



A decision support approach for sustainability management using multiple criteria decision making and statistical techniques

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ARTICLE INFO

Keywords:

Multiple objective decision making
Multiple objective programming
Composite indicators
Sustainability assessment

ABSTRACT

In this paper, we derive a decision support tool to establish the policies a country may carry out to direct its performance toward the Sustainable Development Goals of the 2030 Agenda. A panel data structure for a set of indicators belonging to the three sustainability dimensions (economic, social, and environmental) is used for the countries considered to calculate composite indicators for the three dimensions, and then formulate a multiobjective optimization model to research how to improve each country's sustainability situation. The case of Spain is used as a proof of concept.

1. Introduction

Sustainability is a significant challenge for our societies. In the literature, the most widespread definition of sustainability [1] is “meeting the needs of the present without compromising the ability of future generations to meet their own needs”.

The sustainability study of territories is a current topic of interest because frequent economic crises and environmental disasters have revealed the fragility of our planet and the shortcomings of a development model blindly regarded as fully acceptable [2].

Sustainability assessment allows evaluating the present situation of different territories while identifying the areas to be improved satisfying the needs of the future. As a multidimensional concept, the sustainable development of a territory is usually measured using three basic dimensions, i.e. social, economic, and environmental. A sustainable society could be described as one that is economically viable, environmentally sound, and socially responsible. Ideally, nations pursue these three dimensions uniformly without jeopardizing any of them. Hence, an ideal sustainable entity would maximize the benefits in the economic, social, and environmental dimensions under relevant constraints imposed by nature and socio-economic distributional equity. However, in practice, the three pillars are conflicting, in the sense that improving one of them implicitly means worsening one of the others.

To improve the sustainability of a given territory (in this paper, a country), in general, two steps have to be taken. First, we have to assess

the sustainability situation at a given moment. Second, a decision aid system must be designed to allow policymakers to detect weak points and areas for improvement.

In this paper, we propose a decision support approach that consists of these two steps. Step 1 evaluates the current situation of the set of countries considered and their evolution over a period of time. For this purpose, using panel data of a set of individual sustainability indicators, we propose building three composite indicators (CIs) to measure the countries' performances in the social, economic, and environmental dimensions. These CIs are calculated using the Multiple Reference Point Weak and Strong Composite Indicators methodology (MRP-WSCI) proposed by [3].

The MRP-WSCI approach has two advantages over other schemes for building composite indicators. First, the possibility of using different compensation degrees among the indicators, showing the countries' performances in the three dimensions from different perspectives. While a Weak Composite Indicator (WCI) assesses each country's overall performance, a Strong Composite Indicator (SCI) detects poor or weak behaviors representing areas for improvement to have a better situation in the future. We propose using both CIs in our decision support approach, as their joint analysis would provide a more detailed view of the sustainability situation. As stated in [3], the poor behaviors highlighted by the SCI would remain hidden if we only studied the WCI. In addition, to obtain a single global ranking of the countries, we use a Mixed Composite Indicator (MCI) that combines the information

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provided by the WCI and SCI. The second advantage of the MRP-WSCI approach is that we can use multiple reference values for the single indicators representing different desired levels of achievement for each one. Thus, the evaluation provided by the MRP-WSCI shows how good the performance of each country is for each dimension in comparison to the desired reference levels. By jointly considering the SCI and WCI, national policymakers can assess their countries' performance in comparison with all the countries considered in the study and can detect areas for improvement for their countries.

Once we have a global view of the sustainability performance of the countries, it is natural to assume that national policymakers would like to find possible ways to improve the situation of their countries. Since the social, economic, and environmental dimensions are conflicting by nature, and improving them at the same time is not a trivial matter, information about the real possibilities is needed. Step 2 is designed to assist policymakers in gaining insights to make suitable decisions according to their preferences. This step is country-specific and analyzes the future situation of the country considered from a multiple criteria decision making point of view. The aim is to identify which policies related to the single indicators should be designed in that country to promote its three dimensions at the same time.

To this aim, in Step 2, we formulate a multiobjective optimization model designed ad-hoc for the desired country to simultaneously maximize its performance in the three dimensions. We first conduct a regression analysis using the information produced in Step 1 to estimate each dimension's CI of the country considered according to the single indicators. Note that some of the single indicators may not be easily and rapidly altered by policymakers (e.g. those related to poverty, or the share of people with good or very good perceived health). For this reason, in this step, we only consider the single indicators that can be controlled to a certain extent by the country's policymakers (from now on, we refer to these indicators as *controllable single indicators*). By "controllable" we do not mean that policymakers can decide their exact values at any given time, but that their values can achieve desired levels in the short/middle term by implementing appropriate policies. In a real study, decision makers should decide which single indicators can be considered controllable, and which ones are beyond their immediate control. Once the multiobjective problem has been formulated, we propose using interactive multiobjective optimization techniques to investigate possible compromise solutions, taking into account the decision makers' preferences. Therefore, this scheme provides a decision aid tool for national policymakers to solve the problem according to their preferences.

To illustrate the potential of our decision support approach in practice, we analyze, as a proof of concept, 27 European countries, using panel data for 38 single sustainability indicators extracted from the Eurostat database for the period 2010–2019. In Step 2, we focus on Spain to perform the multiple criteria decision making analysis and review the possible improvements for this country. To solve the problem, we use the interactive multiobjective optimization algorithm IRA-EMO [4]. At each iteration of the algorithm, the decision maker provides preferences as desirable aspiration values for the objective functions, and reservation values regarded as acceptable, beyond which objective function values should be discarded. These values are used to define an aspiration point (AP) and a reservation point (RP). This preferential information is intuitive and can be easily provided by decision makers. Besides, at each iteration, this algorithm can show any prefixed number of Pareto optimal solutions.¹ Nevertheless, our decision support approach is independent of the technique used to solve the problem formulated in Step 2. Hence, any other interactive method can be used in a real application, which will depend on the preferences

¹ In these solutions, no objective function can improve its value without deteriorating the value of another objective function.

given by the decision maker and on the information users want to obtain.

Note that in the literature there are many publications about the use of CIs to study different aspects of sustainability. However, to the best of our knowledge, there are no works that propose decision support systems aimed at both evaluating the sustainability situation of several territories considering its three dimensions and aiding policymakers in making decisions geared at actions to make their territories more sustainable in the future. In this paper, we aim to fill this gap and suggest a decision support approach that can be used by national policymakers not only to analyze and manage the sustainability of their countries but also to gain insights into the possible ways of enabling their territory to improve its situation in the future.

The remainder of this paper is organized as follows. In Section 2, we review the related literature. Our decision support approach is described in Section 3, and the practical example included as a proof of concept is shown in Section 4. In Section 5, we discuss several aspects related to the application of the proposed methodology. Finally, conclusions are presented in Section 6.

2. Literature review

To assess sustainability, a set of individual indicators evaluating different aspects is usually considered [2]. However, as managing a large number of indicators makes it difficult to understand the overall performance of an entity, the information they all provide is commonly synthesized into a CI [5–8]. In [9], the application of multicriteria approaches for building CIs is thoroughly justified and analyzed. In addition, this work discusses several issues to be considered for their application to assess sustainability, taking into account the three dimensions (social, economic, and environmental). A more recent paper [10] provides an overview of the implications of the choices made to construct CIs for sustainability assessment (indicator selection, normalization, weighting, and aggregation processes), concluding that the choices adopted have a serious impact on the sustainability situation for the entities evaluated. There is a vast amount of literature about the application of CIs to evaluate different aspects of sustainability. Next, we will review some of the most recent works.

In [11], different normalization and aggregation rules are combined with weighting systems to calculate different CIs constructed using the uncertainty of the single indicators considered. The countries of the European Union (EU) were ranked in terms of their sustainability to illustrate the approach. [12] introduces a novel approach that utilizes ranked weights and stochastic multicriteria acceptability analysis. Specifically, the authors consider all possible preferences among the indicators used and, for each preference, apply a mathematical transformation to calculate the least and most favorable scores for each entity. These scores define the lower and upper bounds of intervals, which are then used to create an interval decision matrix, representing the problem as a stochastic decision process. The result is a new composite indicator derived from holistic acceptability indices, offering greater discriminating power and robustness.

In [13], the authors present a methodology for validating and assessing the Sustainable Development Goals (SDGs) that transforms moral imperatives into measurable indicators and indexes. They propose a framework to enhance the effectiveness of sustainability initiatives by providing clear criteria for evaluating progress toward achieving the SDGs. [14] proposes a broader measure of sustainability that moves beyond the traditional three-dimensional model, incorporating various definitions and perspectives. To achieve this, a novel multi-level DEA (Data Envelopment Analysis) variation is employed. The method is tested to assess the sustainability of EU countries using three different combinations of inputs and outputs, each reflecting different views on sustainability. In [15], the sustainability of several Spanish cities is studied by applying a comprehensive set of ecological indicators tailored to local contexts. The authors suggest a framework that

includes social, economic, and environmental metrics, allowing for a multidimensional evaluation of urban sustainability that highlights the strengths and weaknesses in sustainability practices across the cities.

A more recent study [16] analyzes the applicability of several multiple criteria decision aid methods to assess sustainability and proposes a framework that enables the selection of an appropriate method depending on the decision maker's needs. In [17], the degree of implementation of SDG in the EU is examined using a CI built from a sensitivity analysis, allowing the removal of strongly correlated indicators. The authors also assess the interactions between the goals using the Spearman correlation coefficient of the country ranking.

To the best of our knowledge, there is a lack of works proposing decision support systems that evaluate the sustainability situation of territories and, at the same time, include an analysis of their future situation to aid in making informed decisions, which is the gap to which we want to contribute. Although it does not focus on the analysis of territories, [18] proposes a framework with a similar purpose, namely to evaluate the quality of service of rural drinking water supply systems. The authors investigate the relationship between environmental management practices and corporate sustainability performance. They provide empirical evidence that effective environmental management systems significantly enhance a company's sustainability outcomes, thereby offering insights for organizations looking to improve their sustainability strategies and align them with broader environmental goals. In addition, [19] propose a decision support framework using the Five Sectors Sustainability Model (SSEnSU) model and Goal Programming to assess and improve sustainability performance in the Brazilian automotive textile sector. Besides, to enhance the accuracy of actions, their proposal helped pinpoint critical areas in sustainability management and suggested strategies for optimizing resources to meet sustainable organizational objectives. The study in [20] analyzes how manufacturing companies incorporate sustainability in their strategic planning and introduces Value Stream Mapping for Sustainability (VSM4S), which combines traditional Value Stream Mapping with the Five Sectors Sustainability Model and its Sustainability Synthetic Indicator of System (SSIS). These indicators are visually represented to aid decision making and promote sustainability in strategic planning.

3. Methodology

This section describes the proposed decision support approach. In Section 3.1, we explain Step 1, aimed at studying the sustainability situation of the countries considered in the time series. Next, Section 3.2 provides the details about Step 2, the purpose of which is to individually analyze the situation of each country from a multiple criteria decision making point of view.

Initially, we need a set of individual indicators that measure the desired aspects of the social, economic, and environmental dimensions. These single indicators must be selected according to the purpose of the study to be performed and taking into account the availability of a database for these indicators in the desired time series. For example, the Eurostat database (<https://ec.europa.eu/eurostat/web/main/data/database>) offers a wide variety of sustainability development indicators related to the 17 SDGs at the heart of the 2030 Agenda [21]. Another option is the United Nations SDGs database (<https://unstats.un.org/sdgs/dataportal>). In what follows, we denote by T the number of years in the time series considered, by N_C the total number of countries, by N_I the total number of single indicators considered (belonging to any of the three dimensions), and by N_k the total number of single indicators belonging to each dimension k , with $k = 1$ (social), 2 (economic), and 3 (environmental). That is, $N_I = N_1 + N_2 + N_3$. It is important to bear in mind that the numbers of single indicators used to measure the three dimensions (i.e. N_1 , N_2 and N_3) do not have to be the same.

3.1. Step 1: Evaluation of the sustainability situation of each country

To determine the countries' performances based on their level of achievement for the selected individual indicators, for every country and year, we calculate CIs for the three dimensions. CIs help monitor the performance of the units under consideration and compare them not only to have an overall view but also to detect possible areas for improvement [22,23]. In this paper, we have considered the Multiple Reference Point Weak and Strong Composite Indicators methodology (MRP-WSCI) [3], which allows aggregating the single indicators for each dimension into three different CIs: a Strong Composite Indicator (SCI), a Weak Composite Indicator (WCI), and a Mixed Composite Indicator (MCI). The SCI does not enable any compensation among the single indicators and reports the single indicator with the worst performance value. On the contrary, the WCI fully compensates all the single indicators and is obtained as a weighted aggregation of the (normalized) single indicator values. Finally, an intermediate situation among the non-compensatory and fully compensatory schemes is provided by the MCI, which is a linear combination of the WCI and SCI.

As said in Section 1, the MRP-WSCI methodology needs some reference values for the single indicators, which represent different desirable levels of achievement for each one. These reference values are used to normalize the single indicators to have all of them on a common scale. They can be set either in an absolute or in a relative way. In our approach, we propose defining them relatively, using statistical information according to the database used.

For every $i = 1, \dots, N_I$ and $t = 1, \dots, T$, the reference values we use for the single indicator i in year t are the minimum value ($q_{i,t}^0$), the percentile 25 ($q_{i,t}^1$), the percentile 50 ($q_{i,t}^2$), the percentile 75 ($q_{i,t}^3$), and the maximum value ($q_{i,t}^4$) achieved by indicator i in year t among all the countries. With this, we form a so-called reference point for the single indicator i in year t , denoted by $\mathbf{q}_{i,t} = (q_{i,t}^0, q_{i,t}^1, q_{i,t}^2, q_{i,t}^3, q_{i,t}^4)^T$. Assuming that all the single indicators have the *more-the-better* direction (if an indicator is *the-lesser-the-better*, the indicator values are multiplied by -1), the normalized value $s_{j,i,t}$ of country j ($j = 1, \dots, N_C$) for indicator i in year t is obtained as:

$$s_{j,i,t} = s_{i,t}(x_{j,i,t}, \mathbf{q}_{i,t}) = \alpha^{r-1} + \frac{\alpha^r - \alpha^{r-1}}{q_{i,t}^r - q_{i,t}^{r-1}}(x_{j,i,t} - q_{i,t}^{r-1}) \quad \text{if } x_{j,i,t} \in [q_{i,t}^{r-1}, q_{i,t}^r], \quad (1)$$

where $x_{j,i,t}$ is the value of country j for indicator i in year t . Each α^r ($r = 0, 1, 2, 3, 4$) is a real value assigned (in the common scale) to the reference values $q_{i,t}^r$ of all the indicators i in all the years t .

The achievement function $s_{i,t}$ in (1) takes values ranging from α^{r-1} to α^r when $x_{j,i,t}$ is between $q_{i,t}^{r-1}$ and $q_{i,t}^r$. This way, the normalized value $s_{j,i,t}$ gives us the relative position of country j for indicator i in year t concerning the considered reference levels for that indicator. Actually, $s_{j,i,t}$ also informs us about the relative performance of country j on indicator i in year t concerning the other countries in the database, as the reference values have been set statistically according to the database. We have set the common scale values as $\alpha^0 = 0$, $\alpha^1 = 1$, $\alpha^2 = 2$, $\alpha^3 = 3$, and $\alpha^4 = 4$. Hence, in comparison with the other countries, we could say that the performance of country j for indicator i in year t is very poor if the normalized indicator value $s_{j,i,t}$ is between 0 and 1; it is poor if $s_{j,i,t}$ ranges from 1 to 2; the country has good performance if $s_{j,i,t}$ is between 2 and 3; and its performance is very good if $s_{j,i,t}$ is between 3 and 4. Note that the MRP-WSCI allows using a higher number of performance ranges if desired to have more detailed information about the countries' performances every year.

After this normalization, we calculate the WCI, SCI, and MCI for each dimension using the single indicators belonging to each dimension. Thus, a total of three CIs are obtained for the social, economic, and environmental spheres. For every $k = 1, 2, 3$, we have to assign a weight μ_i^k to every single indicator i in dimension k ($i = 1, \dots, N_k$), which reflects this indicator's contribution to the final composite measure of that dimension. Many different procedures to assess weights have been defined, ranging from (objective) statistical methods (such as

principal component analysis) to pure preferential schemes involving the decision maker [6]. In the latter case, a wide variety of elicitation methods exists [24]. When the weights are to be used within an additive aggregation scheme (like in our case), tradeoff or ratio weights are advisable, given that they define the compensation [25]. Making use of the achievement function in (1) and the weights, we build the three CIs as follows:

- WCI of dimension k for country j in year t ($WCI_{j,t}^k$): First, we normalize the weights of the indicators in this dimension (i.e. $\bar{\mu}_i^k = \frac{\mu_i^k}{\sum_{j=1}^{N_k} \mu_j^k}$, for every $i = 1, \dots, N_k$), and next, we calculate the WCI as:

$$WCI_{j,t}^k = \sum_{i=1}^{N_k} \bar{\mu}_i^k s_{j,i,t}^k. \quad (2)$$

- SCI of dimension k for country j in year t ($SCI_{j,t}^k$): This CI is built upon a corrected achievement function formulated on the basis of the idea that a bad performance in a given indicator is not that bad if the indicator is not highly weighted. First, we normalize the weights assigned to the single indicators of this dimension as follows:

$$\hat{\mu}_i^k = \frac{\mu_i^k}{\max_{j=1, \dots, N_k} \{\mu_j^k\}}, \quad i = 1, \dots, N_k. \quad (3)$$

Second, we use these weights to transform the normalized value $s_{j,i,t}$ into the new corrected normalized value $\bar{s}_{j,i,t}$ as follows:

$$\bar{s}_{j,i,t} = \bar{s}_{i,t}(x_{j,i,t}, \mathbf{q}_{i,t}) = \alpha^r + \hat{\mu}_i^k (s_{j,i,t} - \alpha^r) \quad \text{if } s_{j,i,t} \in [\alpha^{r-1}, \alpha^r]. \quad (4)$$

Finally, the SCI is calculated as the following minimum:

$$SCI_{j,t}^k = \min_{i=1, \dots, N_k} \bar{s}_{j,i,t}. \quad (5)$$

- MCI of dimension k for country j in year t ($MCI_{j,t}^k$): This CI is a linear combination of the former two, for a compensation degree $\lambda \in [0, 1]$:

$$MCI_{j,t}^k = \lambda \cdot WCI_{j,t}^k + (1 - \lambda) \cdot SCI_{j,t}^k. \quad (6)$$

As can be easily observed, $SCI_{j,t}^k \leq MCI_{j,t}^k \leq WCI_{j,t}^k$ and λ is the compensation among both CIs.

This building process assures that the three CIs obtained take values on the same scale as the normalized single indicators, i.e. from 0 to 4, which can be interpreted as each country's global position with respect to some hypothetical global reference levels (in our case with respect to the quartiles). The information generated in this step can be used in different ways. As mentioned before, the joint use of the WCI and SCI is highly advisable, and the MCI can be useful in obtaining a single ranking of the countries. For example, the situation of all the countries considered can be studied for one specific year, or the evolution of the three dimensions can be analyzed for the whole time series or for just a few years. Furthermore, the sustainability situation of one specific country can be analyzed in more detail by studying, e.g. the WCI and SCI for the three dimensions in the whole time series.

3.2. Step 2: Multiple criteria decision making analysis of the sustainability situation of each country

Once the information obtained in Step 1 has been studied, it is natural to assume that national policymakers would like to find possible ways to improve the situation of their countries and reach a better level of sustainability. The purpose of Step 2 of our approach is to focus on the analysis of one specific country and gain insights into the real possibilities for improving its sustainability performance. To this aim, this step consists of two phases. First, a statistical analysis is carried out (Section 3.2.1) to estimate the CIs of the three dimensions as

functions of just the controllable single indicators, which are the ones whose values can be altered by policymakers to a certain extent (as described in Section 1). Second, a multiobjective optimization model is formulated (Section 3.2.2). This problem is designed to find ways of improving the sustainability situation of policymakers' countries. This methodological approach that uses statistical analysis to build a multiobjective optimization model is based on the framework proposed in [26].

Once the information obtained in Step 1 is studied, it is natural to think that national policymakers would like to find out possible ways to improve the situation of their countries, to reach a better level of sustainability. The purpose of Step 2 of our approach is to focus on the analysis of one specific country and gain insight into the real possibilities for improving its sustainability performance. To this aim, this step consists of two phases. First, a statistical analysis is carried out (Section 3.2.1) to estimate the CIs of the three dimensions as functions of just the controllable single indicators, which are the single indicators whose values can be altered by policymakers to a certain extent (as described in Section 1). Second, a multiobjective optimization model is formulated (Section 3.2.2). This problem is designed to find ways of improving the sustainability situation of their countries. This methodological approach, which uses statistical analysis to build a multiobjective optimization model, is based on the framework proposed in [26].

3.2.1. Statistical analysis to estimate the dimensions' composite indicators

In this phase, we analyze the dependence relations of the CIs built for the three dimensions in Step 1 regarding the individual indicators identified as controllable (as discussed in Section 1) for all the dimensions. The purpose of this analysis is to have a function to estimate the country's performance for each dimension. Although three CIs (weak, strong, and mixed) are calculated in Step 1 for each dimension, now we just estimate the MCI for each dimension of the country considered, given that this indicator combines the WCI and the SCI. Once again, note that we only focus on the single indicators that can be controlled to a certain extent by implementing certain policies at the country level (controllable single indicators). The single indicators that are beyond the control of policymakers cannot be considered if we want to obtain information on how to improve the sustainability of a country in the future by implementing policies to change the situation of the single indicators.

We perform a regression analysis to learn how marginal variations in the controllable single indicators are associated with changes in the MCI of each dimension and to identify the key single indicators to explain their values. Panel data analysis examines not only changes in variables over time but also the differences in variables across the selected units. In a country-level panel like the one of our study, the CI values are subject to some variation due to some country-specific aspects (e.g. government goals and public policies, labor market singularities, etc.). However, part of this country-specific variation is likely to remain unobserved (unobserved heterogeneity), and may potentially influence the countries' performance of the single indicators (e.g. the country-specific effects are correlated with the single indicators). Ignoring this unobserved heterogeneity would result in a biased estimate. To control the omitted variables bias due to unobserved heterogeneity, a fixed effects model is frequently used in panel data analysis, especially when this heterogeneity is constant over time [27]. For N units and T time periods, a fixed effects panel data model is commonly formulated as:

$$Y_{j,t} = \beta X_{j,t} + \alpha_j + u_{j,t}, \quad \text{for } j = 1, \dots, N, t = 1, \dots, T, \quad (7)$$

where $Y_{j,t}$ denotes the dependent variable observed for unit j at time t , $X_{j,t} \in \mathbb{R}^M$ is the vector of M independent or explanatory variables observed for unit j at time t , $\beta \in \mathbb{R}^M$ is the vector of correlation coefficients, α_j is the unobserved time-invariant individual effect coefficient of unit j , and $u_{j,t}$ is the error term. The fixed effects model

deals with the unobserved heterogeneity by allowing the presence of correlation between the explanatory variables and the time-invariant individual effects (measured by α_j), assuming that the error term $u_{j,t}$ is independent of the regressors.

There are several ways to estimate the fixed effects model. Here we describe the Ordinary Least Squares Dummy Variable (FE-OLSDV) estimator [28], which is the method applied in the practical example described later in Section 4 to estimate the fixed effects model (7). We assume that we want to regress $MCI_{j,t}^1$, $MCI_{j,t}^2$, and $MCI_{j,t}^3$ as three dependent variables on the set of independent variables formed by the controllable single indicators. Let us assume that we have M controllable single indicators (with $M \leq N_j$). The FE-OLSDV estimator is an Ordinary Least Square model including a dummy variable for each unit, known as the unit fixed effects variable. In our case, we define a dummy variable d_j^k for each dimension k ($k = 1, 2, 3$) and for each country j as follows:

$$d_j^k(h) = \begin{cases} 1 & \text{if } h = j, \\ 0 & \text{if } h \neq j. \end{cases} \quad (8)$$

Thus, the regression model to estimate the MCI of dimension k (calculated using (6)) as functions of the normalized single indicator values (obtained with (1)) would be:

$$MCI_{j,t}^k = \sum_{h=1}^{N_C} \alpha_h^k \cdot d_j^k(h) + \sum_{i=1}^M \beta_i^k \cdot s_{j,i,t} + u_{j,t}^k, \quad \text{for } j = 1, \dots, N_C, t = 1, \dots, T, \quad (9)$$

where α_j^k is the fixed effect of country j of dimension k ; β_i^k is the correlation coefficient of the single indicator i in dimension k ; and $u_{j,t}^k$ is the error term.

By estimating the regression coefficients with FE-OLSDV, we reach the usual statistical inferences that allow us to identify the most relevant single indicators to regress the MCIs of the three dimensions. In addition, a correlation analysis between the controllable single indicators must be performed to identify significant joint variances and to calculate their confidence intervals (for the probability p desired, usually 95%). As explained below, these dependencies play a crucial role in formulating the multiobjective optimization problem for the desired country, in particular, to define the feasible values for the single indicators.

3.2.2. Multiobjective optimization model for the improvement of sustainability in each country

Next, we first introduce the basic concepts of multiobjective optimization. Second, we assume that we want to analyze the situation of a country J (with $J \in \{1, \dots, N_C\}$), and we describe how to formulate a multiobjective optimization problem to individually study how to enhance this country's sustainability situation, based on the information extracted in the statistical analysis.

Commonly, a multiobjective optimization problem is formulated as:

$$\begin{aligned} & \max && \{f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_p(\mathbf{x})\} \\ & \text{subject to} && \mathbf{x} \in X, \end{aligned} \quad (10)$$

where a solution $\mathbf{x} = (x_1, \dots, x_n)^T$ is a vector with n decision variables, $f_1, f_2, \dots, f_p : \mathbb{R}^n \rightarrow \mathbb{R}$ are the p (with $p \geq 2$) conflicting objective functions to be optimized, and $X \in \mathbb{R}^n$ is the feasible set formed by the feasible solutions. In general, there is no single feasible solution that simultaneously optimizes all the objectives. Instead, the so-called Pareto optimal solutions are considered, whereby no objective can be improved without impairing another one. For $\mathbf{z}, \bar{\mathbf{z}} \in \mathbb{R}^p$, we say that $\bar{\mathbf{z}}$ dominates \mathbf{z} if and only if $z_r \leq \bar{z}_r$ for all $r = 1, \dots, p$, and $z_s < \bar{z}_s$ for, at least, one index s . If \mathbf{z} and $\bar{\mathbf{z}}$ do not dominate each other, it is said that they are *non-dominated*. Then, a solution $\bar{\mathbf{x}} \in X$ is *Pareto optimal* if there is not any other $\mathbf{x} \in X$ such that $\mathbf{f}(\mathbf{x})$ dominates $\mathbf{f}(\bar{\mathbf{x}})$. All Pareto optimal solutions

define the Pareto optimal set in the decision space (E) and the Pareto optimal front in the objective space ($\mathbf{f}(E)$). For further details, see [29].

It is important to know the ranges of values that the objective functions can take since there is usually more than one Pareto optimal solution. The lower bounds are defined by the nadir point $\mathbf{z}^{nad} = (z_1^{nad}, \dots, z_p^{nad})^T$, while the upper bounds are given by the ideal point $\mathbf{z}^* = (z_1^*, \dots, z_p^*)^T$, which are calculated as $z_r^{nad} = \min_{\mathbf{x} \in E} f_r(\mathbf{x})$ and $z_r^* = \max_{\mathbf{x} \in S} f_r(\mathbf{x}) = \max_{\mathbf{x} \in E} f_r(\mathbf{x})$ ($r = 1, \dots, p$), respectively. Calculating \mathbf{z}^{nad} is difficult, given that the set E is normally unknown and it is usually estimated [30].

Next, let us formulate the multiobjective optimization model to analyze the sustainability of country J , whose main objective is to optimize the level of achievement of this country in the three dimensions of sustainability:

- **Decision variables:** Given that the objective functions will represent the performance of country J in the three dimensions, and we want to learn how to improve them according to achievement in the controllable single indicators, the decision variables are the normalized values of the M controllable single indicators, denoted by x_1, \dots, x_M , which are bounded by 0 and 4.
- **Objective functions:** As said, the three dimensions of sustainability are regarded as three objective functions to be maximized. They are obtained by making use of the estimated regression coefficients of the panel data model (9) formulated for each dimension, as follows:

$$\begin{aligned} soc^J(\mathbf{x}) &= \hat{\alpha}_J^1 + \sum_{i=1}^M \hat{\beta}_i^1 \cdot x_i, \\ eco^J(\mathbf{x}) &= \hat{\alpha}_J^2 + \sum_{i=1}^M \hat{\beta}_i^2 \cdot x_i, \\ env^J(\mathbf{x}) &= \hat{\alpha}_J^3 + \sum_{i=1}^M \hat{\beta}_i^3 \cdot x_i, \end{aligned} \quad (11)$$

These objective functions can be formulated using all the regression coefficients $\hat{\beta}_i^k$ or just some of them, taking into account their significance level (usually, at 1%, 5%, and 10%). In case all the regression coefficients in (11) are considered, however, each one should be weighted according to its significance level in order to have the most realistic estimation (e.g. by multiplying in (11) each $\hat{\beta}_i^k$ by $(1 - p_i^k)$, where p_i^k is its p -value). This enables introducing into the model information obtained according to the data that would be missed if we just include the regression coefficients with a significant level of less than 10%. Indeed, in light of the statistical results obtained in each concrete application, it may be even more suitable to consider an intermediate situation, rather than using all the regression coefficients or using just those of the most significant variables. For example, to enrich the formulation and have the best-suited estimations, it may be beneficial to formulate the objective functions including the regression coefficients with significance levels up to 55% (as will be shown later in the practical example in Section 4). In this case, we also recommend weighting the considered coefficients using their significance levels, as previously described. Nevertheless, this must be decided in each application of our decision support approach according to the statistical results obtained.

- **Feasible set:** The constraints defining the feasible set ensure that only meaningful and realistic values of the controllable single indicators are possible. These constraints are formulated according to the data set, using the dependencies observed in the previous correlation analysis. Note that the values of the single indicators that show significant dependencies have to be controlled to ensure that only solutions within their correlations' confidence intervals are allowed. The scheme followed to define these linear and possible non-linear constraints is described in [26]. Let us denote the total set of constraints by $g_l(\mathbf{x}) \leq 0$ with $l = 1, \dots, L$. Finally, the decision variable values are bounded by 0 and 4 (as they represent the normalized values of the controllable single indicators). However, more restrictive lower and upper bounds for

them can be additionally imposed for the country J considered. Let us denote by l_i^J and u_i^J the lower and upper bounds set for every controllable single indicator x_i ($i = 1, \dots, M$) for country J . To realistically fix these bounds, we must observe not only the single indicators' maximum and minimum values attained by this country in the time series but also consider the opinions and preferences of the country's policymakers concerning these single indicators.

- **Multiobjective optimization model for country J :** The model, which aims to identify the values of the controllable single indicators that would allow achieving the most desired compromise among the three dimensions for country J , is formulated as:

$$\begin{aligned} \max \quad & \{soc^J(\mathbf{x}), eco^J(\mathbf{x}), env^J(\mathbf{x})\} \\ \text{subject to} \quad & g_l(\mathbf{x}) \leq 0, \quad \text{for } l = 1, \dots, L, \\ & l_i^J \leq x_i \leq u_i^J, \quad \text{for } i = 1, \dots, M. \end{aligned} \quad (12)$$

Theoretically, the objective function can take values between 0 and 4. However, given that real data is used to limit the single indicator values, the possible values of the objective functions are limited as well. Hence, it is not sensible to expect that the current situation of country J in each dimension can be improved up to 4 (or impaired down to 0).

Once the problem for country J has been formulated, it is important to first maximize each objective function individually to have information about the best possible values (i.e. the ideal values) that can be attained separately at each dimension. In addition, it is also desirable to have an estimation of the worst possible values (i.e. the nadir values). This estimation can be obtained either by building the so-called pay-off table, or by using the lowest objective function values achieved by a set of solutions approximating the Pareto optimal front (which can be obtained e.g., using evolutionary algorithms [31]). This will inform policymakers about the real possibilities for improvement and the worst situation that could happen in each dimension. The solution process applied to find a final solution to problem (12) must be selected depending on the information to be extracted from the study and according to the policymakers' needs. In addition, the type of problem obtained (which depends on the regression models used in the statistical analysis) is also an important aspect in deciding the solution technique to be used. For example, if problem (12) is linear or quadratic, it could be easily solved by classical methods, such as reference point-based techniques [32] or goal programming [33, 34]. However, if the problem is non-linear and non-quadratic, other preference-based or interactive techniques based on e.g. evolutionary algorithms [35,36] may be needed to solve it.

Independently of the solution technique applied, understanding the meaning of the Pareto optimal solution/s obtained for problem (12) is crucial. A Pareto optimal solution to this problem would inform us of the values for the controllable single indicators that would permit achieving, in the future, the values attained by the three objective functions in this solution. Therefore, these single indicator values describe a desirable situation (regarding the controllable single indicators) that policymakers should promote with specific policies if they want their country to reach, in the future, the (optimal) levels attained in the three dimensions by this solution. If the Pareto optimal solution is generated based on the policymakers' expectations, different preferential scenarios should be tested to inform them about what is feasible or not in the future, the extent to which the three dimensions can be improved, and the trade-offs existing among them. Furthermore, we can foresee the impact on the country's sustainability when more importance is given to the improvement of one dimension than to the other two since the solution found using this information will show the sacrifices required in the other dimensions. In addition, a post-optimization analysis of the results obtained is recommended in order to know the impact on the three dimensions of a change of the controllable single indicators,

allowing a better foresight of the future situation if certain decisions are made.

For the sake of clarity, Fig. 1 summarizes the steps in which our decision support approach is divided. At a glance, we see that our proposal combines the use of CIs based on multiple criteria decision making with statistical techniques and multiobjective optimization. As a result, it provides a tool to study not only the past and current achievements of the countries considered, but also to review how each country could improve its situation in the future.

4. Practical example

This section provides an example to demonstrate how to apply our decision support approach for a concrete set of countries. The aim of this example is just to illustrate how the proposed methodology works, as a proof of concept. Given that no actual policymaker has given real preferences in Step 2, the results cannot be interpreted as real recommendations for the country considered (Spain). As in [37], we will analyze the sustainability of 27 European countries ($N_C = 27$): Belgium, Bulgaria, Czechia, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, and Sweden.

We have considered a set of $N_I = 38$ individual indicators from the Eurostat database (freely accessible at <https://ec.europa.eu/eurostat/web/main/data/database>), which can be seen in Tables 1 and 2, with $N_1 = 17$ single indicators in the social dimension, $N_2 = 11$ in the economic dimension, and $N_3 = 10$ in the environmental one (their units of measure can be seen in Tables 1–3 of the supplementary document²). Within each dimension, the single indicators have been classified into several sub-dimensions (as can be seen in Tables 1 and 2) based on their meaning for weighting purposes (as explained in Section 4.1). We have used annual data corresponding to the period 2010 to 2019 ($T = 10$ years).

4.1. Step 1: Evaluation of the sustainability situation of each country

For every dimension k , every country j and every year t (with $k = 1, 2, 3$, $j = 1, \dots, 27$, and $t = 1, \dots, 10$), the weak, strong and mixed CIs ($WCJ_{j,t}^k$, $SCJ_{j,t}^k$ and $MCJ_{j,t}^k$) have been calculated as explained in Section 3.1. For calculation purposes, all individual indicators have been considered in the *the-more-the-better* direction (i.e. those of the *the-less-the-better* type were multiplied by -1). To this aim, we have considered the following:

- Reference values: For every single indicator and every year, the reference values used to calculate the CIs (i.e. the minimum value, the percentiles 25, 50, and 75, and the maximum value reached by the individual indicator among all countries in the year considered) can be seen in Tables 4–13 of the supplementary document.
- Weights: As discussed in Section 3.1, different schemes can be used to elicit preferential weights. As a simple example in this present case when building the CIs of every dimension, the weights assigned to the single indicators have been set to give the same importance to each sub-dimensions of the considered dimension, and to all the indicators within each sub-dimension as well.³ Let us denote by C_k the number of sub-dimensions in

² This document contains certain results that support the research findings reached, but have been excluded from the main manuscript due to space limitations.

³ It is worth noting that weights can be defined as desired by the decision maker.

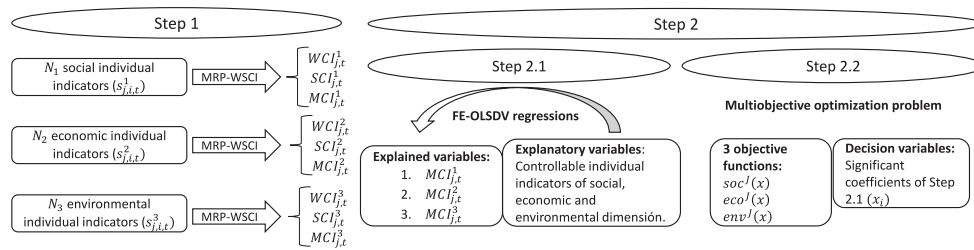


Fig. 1. Steps of the methodology followed in our decision support approach.

Table 1
Individual indicators to study the sustainability of the countries.
Source: Eurostat.

Ind.	Description	Direction	Sub-dimension
Social dimension			
soc ₁	People at risk of poverty or social exclusion	↓	Poverty
soc ₂	In work at-risk-of-poverty rate	↓	Poverty
soc ₃	Agricultural factor income per annual work unit	↑	Agriculture
soc ₄	Government support to agricultural research and development	↑	Agriculture
soc ₅	Healthy life years at birth	↑	Health
soc ₆	Share of people with good or very good perceived health	↑	Health
soc ₇	Self-reported unmet need for medical examination and care	↓	Health
soc ₈	Early leavers from education and training	↓	Education
soc ₉	Tertiary educational attainment	↑	Education
soc ₁₀	Adult participation in learning	↑	Education
soc ₁₁	Gender pay gap in unadjusted form	↓	Gender equality
soc ₁₂	Gender employment gap	↓	Gender equality
soc ₁₃	Positions held by women in senior management positions	↑	Gender equality
soc ₁₄	Population having neither a bath, nor a shower, nor indoor flushing toilet in their household	↓	Poverty
soc ₁₅	Population reporting occurrence of crime, violence or vandalism in their area	↓	Peace/safety
soc ₁₆	General government total expenditure on law courts	↑	Institutional
soc ₁₇	Population with confidence in EU institutions by institution	↑	Institutional

In the 'Direction' column, ↑ means that the indicator is of *the-more-the-better* type, while ↓ indicates that the indicator is of *the-less-the-better* type.

dimension k and by n_k^l the number of single indicators in sub-dimension l of the dimension k , with $l = 1, \dots, C_k$. Based on Tables 1 and 2, $C_1 = 7$, $C_2 = 4$, and $C_3 = 4$, and the values of n_k^l can be obtained accordingly. This way, the weight of every single indicator i of sub-dimension l of dimension k (which was denoted by μ_i^k) is calculated as:

$$\mu_i^k = \frac{1}{C_k} \cdot \frac{1}{n_k^l}$$

- Degree of compensation for the MCI: $\lambda = 0.5$.

The full numerical results obtained can be seen in Tables 14–23 of the supplementary document, which show the WCI, SCI, and MCI for all the countries every year. The information generated in Step 1 can be used to analyze the countries from different points of view. We can study the situation of the countries in one specific year just by looking at the CIs of the three dimensions for all the countries in the desired year.

For example, Fig. 2 shows the WCI values obtained for all the countries in the social (in blue), economic (in orange), and environmental (in green) spheres in 2019. Let us recall that the WCI measures the overall performance of countries in each dimension. We can observe different situations among the countries, and we can compare them to know which one has the best or the worst performance in any of the dimensions. For example, Sweden is the country with the best

performance in the social dimension, since it reaches the highest WCI value, between 2.5 and 3, meaning that it is over the percentile 50, i.e. in 2019 it performed better in the social dimension than at least half of the countries. The worst situation in terms of the social dimension is attributed to Bulgaria.

Concerning the economic sphere, the Netherlands stands out as the country with the best situation from the economic point of view that year, with a WCI value over 3, indicating that in 2019 it performed over the percentile 75 of all countries in this dimension. On the other hand, Romania is the country in the worst situation in this dimension, with a score of about 0.5, meaning that its economic situation in the social sphere was below the percentile 25 in 2019. Similar conclusions can be extracted at a glance for the environmental dimension: Slovenia is at the top of the ranking with a performance between percentile 50 and 75 (i.e. its WCI value for that dimension is over 2.5), while Poland is in the last position with a value of about 1, indicating that it was performing below percentile 25 in this dimension. Apart from this analysis, we can also examine the evolution of the three dimensions in the whole time series, or in part of it, for all the countries under study, although we do not go into more detail to reduce the length of the paper.

In addition, the situation of any of the countries can be studied by revising the three CIs for the three dimensions, in the whole time series. For example, Fig. 3 shows the evolution of the WCI and SCI for Spain from 2010 to 2019. In the left image, we can see the WCI for the three dimensions, giving us an idea of the overall performance of this country

Table 2
Individual indicators to study the sustainability of the countries.
Source: Eurostat.

Ind.	Description	Direction	Sub-dimension
Economic dimension			
eco ₁	Real GDP per capita	↑	GDP
eco ₂	Employment rate	↑	Socio-economic
eco ₃	Investment share of GDP by institutional sectors	↑	GDP
eco ₄	Gross domestic expenditure on R&D by sector	↑	R&D
eco ₅	R&D personnel by sector	↑	R&D
eco ₆	Purchasing power adjusted GDP per capita	↑	GDP
eco ₇	Relative median at-risk-of-poverty gap	↓	Socio-economic
eco ₈	Circular material use rate	↑	Circular economy
eco ₉	Resource productivity	↑	GDP
eco ₁₀	EU imports from developing countries by country income groups	↑	GDP
eco ₁₁	General government gross debt	↓	GDP
Environmental dimension			
env ₁	Primary energy consumption	↓	Energy
env ₂	Energy productivity	↑	Energy
env ₃	Share of renewable energy in gross final energy consumption	↑	Energy
env ₄	Overcrowding rate	↓	Sustainable cities
env ₅	Exposure to air pollution by particulate matter	↓	Pollution
env ₆	Recycling rate of municipal waste	↑	Sustainable cities
env ₇	Greenhouse gas emissions	↓	Pollution
env ₈	Average CO2 emissions per km from new passenger cars	↓	Pollution
env ₉	Bathing sites with excellent water quality by locality	↑	Quality of land/water
env ₁₀	Surface of terrestrial sites designated under NATURA 2000	↑	Quality of land/water

Source:

In the 'Direction' column, ↑ means that the indicator is of *the-more-the-better* type, while ↓ indicates that the indicator is of *the-less-the-better* type.

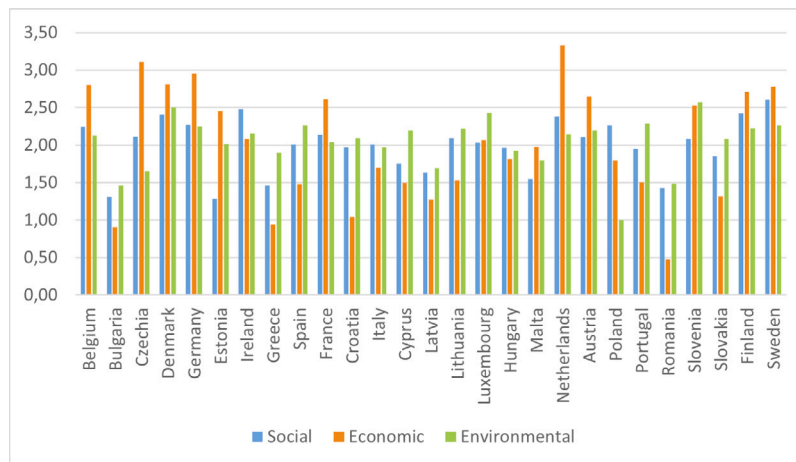
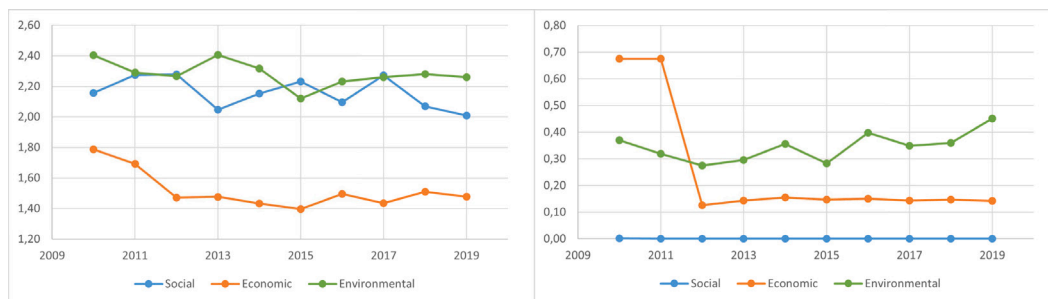


Fig. 2. Sustainability of the European countries in 2019 (WCI).



Weak composite indicator

Strong composite indicator

Fig. 3. Sustainability in Spain, 2010–2019.

Table 3
Controllable single indicators.
Source: Eurostat.

Indicator	Variable	Description	Sub-dimension
<i>soc</i> ₄	<i>x</i> ₁	Government support to agricultural research and development	Agriculture
<i>soc</i> ₇	<i>x</i> ₂	Self-reported unmet need for medical examination and care	Health
<i>soc</i> ₈	<i>x</i> ₃	Early leavers from education and training	Education
<i>soc</i> ₁₃	<i>x</i> ₄	Positions held by women in senior management positions	Gender equality
<i>soc</i> ₁₆	<i>x</i> ₅	General government total expenditure on law courts	Institutional
<i>eco</i> ₃	<i>x</i> ₆	Investment share of GDP by institutional sectors	GDP
<i>eco</i> ₄	<i>x</i> ₇	Gross domestic expenditure on R&D by sector	R&D
<i>eco</i> ₅	<i>x</i> ₈	R&D personnel by sector	R&D
<i>eco</i> ₈	<i>x</i> ₉	Circular material use rate	Circular economy
<i>eco</i> ₁₁	<i>x</i> ₁₀	General government gross debt	GDP
<i>env</i> ₃	<i>x</i> ₁₁	Share of renewable energy in gross final energy consumption	Energy
<i>env</i> ₆	<i>x</i> ₁₂	Recycling rate of municipal waste	Sustainable cities
<i>env</i> ₇	<i>x</i> ₁₃	Greenhouse gas emissions	Pollution
<i>env</i> ₈	<i>x</i> ₁₄	Average CO2 emissions per km from new passenger cars	Pollution

in the three spheres during these 10 years. The right image shows the SCI for the three dimensions, indicating the worst level of performance in the three spheres each year. The WCI shows that Spain has the worst overall situation in the economic dimension, with values of about 1.5 in most years, indicating that in this dimension Spain is performing between the percentile 25 and 50. If, at the same time, we look at the SCI for that dimension, we observe that in 2012 an individual indicator obtained the worst value and that this poor behavior has not improved in the whole time series. This indicator, “General government gross debt” (*eco*₁₁), was greatly affected by the economic crisis in Spain in the years considered. Besides, the SCI of the social dimension reveals that Spain reached the minimum value of all the countries for all the years (its SCI is 0 for this sphere in the entire time series). The data shows that the individual indicator attaining such a bad value was “Early leavers from education and training” (*soc*₈), so special attention should be paid to this aspect in Spain to enhance the social dimension.

4.2. Step 2: Multiple criteria decision making analysis of the sustainability situation of Spain

To show how Step 2 can help learn how a country could improve its level of sustainability, we focus next on the Spanish case as an example.

4.2.1. Statistical analysis to estimate the dimensions’ composite indicators

Here, we use model (9) to regress the MCI of each dimension for Spain (*j* = 9) in 2019 (*t* = 10) (i.e. *MCI*_{9,10}¹, *MCI*_{9,10}², and *MCI*_{9,10}³) on the subset of individual indicators that will be identified as controllable. To simplify the notation, we will refer to these Spanish composite indexes as *MCI*^{soc}, *MCI*^{eco}, and *MCI*^{env}, respectively. From the 38 initial single indicators considered, the indicators in Table 3 are the ones that have a controllable nature. Hence, these 14 individual indicators represent the explanatory variables (*M* = 14) in (9). As shown, five of these controllable indicators belong to the social dimension; there are another five from the economic dimension, and four from the environmental one.⁴ The column “Variable” in Table 3 contains the variable notation used for each controllable indicator.

In Tables 24 and 25 of the supplementary document, we show the descriptive statistics of the MCI and the controllable individual indicators for all the countries in the time series (overall, between, and within). In general terms, the variation in the single indicators arises between countries, reflecting that there are no abrupt changes in the country series. However, the FE model essentially exploits each country’s annual variation (within). The individual indicators with the largest within-country variation are “Self-reported unmet need for

⁴ We would like to clarify that to apply our decision support tool, the number of controllable single indicators chosen from each dimension do not have to be similar, as occurs in this practical example.

Table 4
Estimated regression coefficients of model (9).
Source: Authors’ own calculations.

Indicator	Variable	Social	Economic	Environmental
		(<i>MCI</i> ^{soc})	(<i>MCI</i> ^{eco})	(<i>MCI</i> ^{env})
		$\hat{\beta}_i^1$	$\hat{\beta}_i^2$	$\hat{\beta}_i^3$
<i>soc</i> ₄	<i>x</i> ₁	0.010 (0.756)	-0.007 (0.872)	0.005 (0.914)
<i>soc</i> ₇	<i>x</i> ₂	0.055*** (0.003)	0.007 (0.796)	0.005 (0.871)
<i>soc</i> ₈	<i>x</i> ₃	0.044* (0.058)	0.003 (0.919)	-0.002 (0.899)
<i>soc</i> ₁₃	<i>x</i> ₄	0.027** (0.035)	-0.029** (0.024)	0.010 (0.612)
<i>soc</i> ₁₆	<i>x</i> ₅	0.111 (0.474)	-0.033 (0.816)	0.064 (0.438)
<i>eco</i> ₃	<i>x</i> ₆	0.007 (0.636)	0.052 (0.120)	-0.005 (0.671)
<i>eco</i> ₄	<i>x</i> ₇	-0.045 (0.301)	0.049 (0.421)	-0.0110 (0.804)
<i>eco</i> ₅	<i>x</i> ₈	0.025 (0.786)	0.0508 (0.445)	-0.0322 (0.529)
<i>eco</i> ₈	<i>x</i> ₉	0.003 (0.879)	0.171*** (0.000)	0.072*** (0.008)
<i>eco</i> ₁₁	<i>x</i> ₁₀	0.024 (0.677)	0.186*** (0.004)	0.072 (0.127)
<i>env</i> ₃	<i>x</i> ₁₁	-0.018 (0.638)	-0.007 (0.906)	0.015 (0.811)
<i>env</i> ₆	<i>x</i> ₁₂	0.0048 (0.778)	0.017 (0.573)	0.087*** (0.001)
<i>env</i> ₇	<i>x</i> ₁₃	-0.085** (0.026)	-0.017 (0.689)	0.161*** (0.003)
<i>env</i> ₈	<i>x</i> ₁₄	0.008 (0.790)	0.0135 (0.787)	0.060** (0.025)

Method: FE-OLSDV. Country of reference: Spain. Robust *p*-values in parentheses.

* *p* < 0.1.
** *p* < 0.05.
*** *p* < 0.01

medical examination” (*soc*₇), “Early leavers from education and training” (*soc*₈), “Positions held by women in senior management” (*soc*₁₃), and “Investment share of GDP” (*eco*₃). In contrast, the indicators with the smallest within-country variation are “Government support for agricultural R&D” (*soc*₄), “General government total expenditure on laws” (*soc*₁₆), “Share of renewable energy consumption” (*env*₃), and “R&D personnel” (*eco*₅).

The fixed effects model (9) is estimated using Ordinary Least Squares. Besides, the country-fixed effects and panel-robust standard errors are included to control the serial correlation and heteroskedasticity [38]. The estimated regression coefficients are shown in Table 4, which illustrates the relationships between the controllable single indicators and the MCI of the three dimensions. In addition, we report the

country-specific intercepts in Table 26 of the supplementary document, where Spain is set as the country of reference.

According to these results, the MCI of the social dimension is explained by some of the social individual indicators with a positive slope, considering a statistical significance level of at least 10%, such as “Self-reported unmet need for medical examination and care” (soc_7), “Early leaver from education and training” (soc_8), and “Positions held by women in senior management” (soc_{13}). In contrast, the environmental indicator “Greenhouse gas emissions” (env_7) shows a significant link with the social MCI with a negative slope. Interestingly, this indicator is also positively significant for the environmental sphere. This reflects the conflict between the social and environmental dimensions: while an increase of the value of env_7 would positively affect the environmental MCI, it would imply a negative effect on the social MCI.

The MCI of the economic dimension is significantly described by “Circular material use” (eco_8) and “General government debt” (eco_{11}). Additionally, it shows a negative relationship with “Positions held by women in senior management” (soc_{13}), which is a social sphere indicator that has been found positively relevant for the social MCI. Thus, once again, our results reveal the conflict that exists between the economic and social dimensions. The other economic single indicators, that is, “Investment share of GDP by institutional sectors” (eco_3), “Gross domestic expenditure on R&D” (eco_4), and “R&D personnel by sector” are not significant to estimate the economic MCI.

Finally, the environmental MCI is positively correlated with “Recycling rate of municipal waste” (env_6), “Greenhouse gas emissions” (env_7), and “Average CO2 emissions per km from new passenger cars” (env_8). Reasonably, it is also positively related to the economic indicator “Circular material use” (eco_8). However, the indicator “Share of renewable energy in gross final energy consumption” (env_3) seems to be statistically insignificant.

4.2.2. Multiobjective optimization model for the improvement of sustainability in Spain

Having observed the conflicts between the MCIs of the three dimensions using the statistical analysis, we can formulate the multiobjective optimization problem to examine possible ways to improve the current situation in Spain, as explained in Section 3.2.2.

Using the normalized values of the controllable single indicators described in Table 3, we define the vector of decision variables $\mathbf{x} = (x_1, \dots, x_{14})^T$. To build the objective functions soc , eco , and env in (11) representing Spain’s performance in the three dimensions (for simplicity in the notation, in this example, we have removed the super-index J), we have only considered the regression coefficients β_i^k of the variables in Table 4 with a p -value up to 0.55 (i.e. significant up to 55%). As explained in Section 3.2.2, these regression coefficients have been weighted using their significance level, so they have been multiplied by $(1 - p_i^k)$, where p_i^k denotes their p -value. The same reasoning has been applied to the constant in each objective function (extracted from Table 24–25 of the supplementary document) to also take into account its significance.

We have studied the relationship between the decision variables to formulate the most realistic problem. Given the panel structure of the data, the correlation between the variables has been examined through the overall- R^2 of a panel data model. The results indicated that a strong dependency only existed between $eco_4(x_7)$ and $eco_5(x_8)$. Then, as described in Section 3.2.2, the following two constraints are defined based on the confidence interval of their linear regression coefficients:

$$\begin{aligned} (0.415 \cdot x_8 + 0.237) - x_7 &\leq 0, \\ x_7 - (0.884 \cdot x_8 + 1.180) &\leq 0. \end{aligned}$$

Additionally, lower and upper bounds have been considered for each decision variable. They have been set taking into account not only the maximum and minimum values attained by Spain in each controllable single indicator in the time series but also based on what may be

Table 5

Lower and upper bounds for the decision variables.
Source: Authors’ own calculations.

Variable	x_1	x_2	x_3	x_4	x_5	x_6	x_7
Lower bound	3.00	0.000	0.000	0.000	0.000	0.000	0.000
Upper bound	3.630	4.000	4.000	4.000	4.000	3.540	4.000

Variable	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}
Lower bound	0.000	0.000	0.610	0.390	0.720	0.000	0.970
Upper bound	3.680	3.730	1.050	3.400	3.280	4.000	3.910

Table 6

Values for the three sustainability dimensions (objective functions) in Spain.
Source: Authors’ own calculations.

	Social	Economic	Environmental
Ideal (best) values	1.091	1.251	2.017
Spanish values in 2019	1.004	0.810	1.356
Nadir (worst) values	0.227	0.355	1.136

realistically expected for Spain in the future. Note that we set the bounds according to the original values of the single indicators, and then we normalized them internally according to Eq. (1) to have the bound values in the 0–4 range, as shown in Table 5.

Finally, the multiobjective optimization model for Spain is the following:

$$\begin{aligned} \max \quad & soc(\mathbf{x}) = 0.317 + 0.003 \cdot x_1 + \dots + 0.002 \cdot x_{14} \\ \max \quad & eco(\mathbf{x}) = 0.623 - 0.001 \cdot x_1 + \dots + 0.003 \cdot x_{14} \\ \max \quad & env(\mathbf{x}) = 0.359 + 0.000 \cdot x_1 + \dots + 0.059 \cdot x_{14} \\ \text{subject to} \quad & (0.415 \cdot x_8 + 0.237) - x_7 \leq 0, \\ & x_7 - (0.884 \cdot x_8 + 1.180) \leq 0, \\ & l_i \leq x_i \leq u_i, \quad \text{for } i = 1, \dots, 14. \end{aligned} \quad (13)$$

Next, we investigate the Pareto optimal solutions to this problem to have insights regarding the possible improvements that Spain can attain, the sacrifices needed, and the conflicts among the three dimensions (trade-offs among the objective functions). To this aim, first, we have solved (13) using three evolutionary multiobjective optimization algorithms to approximate its Pareto optimal front: NSGA-II [39], NSGA-III [40] and MOEA/D [41]. The non-dominated solutions obtained by these algorithms have been combined and then filtered to have only the non-dominated ones of all the solutions generated. Fig. 4 shows the approximation of the Pareto optimal front obtained with the resulting non-dominated solutions. In addition, each pair of objective functions is represented in bi-dimensional images (which show the values attained of the two corresponding functions). Table 6 describes the sustainability situation of Spain in 2019 (the last year of the time series) and the ideal (best) and nadir (worst) values that each objective function (i.e. dimension) can attain. Observe that this information supports the fact that the Spanish situation in 2019 could be improved, given that the performance in the three dimensions that year did not reach their best possible values.

Next, we demonstrate which type of information can be extracted from a final Pareto optimal solution of problem (13). As there are multiple Pareto optimal solutions, and all of them are equal from a mathematical point of view, we have used preference information to finally select a satisfactory final solution. To this aim, an interactive multiobjective optimization method is applied, where the decision maker actively participates in the solution process by expressing preferences and progressively refining the solutions generated according to what it learns as the iterations are performed [29]. In this example, as mentioned in Section 1, we have used the interactive evolutionary multiobjective optimization algorithm IRA-EMO [4]. In what follows, we simulate a hypothetical interaction with the Spanish policymakers, and

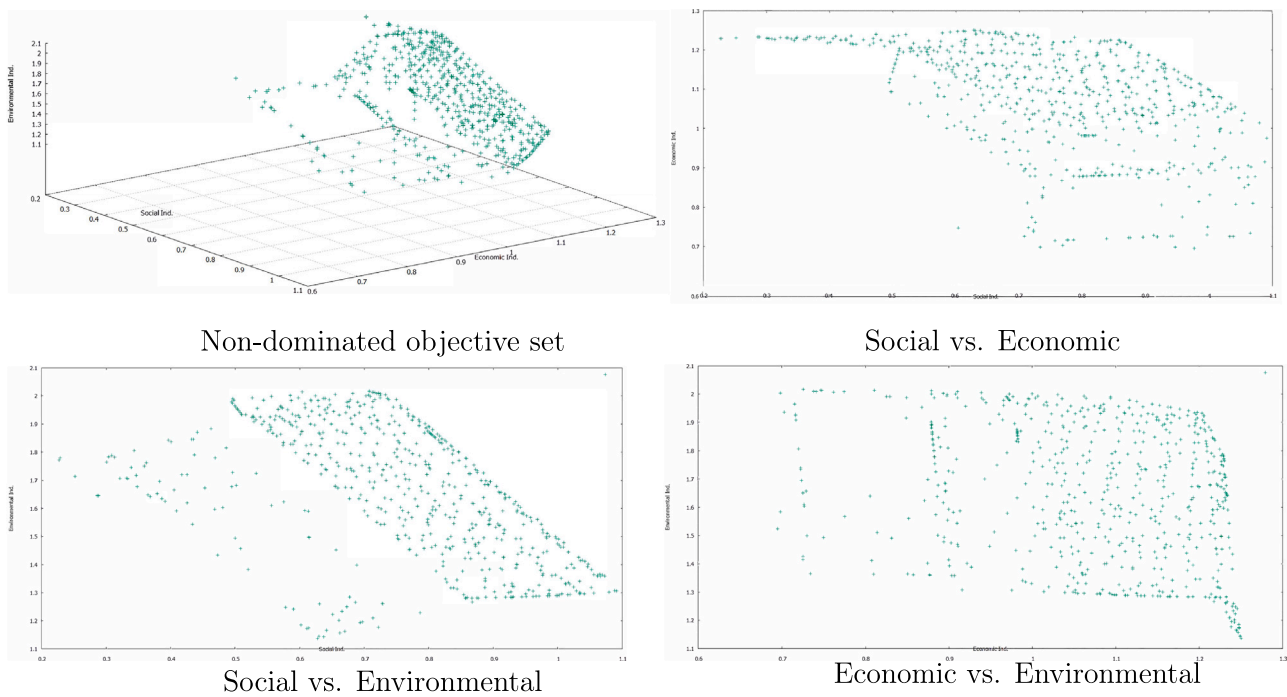


Fig. 4. Approximation of the Pareto optimal front of problem (13).

Table 7
Objective function values of the solutions generated at every iteration.
Source: Authors' own calculations.

Iteration	Sol.	<i>soc</i>	<i>eco</i>	<i>env</i>
<i>Spanish values in 2019</i>				
1	S1	0.525	1.244	1.334
	S2	0.952	1.075	1.413
	S3	0.561	1.182	1.912
	S4	0.828	0.881	1.834
2	S1	0.880	1.142	1.406
	S2	1.032	0.996	1.421
	S3	0.904	1.028	1.585
	S4	0.970	0.890	1.559
3	S1	0.869	1.043	1.629
	S2	0.876	0.973	1.726
	S3	0.901	0.885	1.692
	S4	0.946	0.888	1.605
<hr/>				
Iteration	Sol.	<i>soc</i>	<i>eco</i>	<i>env</i>
<i>Spanish values in 2019</i>				
4	S1	0.799	1.092	1.659
	S2	0.817	0.937	1.845
	S3	0.936	0.888	1.625
	S4	0.858	0.883	1.775
5	S1	0.806	1.156	1.514
	S2	0.836	1.001	1.765
	S3	1.008	0.892	1.486
	S4	0.899	0.885	1.695

therefore, the preferential information used is not real. The solutions produced at every iteration can be seen in Table 7 and their objective function values have also been represented using parallel coordinate bars in Fig. 5. In the following, we describe the reasoning behind every iteration:

- **First iteration:** Initially, we set the RP and the AP using the nadir and the ideal points, respectively, $RP = (0.227, 0.355, 1.136)$ and $AP = (1.091, 1.251, 2.017)$, to review the improvements that can be

achieved for the three dimensions in Spain. Taking into account the situation of Spain in 2019 (in Table 6), none of the solutions obtained could improve the three spheres at the same time (see Table 7). Although nearly all the solutions enhanced the 2019 Spanish values in the economic and environmental dimensions, the social sphere had to be sacrificed in all of them below the 2019 value.

- **Second iteration:** Given that all the social values of the previous solutions remained very close to the ideal value, let us imagine that the policymakers decided to use a higher reservation level. Moreover, we assume that the reservation values for the economic and environmental spheres were set to ensure that the values obtained would not be worse than the ones in 2019. The AP was not changed, so we used $RP = (0.840, 0.810, 1.356)$ and $AP = (1.091, 1.251, 2.017)$. Only S2 improved the 2019 values in the three dimensions (see Table 7). The others reached higher values in economic and environmental performances, but the social dimension got worse. This is due to the limited room for improvement in the social sphere. Furthermore, graphically we can see that the environmental indicator has a wide range of room for improvement (see Fig. 5).
- **Third iteration:** This iteration focuses on the environmental dimension. Since it could achieve values higher than those previously reached, let us assume that the policymakers decided to increase its reservation level. This was the only preference value that changed in this iteration; so $RP = (0.840, 0.810, 1.576)$ and $AP = (1.091, 1.251, 2.017)$. While the solutions obtained performed better in the environmental dimension, as desired, they achieved worse values in the economic and social spheres (see Table 7). However, the environmental values obtained were still far from its aspiration level.
- **Fourth iteration:** Given the sacrifice detected in the social and economic dimensions when enhancing the environmental one, let us assume now that policymakers decided to relax the social and economic reservation levels in order to allow the environmental dimension to reach values closer to its aspiration level. Thus, we used $RP = (0.754, 0.713, 1.576)$ and $AP = (1.091, 1.251, 2.017)$. The solutions obtained were similar to the previous one (see Table 7),

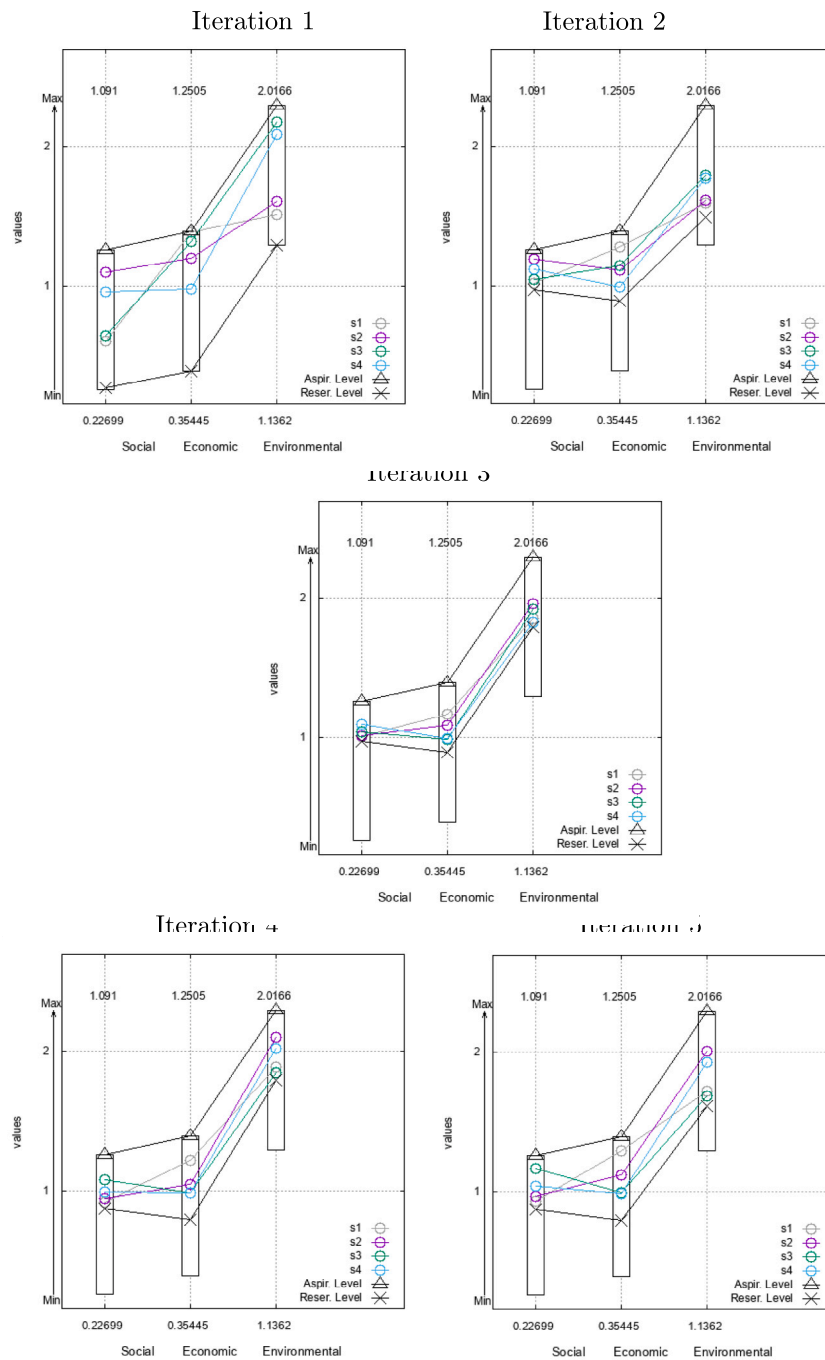


Fig. 5. AP and RP used and solutions generated at every iteration of the solution process.

reaching slightly better values in the environmental dimension, but not as high as desired.

- Fifth iteration:** To obtain balanced solutions, in the last iteration we assume that policymakers decided to reduce the reservation level of the environmental dimension to broaden its range of values. The preferences used were $RP = (0.754, 0.713, 1.418)$ and $AP = (1.091, 1.251, 2.017)$. From the solutions generated (see Table 7), we observed that $S3$ improved the 2019 values of the three indicators, so it was selected as the most satisfactory final solution. The values attained by decision variables of this solution are the following:
 (3.630, 4.000, 4.000, 4.000, 3.540, 0.000, 0.0005, 3.730, 1.050, 0.610, 3.280, 0.777, 3.910).

After the interactive process, we have managed to improve the levels achieved in 2019 in the three areas: in the social dimension, the improvement is minimal (under 1%); in the economic one, we have achieved the greatest improvement (more than 25%), and the environmental sphere has reached 9.5% of improvement. To achieve these values in the three dimensions, it is necessary to improve the results in all single indicators except those corresponding to variables x_7, x_8, x_{11} . The closer the variable values are to 4 (the maximum (best) possible value), the bigger the improvement needed.

5. Discussion

Next, we discuss several aspects to be considered when applying our proposal. First, it must be noted that the theoretical foundations of our

decision support tool do not depend on the time period used. Experts interested in applying our proposal must set the period for the study according to both the availability of data for the single indicators to be used and the purpose for which our methodology is to be applied.

In a real case, an exhaustive sensitivity analysis of some of the parameters used would be needed to study the robustness of the results. For example, different degrees of compensation close to the one chosen (in our example, 0.5) must be tested to define its value knowing its impact on the results. In addition, the threshold correlation level (in our case 55%) must be analyzed. Further sensitivity analyses can be performed on the reference levels used to build the WCI, SCI, and MCI in Step 1. In every case, a sensitivity analysis has to show whether the results obtained are stable and robust if these values are slightly perturbed.

Weights can have a significant effect on the calculation of WCI, SCI, and MCI built in Step 1, and therefore on the results obtained in Step 2 as well. The procedure chosen to set values for the weights in the practical example (see Section 4.1) is just used to show an application of our proposal. For this purpose, in every dimension we assign the same importance to all the single indicators that somehow provide information about the same aspect (i.e. which belong to the same sub-dimension of every dimension). Nevertheless, in the literature, there are many different methodologies to build weights that can be considered instead. For example, the weights can be directly calculated from the data using, e.g. factor analysis, principal component analysis, or data envelopment analysis (DEA). Alternatively, the weights can be estimated without relying on the data using, e.g. Multicriteria Decision Making Methods such as the Analytic Hierarchy Process (AHP) [42,43] or MACBETH [44].

Finally, we would like to remark that the solution techniques applied in the practical example are just used as a proof of concept and can be replaced by more suitable ones if so desired. In Step 1, the OLS method was applied to estimate the regression model because of its simplicity and its widespread use in econometric modeling, although other econometric options can be considered, such as Generalized Least Squares (GLS), ridge regression, or even more advanced techniques such as models based on machine learning. In Step 2, we have solved the multiobjective optimization problem using EMO algorithms for approximating the whole set of Pareto optimal solutions, and with the interactive method IRA-EMO for reaching a final satisfactory solution. Nevertheless, we can apply any other methodology of multiobjective optimization to gain more insights into the possible solutions and to find a satisfactory final solution, which in turn must be selected depending on the needs and preferences of the policymakers.

6. Conclusion

Improving sustainable development and especially sustainability indicators has become a matter of urgency that countries must address without excuses. Although some steps are being taken in the right direction, there are still major challenges that cannot wait. This paper proposes a decision support approach for policymakers to study and analyze how to improve the three main dimensions of sustainability (social, economic, and environmental) for any set of territories. To apply our proposal, panel data is needed for the set of individual indicators intended to analyze the three sustainability dimensions. Step 1 of our decision support approach consists of building CIs for the social, economic, and environmental dimensions, in order to evaluate the performance of the territories. For this purpose, we suggest using a multiple reference point approach to obtain a snapshot of the situation in each country. Once this step has been completed, we propose Step 2, where the focus is the analysis of the possibilities for improving the sustainability situation of any of the territories considered. To this end, we propose building a multiobjective optimization model, given that the three dimensions are in conflict and cannot be enhanced at the same time without sacrifice. The problem is formulated according to

several statistical regressions that allow the CIs of the three dimensions, expressed as functions of the individual indicators identified as controllable.

As a proof of concept, we applied our decision support approach to analyze 27 European countries according to a set of 38 individual indicators from the Eurostat database, from 2010–2019. In Step 2, we focused on Spain. We were able to detect the scope for improving the country's situation and how to achieve good and mutually compensated performances in the three dimensions.

CRedit authorship contribution statement

Ana B. Ruiz: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Sandra González-Gallardo:** Writing – original draft, Validation, Methodology, Investigation. **Mariano Luque:** Writing – review & editing, Validation, Supervision, Methodology, Data curation. **Pedro M. Fernández-Rodero:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Francisco Ruiz:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the Spanish Ministry of Science and Innovation (projects PID2022-139543OB-C42 and PID2020-115429GB-I00) and by the Andalusian Regional Ministry of Economy, Knowledge, Business and University (PAI group SEJ-532).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.sfr.2025.100484>.

Data availability

Data will be made available on request.

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