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Review

ASSESSMENT OF DATA QUALITY AND VALIDITY OF COMPOSITE INNOVATION INDICATORS WITH A NEUTROSOPHIC MULTI-CRITERIA APPROACH

Javier REIG-MULLOR [1✉], Ana GARCIA-BERNABEU [2], Francisco SALAS-MOLINA [3], David PLA-SANTAMARIA [4]

[1] *Universitas Miguel Hernandez, Avd. Universidad, Elche (Alicante), Spain*
[2,3,4] *Universitat Politècnica de València, Alcoy Campus, Plaza Ferrándiz y Carbonell, Alcoy (Alicante), Spain*

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Abstract. In light of the emphasis on innovation as a driver of economic growth, new tools are needed to measure and compare national innovation systems. Improving methodological approaches to constructing composite innovation indicators also requires exploring issues related to aggregation, weighting, and reviewing the quality and validity of the data. This paper aims to support this debate by assessing the process and outcomes of innovation using fuzzy theory combined with a multicriteria technique to address the uncertainty attached to the underlying data used in constructing the composite indicator. Mainly, we deal with the problems related to the uniformity of the period covered by the indicator and the origin and reliability of the source of information by incorporating degrees of truth, indeterminacy, and falsity into the assessment process by applying neutrosophic numbers. To test the effectiveness of our approach, an empirical analysis is carried out based on the European Innovation Scoreboard and the assessment of the elementary criteria over the period 2020–2023.

Keywords: innovation measurement, fuzzy sets, neutrosophic numbers, multicriteria decision making, data quality.

JEL Classification: D81, O30, O52.

✉Corresponding author. E-mail: ***javier.reig@umh.es***

1. Introduction

Promoting innovation is seen as a major policy vehicle for advancing a country's ability to compete and progress. It is widely agreed that innovation involves a dynamic interaction of economic, social, technological and institutional factors. Therefore, these factors that define a national innovation system cannot be easily captured or measured by a single, simplistic approach. Moreover, these relationships evolve over time, making it difficult to reduce such complexity to straightforward metrics or linear models (Grupp, 1998). This is why composite indicators have recently been used to assess countries' innovation performance to transform the complex multidimensional phenomenon of innovation into a single figure.

Two remarkable examples are the WIPO Global Innovation Index (GII) introduced in 2007, which is a key tool in this growth narrative covering more than 130 countries, and the European Commission's Summary Innovation Index (SII) at the European level previously introduced in 2001, which is used in our study to address the issue of data quality and reliability. Other proposals for innovation indicators are also discussed in Grupp and Schubert (2010).

As a point of departure for this work, it is worth mentioning that in the current landscape of national innovation appraisal approaches, there is no commonly accepted methodology, as each proposal is based on different indicators' frameworks and methodologies. From the outset, those developing and using innovation indices have discussed them primarily from a statistical perspective. An example of this is the chapter on innovation scoreboards in the leading Handbook of Innovation Indicators (Hollanders & Janz, 2013). Thus, the improvement of methodological approaches for the design of composite indicators as a framework for tracking national innovation systems has been the subject of continuous research over recent years (Alnafrah, 2021; Edquist et al., 2018; Freeman & Soete, 2009). Suggested improvements in the construction of innovative metrics have mainly focused on challenges that broadly concern the construction of any composite indicator: (1) the weighting system which is attached to dimensions and indicators, (2) the way they aggregate the different components of the index, either by taking into account compensation or not (Garcia-Bernabeu et al., 2020, 2022), and (3) its consistency and stability under different conditions or scenarios, i.e., its robustness (Corrente et al., 2023; Freudenberg, 2003; Greco et al., 2019; Munda & Nardo, 2005, 2009; Saisana & Tarantola, 2002).

To construct composite innovation indicators, a variety of data sources are utilized, drawing primarily from the recommendations outlined in the Frascati Manual (Organisation for Economic Co-operation and Development [OECD], 2002). A significant portion of innovation data, particularly for individual indicators, is derived from R&D surveys that many countries have been conducting since the mid-20th century. In some cases, such as patent data, collection efforts began even earlier. In addition to R&D surveys, innovation surveys serve as a key source of information for measuring innovation. Other types of surveys and data sources may also be employed depending on the specific type of data being analyzed.

Although, in recent years, several studies have addressed these more generic problems in the specific domain of innovation, the assessment of the quality and reliability of the underlying data on which these indexes are constructed is often missing. This gap highlights the need for a more thorough evaluation of data quality to ensure the robustness of composite innovation indicators.

Concerning data quality and validity, we encounter two main types of problems:

- The first is the time period uniformity. Mainly, data from innovation surveys are of a cross-cutting type, but not all indicators are always constructed considering a uniform and as recent period as possible. It is common to find that the availability of data for some indicators refers to the latest available year in which the measurement was made, which often does not coincide with the rest of the years considered for most indicators.
- The second is the data source's reliability. While some indicators come from official public institutions such as statistical offices that publish the R&D data collection methodology, others come from private institutions in which their veracity is not always assured, or it is difficult to know to what extent a conflict of interest exists. Often, the underlying data come from sample surveys, and therefore, the reliability of the indicators largely rests on the sampling design and other quality-related aspects. As Arundel and Hollanders (2008) pointed out, when assessing different sources of information, survey data are less reliable than hard data. However, they consider that they should be included as in the absence of hard data for many aspects of innovation, surveys can

provide a rough assessment. Again, Mairesse and Mohnen (2010) work considers that much of the information that comes from innovation surveys is not of significant quality for robust econometric analysis. Therefore, the degree of reliability of data obtained from innovation surveys and from indirect measures can be diverse.

Overall, concerns about the quality and reliability of data, coupled with the lack of a single widely agreed method for constructing composite indicators to assess national innovation performance, have favored the application of fuzzy set approaches in the construction of composite innovation indices (Crespo & Crespo, 2016; Fabri et al., 2023).

In the context of fuzzy theory Zadeh (1965), certain subsets of fuzzy numbers, such as neutrosophic numbers, are considered particularly effective for assessing the reliability of data. While fuzzy sets facilitate the handling of imprecise information provided by decision-makers, they are generally regarded as inadequate for managing inconsistent and indeterminate information. To address this limitation, Smarandache (1999) introduced the concept of Neutrosophic Fuzzy Sets (NFS), which offer an effective framework for dealing with imprecise, incomplete, indeterminate, and inconsistent information encountered in decision-making processes (Biswas et al., 2018). Neutrosophic Fuzzy Sets (NFS) represent an evolution of Intuitionistic Fuzzy Sets (IFS) (Atanassov, 1986) by explicitly introducing indeterminacy as a distinct component. This enhancement allows NFS to address scenarios where traditional fuzzy logic frameworks – such as fuzzy sets (FS), type-2 fuzzy sets, or IFS – fall short in capturing the complexity of uncertainty. While IFS offers a simpler framework by modeling both membership and non-membership, it lacks the ability to address indeterminacy effectively. This limitation often reduces its effectiveness in handling ambiguous or conflicting information, particularly in complex decision-making scenarios (Smarandache, 2006). In contrast, NFS provides a more comprehensive framework by incorporating three independent dimensions: truth, indeterminacy, and falsehood. Unlike FS, which models uncertainty through membership grades, or IFS, which accounts for both membership and non-membership, NFS explicitly captures indeterminacy as an integral component. This multidimensional structure enables NFS to model inconsistent, incomplete, or ambiguous data more effectively, ensuring greater flexibility and accuracy in decision-making. These advantages underscore the growing preference for neutrosophic sets in advanced decision-making contexts. By explicitly addressing the relationships between truth, indeterminacy, and falsehood, NFS outperforms traditional approaches, providing reliable and informed outcomes even in highly uncertain or complex real-world applications (Görçün, 2022; Khan et al., 2018).

Singled-Value Triangular Neutrosophic Numbers (SVTNs), a subset of NFS, have emerged as a powerful tool for handling uncertainty and imprecision in decision-making problems. Research has explored their applications in various fields, including engineering (Vázquez & Torres, 2024), finance (Nagalakshmi, 2023), and medical diagnosis (Abdel-Basset et al., 2022). The ability of SVTNs to capture both uncertainty and indeterminacy has made them a valuable asset in modeling complex real-world systems. Their triangular shape offers a simple yet effective means of representing fuzzy information, facilitating easy visualization and intuitive interpretation of uncertainty.

Operations involving SVTNs are often more complex than those based on traditional fuzzy numbers. In this context, score functions offer several advantages when working with SVTNs, simplifying the representation of complex SVTNs by transforming them into a single numerical value (Bano et al., 2023). However, many current SVNs score functions are derived from fuzzy set methodologies, which can lead to inconsistencies in ranking outcomes (Wang, 2024). The design of score functions can be tailored to specific decision-making problems and the characteristics of SVTNs. Selecting an appropriate scoring function depends on the application and the nature of the data, as some functions may produce counterintuitive rankings in certain cases. Therefore, evaluating score functions for SVTNs is particularly critical in Multi-Criteria Decision-Making (MCDM) contexts, where the choice of function can significantly impact the consistency and coherence of rankings. One of the key objectives of this article is to empirically assess various score functions designed for SVTNs, aiming to identify those that enhance consistency and coherence in ranking outcomes within MCDM problems. By conducting a comprehensive evaluation, we seek to determine the most effective scoring functions that mitigate potential inconsistencies, thereby improving the reliability and robustness of decision-making processes.

Given the multidimensional nature of innovation, Multi-Criteria Decision-Making (MCDM) models have recently been employed in the construction of composite indices to evaluate and benchmark innovation systems (Corrente et al., 2023; Garcia-Bernabeu et al., 2020). One of the most widely implemented and effective ranking approaches within MCDM is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), originally developed by Hwang and Yoon (1981). This method, grounded in compromise theory, aids in selecting options that are closest to the ideal solution while being farthest from the anti-ideal solution, according to a predefined order of preference. In recent years, numerous studies have applied the TOPSIS technique within neutrosophic environments, reflecting its adaptability to handling uncertainty and imprecision.

The main objective of this study on European innovation performance using a new approach is to leverage neutrosophic numbers to address the critical issue of data quality and reliability in the assessment of innovation performance within EU member states. By integrating neutrosophic numbers into the TOPSIS technique, the study aims to develop a more robust and comprehensive framework for constructing composite indicators that accurately reflect the innovation landscape in Europe. The study seeks to enhance the reliability and accuracy of the innovation assessment process by applying neutrosophic sets, which capture the degrees of truth, indeterminacy, and falsity in data. By utilizing neutrosophic numbers in conjunction with the TOPSIS methodology, in what follows N-TOPSIS, the study aims to provide a novel and effective approach for benchmarking innovation in Europe that takes into account the quality and reliability of underlying data, ultimately contributing to the advancement of methodologies for evaluating national innovation systems.

The remainder of the paper is organized as follows: Section 2 offers a literature review and introduces key concepts related to neutrosophic sets. Additionally, it outlines the methodological approach, which combines the TOPSIS multi-criteria method with neutrosophic numbers. Section 3 presents the results and discussion of the proposed methodology for evaluating the innovation performance of EU countries, along with a sensitivity analysis using five different score functions. Finally, Section 4 provides the conclusions and suggests potential avenues for future research.

2. Materials and methods

2.1. Literature review

To address the problems of innovation data quality, we turn to the tools of fuzzy theory, including neutrosophic numbers. In general, although fuzzy sets introduced by Zadeh (1965) provide a mathematical framework that facilitates the treatment of imprecise information provided by decision-makers, their usefulness is often questioned when incoherent and indeterminate information must also be managed. To overcome this limitation, Smarandache (1999) introduced the concept of Neutrosophic Fuzzy Sets (NFS), which offer a practical framework for dealing with imprecise, incomplete, indeterminate, and inconsistent information encountered in decision-making processes (Biswas et al., 2018).

This is of particular importance when dealing with real-world problems where data may be incomplete, inconsistent, or contradictory, challenges that classical fuzzy sets struggle to address. Neutrosophic numbers have been widely applied in decision-making contexts, particularly through Multi-Criteria Decision-Making (MCDM) techniques. For example, TOPSIS, traditionally employed in fuzzy decision-making, has been adapted to incorporate neutrosophic numbers, enhancing its ability to deal with data uncertainty and inconsistency (Biswas et al., 2018).

Table 1 provides a recent overview of previous works in which the fuzzy analysis and reflects the evolving application of neutrosophic numbers in conjunction with TOPSIS.

Table 1. Review of studies for neutrosophic TOPSIS applications

Authors	Field/Application	MCDM	Separate mesure	Fuzzy number
Nădăban and Dzitac (2016)	Theoretical paper	TOPSIS	Hamming	SVNN
Biswas et al. (2018)	Theoretical paper / Doctor recruitment in a pharmaceutical company	TOPSIS	Hamming	SVTrN
Zaied et al. (2019)	Assessment of airline service quality	TOPSIS	Score function	BNN
Nancy and Garg (2019)	Software selection by a travel agent	TOPSIS	Divergence	SVNN
Elhassouny and Smarandache (2019)	Numerical examples	TOPSIS	Manhattan	SVNN
Abdel-Basset et al. (2019)	Car importer supplier selection	TOPSIS	Score function	T2SVN
Biswas et al. (2019)	Group decision making	TOPSIS	Hamming	SVNN INS
Karabašević et al. (2020)	E-commerce development strategies selection	TOPSIS	Hamming	SVNN
Karaaslan and Hunu (2020)	Selecting investment alternatives	TOPSIS	Hamming Euclidean	T2SVN
Abdel-Basset et al. (2021)	Targeting sustainable renewable energy systems	AHP-TOPSIS-VIKOR	Score Function	SVTN

End of Table 1

Authors	Field/Application	MCDM	Separate mesure	Fuzzy number
Nafei et al. (2021)	Selection of automotive companies	TOPSIS	Hamming	SVNN
Reig-Mullor et al. (2022)	Theoretical paper / Evaluating ESG Corporate performance	AHP-TOPSIS	Possibilistic Score Function	SVTN
Our study	European Innovation Ranking	TOPSIS	Differents score fuctions	SVTN

Notes: SVNN – Single-Value Neutrosophic Number; SVTrN – Single-Value Trapezoidal Nuetrosophic Number; BNN – Bipolar Neutrosophic Number; T2SVN – Type 2 Single-Value Neutrosophic Number; SVTN – Single-Value Triangular Neutrosophic Numbers: INS – Interval Nueotrosophic Number.

However, no such approach has been proposed in which a TOPSIS-based method is formulated using single-value triangular neutrosophic numbers, incorporating data quality and uncertainty into evaluating composite indicators. The main contribution of this work is to develop a methodology in which to construct a composite indicator that assesses countries' innovation performance the quality and reliability of the underlying data are integrated into the model. To this end, the combination of a novel neutrosophic model with the TOPSIS methodology enhances the reliability of innovation performance assessments.

2.2. Methodology

The concept of a single-valued neutrosophic set (SVNS), as introduced by (Smarandache, 1999) is defined for a universe of discourse X containing a generic element x. A SVNS $\tilde{N}$ over X is characterized by three membership functions: the truth membership function $T(x)$, the indeterminacy membership $I(x)$, and the falsity membership function $F(x)$, where for each point each point x in X, $T(x)$, $I(x)$, $F(x) \in [0, 1]$.

Definition 1. (Smarandache, 1999). Let X be a universe of discourse with a generic element x. A single valued neutrosophic set (SVNS) $\tilde{N}$ over X is defined by three membership functions: truth membership $T(x)$, indeterminacy membership $I(x)$ and falsity membership $F(x)$. For each point x in X, $T(x)$, $I(x)$, $F(x) \in [0, 1]$,
where,

$$0 \le T_A(x) + I_A(x) + F_A(x) \le 3. \tag{1}$$

Definition 2. (Deli & Şubaş, 2017). Let $\tilde{N} = ((\alpha, \beta, \mu); \varphi, \psi, \delta)$ is a special SVNS on the real numbers $\mathbb{R}$, denoted Single-Valued Triangular Neutrosophic Number (SVTN), whose $T(x)$, $I(x)$ and $F(x)$ functions are given as follows:

$$T(x) = \begin{cases} \dfrac{x-\alpha}{\beta-\alpha}\varphi, & \text{if } \alpha \le x \le \beta \\ \varphi, & \text{if } x = \beta \\ \dfrac{\mu-x}{\mu-\beta}\varphi, & \text{if } \beta < x \le \mu \\ 0, & \text{Otherwise} \end{cases}; \tag{2}$$

$$I(x)=\begin{cases}\dfrac{\beta-x+(x-\alpha)\psi}{\beta-\alpha}, & \text{if } \alpha\le x\le\beta\\ \psi, & \text{if } x=\beta\\ \dfrac{x-\beta+(\mu-x)\psi}{\mu-\beta}, & \text{if } \beta<x\le\mu\\ 1, & \text{Otherwise}\end{cases}; \tag{3}$$

$$F(x)=\begin{cases}\dfrac{\beta-x+(x-\alpha)\delta}{\beta-\alpha}, & \text{if } \alpha\le x\le\beta\\ \delta, & \text{if } x=\beta\\ \dfrac{x-\beta+(\mu-x)\delta}{\mu-\beta}, & \text{if } \beta<x\le\mu\\ 1, & \text{Otherwise}\end{cases}. \tag{4}$$

The main properties and operations of SVTNs can be found in earlier works, such as those by Deli and Subas (2014) and Khatter (2020).

Lastly, various authors have developed different definitions to derive fuzzy score functions $S(\tilde{N})$ from SVTN numbers. Given an SVTN, the score function $S(\tilde{N})$ is defined by the following Equation:

Abdel-Basset et al. (2017):

$$S_1(\tilde{N})=\frac{\alpha+\beta+\mu}{16}\times(2+\varphi-\psi-\delta). \tag{5}$$

Broumi et al. (2019):

$$S_2(\tilde{N})=\frac{\alpha+2\beta+\mu}{12}\times(2+\varphi-\psi-\delta). \tag{6}$$

Li and Huang (2019):

$$S_3(\tilde{N})=\frac{\alpha+\beta+\mu}{9}\times(2+\varphi-\psi-\delta). \tag{7}$$

Junaid et al. (2020):

$$S_4(\tilde{N})=\frac{\alpha+\beta+\mu}{3}\times(\varphi-\psi-\delta). \tag{8}$$

Reig-Mullor et al. (2022):

$$S_5(\tilde{N})=\frac{\alpha+4\beta+\mu}{18}\times(2+\varphi-\psi-\delta)+\frac{(\mu-\alpha)(\sqrt{\varphi}+\sqrt{(1-\psi)}+\sqrt{(1-\delta)})}{\sqrt{72}}. \tag{9}$$

To apply SVTN numbers in the TOPSIS method, the process, as described in Figure 1, begins by obtaining the values of the single criteria n_{qst}, where, $q=1,2,\dots,Q$ (criteria), $s=1,2,\dots,S$ (alternative), and $t=1,2,\dots,T$ (years). Next, the normalized indicators $\tilde{n}_{qst}$ are quantified, following the same structure for criteria, alternatives, and years as follows:

$$\tilde{n}_{qs}=((\alpha_{\tilde{n}_{qs}},\beta_{\tilde{n}_{qs}},\mu_{\tilde{n}_{qs}});\varphi_{\tilde{n}_q},\psi_{\tilde{n}_q},\delta_{\tilde{n}_q})=\left(\left(\min_t n_{qst},\frac{1}{t}\sum_t n_{qst},\max_t n_{qst}\right);\varphi_{\tilde{n}_q},\psi_{\tilde{n}_q},\delta_{\tilde{n}_q}\right). \tag{10}$$

Then, these normalized indicators are used to construct the neutrosophic normalized matrix $\tilde{N} = \left(\tilde{n}_{qs}\right)$, where the data are represented as single-valued triangular neutrosophic numbers (SVTN). This matrix serves as the basis for incorporating SVTN into the decision-making process, allowing for the evaluation of alternatives under uncertainty and indeterminacy, key features of neutrosophic sets.

The next step involves calculating the weighted matrix $\tilde{W} = \left(\tilde{w}_{qs}\right)$ by multiplying the normalized matrix $\tilde{N} = \left(\tilde{n}_{qs}\right)$ by the weight of each variable, as shown in expression.

$$\tilde{W}_{qs} = \nu_q \times \tilde{N}_{qs} = ((\nu_q \alpha_{\tilde{n}_{qs}}, \nu_q \beta_{\tilde{n}_{qs}}, \nu_q \mu_{\tilde{n}_{qs}}); \varphi_{\tilde{n}_q}, \psi_{\tilde{n}_q}, \delta_{\tilde{n}_q}) = ((\alpha_{\tilde{w}_{qs}}, \beta_{\tilde{w}_{qs}}, \mu_{\tilde{w}_{qs}}); \varphi_{\tilde{n}_q}, \psi_{\tilde{n}_q}, \delta_{\tilde{n}_q}). \quad (11)$$

Following this, the formulation of the SVTN ideal solution $\tilde{A}^{+}$ and the SVTN anti-ideal solution $\tilde{A}^{-}$ for each criterion is carried out, as expressed in:

$$\begin{aligned} \tilde{A}_q^{+} &= ((\max_q \alpha_{\tilde{w}_{qs}}, \max_q \beta_{\tilde{w}_{qs}}, \max_q \mu_{\tilde{w}_{qs}}); \varphi_{\tilde{n}_q}, \psi_{\tilde{n}_q}, \delta_{\tilde{n}_q}) = ((A_{\alpha q}^{+}, A_{\beta q}^{+}, A_{\mu q}^{+}); \varphi_{\tilde{n}_q}, \psi_{\tilde{n}_q}, \delta_{\tilde{n}_q}), \\ \tilde{A}_q^{-} &= ((\min_q \alpha_{\tilde{w}_{qs}}, \min_q \beta_{\tilde{w}_{qs}}, \min_q \mu_{\tilde{w}_{qs}}); \varphi_{\tilde{n}_q}, \psi_{\tilde{n}_q}, \delta_{\tilde{n}_q}) = ((A_{\alpha q}^{-}, A_{\beta q}^{-}, A_{\mu q}^{-}); \varphi_{\tilde{n}_q}, \psi_{\tilde{n}_q}, \delta_{\tilde{n}_q}). \end{aligned} \quad (12)$$

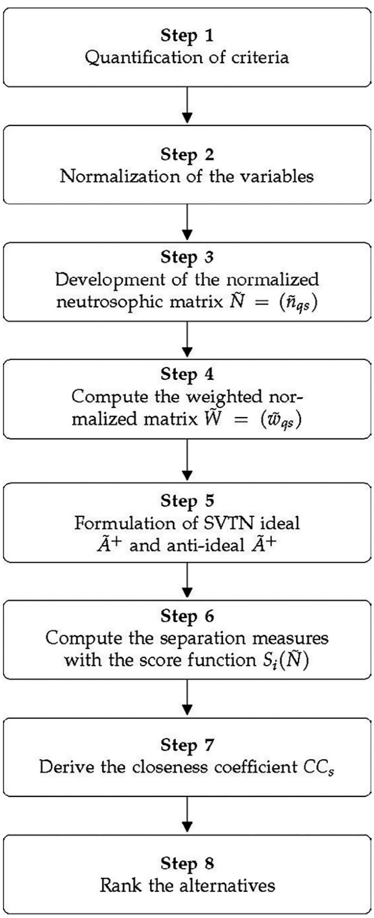

Figure 1. Flowchart of the proposed N-TOPSIS approach

The separation measures of each alternative from the ideal and anti-ideal solutions should be computed using the suggested score functions in Eqs. (5)–(9), namely, for each $S_i(\tilde{W})$, $i = 1, \ldots, 5$. Then, the closeness coefficient for each alternative is determined, representing its relative proximity to the ideal solution.

$$CC_s = \frac{d_s^{-}}{d_s^{-} + d_s^{+}}, \quad i = 1, \ldots, n. \quad (13)$$

Finally, the alternatives are ranked in descending order based on their closeness coefficients.

These solutions are key to evaluating the best and worst alternatives in the TOPSIS method using SVTN.

3. Results and discussions

In this Section, we apply the proposed methodology to assess the innovation performance of EU member states following the theoretical framework using the values of the elementary criteria provided by the European Innovation Scoreboard over the period 2021 to 2023. We also compare our results with the Summary Innovation Index (SII) (European Commission, 2023).

3.1. European innovation measurement framework

The EIS 2023 differentiates among four key categories of activities, namely Framework Conditions, Investments, Innovation Activities, and Impacts. These main groups consist of a total of 12 dimensions of innovation, capturing 32 indicators in total. Each principal category has the same number of indicators. Each indicator holds an equal weight in the average performance score and Summary Innovation Index (SII). The detailed methodology for obtaining the values of each criterion can be consulted in the European Innovation Scoreboard 2023 Methodology Report (European Commission, 2023), which provides a comprehensive explanation of the evaluation process, data sources, and computation methods. In this study, we present the hierarchical structure of the framework, emphasizing the data sources and reference year, both of which are clearly specified in Table 2.

Table 2. Indicators included in the EIS 2023 measurement framework (European Commission,2023)

<table>
<tr><th colspan="3">Indicators</th><th>Data source</th><th>Last year</th></tr>
<tr><td rowspan="8">I.1. FRAMEWORK CONDITIONS</td><td rowspan="3">I.1.1 HUMAN RESOURCES</td><td>I.1.1.1 New doctorate graduates</td><td>Public institution</td><td>2020</td></tr>
<tr><td>I.1.1.2 Tertiary education</td><td>Public institution</td><td>2022</td></tr>
<tr><td>I.1.1.3 Lifelong learning</td><td>Public institution</td><td>2022</td></tr>
<tr><td rowspan="3">I.1.2 ATTRACTIVE RESEARCH SYSTEM</td><td>I.1.2.1 Int. Scientific co-publications</td><td>Private institution</td><td>2022</td></tr>
<tr><td>I.1.2.2 Top 10% most cited</td><td>Private Institution</td><td>2020</td></tr>
<tr><td>I.1.2.3 Foreign doctorate students</td><td>Private Institution</td><td>2020</td></tr>
<tr><td rowspan="2">I.1.3 DIGITALIZATION</td><td>I.1.3.1 Broadband penetration</td><td>Survey</td><td>2022</td></tr>
<tr><td>I.1.3.2 Individuals above digital skills</td><td>Survey</td><td>2021</td></tr>
<tr><td rowspan="8">I.2. INVESTMENTS</td><td rowspan="3">I.2.1 FINANCE AND SUPPORT</td><td>I.2.1.1 R&D in public sector</td><td>Survey</td><td>2021</td></tr>
<tr><td>I.2.1.2 Venture capital expenditures</td><td>Private Institution</td><td>2022</td></tr>
<tr><td>I.2.1.3 Government support for business R&D</td><td>Private Institution</td><td>2020</td></tr>
<tr><td rowspan="3">I.2.2 FIRM INVESTMENTS</td><td>I.2.2.1 R&D in the business sector</td><td>Public institution</td><td>2021</td></tr>
<tr><td>I.2.2.2 Non-R&D innovation expenditure</td><td>Survey</td><td>2020</td></tr>
<tr><td>I.2.2.3 Enterprises providing training per person employed</td><td>Survey</td><td>2020</td></tr>
<tr><td rowspan="2">I.2.3 USE OF INFORMATION TECHNOLOGIES</td><td>I.2.3.1 Enterprises providing training to develop ICT skills</td><td>Survey</td><td>2022</td></tr>
<tr><td>I.2.3.2 Employed ICT specialist</td><td>Public institution</td><td>2022</td></tr>
<tr><td rowspan="8">I.3. INNOVATION ACTIVITIES</td><td rowspan="2">I.3.1 INNOVATORS</td><td>I.3.1.1 SMEs with product innovation</td><td>Survey</td><td>2020</td></tr>
<tr><td>I.3.1.2 SMEs with business process innovations</td><td>Survey</td><td>2020</td></tr>
<tr><td rowspan="3">I.3.2 LINKAGES</td><td>I.3.2.1 Inn SMEs collaborating</td><td>Survey</td><td>2020</td></tr>
<tr><td>I.3.2.2 Public-Private co-publications</td><td>Private Institution</td><td>2022</td></tr>
<tr><td>I.3.2.3 Job-to-job mobility</td><td>Public institution</td><td>2020</td></tr>
<tr><td rowspan="3">I.3.3 INTELLECTUAL ASSETS</td><td>I.3.3.1 PCT patent applications</td><td>Private Institution</td><td>2019</td></tr>
<tr><td>I.3.3.2 Trademark applications</td><td>Public institution</td><td>2022</td></tr>
<tr><td>I.3.3.3 Design applications</td><td>Public institution</td><td>2022</td></tr>
</table>

End of Table 2

Indicators			Data source	Last year
I.4. IMPACTS	I.4.1 EMPLOYMENT IMPACTS	I.4.1.1 Employment in knowledge act	Public institution	2021
		I.4.1.2 Employment in innovative enterprises	Survey	2020
	I.4.2 SALES IMPACT	I.4.2.1 High-tech exports	Public institution	2022
		I.4.2.2 Knowledge service exports	Private institution	2021
		I.4.2.3 Sales of product innovations	Survey	2020
	I.4.3 ENVIRONMENTAL SUSTAINABILITY	I.4.3.1 Resource productivity	Public institution	2021
		I.4.3.2 Air emissions by fine PM2.5	Public institution	2020
		I.4.3.3 Development of environment technologies	Private institution	2019

3.2. Empirical results

The ranking of EU countries is determined through the application of the algorithm described in Figure 1. We consider a period of three years ranging from 2021 to 2023 in which the EU countries are considered as the set of alternatives (s), and the criteria (q) are those indicated in Table 2. It will be assumed that, as in the case of the EIS, an equal weighting scheme is used to assess each criterion. Consequently, the relative weight of each indicator is inversely proportional to the total number of indicators to be aggregated, which, in this case, is equal to 1/32.

As noted earlier, the quality of the information gathered for each of the 32 indicators varies due to two main reasons:

- Time period uniformity. When analyzing the values of each criterion, we find data from different periods, i.e., some data in each indicator are older than others. For example, the most recent year for indicators I.3.3.1 PCT patents applications and I.4.3.3 Development of environment technologies is 2019 as shown in Table 2. Derived from the previous conditioning factor, considering only one year for each indicator does not facilitate homogeneity in the time origin of the data for each indicator.
- Data source reliability. On the other hand, there is the problem of the origin of the data. While some criterion relies on official and recognized institutional public sources such as Eurostat, others come from private international bodies or even from surveys. For example, the source of indicator I.1.3.1 Broadband penetration is a survey of ICT Usage and E-commerce in Enterprises, the data for indicator I.2.1.2 Venture capital expenditures comes from a private institution, which is Invest Europe. Another example the is the indicator I.3.3.2 Trademark applications, which data source is the European Union Intellectual Property Office (EUIPO) (see all data sources in Table 2).

To overcome these drawbacks, our model allows an individualized management of the quality and reliability of innovation data that make up each indicator. Table 3 shows the quality of the information according to the time period and origin of the indicator data.

The ranking generation process is outlined below, following the flowchart of the proposed N-TOPSIS approach in Figure 1.

Table 3. Assigned values according to the quality of the data considering time period uniformity and data source reliability $(\varphi_{\tilde{n}_q}, \psi_{\tilde{n}_q}, \delta_{\tilde{n}_q})$

Time period uniformity / Data sources	Year t	Year (t – 1, t – 2, ...)
Public institutions	(0.9, 0.1, 0.1)	(0.9, 0.2, 0.1)
Private institutions	(0.8, 0.1, 0.2)	(0.8, 0.2, 0.2)
Surveys	(0.7, 0.1, 0.3)	(0.7, 0.2, 0.3)

Step 1 and 2. Quantification and normalization of criteria. The data used is sourced from EIS for the years 2021, 2022, and 2023, and is already normalized. Specifically, for criterion I.1.2.2 in Sweden (Table 4), the corresponding values are:

Table 4. Criterion values for Sweden 2021–2023

	I.1.2.2 Top 10% most cited		
Sweden	2021 0.802	2022 0.786	2023 0.724

Step 3. Construction of the order matrix $\tilde{N} = (\tilde{n}_{qs})$ whose elements are SVTNs, applying the equation (10) based on the data contained in Tables 2–3. Specifically, in the case at hand, for criterion I.1.2.2 in Sweden, the SVTN is:

$$\tilde{n}_{I.1.2.2-Sweden} = ((0.724, 0.771,\ 0.802);\ 0.8, 0.2, 0.2).$$

Step 4. Computation of the weighted matrix $\tilde{W} = (\tilde{w}_{qs})$. The weighted matrix is then calculated, assuming an equal weighting scheme consistent with the EIS methodology (ν_q = 0.0312). That is, criterion I.1.2.2 for Sweden, the SVTN would be applying the Eq. (11).

$$\tilde{w}_{I.1.2.2-Sweden} = ((0.0226, 0.0241,\ 0.0251);\ 0.8, 0.2, 0.2).$$

Step 5. Computation of the SVTNs ideal solution $\tilde{A}^{+}$ and the anti-ideal solution $\tilde{A}^{-}$ applying formulation (12). Regarding criterion I.1.2.2, the corresponding values are:

$$\tilde{A}^{+}_{I.1.2.2} = ((0.0274, 0.0289, 0.0297);\ 0.8, 0.2, 0.2),$$
$$\tilde{A}^{-}_{I.1.2.2} = ((0.0032, 0.0035, 0.0038);\ 0.8, 0.2, 0.2).$$

Step 6. Calculation of the separation measures. They are computed using the suggested score functions in Eqs. (5)–(9), namely, for each score function $(S_i,\ i = 1, \ldots, 5)$. Specifically, for Sweden, the resulting values are displayed in Table 5:

Table 5. Separation measures for each score function for Sweden

S_1		S_2		S_3		S_4		S_5	
d^{+}_{Sweden}	d^{-}_{Sweden}	d^{+}_{Sweden}	d^{-}_{Sweden}	d^{+}_{Sweden}	d^{-}_{Sweden}	d^{+}_{Sweden}	d^{-}_{Sweden}	d^{+}_{Sweden}	d^{-}_{Sweden}
0.115	0.291	0.362	0.358	0.204	0.517	0.730	0.157	0.194	0.522

Step 7. Obtaining the closeness coefficient for each, reflecting its relative proximity to the ideal solution by applying the Eq. (13). The result for each country and score function $\left(S_i,\ i=1,\dots,5\right)$ are summarized in Table 6:

Table 6. The closeness coefficient CC_s for each country

CC_s	S_1	S_2	S_3	S_4	S_5
Austria	0.623	0.428	0.623	0.145	0.631
Belgium	0.649	0.650	0.649	0.656	0.659
Bulgaria	0.167	0.166	0.167	0.166	0.173
Croatia	0.282	0.169	0.282	0.033	0.292
Cyprus	0.577	0.381	0.577	0.130	0.604
Czechia	0.409	0.264	0.409	0.411	0.420
Denmark	0.738	0.510	0.738	0.736	0.754
Estonia	0.508	0.326	0.508	0.509	0.543
Finland	0.682	0.469	0.682	0.166	0.696
France	0.535	0.366	0.535	0.116	0.536
Germany	0.567	0.391	0.567	0.571	0.568
Greece	0.355	0.223	0.355	0.059	0.368
Hungary	0.300	0.185	0.300	0.037	0.305
Ireland	0.640	0.434	0.640	0.151	0.659
Italy	0.452	0.297	0.452	0.089	0.465
Latvia	0.232	0.135	0.232	0.014	0.236
Lithuania	0.371	0.240	0.371	0.061	0.375
Luxembourg	0.708	0.482	0.708	0.171	0.732
Malta	0.483	0.303	0.483	0.096	0.522
Netherlands	0.721	0.499	0.721	0.177	0.733
Poland	0.250	0.144	0.250	0.019	0.260
Portugal	0.444	0.287	0.444	0.086	0.461
Romania	0.111	0.046	0.111	-0.026	0.113
Slovakia	0.293	0.178	0.293	0.034	0.300
Slovenia	0.499	0.330	0.499	0.103	0.513
Spain	0.448	0.290	0.448	0.086	0.465
Sweden	0.717	0.497	0.717	0.177	0.729

Step 8. Rank the countries. Table 7 shows the rankings both using the SII 2023 classification, and the rankings obtained by applying our proposed N-TOPSIS for the different scoring functions $S_i,\ i=1,\dots,5$.

Table 7. Benchmarking of EU country rankings

	SII 2023	S_1	S_2	S_3	S_4	S_5
Austria	6	8	8	8	12	8
Belgium	5	6	1	6	2	7
Bulgaria	26	26	24	26	10	26
Croatia	22	23	23	23	24	23
Cyprus	10	9	10	9	13	9
Czechia	14	18	18	18	5	18
Denmark	1	1	2	1	1	1
Estonia	12	12	13	12	4	11
Finland	3	5	6	5	9	5
France	11	11	11	11	14	12
Germany	7	10	9	10	3	10
Greece	20	20	20	20	21	20
Hungary	21	21	21	21	22	21
Ireland	9	7	7	7	11	6
Italy	15	15	15	15	17	16
Latvia	25	25	26	25	26	25
Lithuania	19	19	19	19	20	19
Luxembourg	8	4	5	4	8	3
Malta	17	14	14	14	16	13
Netherlands	4	2	3	2	7	2
Poland	24	24	25	24	25	24
Portugal	18	17	17	17	18	17
Romania	27	27	27	27	27	27
Slovakia	23	22	22	22	23	22
Slovenia	13	13	12	13	15	14
Spain	16	16	16	16	19	15
Sweden	2	3	4	3	6	4

Looking at the results, we see that Denmark consistently ranks 1st across all methodologies, demonstrating its strong and undisputed innovation performance, while Romania remains consistently last (27th) in all rankings, indicating uniformly poor innovation performance. However, Belgium's ranking varies significantly, from 5th in the SII 2023 to as high as 1st with one alternative score function, highlighting the sensitivity of its innovation performance assessment to the chosen methodology and potential underlying data reliability issues. Similarly, Bulgaria's ranking fluctuates notably, from 26th in SII 2023 to 10th in another ranking, indicating significant discrepancies possibly due to data inconsistencies or methodological differences.

Countries like Austria, Croatia, Greece, and Hungary exhibit relatively stable rankings across all methods, indicating consistent performance assessment regardless of the methodology applied. Similarly, Germany and France show moderate stability with minor deviations, suggesting that their innovation performance is reliably measured. On the other hand, countries such as the Netherlands and Sweden, which are top performers in the SII 2023, experience some rank variability, suggesting that while their innovation capabilities are strong, their exact positions can shift depending on the evaluation criteria and methods used. Additionally, Estonia and Finland's noticeable rank changes may reflect sensitivity to data quality or methodological differences in the scoring functions.

The use of neutrosophic numbers introduces variability in rankings, highlighting or obscuring the true innovation performance of countries depending on how data uncertainty and indeterminacy are managed. For instance, Czechia's ranking drops from 14th in SII 2023 to as low as 18th, suggesting that traditional metrics might overestimate its performance by not fully accounting for data uncertainties.

To analyze the results obtained in the application of the N-TOPSIS methodology, each of the rankings is compared with the rest by means of Spearman's correlation coefficient (r_s). These results are displayed in Table 8.

Table 8. Spearman's correlation coefficient (r_s)

	SII 2023	S_1	S_2	S_3	S_4	S_5
SII 2023	1	0.978	0.973	0.978	0.825	0.968
S_1	0.978	1	0.988	1	0.784	0.997
S_2	0.973	0.988	1	0.988	0.816	0.980
S_3	0.978	1	0.988	1	0.784	0.997
S_4	0.825	0.784	0.816	0.784	1	0.782
S_5	0.968	0.997	0.980	0.997	0.782	1

In order to complete the analysis, the following section presents an in-depth insight into the behavior of the proposed N-TOPSIS model in the face of changes in the weights of the four main categories.

3.3. Sensitivity analysis

By taking as a baseline the ranking obtained with the score function S_5, we have performed a sensitivity analysis that allows us to evaluate the changes in the positions of the EU countries when considering different weights in the four main categories I.1 Framework Conditions (FC), I.2 Investments (IN), I.3 Innovation Activities (IA), and I.4 Impacts (IM). Instead of considering equal weights for each category, a total of 15 weighting sets have been designed where the importance assigned to each group varies between 0.1 and 0.5. Spearman's correlation coefficient is calculated (r_s) to analyze the correlation between the rankings generated from the set of combinations of weights (SET_i) in front of SET* (ν_q = 0.0312). The results of this analysis are shown in Table 9.

The results obtained from Spearman´s correlation coefficient (r_s) show that the different rankings obtained for each set proposed do not present any significant differences with respect to the ranking solution (SET*), where r_s does not go below 0.967. In addition to analyzing Spearman's correlation coefficient, we provide two figures to visually examine the changes in rankings under different weighting variations. Figure 2 illustrates how the ranking of EU countries fluctuates for each set.

Table 9. Sensitivity analysis for different weigh schemes (sets) using Spearman's correlation coefficient (r_s)

Weighting sets for each dimension	SET*
SET 1 (FC = 0.25/IN = 0.25/ IA = 0.25/ IM = 0.25)	0.994
SET 2 (FC = 0.50/IN = 0.17/ IA = 0.17/ IM = 0.17)	0.995
SET 3 (FC = 0.17/IN = 0.50/ IA = 0.17/ IM = 0.17)	0.990
SET 4 (FC = 0.17/IN = 0.17/ IA = 0.50/ IM = 0.17)	0.967
SET 5 (FC = 0.17/IN = 0.17/ IA = 0.17/ IM = 0.50)	0.983
SET 6 (FC = 0.30/IN = 0.30/ IA = 0.20/ IM = 0.20)	0.996
SET 7 (FC = 0.30/IN = 0.20/ IA = 0.30/ IM = 0.20)	0.992
SET 8 (FC = 0.30/IN = 0.20/ IA = 0.20/ IM = 0.30)	0.996
SET 9 (FC = 0.20/IN = 0.30/ IA = 0.30/ IM = 0.20)	0.993
SET 10 (FC = 0.20/IN = 0.30/ IA = 0.20/ IM = 0.30)	0.995
SET 11 (FC = 0.20/IN = 0.20/ IA = 0.30/ IM = 0.30)	0.993
SET 12 (FC = 0.30/IN = 0.30/ IA = 0.30/ IM = 0.10)	0.991
SET 13 (FC = 0.30/IN = 0.30/ IA = 0.10/ IM = 0.30)	0.992
SET 14 (FC = 0.30/IN = 0.10/ IA = 0.30/ IM = 0.30)	0.993
SET 15 (FC = 0.10/IN = 0.30/ IA = 0.30/ IM = 0.30)	0.990

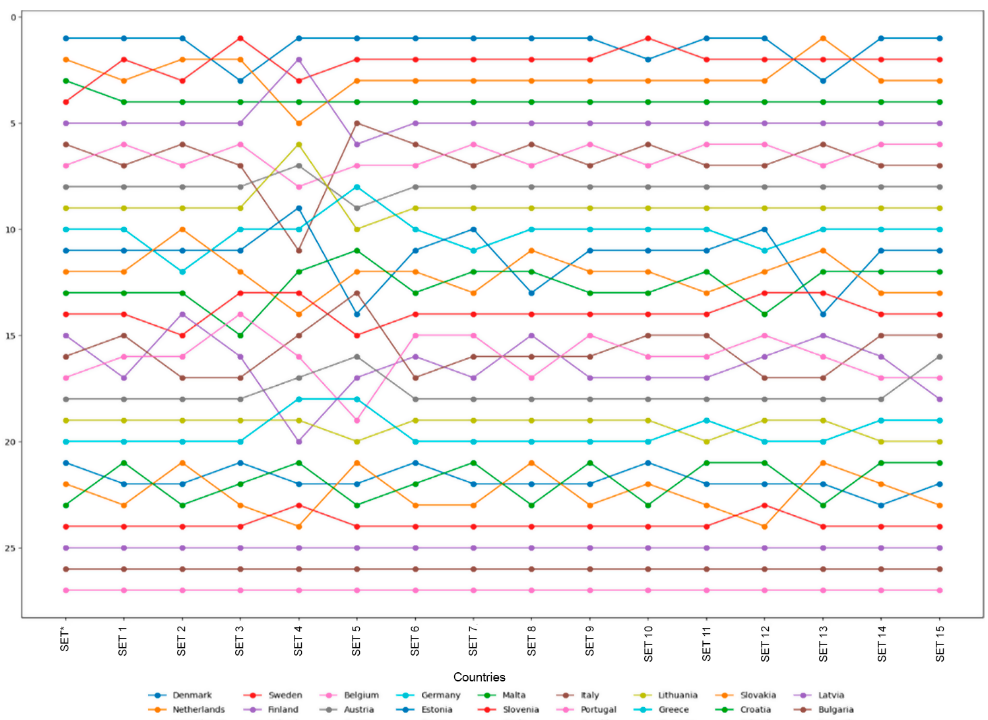

Figure 2. Sensitivity analysis of EU's countries' rankings under different weighting sets

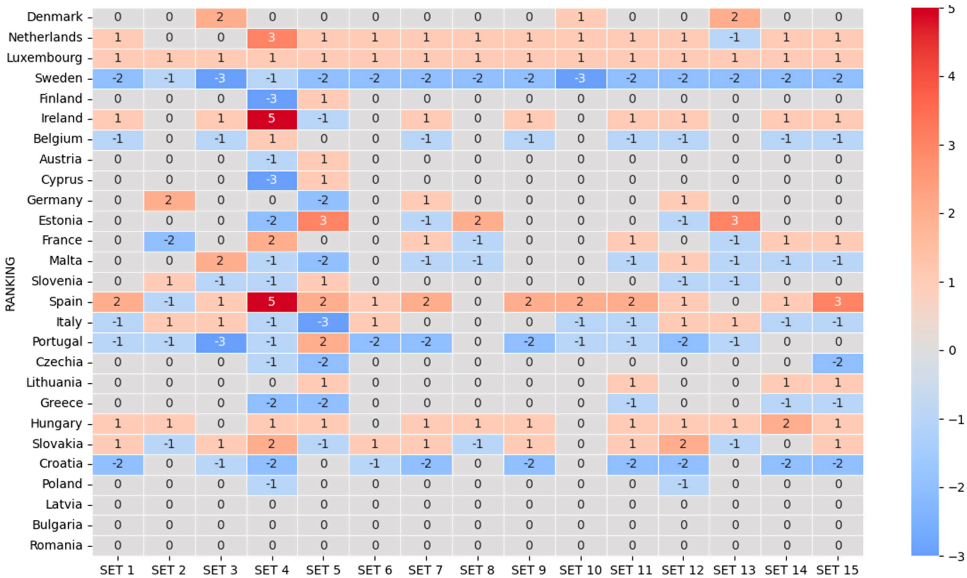

Figure 3. Gaps between SET i (i = 1,..., 15) and SET*

Moreover, Figure 3 shows the differences in country positions between the reference SET*, which consider equal weights for all categories, and the various rankings generated by the SET i (i = 1,..., 15).

3.4. Discussion

The present study uses fuzzy theory and a multi-criteria approach to improve the assessment of composite innovation indicators. While previous studies (Alnafrah, 2021; Corrente et al., 2023; Garcia-Bernabeu et al., 2020) have looked at the impact of the methodological choices such as weighting or aggregation of single indicators, they have not explicitly addressed key concerns of data quality and validity.

Based on the previous results, several key conclusions can be drawn that shed light on the effectiveness and implications of our methodology.

- Firstly, integrating data quality measurement to assess the elementary indicators results in a ranking that differs from the one proposed by the SII 2023. This highlights the impact of incorporating data quality into the evaluation process, leading to potentially different insights and policy implications.
- Secondly, the N-TOPSIS methodology generated rankings that varied according to the score function used, except in the case of the score functions S_1 and S_3, with a r_s = 1. This suggests that the choice of score function can significantly influence the outcome, although minor variations in formulation may have negligible effects.
- Thirdly, the ranking calculated with the score function S_4 exhibited the greatest divergence from the others, with a score difference r_s not exceeding 0.82, emphasizing the sensitivity of rankings to the specific score function applied.

- Lastly, the score function S_2 demonstrated a high correlation with score functions S_1, S_3 and S_5, where r_s exceeds 0.98 in all cases. Yet, it presented an extreme case with Belgium, placing it first instead of 6th or 7th in other rankings. This discrepancy highlights the importance, in order to ensure accurate and meaningful assessments, of carefully selecting and understanding the scoring functions.

In brief, the choice of ranking would be between those obtained with the score function S_1, S_3 or S_5, although while the formulations of the score functions S_1 and S_3 are based on approximations of the SVTN mean, the score function S_5 not only considers the possibility mean, but also incorporates the possibility standard deviation (Reig-Mullor et al., 2022).

The findings of this research have significant implications for policymaking and the evaluation of national innovation systems. By providing a more reliable and insightful analysis of innovation performance, our methodology facilitates better informed decisions. Policymakers can use these enhanced indicators to identify strengths and weaknesses in their national innovation systems more accurately, leading to more targeted and effective innovation policies. Moreover, the improved assessment of data quality and validity can foster greater trust and confidence in innovation indicators among stakeholders. This is crucial for ensuring that the measures used to monitor and benchmark national innovation systems are both credible and actionable.

The integration of fuzzy theory with a multi-criteria technique (Biswas et al., 2018; Smarandache, 1999), proved to be a robust method for addressing the complexities and uncertainties in data quality assessment. The use of neutrosophic numbers enabled a flexible and detailed representation of uncertainty, which is often overlooked in conventional composite indicator construction. This methodological advancement is particularly important in the context of innovation indicators, where data is frequently subject to variability and ambiguity.

Furthermore, our empirical analysis over the period 2020–2023 demonstrated this approach's practical applicability and effectiveness. By evaluating the European Innovation Scoreboard, we confirmed that our method not only improves the accuracy of innovation performance measurement but also provides valuable insights into the stability and reliability of the data over time.

4. Conclusions

The search for robust and reliable composite indicators to assess national innovation performance is becoming increasingly relevant for supporting policy decisions aimed at fostering competitiveness and progress. Besides the general debate on the use and development of composite indicators that focuses on the inherent simplification of their construction, in the context of indicators to monitor country innovation, there is also the debate on the reliability of the data. This study addresses critical challenges related to data quality and reliability in innovation measurement by integrating neutrosophic numbers into the TOPSIS methodology, resulting in the novel N-TOPSIS approach.

Our analysis highlights two main issues: the lack of uniformity in the time period covered by innovation indicators and the variability in the reliability of data sources. By applying neutrosophic sets that capture degrees of truth, indeterminacy and falsity, we have developed a more sensitive and robust framework for constructing composite innovation indicators. This approach reflects and manages the inherent uncertainties and inconsistencies in innovation data, thereby enhancing the credibility and utility of the resulting indices.

An empirical application using the framework of the European Innovation Scoreboard for the period 2020–2023 demonstrates the effectiveness of the N-TOPSIS method. The study's findings indicate that this approach provides different rankings compared to the SII highlighting the importance of considering data reliability in innovation assessments. In summary, while the traditional SII provides a useful benchmark, the incorporation of neutrosophic numbers into composite innovation indices offers a promising approach to address data quality issues, albeit with some range variability. By incorporating neutrosophic sets, the study has demonstrated the potential for a more accurate evaluation of innovation performance within EU member states, ultimately supporting better-informed policy decisions.

Future research in the field of innovation assessment could focus on examining the scalability and adaptability of the N-TOPSIS approach for assessing innovation performance at regional or global levels. Additionally, we consider as a further exploration the potential integration of neutrosophic numbers with other multi-criteria decision-making methods to enhance the robustness of decision support systems.

Author contributions

Javier Reig-Mullor: conceptualization, methodology and investigation. Ana Garcia-Bernabeu: formal analysis, investigation, writing – original draft preparation. Francisco Salas-Molina: formal analysis, investigation, writing – original draft preparation. David Pla-Santamaria: data curation and writing – reviewing and editing.

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We have any competing financial, professional, or personal interests from other parties.

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