	11
Canada	13	13	13	13	13	13
Israel	2	5	2	5	1	5
r	1	0.962	0.995	0.962	0.978	0.962

A closer examination of Table 9 indicates a high level of ranking agreement between CREA and the selected comparison methods. The Spearman correlation coefficients between CREA and RAM, COPRAS, MOORA, MOOSRA, and MULTI-MOORA are 0.962, 0.995, 0.962, 0.978, and 0.962, respectively. The USA ranks first under CREA, RAM, COPRAS, MOORA, and MULTI-MOORA, although it ranks third under MOOSRA. Canada ranks thirteenth under all six methods. Israel shows greater variation, ranking second under CREA and COPRAS, first under MOOSRA, and fifth under RAM, MOORA, and MULTI-MOORA. Minor positional differences are also observed for Germany, China, India, Singapore, France, and Russia. Overall, the results indicate strong comparative ranking similarity within the present dataset, while the observed differences reflect the distinct normalization and aggregation mechanisms of the methods. However, these high correlations should not be interpreted as independent evidence of the validity or superiority of CREA, because Spearman correlation measures only the similarity between ranking orders. The comparative ranking performance of CREA and selected MCDM methods is illustrated in Figure 4 Li et al. [60].

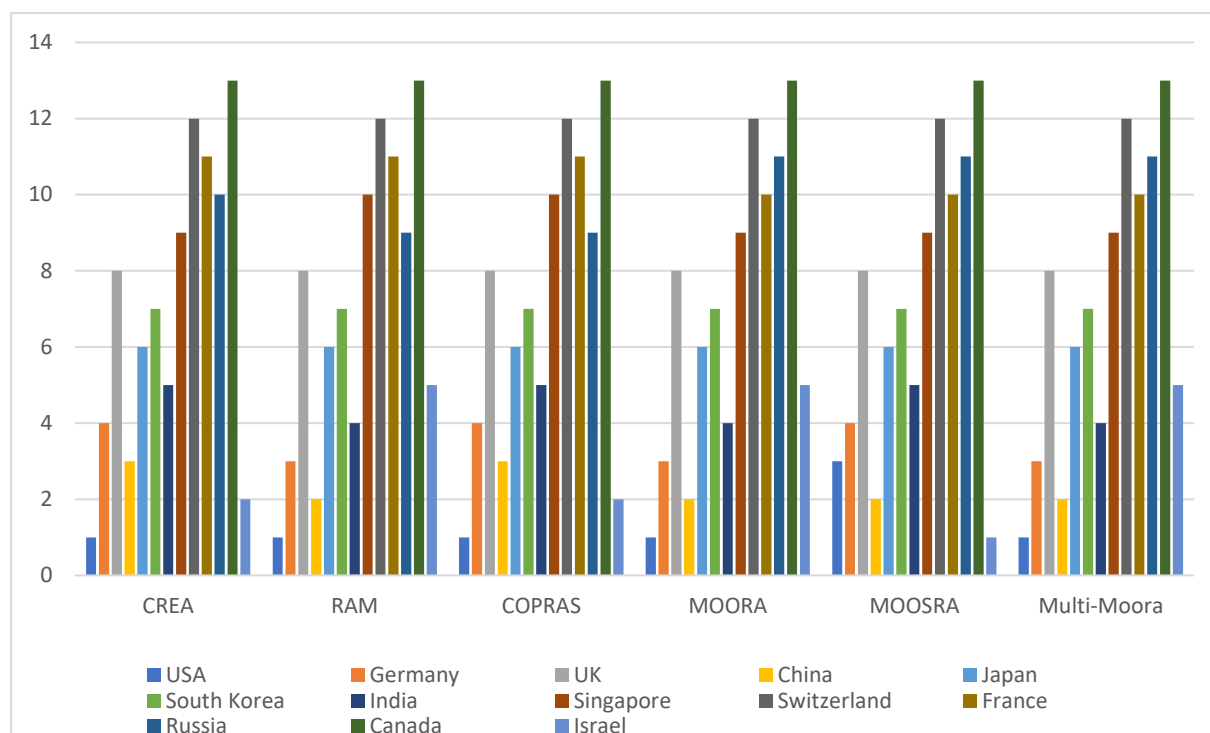


Figure 4. Comparative ranking performance of CREA and selected MCDM methods for assessing biotechnology across countries.

5.2. Spearman rank correlation analysis

A Spearman rank correlation test was used to evaluate the similarities between the ranking outcomes from the CREA and alternate techniques. This technique is well-suited to this scenario since the results from MCDM techniques are presented as an ordered set of numbers (ordinal ranks); therefore, Spearman's coefficient allows for a simple quantitative evaluation of the relationship between these ranked sets Yu and Hutson [61]. The primary objective of this evaluation is to evaluate the consistency of the ranking patterns produced by CREA with the patterns generated from the other methods and to identify how closely related the rankings produced by the different methods are. The Spearman's rank correlation results are summarized in Table 10.

Table 10. Spearman rank correlation matrix for CREA and selected MCDM methods.

Methods	CREA	RAM	COPRAS	MOORA	MOOSRA	MULTI-MOORA
CREA	1	0.961538	0.994505	0.961538	0.978021978	0.961538
RAM		1	0.967033	0.983516	0.923076923	0.983516
COPRAS			1	0.950549	0.967032967	0.950549
MOORA				1	0.93956044	1
MOOSRA					1	0.93956
MULTI-MOORA						1

Table 10 shows that the pairwise Spearman correlation coefficients among the six methods range from 0.923 to 1.000, indicating generally high agreement among the ranking patterns. The correlations between CREA and RAM, COPRAS, MOORA, MOOSRA, and MULTI-MOORA are 0.962, 0.995, 0.962, 0.978, and 0.962, respectively. The highest correlation involving CREA is observed with COPRAS at $r = 0.995$. MOORA and MULTI-MOORA produce identical rankings, resulting in $r = 1.000$. The lowest coefficient in the complete matrix is observed between RAM and MOOSRA at $r = 0.923$.

The Spearman correlations between CREA and the comparison methods range from 0.962 to 0.995, indicating a high degree of comparative ranking agreement within the present dataset. However, correlation measures only the similarity between ranking orders and does not independently establish the validity or superiority of CREA. The results should therefore be interpreted as evidence of comparative consistency.

The Spearman rank correlations between CREA and the selected MCDM methods are illustrated in Figure 5.

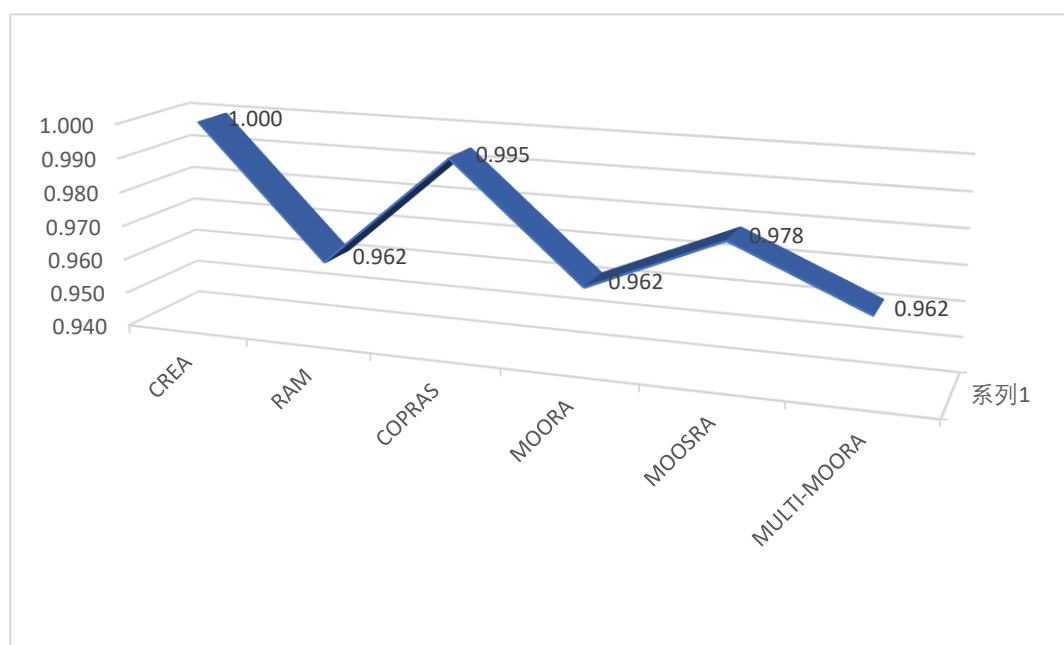


Figure 5. Spearman rank correlation between CREA and selected MCDM methods.

5.3. Sensitivity analysis and ranking stability assessment

This study aims to determine how sensitive the CREA rankings are to variations in input data by performing a sensitivity analysis (SA) on the ranking results from Table 3. SA is one of several critical and required components for validating MCDM outputs and is primarily used in MCDM research to find stable rankings under varying decision parameters. Several researchers have presented many ways to perform SA. Singh et al. [62] provided an example of performing multiple types of SA, including finding the minimum amount of change needed in an alternative's weight to elevate it to the first rank. Additionally, Stević et al. [63] stated that SA can be used to identify the range of weights that can be assigned to each alternative while still producing the same ranking outcome. Another useful approach to conducting SA on the CREA rankings would be to compare CREA ranking outcomes with the results from other MCDM methodologies to assess the degree of consistency between the two methods.

To further evaluate the robustness of the proposed CREA method, a sensitivity analysis is performed to examine how small changes in criterion weights influence the resulting country rankings. Specifically, a series of scenarios is constructed by introducing controlled variations of 5%, 10%, and 20% to the weight of the most influential criterion in the decision matrix shown in Table 3. This scenario-based design enables a systematic assessment of the effect of weight perturbations on the final ranking structure generated by CREA. In each scenario, the weights of the remaining criteria are proportionally recalibrated to ensure that the total weight remains normalized to unity. By analyzing the ranking behavior under these alternative weighting conditions, the sensitivity analysis offers important evidence regarding the stability, consistency, and practical reliability of the proposed framework.

For the present study, the criterion weights obtained through the SITDE method are 0.108, 0.106, 0.091, 0.100, 0.126, 0.113, 0.110, 0.113, 0.085, and 0.048 for C_{t1} to C_{t10} , respectively. Among these, C_{t5} is identified as the most influential criterion because it has the highest weight value ($w_5 = 0.126$). To evaluate the sensitivity of the ranking results, the weight of C_{t5} is varied under a set of controlled scenarios. Specifically, the adjusted values are 0.120 and 0.132 for the -5% and 5% cases, 0.113 and 0.139 for the -10% and 10% cases, and 0.101 and 0.151 for the -20% and 20% cases, respectively. These modified weights are then used to generate alternative weighting scenarios for examining the stability of the CREA ranking results.

The sensitivity analysis considered the original weighting condition together with six C_{t5} weight-perturbation scenarios of -5% , $+5\%$, -10% , $+10\%$, -20% , and $+20\%$. In each scenario, the remaining criterion weights were proportionally adjusted so that the total weight remained equal to one. The resulting CREA rankings are presented in Table 11. Across all seven conditions, the ranking positions of all 13 countries remained unchanged. The USA retained the first rank, Israel remained second, and Canada remained thirteenth in every scenario.

Since unchanged ranks may still conceal changes in score magnitude, the CREA scores were also recalculated for all C_{t5} perturbation scenarios. The corresponding results are presented in Table 12. The maximum absolute changes in CREA scores ranged from 0.17% to 4.45%. The USA recorded the largest change of 4.45%, followed by India at 3.90% and Germany at 2.75%, while South Korea recorded the smallest change of 0.17%. Thus, although the CREA scores varied to some extent, the ranking positions of all 13 countries remained unchanged under the tested scenarios.

For comparison, the Weighted Sum Method (WSM) was evaluated under the same C_{t5} weight-perturbation conditions. The resulting WSM rankings are presented in Table 13. Unlike CREA, WSM showed a few positional changes among closely ranked countries. Singapore and Switzerland exchanged the eleventh and twelfth positions under some increases in the C_{t5} weight, while Japan and India exchanged the fifth and sixth positions under the -20% C_{t5} scenario.

The corresponding WSM scores are presented in Table 14. The maximum absolute percentage changes in WSM scores ranged from 0.57% to 5.05%. Russia recorded the largest change of 5.05%, while the USA recorded the smallest change of 0.57%. Overall, CREA showed greater ranking stability than WSM under the specific C_{t5} weight-perturbation scenarios examined in this study. These findings are limited to the present dataset and perturbation design and should not be interpreted as evidence of general robustness or universal superiority.

Table 11. Sensitivity analysis outcomes of the proposed CREA method under Ct5 weight perturbations.

Criteria weights											Revised ranking of alternatives												
Scenarios	Ct 1	Ct 2	Ct 3	Ct 4	Ct 5	Ct 6	Ct 7	Ct 8	Ct 9	Ct 10	A 1	A 2	A 3	A 4	A 5	A 6	A 7	A 8	A 9	A10	A11	A12	A13
Scenario 1	0.108	0.106	0.091	0.100	0.126	0.113	0.110	0.113	0.085	0.048	1	4	8	3	6	7	5	9	12	11	10	13	2
Scenario 2	0.109	0.106	0.092	0.100	0.120	0.113	0.111	0.114	0.086	0.049	1	4	8	3	6	7	5	9	12	11	10	13	2
Scenario 3	0.107	0.105	0.091	0.099	0.132	0.112	0.110	0.112	0.084	0.048	1	4	8	3	6	7	5	9	12	11	10	13	2
Scenario 4	0.110	0.108	0.091	0.102	0.114	0.115	0.110	0.115	0.087	0.050	1	4	8	3	6	7	5	9	12	11	10	13	2
Scenario 5	0.106	0.103	0.089	0.097	0.139	0.113	0.108	0.114	0.084	0.047	1	4	8	3	6	7	5	9	12	11	10	13	2
Scenario 6	0.114	0.111	0.092	0.103	0.101	0.113	0.112	0.118	0.089	0.051	1	4	8	3	6	7	5	9	12	11	10	13	2
Scenario 7	0.105	0.100	0.089	0.095	0.151	0.110	0.108	0.107	0.084	0.047	1	4	8	3	6	7	5	9	12	11	10	13	2

Note: Ct5 represents the most influential criterion identified by the SITDE weighting method. In each perturbation case, the remaining criterion weights are proportionally recalibrated to maintain $\sum w_j = 1$.

Table 12. Changes in CREA scores under Ct5 weight perturbations.

Country	Original	−5%	5%	−10%	10%	−20%	20%	Maximum change (%)
USA	3.575	3.539	3.614	3.502	3.654	3.432	3.735	4.45
Germany	2.836	2.818	2.855	2.800	2.874	2.766	2.914	2.75
UK	1.674	1.669	1.678	1.666	1.682	1.660	1.690	0.96
China	3.279	3.265	3.293	3.251	3.308	3.226	3.338	1.8
Japan	2.031	2.024	2.038	2.019	2.044	2.009	2.056	1.23

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Country	Original	−5%	5%	−10%	10%	−20%	20%	Maximum change (%)
South Korea	1.780	1.778	1.782	1.778	1.782	1.779	1.783	0.17
India	2.282	2.262	2.303	2.241	2.325	2.202	2.371	3.9
Singapore	1.467	1.466	1.469	1.466	1.469	1.466	1.470	0.2
Switzerland	1.125	1.122	1.129	1.120	1.131	1.117	1.136	0.98
France	1.369	1.365	1.374	1.361	1.378	1.355	1.386	1.24
Russia	1.411	1.413	1.410	1.418	1.405	1.426	1.397	1.06
Canada	1.058	1.058	1.059	1.059	1.058	1.063	1.056	0.47
Israel	3.297	3.287	3.307	3.278	3.317	3.261	3.337	1.21

Table 13. Sensitivity analysis outcomes of the WSM benchmark method under Ct5 weight perturbations.

Criteria weights											Revised ranking of alternatives												
Scenarios	Ct 1	Ct 2	Ct 3	Ct 4	Ct 5	Ct 6	Ct 7	Ct 8	Ct 9	Ct 10	A	A	A	A	A	A	A	A	A	A10	A11	A12	A13
											1	2	3	4	5	6	7	8	9				
Scenario 1	0.108	0.106	0.091	0.100	0.126	0.113	0.110	0.113	0.085	0.048	1	4	8	2	6	7	5	11	12	10	9	13	3
Scenario 2	0.107	0.105	0.091	0.099	0.132	0.112	0.110	0.112	0.084	0.048	1	4	8	2	6	7	5	12	11	10	9	13	3
Scenario 3	0.109	0.106	0.092	0.100	0.120	0.113	0.111	0.114	0.086	0.049	1	4	8	2	6	7	5	11	12	10	9	13	3
Scenario 4	0.106	0.103	0.089	0.097	0.139	0.110	0.108	0.110	0.083	0.047	1	4	8	2	6	7	5	12	11	10	9	13	3
Scenario 5	0.110	0.108	0.093	0.102	0.113	0.115	0.113	0.115	0.087	0.050	1	4	8	2	6	7	5	11	12	10	9	13	3
Scenario 6	0.103	0.100	0.087	0.095	0.151	0.107	0.105	0.107	0.081	0.046	1	4	8	2	6	7	5	12	11	10	9	13	3
Scenario 7	0.114	0.111	0.096	0.105	0.101	0.118	0.116	0.118	0.089	0.051	1	4	8	2	5	7	6	11	12	10	9	13	3

Table 14. Changes in WSM scores under Ct5 weight perturbations.

Country	Original	−5%	5%	−10%	10%	−20%	20%	Maximum change (%)
USA	0.699	0.697	0.701	0.699	0.699	0.703	0.696	0.57
Germany	0.433	0.435	0.432	0.439	0.428	0.447	0.420	3.23
UK	0.340	0.342	0.339	0.346	0.335	0.354	0.327	4.12
China	0.505	0.507	0.503	0.513	0.497	0.524	0.486	3.76
Japan	0.403	0.405	0.402	0.409	0.397	0.419	0.388	3.97
South Korea	0.382	0.384	0.380	0.389	0.376	0.399	0.367	4.45
India	0.411	0.410	0.411	0.413	0.408	0.418	0.403	1.95
Singapore	0.303	0.305	0.301	0.309	0.297	0.317	0.289	4.62
Switzerland	0.302	0.303	0.301	0.307	0.298	0.313	0.292	3.64
France	0.311	0.312	0.309	0.315	0.306	0.322	0.300	3.54
Russia	0.317	0.320	0.315	0.324	0.311	0.333	0.302	5.05
Canada	0.266	0.267	0.264	0.270	0.261	0.277	0.255	4.14
Israel	0.452	0.455	0.449	0.460	0.444	0.472	0.432	4.42

Note: The WSM results are used as a benchmark to compare the ranking stability of the proposed CREA method under identical criterion-weight perturbation conditions.

Tables 11–14 show the effect of the Ct5 weight perturbations on both ranking positions and score values. Under CREA, the ranking positions of all 13 countries remained unchanged across the original condition and the six perturbation scenarios. The maximum absolute change in CREA scores ranged from 0.17% to 4.45%, with the USA recording the largest change of 4.45% and South Korea the smallest change of 0.17%. In comparison, the WSM scores changed by 0.57% to 5.05%, and a few positional changes occurred among closely ranked countries. Singapore and Switzerland exchanged positions under some scenarios, while Japan and India exchanged the fifth and sixth positions under the -20% Ct5 scenario. These results indicate that CREA showed greater ranking stability than WSM under the specific Ct5 weight-perturbation conditions examined in this study. However, the findings are limited to the present dataset and perturbation design and should not be interpreted as evidence of general robustness.

The ranking patterns obtained under the Ct5 weight-perturbation scenarios are further illustrated in Figures 6 and 7 for CREA and WSM, respectively.

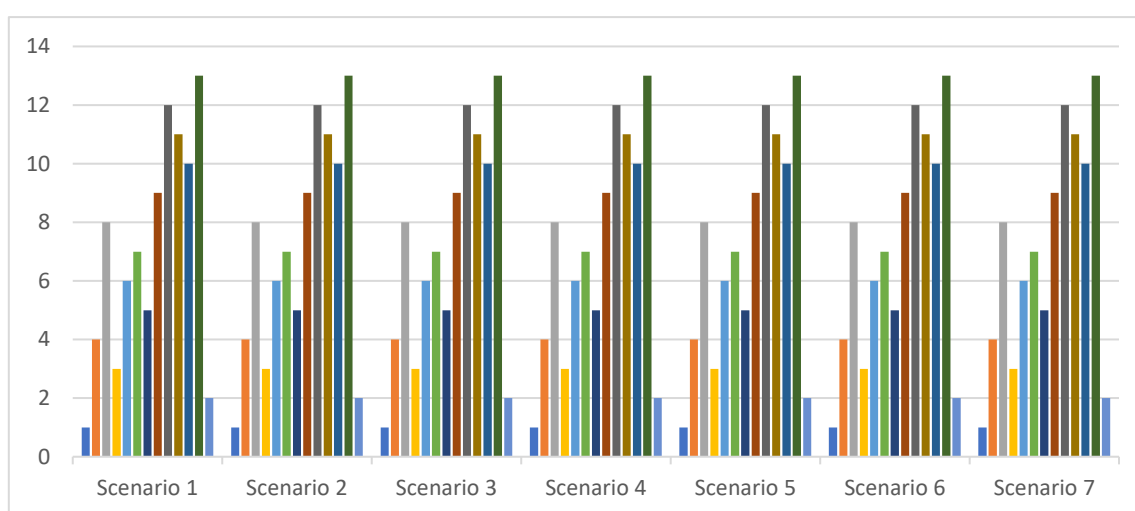


Figure 6. Sensitivity analysis of CREA rankings under Ct5 weight perturbations.

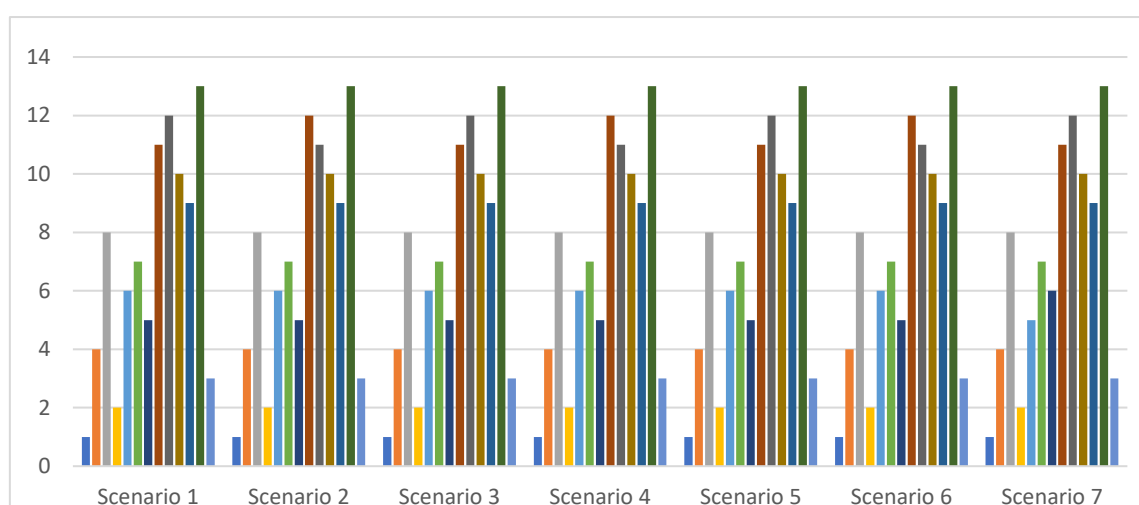


Figure 7. Sensitivity analysis of WSM rankings under Ct5 weight perturbations.

5.4 Rank-reversal analysis under alternative-set expansion

Rank reversal is an important concern in multi-criteria decision-making because the relative ordering of existing alternatives may change when a new alternative is added or an existing alternative is removed, even when the criteria and weights remain unchanged. This issue has been widely discussed in MCDM literature and is particularly relevant when assessing the robustness of ranking-based decision methods Triantaphyllou [29], Wang and Luo [49], García-Cascales and Lamata [50]. TOPSIS, originally introduced by Hwang and Yoon [64], is one of the most widely used distance-based MCDM methods; however, previous studies have reported that TOPSIS may be affected by rank reversal under certain alternative-set changes García-Cascales and Lamata [50], de Farias Aires and Ferreira [65], Shyur and Shih [66].

To isolate the effect of alternative-set expansion, the original criterion values, criterion classifications, normalization bounds, and criterion weights were retained without recalculation after Denmark was added. Therefore, the experiment examines rank reversal caused specifically by the expansion of the alternative set under fixed model parameters.

To evaluate the ranking stability of the proposed CREA method, a rank-reversal analysis was conducted by expanding the original set of alternatives. Initially, 13 countries were evaluated and ranked using the proposed CREA method and the TOPSIS method. Denmark was incorporated into the earlier ranking, and the rankings for the 14 countries were finished using the same criteria and weights. The objective of this analysis is to determine if the addition of Denmark made any changes to the relative rank of the original 13 countries.

During alternative-set expansion, the predetermined reference bounds are retained without recalculation. If a newly introduced alternative contains a value outside a specified reference interval, the bounded-normalization rule presented in Section 3.3.2 is applied, assigning the corresponding endpoint value of 0 or 1.

The change in ranking is determined by finding the difference between the new ranking, which is determined after adding Denmark, and the original ranking for the 13 countries. The calculation is as follows:

$$\Delta R_i = R_i^{after} - R_i^{before}$$

where ΔR_i represents the change in rank of country i , R_i^{before} denotes the rank before adding Denmark, and R_i^{after} denotes the rank after adding Denmark. A value of zero indicates no rank change, whereas a non-zero value indicates the occurrence of rank reversal. Positive values indicate a deterioration in rank position, while negative values indicate an improvement in rank position. The results of the rank-reversal analysis are presented in Table 15. To provide a clearer visual representation of the rank-reversal behavior, the absolute rank changes obtained from CREA and TOPSIS are also illustrated in Figure 8. The figure enables a direct comparison of ranking stability between the two methods by showing whether the original countries experienced any positional changes after the inclusion of Denmark. As such, Table 15 provides numerical evidence, while Figure 8 offers graphical confirmation of the relative stability of CREA and the rank fluctuations observed under TOPSIS.

Table 15. Rank-reversal analysis of CREA and TOPSIS after adding Denmark.

Country	CREA rank with 13 countries	CREA rank after adding Denmark	Change in CREA rank	TOPSIS rank with 13 countries	TOPSIS rank after adding Denmark	Change in TOPSIS rank
USA	1	1	0	1	1	0
Germany	4	4	0	4	10	6
UK	8	8	0	9	11	2
China	3	3	0	3	8	5
Japan	6	6	0	7	7	0
South Korea	7	7	0	8	3	-5
India	5	5	0	2	4	2
Singapore	9	9	0	10	12	2
Switzerland	12	12	0	12	6	-6
France	11	11	0	11	9	-2
Russia	10	10	0	6	2	-4
Canada	13	13	0	13	5	-8
Israel	2	2	0	5	13	8
Denmark	—	14	—	—	14	—

Note: Denmark is the newly added alternative and was not included in the original 13-country ranking; therefore, rank change is not computed for Denmark. A positive ΔR indicates deterioration in rank position, whereas a negative ΔR indicates improvement.

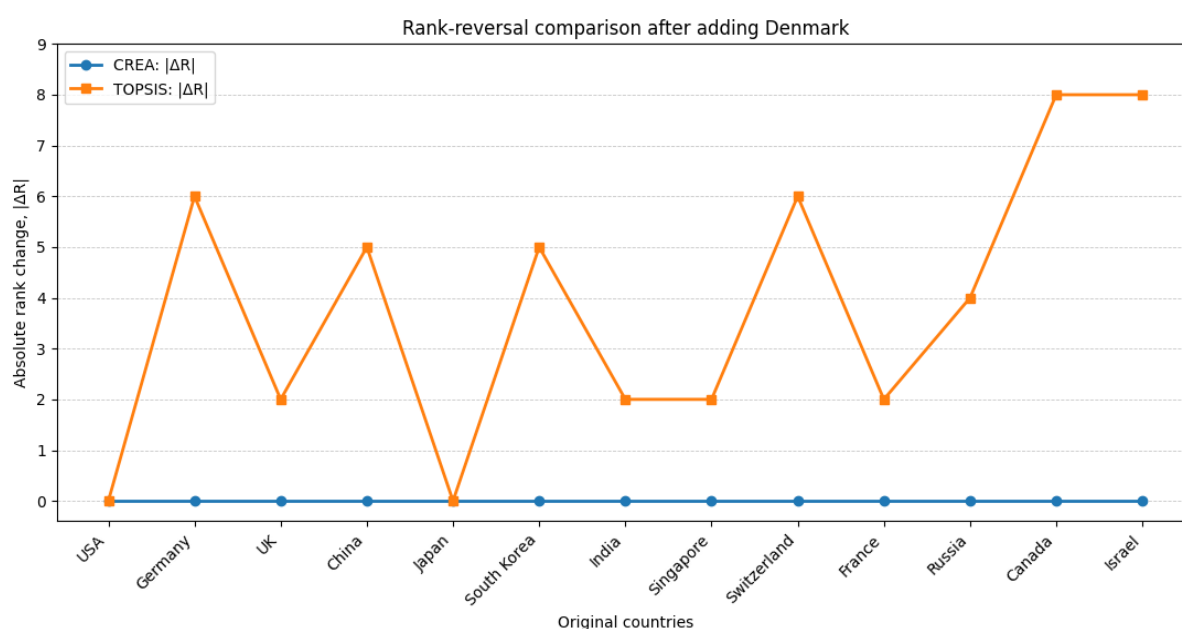
**Figure 8.** Rank-reversal comparison of CREA and TOPSIS after adding Denmark.

Table 15 shows that adding Denmark did not change the ranking of any of the original 13 countries under the new method of ranking (CREA). All 13 countries received the same CREA ranks; therefore, there was no change in CREA rank for these countries. In the present experiment, CREA preserved the

relative rankings of the original alternatives after Denmark was added. This is further confirmed by Figure 8, where the rank change for all countries under CREA remained at zero. Therefore, the results provide application-specific evidence of ranking stability under this single alternative-addition experiment.

In contrast, the TOPSIS method shows considerable changes in the ranking positions of several countries after the addition of Denmark. Except for the USA and Japan, all other original countries experienced rank changes under TOPSIS. For instance, Germany changed from fourth to tenth position, China from third to eighth position, Canada from thirteenth to fifth position, and Israel from fifth to thirteenth position. Similarly, Switzerland improved from twelfth to sixth position, while South Korea improved from eighth to third position. These changes indicate the occurrence of rank reversal in TOPSIS under the same alternative-set expansion condition.

The comparison further shows that the proposed CREA method recorded zero total absolute rank change, whereas TOPSIS recorded a total absolute rank change of 50 across the original 13 countries. In addition, 11 out of the 13 original countries experienced rank changes in TOPSIS, while none of the original countries experienced rank changes in CREA. Under the tested conditions, CREA produced fewer rank changes than TOPSIS in the present biotechnology country-evaluation problem.

The observed ranking stability of CREA under the present experiment can be associated with its fixed-reference normalization structure and separate aggregation of benefit performance and non-benefit burden. The normalization of existing alternatives is done without having to recalculate the normalized values of existing alternatives based on the newly expanded set of alternatives, due to existing lower and upper bounds for the normalization. Therefore, CREA has less of a dependency on the set of alternatives García-Cascales and Lamata [50], de Farias Aires and Ferreira [65]. In addition, because benefits and non-benefit criteria are aggregated separately, the contribution of favorable and unfavorable criteria remains intact before computing the final score. On the other hand, with the traditional TOPSIS method Hwang and Yoon [64], the positive ideal solution and negative ideal solution are determined from the available alternatives; thus, when the new alternative is introduced, the reference points may change, which in turn will affect the separation measures and relative closeness coefficients, and hence change the final rank order. These findings support the findings of other studies that have pointed out the potential for rank reversal in TOPSIS associated with the normalization processes García-Cascales and Lamata [50], the distance measures de Farias Aires and Ferreira [65], and the way that the ideal reference points are constructed Shyur and Shih [66].

The results of the rank-reversal analysis provide application-specific evidence regarding the ranking stability of the proposed CREA method. In the present experiment, the addition of Denmark did not change the relative ordering of the original 13 countries under CREA, whereas several rank changes occurred under TOPSIS. This finding suggests that CREA reduced alternative-set dependence under the tested conditions. However, because the analysis was based on one dataset and a single alternative-set expansion experiment, the result should be interpreted as preliminary evidence rather than as proof that CREA is universally immune to rank reversal. Additional experiments involving the addition and removal of different alternatives, larger datasets, and other decision-making applications are required to establish the broader robustness of the method.

Accordingly, the observed result should be interpreted as conditional ranking invariance under fixed bounds, weights, criterion directions, and original performance data rather than as universal immunity to rank reversal.

6. Discussion

6.1. Discussion of study findings

This study's results indicate that the CREA method is appropriate for assessing the biotechnology capabilities of various countries. Due to the heterogeneous nature of national biotechnological performance and the multiple indicators (e.g., regulation, innovation, research output, market size, clinical trials, human resource potential, intellectual property protections) involved in evaluating this performance, there was a need for a structured multi-criteria approach. To satisfy this requirement, CREA provides a structured, unified, and interpretable evaluation of national biotechnology capability by integrating benefit and non-benefit criteria into a single framework.

The observed rankings arise from the hybrid aggregation structure of CREA rather than from a simple summation of all criteria. The Euclidean component captures the combined magnitude of the benefit and non-benefit aggregates, while the ratio component gives greater influence to alternatives having a relatively large benefit aggregate and a smaller denominator. For example, the USA combines the highest benefit aggregate of 0.601 with a non-benefit aggregate of 0.204, producing the highest CREA score of 3.575. Israel and China also obtain high rankings because their benefit-to-non-benefit ratios are comparatively strong. Israel has a benefit aggregate of 0.194 and a non-benefit aggregate of 0.063, producing a CREA score of 3.297 and the second rank. China has a benefit aggregate of 0.299 and a non-benefit aggregate of 0.101, producing a CREA score of 3.279 and the third rank. In contrast, Canada has a benefit aggregate of 0.182 and a non-benefit aggregate of 0.241, resulting in a CREA score of 1.058 and the lowest ranking.

These findings differ from those produced by conventional additive and distance-based methods because CREA preserves the benefit and non-benefit aggregates separately until the final stage. This explains why Israel ranks second under CREA but first or fifth under some comparison methods, while Germany ranks fourth under CREA but third under RAM, MOORA, and MULTI-MOORA. These differences reflect the distinct Euclidean–ratio aggregation logic rather than inconsistencies in the data.

The study also differs from earlier biotechnology and innovation evaluations that mainly emphasized individual indicators such as patents, publications, or innovation output. CREA integrates regulatory, research, market, clinical, human-capital, and intellectual-property dimensions within one framework. Therefore, the resulting ranking represents multidimensional biotechnology capacity rather than performance based on a single output indicator.

The sensitivity analysis provides additional evidence regarding the stability of CREA under the tested $Ct5$ weight perturbations. The CREA scores changed by approximately 0.17%–4.45%, while the ranking positions of all 13 countries remained unchanged. Similarly, WSM scores changed by approximately 0.57%–5.05%, with limited positional changes among closely ranked alternatives. These results indicate substantial overall stability and demonstrate the importance of examining both score magnitude and ranking position.

The rank-reversal analysis provides application-specific evidence regarding the stability of CREA. Adding Denmark did not change the relative positions of the original 13 countries under CREA. In contrast, TOPSIS produced rank changes for 11 countries, with a total absolute rank change of 50. This difference arises partly because CREA retains fixed normalization bounds, whereas the ideal reference points used by conventional TOPSIS may change when the alternative set is expanded. Nevertheless, the findings are limited to the present dataset and one alternative-addition experiment.

The methodological structure of CREA lends to its stability. Fixed-reference normalization of the alternative set reduces the amount of reliance on the alternative set; therefore, it does not depend only

on the alternative set but, equally importantly, also preserves the bi-directional nature of the evaluation problem through separate aggregation of benefit and non-benefit criteria. The final Euclidean ratio index reflects both the overall performance and the degree to which the beneficial criteria dominated. Thus, these characteristics and the method's inherent features improve the interpretability and reliability of the ranking process. The derivative-based analysis further demonstrates that CREA permits a state-dependent trade-off between the benefit and non-benefit aggregates, while the unequal marginal effects and non-invariance under component interchange establish its asymmetric compensatory structure.

Overall, CREA provides an interpretable and practically useful decision-support framework for biotechnology country benchmarking. Its ranking agreement with established methods, sensitivity results, and rank-reversal experiment provide preliminary evidence of comparative consistency and stability under the tested conditions. However, these findings do not establish universal validity or superiority. Further evaluation using larger datasets, alternative weighting methods, multiple rank-reversal scenarios, fuzzy environments, and longitudinal data is required.

7. Study contributions, limitations, and future research directions

The current investigation presents a new method for evaluating the performance of countries regarding biotechnology in the field of MCDM. The method presented by this research project is the composite ratio and Euclidean aggregation (CREA). CREA incorporates both the normalization of fixed reference values and the aggregation of both benefits and no benefits within one overall model for decision-making. This model combines the use of both hybrid Euclidean and ratio-based scoring systems for scoring indicators. The merging of these two models allows for easier interpretation of results and provides greater stability than traditional methods in ranking countries based on biotechnology. Utilizing this method, the authors of this research article present a complete methodology for comparing countries' biotechnology performance across multiple dimensions (i.e., regulatory environment, innovation capacity, research output, market potential, clinical activities, availability of talent, and rights to intellectual property).

Despite the benefits of this study, it also has certain limitations. First, the analysis included only a limited number of countries and criteria, so any additional countries or alternate biotechnology criteria may produce differing ranking results. In addition, SITDE weights are sample-dependent and reflect distributional asymmetry rather than expert-assessed or policy-based importance. A highly skewed criterion may receive a relatively high objective weight because it differentiates the alternatives strongly, but this does not establish that it is inherently more important to biotechnology performance. Future studies should therefore compare SITDE weights with equal weighting, conventional objective methods such as entropy or CRITIC, and hybrid expert-objective weighting approaches to examine the effect of alternative interpretations of criterion importance. Third, the study utilized available secondary data sources; therefore, the quality, reporting standards, and timeframes for these data sources may differ from each country. Although common definitions were used wherever possible, differences in observation years, data coverage, and national reporting standards may affect cross-country comparability; moreover, the absence of a separate inflation adjustment should be considered when interpreting the monetary indicators. Lastly, although the sensitivity and rank-reversal analyses provide application-specific evidence of ranking stability under the tested conditions, CREA requires further examination in other decision-making contexts before its broader applicability can be assessed. In particular, the rank-reversal assessment was limited to a single alternative-set expansion involving the addition of Denmark. Therefore, the observed ranking stability should be

interpreted as evidence specific to the present dataset and experimental condition rather than as confirmation of universal resistance to rank reversal.

Future research can build off this work in several areas. CREA may be utilized with larger sample sizes of countries and/or a selected biotechnology sector (e.g., biopharmaceuticals, agricultural biotechnology, industrial biotechnology, or medical biotechnology). Future research may compare CREA with other robust MCDM methods under varying systems of normalization and weighting. Future research may extend CREA to fuzzy and interval-valued decision environments to account for uncertainty, ambiguity, and imprecision in country-level indicators and expert assessments. Cubic Fermatean fuzzy, interval-valued Fermatean fuzzy, and linear Diophantine fuzzy representations may be investigated by reformulating the normalization procedure, benefit and non-benefit aggregates, and final Euclidean–ratio operator under fuzzy arithmetic. Such extensions would enable CREA to be applied when exact numerical observations are unavailable, and assessments are expressed through linguistic or interval-valued information Liu et al. [53], Liu et al. [54], Liu et al. [55], Liu et al. [56].

Future studies should examine size-adjusted indicators, such as patents and clinical trials per million population, publications per researcher, and biotechnology market size relative to GDP, to distinguish national scale from biotechnology efficiency.

8. Conclusion

For this research study, the composite ratio and Euclidean aggregation (CREA) method was developed as a structured MCDM methodology for evaluating and comparing the performance of biotechnology across multiple nations. As the nature of biotechnology benchmarking is multidimensional, a single unified evaluation framework was necessary to provide an integrated process of both benefit and non-benefit criteria. CREA's components included the fixed-reference normalization methodological approach, separate aggregation of criteria, and a hybrid Euclidean-ratio index. As a result of these three elements combined, CREA provides an interpretable and structured foundation for assessing performance at the country level.

In the empirical application, CREA ranked the United States first with a score of 3.575, followed by Israel with 3.297 and China with 3.279, while Canada ranked thirteenth with a score of 1.058. Furthermore, the results demonstrated that CREA could successfully distinguish countries from one another based on regulatory indicators, innovation indicators, research indicators, market indicators, clinical indicators, human capital indicators, and intellectual property indicators. The comparison of CREA's outcomes to the outcomes of the other MCDM methods (RAM, COPRAS, MOORA, MOOSRA, and MULTI-MOORA) demonstrated the consistency of the rankings produced by CREA.

The sensitivity analysis examined perturbations only in the weight of Ct5, while the rank-reversal analysis considered only one alternative-set expansion involving the addition of Denmark. Under these specific conditions, the CREA scores showed relatively limited changes, the ranking positions remained unchanged, and the original country rankings were preserved after Denmark was added. These findings provide preliminary, application-specific evidence of ranking stability under the tested conditions; they do not establish the general robustness or universal resistance to rank reversal of CREA. Further validation should examine changes in all criterion weights, simultaneous multi-criterion weight variations, multiple additions and removals of alternatives, alternative normalization bounds, different weighting methods, larger datasets, and other application domains.

In conclusion, CREA offers a structured and interpretable decision-support framework for comparing national biotechnology capacity across multiple dimensions. In the present application, it supports the identification of comparative strengths, weaknesses, and structural differences among the

evaluated countries. However, its broader applicability, stability, and practical usefulness require further examination using more diverse datasets, experimental conditions, biotechnology sectors, uncertainty environments, and longitudinal evaluations.

Author Contributions

Yalamanda Babu Gopisetty.: Conceptualization, Methodology, Software, Formal analysis, Visualization, and Writing - original draft. E. Hymavathi: Investigation, Validation, and Writing - review and editing. Vijaya Ramu Dirisala: Validation, Supervision, Methodological review, and Writing - review and editing. Ravitez Dondeti: Data curation, Investigation, Domain validation, and Writing - review and editing. All authors reviewed, edited, and approved the final version of the manuscript.

Use of Generative-AI Tools Declaration

The authors declare that no generative artificial intelligence tools were used in the preparation, writing, editing, analysis, or creation of this article.

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Data Availability declaration

The datasets used and/or analysed during the current study are available from the corresponding author upon reasonable request.

Conflict of interest

The authors declare that they have no competing interests.

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