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# DEA-BASED COMPOSITE INDEX FOR INNOVATION-INTEGRATED HUMAN DEVELOPMENT PERFORMANCE ASSESSMENT OF COUNTRIES

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**Abstract.** The Human Development Index (HDI) introduced by United Nations Development Programme (UNDP) offers a unique quantitative measure that encompasses advancements in three fundamental aspects of human development: health, education, and living standards. However, focusing on only three dimensions when evaluating human development performance of countries is not adequate in today's digital world. This study proposes a data envelopment analysis (DEA)-based composite index to provide an innovation-integrated human development performance assessment tool for countries. The novel two-stage common-weight DEA-based approach proposed in here is applied in a case study examining the performance assessment of European Union (EU) countries. The first stage of the developed methodology consists of solving the novel common-weight DEA-based approach with HDI indicators as the outputs and the Gini coefficient as the input. At the second stage, innovation-based indicators from World Bank database are used to evaluate innovation efficiency of EU countries. The composite index that yields the complete ranking of EU countries in terms of innovation-integrated human development performance is computed as the product of the efficiency scores resulting from these two stages. The rankings produced by the proposed approach are compared with the HDI rankings as well as the results obtained from various common-weight DEA-based models.

**Keywords:** human development, composite index, performance assessment, data envelopment analysis, common-weight DEA-based approach.

**JEL Classification:** C44, C61, D80, O32.

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## 1. Introduction

The 2030 Agenda for sustainable development presents a favorable occasion to eradicate poverty, safeguard the environment, and guarantee enduring peace and prosperity. Although human development and the 2030 Agenda are interrelated, it is important to bear in mind that these two entities are essentially distinct. The Sustainable Development Goals (SDGs) serve as a universally accepted framework for evaluating advancements in development. Human development is a comprehensive philosophy or perspective that may be used to analyze various development issues. In essence, the SDGs serve as a clear objective for sustainable development, while human development enables countries to strategically plan and chart their path towards progress (Conceião, 2019).

The 2021/2022 Human Development Report is the most recent publication in the long-standing series of global human development reports issued by the United Nations Development Programme (UNDP) since 1990. These reports provide objective and well-researched discussions on significant development topics, trends, and policies. The Human Development Index (HDI), which facilitates cross-national comparisons that are comparable to, but more comprehensive than, those offered by Gross Domestic Product (GDP), offers a method of quantifying progress in three fundamental aspects: health, education, and living conditions. Nevertheless, the HDI has been criticized for relying on inherently arbitrary weighting schemes when aggregating its components with measurement in differing units – such as education (measured in years of schooling), income (in purchasing power), and life expectancy (in years) (United Nations Development Programme [UNDP], 2022).

To address these criticisms, numerous studies have proposed Data Envelopment Analysis (DEA)-based approaches for the evaluation of human development. DEA, a mathematical programming technique introduced by Charnes et al. (1978), serves as a decision-support tool for assessing the relative efficiency of homogeneous Decision-Making Units (DMUs). While conventional DEA is widely recognized as an effective method for performance evaluation, it has certain limitations. Specifically, the conventional DEA model categorizes DMUs simply as efficient or inefficient, without offering the means to further differentiate or rank those deemed efficient. Therefore, the model's discriminatory features are generally insufficient for producing a complete ranking of DMUs (Karsak & Goker, 2020). Moreover, it is important to emphasize that the classical DEA model, when executed separately for each Decision-Making Unit (DMU), produces a unique set of input and output weights customized to that particular unit. This structure has the potential to result in an excessive degree of weight flexibility, which might hinder realistic evaluation of DMUs' performance. The subsumption of such weight flexibility in DEA allows a DMU to potentially achieve efficiency by assigning overly high weights to some input criteria and/or output criteria, while assigning negligible weights to others (Karsak & Ahiska, 2007).

To address the limitations inherent in traditional DEA models and respond to critiques of the Human Development Index (HDI) calculation, this study introduces a composite index aimed at assessing countries' human development performance with an integrated focus on innovation. The proposed framework employs a novel common-weight DEA model that minimizes the maximum deviation from the CCR efficiency scores, which are computed by the conventional DEA model introduced by Charnes et al. (1978). By applying a uniform set of weights across all Decision-Making Units (DMUs), the common-weight approach mitigates the issue of excessive weight flexibility typical of standard DEA models and improves the model's discriminatory power, particularly in distinguishing between efficient units.

The HDI has the potential to include additional dimensions in order to encompass many innovative factors while comparing human development across nations (Tunsi & Alidrisi, 2023). Taking into account only three dimensions when evaluating human development performance of countries is not adequate in today's digital world, and thus, considering the fourth industrial revolution, introducing the innovation dimension has become a crucial topic to be addressed. Au (2024) examined the effect of various forms of digitalization on income inequality in Europe and showed that the decreases in income inequality are possible with the digital transformation of human capital and the adoption of digital technologies within Small and Medium-Sized Enterprises (SMEs). Therefore, it is appropriate to consider an income inequality indicator in addition to the innovation dimension when evaluating human development performance.

The proposed two-stage decision-making approach is applied in a case study evaluating the performance of European Union (EU) countries. The first stage of the developed methodology consists of solving the novel common-weight DEA-based approach with HDI indicators as the outputs and the Gini coefficient as the input. The Gini coefficient is computed by examining the cumulative distribution of income across corresponding cumulative segments of the population, where a lower Gini coefficient indicates a more equitable income distribution (Organisation for Economic Co-operation and Development [OECD], n.d.). Being a well-established measure of income and wealth inequality that affects human development of populations, the Gini coefficient is considered along with HDI indicators throughout the analysis. In the second stage, innovation-based indicators from World Bank database are used to evaluate innovation efficiency of EU countries. The efficiency scores resulting from these stages are aggregated to yield the composite index that provides the complete ranking of EU countries in terms of innovation-integrated human development performance.

Considering just three factors, i.e., health, education, and living conditions, when evaluating a country's human development falls short of offering a comprehensive viewpoint. As the HDI is influenced by the inequality of income distribution, it is essential to examine how human development performance is affected in countries where income inequality is prevalent. Studies demonstrate a negative relationship between the Gini coefficient and human development in a country (Kabakci Gunay & Topbas, 2021). In order to incorporate the effect of income inequality in human development performance assessment, the Gini coefficient is selected as an input for the first stage model in line with DEA terminology, where inputs are considered as criteria to be minimized.

Measuring the performance of countries with an index provides an objective assessment and creates a roadmap for countries to make improvements in the relevant area. Paraschiv et al. (2021) introduced a Social Inclusion Index for EU member states, designed to measure the extent of social inclusion as a way to complement conventional indicators that focus on reducing social exclusion. This index helps provide a more comprehensive understanding of social conditions and supports the refinement of EU social policy strategies. In this study, a similar logic is used to quantify human development performance of countries with a composite index.

The increasing complexity and interdependence of various socio-economic issues at both national and international levels limit the effectiveness of single-topic analyses, as they fail to capture the full scope of interrelated factors. Consequently, there is a growing trend in the literature toward interdisciplinary studies that aim to illuminate these intricate connections and relationships. Łącka and Brzezicki (2022) conducted a combined analysis of eco-efficiency, eco-innovation, and Sustainable Development Goals (SDGs) of EU countries with a DEA-based approach that includes Dynamic Network SBM and Dynamic Divisional Malmquist Index. Considering the importance of multi-topic analyses of countries, this study focuses on integrating human development and innovation performance.

The proposed methodology provides important advancements to the existing literature. Primarily, the common-weight DEA-based framework allows for the creation of a tool that evaluates performance with a common set of input and output weights across all decision-making units. Second, the developed method avoids the impracticality of output weight dispersions and exhibits improved discriminatory features. Third, integration of innovation dimension not only allows to incorporate an essential element for assessment but also provides a more comprehensive performance index.

The structure of the paper is organized as follows: Section 2 offers a comprehensive review of the existing literature concerning the application of Data Envelopment Analysis (DEA) in the context of human development assessment. Section 3 details the methodological foundation and introduces the novel approach. A case study that evaluates the performance of European Union member states with respect to innovation-enhanced human development is presented in Section 4. Section 5 provides a discussion of the managerial implications derived from the findings. The paper concludes with final remarks presented in the closing Section.

## 2. Literature review

Recently, several studies have made valuable contributions to the existing body of literature on human development performance assessment through implementing numerous decision-making procedures. A considerable number of scholars have concentrated on developing evaluation frameworks based on DEA.

Despotis (2005) applied a DEA model to evaluate the performance of countries in human development and converting income to knowledge and life opportunities. Hatefi and Torabi (2010) introduced a common-weight DEA-based approach for the development of composite indicators – specifically the Sustainable Energy Index (SEI) and the Human Development Index (HDI) – aimed at evaluating the performance of countries within the Asia-Pacific region.

Reig-Martínez (2013) developed a human Wellbeing Composite Index (WCI) for the comparative evaluation of 42 countries using DEA models as an aggregation framework. Blancard and Hoarau (2013) introduced a novel DEA-based human development indicator for developing economies and added sustainability dimension to the evaluation scheme. Sayed et al. (2015) used a benefit of doubt-based meta-goal programming framework, which is another form of conventional DEA, to propose a novel human development indicator by using HDI 2012 data.

More recently, Sayed et al. (2018) introduced a goal programming BoD approach as an alternative way to compare human development performance of countries. The rank reversal phenomenon was also addressed in the proposed approach. Hatefi and Torabi (2018) proposed a DEA-based slack analysis method to identify improvement ways for countries that were identified as inefficient in terms of human development.

Lately, Mariano et al. (2021) applied DEA and BoD models to conduct HDI-based performance assessment of countries. The results were compared by employing Social Network Analysis (SNA). Shi and Land (2021) used DEA and equal weights/minimax methods to evaluate well-being of 50 U.S. states and human development of 188 countries. Goker et al. (2022) developed a decision-making procedure that integrates Quality Function Deployment (QFD) and DEA for the comparative assessment of Latin American countries in terms of human development and sustainable development goals.

In addition to these research works, authors have used several other decision-making techniques to evaluate human development performance. Erpolat Tasabat and Morais (2019) built a decision-making procedure based on TOPSIS to rank 188 nations with HDI indicators. In the study, a comparative analysis was conducted between the rankings obtained from the proposed framework and rankings attained from HDI outcomes. In a recent study, Ecer et al. (2019) assessed the performance of the Organization of the Petroleum Exporting Countries (OPEC) using Compromised Solution (CoCoSo). This assessment included 41 sustainable development indicators across 10 distinct dimensions. Tunsi and Alidrisi (2023) employed PROMETHEE II to evaluate innovation-based HDI performance of G8 countries. The results obtained from this method were used to propose a novel indicator for these countries.

These reviewed studies are classified according to the dimensions in which human development performance is addressed as illustrated in Table 1.

**Table 1.** Classification of human development assessment studies

| Dimensions<br>Articles | Sustainability/ Sustainable Development | Energy | Social/ Economic Wellbeing | Innovation |
|---|---|---|---|---|
| Despotis (2005) | | | x | |
| Hatefi and Torabi (2010) | x | x | | |
| Reig-Martínez (2013) | | | x | |
| Blancard and Hoarau (2013) | x | | | |
| Sayed et al. (2015) | | | x | |
| Sayed et al. (2018) | | | x | |
| Hatefi and Torabi (2018) | x | x | | |
| Erpolat Tasabat and Morais (2019) | | | x | |
| Ecer et al. (2019) | x | | | |
| Mariano et al. (2021) | | | x | |
| Shi and Land (2021) | | | x | |
| Goker et al. (2022) | x | | | |
| Tunsi and Alidrisi (2023) | | | | x |

As previously noted, several studies have employed common-weight DEA-based approaches to evaluate human development performance. DEA can also be used to measure a country's innovation performance. Shi et al. (2022) evaluated the efficiency of regional knowledge innovation and technological innovation of China with a network DEA-based model which includes a parallel system and divides innovation performance into two stages: theory and application. Although this study includes a detailed innovation performance analysis, it does not address the human development dimension. Therefore, there is still open space for introducing innovation dimension in human development evaluation framework as none of these studies integrated innovation and human development performance through a common-weight DEA-based model. In order to address these limitations and conduct a more comprehensive analysis, the integration of innovation dimension to human development assessment is proposed in this study through a novel common-weight DEA-based framework.

# 3. Preliminaries and methods

## 3.1. Data envelopment analysis

Data Envelopment Analysis (DEA), originally proposed by Charnes et al. (1978), is a mathematical programming-based decision-making technique. It is widely applied to evaluate the relative efficiency of homogeneous Decision-Making Units (DMUs) by simultaneously considering multiple inputs and outputs. Throughout efficiency analysis, DEA assumes that any input can be replaced by any other input. This is the case as DEA employs a weighted mixture of all the inputs (Tofallis, 1997). However, this critical assumption is invalid in situations when the inputs cannot be used interchangeably. Tofallis (1997) asserts that considering inputs individually circumvents the problem of assigning excessively high or implausible weights, since no weights are allocated to the inputs in the analysis. Multiple outputs and single input are evaluated using the conventional DEA formulation as follows:

$$\max E_{j0} = \frac{\sum_{r=1}^{s} \mu_r y_{rj0}}{w x_{j0}} \tag{1}$$

subject to

$$\frac{\sum_{r=1}^{s} \mu_r y_{rj}}{w x_j} \leq 1, \ \forall j,$$
$$\mu_r \geq \varepsilon, \ \forall r,$$
$$w \geq \varepsilon.$$

where, $y_{rj}$ is the quantity of output $r$ generated by $DMU_j$, $x_j$ represents the quantity of the single input consumed by $DMU_j$, $\mu_r$ denotes the weight assigned to output $r$, and $E_{j0}$ is the relative efficiency score of the evaluated DMU. Model (1) is non-linear, and it can be linearized by replacing $\mu_r / w$ with $u_r$, for $\forall r$. Employing this transformation, Model (1) takes the following form:

$$\max E_{j0} = \frac{\sum_{r=1}^{s} u_r y_{rj0}}{x_{j0}} \tag{2}$$

subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{x_j} \leq 1, \ \forall j,$$
$$u_r \geq \varepsilon, \ \forall r,$$

where $\varepsilon$, which prevents zero-weights, is a small positive number.

As Model (2) is a single input version of the classical DEA model, the limitations of the classical DEA are still valid. To assess the efficiency of all DMUs, it is necessary to compute Model (2) $n$ times, where $n$ is the number of DMUs under evaluation. Albeit decision-makers generally prefer to conduct an analysis with a set of weights common to all DMUs, Model (2) does not evaluate DMUs based on common weights assigned to performance attributes, which may yield impractical outcomes. Furthermore, the DEA methodology is based on the assumption that DMUs with an efficiency score of 1 are referred to as "efficient" and are positioned on the efficient frontier. Conversely, DMUs with a score below 1 are labeled as "inefficient". Hence, DMUs are categorized into two distinct categories: efficient and inefficient. Since all efficient DMUs possess an efficiency score of 1, Model (2) does not allow for any further differentiation among them. The DEA model delineated above may prove to yield insufficient discriminatory capacity when the decision-maker needs to identify the best performing DMU or obtain a complete ranking. Furthermore, Model (2) enables each DMU to select weights that are most favorable to specifically optimize its efficiency score. Permitting such flexibility in weight assignment may result in a Decision-Making Unit (DMU) being deemed efficient by allocating disproportionately high weights to the criteria where it performs exceptionally well, while assigning an improperly low weight to attributes in which it has performed poorly. The excessive weight flexibility is impractical as well as resulting in the DEA model to have limited discriminatory capacity (Karsak & Ahiska, 2007). To address the issues of unrealistic weight flexibility and the limited discriminatory power associated with conventional DEA models, researchers focused on alternative approaches based on common-weight DEA-based models.

## 3.2. Minmax approach for common-weight DEA

The idea of employing a common set of weights for performance evaluation of DMUs is realized with common-weight approaches that address the issue of impractical weight flexibility problem of conventional DEA models and enhance the model's discriminatory power. A substantial body of research has adopted common-weight DEA methodologies to overcome the limitations associated with conventional DEA frameworks (Karsak & Ahiska, 2005; Mavi et al., 2022; Toloo, 2015). Karsak and Ahiska (2005) proposed a minmax efficiency approach for the common assessment of DMUs that produce multiple outputs by consuming a single input. The developed model is as follows:

$$\begin{aligned} & \min M \\ & \text{subject to} \\ & M - d_j \geq 0, \ \forall j, \\ & \left. \sum_{r=1}^{s} u_r y_{rj} \middle/ x_j \right. + d_j = 1, \ \forall j, \\ & u_r \geq \varepsilon, \ \forall r, \\ & d_j \geq 0, \ \forall j, \end{aligned} \tag{3}$$

where $M$ represents the maximum deviation from the ideal efficiency, and $d_j$ denotes the deviation from the ideal efficiency for $DMU_j$ (i.e., $d_j = 1 - E_j$). Thus, Model (3) is referred as a minmax efficiency model. Another minmax approach is proposed by Toloo (2015) in a DEA-based framework. The model for multiple outputs and single input can be adapted as follows (Toloo, 2015):

$$\begin{aligned} & \min d_{\max} \\ & \text{subject to} \\ & \left. \sum_{r=1}^{s} u_r y_{rj} \middle/ x_j \right. + d_j - \beta_j = 1, \ \forall j, \end{aligned} \tag{4}$$

$$d_{\max} - d_j + \beta_j \geq 0,\ \forall j$$
$$\sum_{j=1}^{n} d_j = n-1,$$
$$d_j \in \{0,1\},\ \forall j,$$
$$\beta_j \leq 1,\ \forall j,$$
$$u_r \geq \frac{1}{(1+s)\max_j\left(y_{rj}\right)},\ \forall r,$$

where $d_{\max}$ denotes the maximum deviation, and $d_j - \beta_j$ is a deviation from the ideal efficiency. $DMU_k$ is recognized as the best performing DMU if and only if $d_k^* - \beta_k^* = \min\left\{d_j^* - \beta_j^* : j = 1,2,\ldots,n\right\}$ or equivalently $d_k^* = 0$.

Where, the ideal efficiency is considered to be '1' for all DMUs. However, several DMUs cannot achieve this ideal situation in real-life due to their insufficient capacity. Therefore, the deviation from ideal efficiency may not be a practical measure for this type of DMUs. In order to deal with this issue, a novel approach that uses the CCR efficiency score of the respective DMU in lieu of the ideal efficiency score is proposed.

## 3.3. Proposed common-weight DEA-based approach

This study proposes a novel approach based on Model (3), which minimizes the maximum of the deviations from the CCR efficiency scores of the corresponding Decision-Making Units (DMUs) to facilitate a more accurate analysis and achieve enhanced dispersion of output weights. The proposed model for multiple outputs and single input is formulated as:

$$\min M \tag{5}$$
subject to
$$M - d_j \geq 0,\ \forall j,$$
$$\sum_{r=1}^{s} u_r y_{rj} \Big/ x_j + d_j = E_j^*,\ \forall j,$$
$$u_r \geq \varepsilon,\ \forall r,$$
$$d_j \geq 0,\ \forall j,$$

where $E_j^*$ represents the CCR efficiency score of $DMU_j$ computed using the CCR model, also known as the conventional DEA model developed by Charnes et al. (1978), and $d_j$ is the deviation from $E_j^*$ for $DMU_j$.

As noted earlier, numerous studies have utilized various DEA-based methodologies to assess human development performance at the national level. Despite existing efforts, there remains potential to improve the accuracy of performance evaluations by incorporating CCR efficiency scores within a common-weight DEA approach. Conventional common-weight DEA models generally use the ideal efficiency score of "1" as a uniform target for all Decision-Making Units (DMUs). However, due to practical capacity limitations, many DMUs may not realistically achieve this ideal score when actual input and output weight distributions are taken into account. As a result, deviations from the efficiency score of "1" may not provide meaningful insights for these units. To overcome this issue, the current study proposes a novel framework that sets the CCR efficiency scores of individual DMUs as their specific aspiration levels, instead of relying on the ideal efficiency score.

### 3.4. Innovation-integrated human development performance assessment using the proposed methodology

This Section initially presents the composite index that evaluates the innovation-based human development performance of countries. First, Model (5) is solved by considering human development indicators as the outputs and the Gini coefficient as the single input. The efficiency scores of countries resulting from the human development assessment model are noted as E′. Then, Model (5) is computed by employing innovation performance indicators as the outputs and a dummy input, which equals to 1 for all countries. The efficiency scores of countries resulting from the innovation performance assessment model are noted as E′′. Finally, the composite index that integrates human development and innovation performance is obtained by multiplying E′ and E′′ for all countries under evaluation. The overall ranking of countries is obtained by considering the composite index. Figure 1 provides a stepwise illustration of the proposed decision-making procedure.

Afterwards, the introduced decision approach is implemented for the performance assessment of 24 EU countries (commonly termed DMUs within the framework of DEA). Considering the GNI per capita of Luxembourg, which is 84,649 $ (2017 PPP) for 2021, and its relatively small population, this country is identified as an outlier and excluded from the dataset used throughout the analysis. The relevant data for Gini coefficient is extracted from the OECD database, where data for Cyprus and Malta are missing (OECD, n.d.). At the first stage of the proposed framework, the novel common-weight DEA-based model is employed with four outputs that are used for calculating the HDI and a single input, namely Gini coefficient.

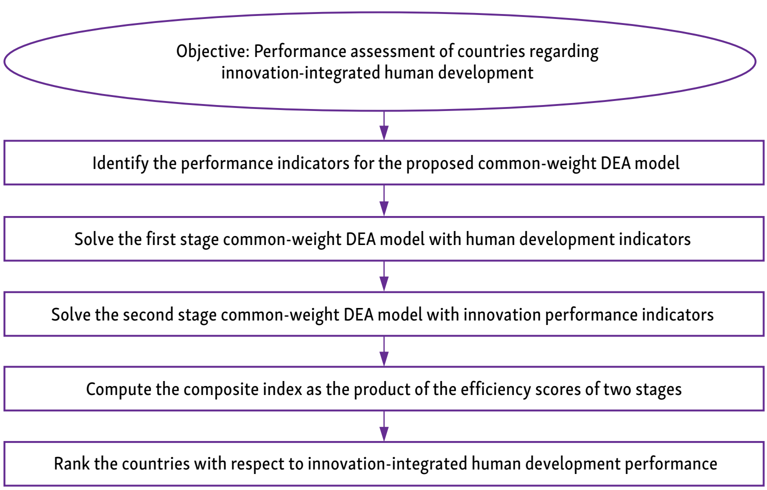


**Figure 1.** The stepwise illustration of the introduced decision-making procedure

The Gini coefficient can vary from 0, indicating complete equality, to 1, indicating perfect inequality. The data for human development indicators are obtained from the Human Development Reports (UNDP, n.d.).

The HDI serves as a composite indicator aimed at capturing overall advancement in fundamental dimensions of human development, specifically health, education, and living standards. The health component is measured using life expectancy at birth, while the education component is assessed by integrating the average years of schooling for individuals aged 25 and older with the expected years of schooling for children entering the education system. The metric used to assess the standard of life is Gross National Income (GNI) per capita. The HDI is calculated as the geometric mean of the outcomes of the three HDI dimensions. The UNDP analysts determined minimum and maximum values for each indicator in order to obtain a standard normalization scheme (UNDP, 2021). The summary of these values is presented in Table 2.

**Table 2.** Minimum and maximum values for human development indicators (UNDP, 2021)

| Indicator | Minimum | Maximum |
|---|---|---|
| Life expectancy (years) | 20 | 85 |
| Expected years of schooling (years) | 0 | 18 |
| Mean years of schooling (years) | 0 | 15 |
| GNI per capita | 100 | 75,000 |

Life expectancy, expected years of schooling and mean years of schooling are normalized with the following Equation as indicated in the technical notes of HDI report (UNDP, 2021):

$$n_{rj} = \frac{y_{rj} - y_r^-}{y_r^* - y_r^-}, \ \forall j. \tag{6}$$

GNI per capita is normalized by using the logarithm as follows (UNDP, 2021):

$$n_{rj} = \frac{ln\left(y_{rj}\right) - ln\left(y_r^-\right)}{ln\left(y_r^*\right) - ln\left(y_r^-\right)}, \ \forall j, \tag{7}$$

where $n_{rj}$ is the normalized value of output $r$ for $DMU_j$, and $y_{rj}$ is the actual value of output $r$ for $DMU_j$. Here, $y_r^-$ is the minimum value for output $r$ obtained from $y_r^- = \min_j\left(y_{rj}\right)$, and $y_r^*$ is the maximum value for output $r$ that is determined as $y_r^* = \max_j\left(y_{rj}\right)$.

The same normalization procedures for data regarding human development indicators are employed for the common-weight DEA-based performance assessment proposed in this study for comparative purposes. The Gini coefficient is not normalized as it ranges between 0 and 1. The dataset used for human development performance assessment of countries is provided in Table 3.

At the second stage of the proposed approach, the innovation performance of countries is measured by the novel common-weight DEA-based model with high technology exports

**Table 3.** The dataset for human development performance of countries (UNDP, n.d.)

| Countries | Gini coefficient | Life expectancy at birth | Expected years of schooling | Mean years of schooling | GNI per capita | HDI 2021 |
|---|---|---|---|---|---|---|
| Austria | 0.272 | 81.6 | 16.0 | 12.3 | 53,619 | 0.916 |
| Belgium | 0.248 | 81.9 | 19.6 | 12.4 | 52,293 | 0.937 |
| Bulgaria | 0.396 | 71.8 | 13.9 | 11.4 | 23,079 | 0.795 |
| Croatia | 0.291 | 77.6 | 15.1 | 12.2 | 30,132 | 0.858 |
| Czechia | 0.255 | 77.7 | 16.2 | 12.9 | 38,745 | 0.889 |
| Denmark | 0.268 | 81.4 | 18.7 | 13.0 | 60,365 | 0.948 |
| Estonia | 0.305 | 77.1 | 15.9 | 13.5 | 38,048 | 0.890 |
| Finland | 0.273 | 82.0 | 19.1 | 12.9 | 49,452 | 0.940 |
| France | 0.292 | 82.5 | 15.8 | 11.6 | 45,937 | 0.903 |
| Germany | 0.296 | 80.6 | 17.0 | 14.1 | 54,534 | 0.942 |
| Greece | 0.32 | 80.1 | 20.0 | 11.4 | 29,002 | 0.887 |
| Hungary | 0.28 | 74.5 | 15.0 | 12.2 | 32,789 | 0.846 |
| Ireland | 0.282 | 82.0 | 18.9 | 11.6 | 76,169 | 0.945 |
| Italy | 0.331 | 82.9 | 16.2 | 10.7 | 42,840 | 0.895 |
| Latvia | 0.343 | 73.6 | 16.2 | 13.3 | 32,803 | 0.863 |
| Lithuania | 0.357 | 73.7 | 16.3 | 13.5 | 37,931 | 0.875 |
| Netherlands | 0.297 | 81.7 | 18.7 | 12.6 | 55,979 | 0.941 |
| Poland | 0.265 | 76.5 | 16.0 | 13.2 | 33,034 | 0.876 |
| Portugal | 0.327 | 81.0 | 16.9 | 9.6 | 33,155 | 0.866 |
| Romania | 0.342 | 74.2 | 14.2 | 11.3 | 30,027 | 0.821 |
| Slovakia | 0.222 | 74.9 | 14.5 | 12.9 | 30,690 | 0.848 |
| Slovenia | 0.238 | 80.7 | 17.7 | 12.8 | 39,746 | 0.918 |
| Spain | 0.329 | 83.0 | 17.9 | 10.6 | 38,354 | 0.905 |
| Sweden | 0.286 | 83.0 | 19.4 | 12.6 | 54,489 | 0.947 |

(% manufactured products), patent applications, researchers in R&D (per million people) and R&D expenditure (% of GDP) used as the outputs. A dummy input, which equals to 1 for all countries, is also included in the model. The innovation indicators that are extracted from World Bank database (World Bank, n.d.) are normalized by employing $y_{rj}/y_r^*$, in which $y_r^* = \max_j \left(y_{rj}\right)$, for $\forall r$ (Karsak & Ahiska, 2007). The dataset including innovation performance assessment is presented in Table 4.

The common-weight DEA-based models introduced by Karsak and Ahiska (2005) and Toloo (2015) are also applied to the datasets used in the first and second stages for comparative purposes. The ranking results obtained in the first stage of the proposed methodology are illustrated in Table 5. Albeit the CCR model classifies three countries as efficient in assessing human development performance, the proposed method provides a complete ranking of the countries, with Belgium ranked first.

**Table 4.** The dataset for innovation performance of countries (World Bank, n.d.)

| Countries | High technology exports | Patent applications | Researchers in R&D | R&D expenditure (% of GDP) |
|---|---|---|---|---|
| Austria | 16 | 1872 | 6342 | 3.26 |
| Belgium | 22 | 799 | 6582 | 3.43 |
| Bulgaria | 9 | 165 | 2339 | 0.77 |
| Croatia | 12 | 77 | 2331 | 1.24 |
| Czechia | 21 | 541 | 4569 | 2 |
| Denmark | 16 | 1090 | 7708 | 2.81 |
| Estonia | 18 | 25 | 4038 | 1.75 |
| Finland | 8 | 1557 | 7871 | 2.99 |
| France | 21 | 13386 | 5175 | 2.22 |
| Germany | 16 | 39822 | 5536 | 3.14 |
| Greece | 14 | 394 | 4326 | 1.46 |
| Hungary | 18 | 433 | 4452 | 1.64 |
| Ireland | 41 | 75 | 5251 | 1.13 |
| Italy | 9 | 10281 | 2678 | 1.45 |
| Latvia | 16 | 104 | 2405 | 0.74 |
| Lithuania | 13 | 81 | 3935 | 1.11 |
| Netherlands | 21 | 2080 | 6074 | 2.31 |
| Poland | 11 | 3377 | 3534 | 1.44 |
| Portugal | 6 | 711 | 5473 | 1.68 |
| Romania | 12 | 772 | 985 | 0.47 |
| Slovakia | 8 | 146 | 3211 | 0.92 |
| Slovenia | 8 | 222 | 5223 | 2.13 |
| Spain | 12 | 1308 | 3252 | 1.43 |
| Sweden | 17 | 1771 | 8131 | 3.42 |

**Table 5.** Rankings with respect to human development performance of countries

| Countries | CCR model | Model (3) by Karsak and Ahiska (2005) | Model (4) by Toloo (2015) | Proposed model (5) | HDI |
|---|---|---|---|---|---|
| Austria | 8 | 8 | 8 | 9 | 9 |
| Belgium | 1 | 1 | 2 | 1 | 7 |
| Bulgaria | 24 | 24 | 24 | 24 | 24 |
| Croatia | 16 | 15 | 15 | 15 | 20 |
| Czechia | 6 | 6 | 5 | 6 | 14 |
| Denmark | 4 | 4 | 4 | 4 | 1 |
| Estonia | 17 | 16 | 16 | 17 | 13 |
| Finland | 7 | 7 | 6 | 5 | 6 |
| France | 12 | 13 | 13 | 13 | 11 |
| Germany | 11 | 12 | 11 | 12 | 4 |
| Greece | 15 | 19 | 17 | 16 | 15 |
| Hungary | 14 | 14 | 14 | 14 | 22 |
| Ireland | 5 | 5 | 7 | 7 | 3 |
| Italy | 19 | 17 | 19 | 19 | 12 |
| Latvia | 21 | 21 | 21 | 21 | 19 |

*End of Table 5*

| Countries | CCR model | Model (3) by Karsak and Ahiska (2005) | Model (4) by Toloo (2015) | Proposed model (5) | HDI |
|---|---|---|---|---|---|
| Lithuania | 22 | 22 | 22 | 22 | 17 |
| Netherlands | 13 | 11 | 12 | 11 | 5 |
| Poland | 9 | 10 | 10 | 10 | 16 |
| Portugal | 20 | 20 | 20 | 20 | 18 |
| Romania | 23 | 23 | 23 | 23 | 23 |
| Slovakia | 1 | 1 | 2 | 3 | 21 |
| Slovenia | 1 | 3 | 1 | 2 | 8 |
| Spain | 18 | 18 | 18 | 18 | 10 |
| Sweden | 10 | 9 | 9 | 8 | 2 |

The ranking results obtained in the second stage of the decision-making methodology are illustrated in Table 6. While the CCR model identifies four countries as efficient in terms of innovation performance, Germany and Sweden are determined as the best performing nations according to the proposed approach.

**Table 6.** Rankings with respect to innovation performance of countries

| Countries | CCR model | Model (3) by Karsak and Ahiska (2005) | Model (4) by Toloo (2015) | Proposed model (5) |
|---|---|---|---|---|
| Austria | 6 | 5 | 9 | 7 |
| Belgium | 1 | 1 | 2 | 3 |
| Bulgaria | 23 | 23 | 24 | 23 |
| Croatia | 20 | 20 | 19 | 22 |
| Czechia | 10 | 9 | 7 | 10 |
| Denmark | 7 | 8 | 8 | 4 |
| Estonia | 13 | 11 | 11 | 13 |
| Finland | 5 | 10 | 12 | 6 |
| France | 9 | 6 | 4 | 9 |
| Germany | 1 | 1 | 3 | 1 |
| Greece | 15 | 13 | 13 | 15 |
| Hungary | 12 | 12 | 10 | 11 |
| Ireland | 1 | 1 | 1 | 5 |
| Italy | 19 | 17 | 20 | 19 |
| Latvia | 21 | 19 | 14 | 20 |
| Lithuania | 16 | 18 | 15 | 16 |
| Netherlands | 8 | 7 | 5 | 8 |
| Poland | 17 | 16 | 17 | 17 |
| Portugal | 11 | 21 | 21 | 14 |
| Romania | 24 | 23 | 22 | 24 |
| Slovakia | 22 | 22 | 23 | 21 |
| Slovenia | 14 | 14 | 18 | 12 |
| Spain | 18 | 15 | 16 | 18 |
| Sweden | 1 | 4 | 6 | 1 |

Weight dispersions of outputs are also an important issue for the common-weight DEA-based models used in the first and second stages of the performance evaluation. It is crucial for these models to assign a value to the output weights that is greater than epsilon, which is taken as $10^{-6}$ in here, to realistically consider the contribution of the outputs on performance evaluation. The weight dispersions of the outputs resulting from respective models are presented in Table 7.

**Table 7.** Weight dispersion of outputs used in the first and second stages of the proposed methodology

| Weights for the first stage | Model (3) by Karsak and Ahiska (2005) | Model (4) by Toloo (2015) | Proposed model (5) | Weights for the second stage | Model (3) by Karsak and Ahiska (2005) | Model (4) by Toloo (2015) | Proposed model (5) |
|---|---|---|---|---|---|---|---|
| $u_1$ | 0.000001 | 0.051 | 0.096982 | $u_1$ | 0.774687 | 1.18171 | 0.429062 |
| $u_2$ | 0.025699 | 0.0474 | 0.066042 | $u_2$ | 0.171256 | 0.2 | 0.233754 |
| $u_3$ | 0.000001 | 0.0516 | 0.027592 | $u_3$ | 0.088686 | 0.2 | 0.617162 |
| $u_4$ | 0.232684 | 0.1113 | 0.064497 | $u_4$ | 0.509087 | 0.2 | 0.195108 |

As illustrated in Table 7, the proposed approach provides a plausible weight distribution for the outputs in both the first and second stages of performance evaluation. On the other hand, one shall observe that the model proposed by Karsak and Ahiska (2005) assigns the epsilon value to two outputs at the first stage while the model proposed by Toloo (2015) assigns the same weight to three outputs at the second stage.

The final ranking of countries is attained with a composite index proposed in this study. The composite index, which is computed by multiplying the efficiency scores of countries obtained in the first stage with the efficiency scores of countries obtained in the second stage of the proposed approach, reflects the innovation-integrated human development performance of EU countries. The final rankings of countries are presented in Table 8.

Considering the composite index rankings, Belgium, the top performer according to "R&D expenditure", is identified as the best performing country by the proposed approach and model developed by Karsak and Ahiska (2005). On the other hand, Romania that has the lowest figures for "researchers in R&D" and "R&D expenditure" is listed in the bottom ranks. Bulgaria, which is the lowest performer for "life expectancy at birth", "expected years of schooling" and "GNI per capita", has the maximum income inequality among EU countries as its Gini coefficient equals to 0.396. Considering these figures, Bulgaria is among the low performers in human development and composite index rankings.

Spearman rank correlation coefficients were calculated to evaluate the association between the composite index rankings derived from the common-weight DEA-based models and the Human Development Index (HDI). The hypotheses for the Spearman rank correlation test are formulated as:

*Null hypothesis* ($H_0$): No statistically significant correlation exists between the rankings produced by the DEA-based approaches and the HDI.

*Alternative hypothesis* ($H_a$): A statistically significant positive correlation exists between the rankings produced by the DEA-based approaches and the HDI.

**Table 8.** Rankings with respect to composite index

| Countries | Model (3) by Karsak and Ahiska (2005) | Model (4) by Toloo (2015) | Proposed model (5) | HDI |
|---|---|---|---|---|
| Austria | 5 | 9 | 7 | 9 |
| Belgium | 1 | 2 | 1 | 7 |
| Bulgaria | 24 | 24 | 23 | 24 |
| Croatia | 17 | 18 | 21 | 20 |
| Czechia | 9 | 6 | 10 | 14 |
| Denmark | 6 | 5 | 3 | 1 |
| Estonia | 13 | 11 | 13 | 13 |
| Finland | 10 | 12 | 6 | 6 |
| France | 7 | 8 | 9 | 11 |
| Germany | 3 | 3 | 4 | 4 |
| Greece | 15 | 14 | 14 | 15 |
| Hungary | 12 | 10 | 12 | 22 |
| Ireland | 2 | 1 | 5 | 3 |
| Italy | 18 | 21 | 20 | 12 |
| Latvia | 22 | 16 | 22 | 19 |
| Lithuania | 21 | 20 | 19 | 17 |
| Netherlands | 8 | 7 | 8 | 5 |
| Poland | 14 | 15 | 15 | 16 |
| Portugal | 20 | 22 | 16 | 18 |
| Romania | 23 | 23 | 24 | 23 |
| Slovakia | 19 | 19 | 17 | 21 |
| Slovenia | 11 | 13 | 11 | 8 |
| Spain | 16 | 17 | 18 | 10 |
| Sweden | 4 | 4 | 2 | 2 |

Table 9 presents the matrix of Spearman rank correlation coefficients corresponding to the composite index rankings of the models under comparison. Given that the critical value of the Spearman coefficient, $r_{s,\alpha}$, is 0.407 for a sample size of $n$ = 24 at a significance level of $\alpha$ = 0.05 (Ramsey, 1989), it can be inferred that the observed similarities in rankings between the common-weight DEA-based models and the HDI are statistically significant.

**Table 9.** Spearman rank correlation matrix for the composite index rankings of respective models

| | Model (3) by Karsak and Ahiska (2005) | Model (4) by Toloo (2015) | Proposed model (5) | HDI |
|---|---|---|---|---|
| Model (3) by Karsak and Ahiska (2005) | 1 | 0.956522 | 0.956522 | 0.836522 |
| Model (4) by Toloo (2015) | | 1 | 0.919130 | 0.778261 |
| Proposed model (5) | | | 1 | 0.846957 |
| HDI | | | | 1 |

## 4. Managerial implications and discussion

The 2021/2022 Human Development Report, issued by the UNDP, is the latest installment in a series of worldwide reports that have been released since 1990. These reports provide objective and well-researched debates on significant development topics, patterns, as well as initiatives. The accumulation and interplay of various levels of uncertainty are causing significant disruption in human lives, beyond anything humans have experienced before. Humanity has encountered illnesses, conflicts, and ecological disturbances throughout the past. The combination of destabilizing planetary pressures and increasing inequities, together with significant social changes provide a set of new, intricate, and interconnected factors of uncertainty for the Earth and its inhabitants (UNDP, 2022). Hence, the objectives of the 2021/2022 Human Development Report are mainly focused on comprehending and addressing these worldwide issues (UNDP, n.d.).

Despite its widespread acceptance, the HDI methodology has faced criticism from several experts. This has led to the emergence of other ideas that seek to more effectively evaluate nations' endeavors towards human development. Within the ongoing fourth industrial revolution, it is clear that innovation plays a crucial role in driving economic prosperity and ensuring sustainable growth for nations. Undoubtedly, there exists a robust link among innovation, human development, and GDP. Hence, nations are diligently striving to cultivate and empower their labor force with the appropriate expertise to actively participate in innovative activities and spearhead new endeavors, while also formulating national plans for fostering innovation (Tunsi & Alidrisi, 2023). When assessing these facts, it is crucial to consider the significance of technological advances and innovation in the digital world for comprehensive evaluation of human development performance.

The aim of this study is to propose a pertinent decision aid for assessing the innovation-integrated human development performance of countries. Considering this aim, a common-weight DEA-based composite index is proposed to combine the innovation and human development performance assessment of EU countries. The common-weight DEA-based method employing a single input applies a uniform set of output weights across all decision-making units, thereby improving the discriminatory power of the analysis by eliminating implausible weight allocations. The proposed model further enhances the evaluation framework by minimizing the maximum deviation from the CCR efficiency scores specific to each country, rather than relying on deviations from the ideal efficiency score of '1' – a benchmark that is often unattainable for several countries given their respective optimal weight configurations.

This methodology contributes to the literature in multiple ways. Firstly, it integrates the innovation dimension into the assessment of human development performance, offering a more comprehensive evaluation that is especially relevant in the context of the contemporary technological landscape. Secondly, the common-weight DEA framework imposes a uniform weighting scheme for all evaluation criteria, thereby addressing the issue of excessive weight flexibility commonly observed in traditional DEA models. Third, the proposed composite index enables to obtain a complete performance ranking of countries. Finally, a case study focusing on the innovation-integrated human development performance assessment of EU countries is presented to illustrate the robustness of the proposed methodology.

According to the final rankings of the proposed approach, Belgium, which possesses the highest "R&D expenditure", is identified as the best performing country. Conversely, Romania that has the lowest figures for "researchers in R&D" and "R&D expenditure" is listed in the bottom ranks. Bulgaria with the lowest "life expectancy at birth", "expected years of schooling" and "GNI per capita" as well as the highest income inequality among EU countries is amidst the low performers in human development and composite index rankings. While both Bulgaria and Romania require higher investment in education and health sectors, Bulgaria would be better off increasing high technology exports, researchers in R&D and R&D funding, and Romania would be in a more favorable position by enhancing innovation performance through allocating higher financial resources in R&D as well as promoting employment of R&D researchers.

On the other hand, Slovakia, which has a relatively high performance in terms of human development while being among the poor performers as for innovation, is ranked as the 17th among 24 EU countries according to composite index. Therefore, it appears that Slovakia would benefit from improving innovation performance measures such as "high technology exports", "patent applications" and "R&D expenditure". Similarly, a decline is observed in the composite index ranking of Slovenia in comparison to its human development performance ranking due to relatively lower performance as for innovation performance indicators, and thus, it may in particular consider focusing on "high technology exports" and "patent applications". In addition, while Germany shows the best performance in the field of innovation, its average performance in the field of human development drops its rank to fourth place in the composite index ranking. In this regard, Germany could attempt to enhance its human development performance by addressing income inequality and improving "GNI per capita".

Although Croatia is placed 15th in human development performance, its third from the bottom position in innovation performance has resulted in this country to end up in the 21st rank according to the composite index. Croatia is positioned second from the bottom as for "researchers in R&D", and has the third lowest "patent applications" among 24 EU countries. Moreover, Croatia lags the average values for "high technology exports", "patent applications", "researchers in R&D" and "R&D expenditure" by 21%, 98%, 50% and 34%, respectively. In order to improve its innovation performance, Croatia needs to focus on increasing its patent applications as well as researchers in R&D through optimizing resource allocation to promote innovation.

Alternately, despite its 13th position in human development performance, France settled in the 9th place as for the composite index due to its 9th position in innovation performance. Upon analyzing France's innovation performance metrics, it can be concluded that it performs better than average in each one of them and ranks second in terms of "patent applications".

Upon evaluating all of these facts, it would be reasonable for countries that exhibit comparatively lower performance in the overall rankings to conduct studies that will improve life standards and income distributions as well as enhance R&D practices.

In the last part of the study, sensitivity analysis is performed to analyze the changes in innovation performance assessment of countries with respect to variations in the set of considered outputs. The number of industrial design applications and trademark applications could have potentially been considered as outputs when assessing countries' innovation performance; however, these data are missing for some EU countries. Belgium and Netherlands would be omitted from the analysis if the number of industrial design applications were selected as an output, leaving 22 countries within the scope of the performance analysis. Belgium, Greece, Ireland, and Netherlands would not be included in the analysis if the number of trademark applications were considered as an output, reducing the total number of countries in the data set down to 20.

Innovation performance indicators of this study are chosen to encompass the maximum number of EU countries in order to maintain the comprehensiveness of the analysis, and thus, sensitivity analysis for innovation performance evaluation is carried out with the following two scenarios. As for Scenario 1, the output possessing the highest weight according to the results of the base-case scenario of the proposed approach, i.e., researchers in R&D, is eliminated from the analysis and performance assessment using the proposed approach is conducted with the remaining three outputs. In Scenario 2, the output with the lowest weight according to the outcomes of the base-case scenario, i.e., R&D expenditure (% of GDP), is excluded from the analysis and the proposed novel model is solved by considering the remaining three outputs. The rankings obtained through conducting sensitivity analysis using these two scenarios are provided in Table 10.

**Table 10.** Ranking results of the sensitivity analysis for innovation performance

| Countries | Base-case Scenario | Scenario 1 | Scenario 2 |
|---|---|---|---|
| Austria | 7 | 4 | 9 |
| Belgium | 3 | 1 | 5 |
| Bulgaria | 23 | 23 | 23 |
| Croatia | 22 | 19 | 22 |
| Czechia | 10 | 10 | 10 |
| Denmark | 4 | 5 | 4 |
| Estonia | 13 | 11 | 12 |
| Finland | 6 | 9 | 6 |
| France | 9 | 6 | 8 |
| Germany | 1 | 1 | 1 |
| Greece | 15 | 14 | 15 |
| Hungary | 11 | 12 | 11 |
| Ireland | 5 | 8 | 1 |
| Italy | 19 | 16 | 19 |
| Latvia | 20 | 21 | 20 |
| Lithuania | 16 | 20 | 16 |
| Netherlands | 8 | 7 | 7 |
| Poland | 17 | 17 | 17 |
| Portugal | 14 | 18 | 13 |
| Romania | 24 | 24 | 24 |
| Slovakia | 21 | 22 | 21 |
| Slovenia | 12 | 13 | 14 |
| Spain | 18 | 15 | 18 |
| Sweden | 1 | 3 | 1 |

In the base-case scenario with four innovation outputs, Germany and Sweden possess an efficiency score of '1', while Belgium and Germany show the best innovation performance according to Scenario 1, and Germany, Ireland and Sweden achieve the highest efficiency score according to Scenario 2. Thus, as for innovation performance assessment, Germany obtains the top ranking for the base case scenario as well as for the two alternative scenarios considered throughout the sensitivity analysis. One shall note that Ireland is the most sensitive country to variations in the set of outputs as it is ranked fifth according to the base-case scenario while ranking eighth and first with respect to Scenario 1 and Scenario 2, respectively. Ireland, which possesses a relatively low R&D expenditure (% of GDP), is top ranked in Scenario 2 where the proposed model is solved with three outputs excluding R&D expenditure. It is also worth noting that Bulgaria and Romania are in the bottom ranks not only for the base-case scenario, but also according to the outcomes of Scenario 1 and Scenario 2. Thus, it is crucial for both countries to revise resource allocation policies in a way to improve innovation performance metrics.

## 5. Conclusions

This paper proposes a novel composite index based on common-weight DEA that integrates human development and innovation performance of countries. The weighting approach used in methods that recommend a composite index is a crucial issue discussed in the literature. The weighting approach proposed in this study provides an objective evaluation with a realistic distribution of criteria weights. Common-weight DEA-based framework employs a common set of weights for the outputs used in measuring performance, hence avoiding the issue of unrealistic weight flexibility encountered in conventional DEA models. This approach generates a full ranking and allows for the determination of the top-performing country.

The decision-making framework outlined in this study involves the construction of a composite index that integrates the results derived from common-weight DEA-based models. This composite index is formulated as the product of two distinct efficiency scores, obtained through the application of a novel common-weight DEA-based model designed to evaluate human development and innovation performance, respectively. The proposed model operates by minimizing the maximum deviation from the CCR efficiency scores of the respective countries, thereby enabling a more realistic and context-sensitive performance assessment based on the most appropriate weight configurations for each country. To assess the robustness of the proposed approach, alternative models developed by Karsak and Ahiska (2005) and Toloo (2015) are also employed to compute the composite index. Comparative analysis of the resulting rankings indicates a positive correlation between the outcomes of the proposed model, those of the referenced models, and the Human Development Index (HDI), thereby supporting the validity of the proposed methodology.

The proposed methodology overcomes numerous shortcomings of conventional DEA models. First of all, comparative performance assessment of countries is employed using a common-weight approach. Likewise, the extreme weight flexibility issue and inapt discriminatory properties of conventional DEA are discarded by the novel approach. Furthermore, this approach enables to consider the innovation dimension of human development performance of countries and attains the complete ranking of countries as regards innovation-integrated human development performance. Moreover, a practical weight distribution for outputs is provided with the novel approach.

To the best of our knowledge, this study is the first to apply a common-weight DEA-based approach for evaluating innovation-integrated human development performance of countries. The evaluation of country performance is conducted by integrating two key dimensions: human development and innovation. Given the widespread recognition of UNDP and World Bank data as authoritative benchmarks in the field of human development at the international level, the output indicators are selected from these reputable databases.

It is noteworthy that the rankings yielded by the proposed approach may vary when different performance evaluation indicators are taken into consideration. For instance, several other innovation performance indicators such as the number of industrial design applications and trademark applications could also have been considered as outputs for performance assessment. However, as the data for these innovation performance indicators are missing for some EU countries, the set of outputs are limited to the ones used in this study in order to consider the highest possible number of countries. Moreover, the developed approach can only be used when crisp data for the outputs is accessible. In future research, efforts will be made to incorporate interval data into the proposed methodology. Finally, it is worth noting that the novel approach is not limited to evaluating human development performance, but it may also be used for addressing other real-world decision-making challenges.

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