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Applying multi-criteria decision analysis to combine life cycle assessment with circularity indicators

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ABSTRACT

Monitoring the transition to a circular economy requires not only the measurement of circularity but also of environmental impacts, which often present trade-offs due to different perspectives when assessing a product. This article proposes a novel approach, named ECI-MCDA, to combine circularity and Life-Cycle Assessment (LCA) indicators via Multi-Criteria Decision Analysis (MCDA) non-compensatory methods (Electre I and Electre TRI). The proposed approach includes a clustering analysis to inform the choice of circularity indicators, and a robustness analysis to assess the influence of the MCDA parameters. The ECI-MCDA approach is applied to a multifunctional building sandwich-block (CleanTechBlock) composed of a thermal insulation layer incorporating over 90% recycled glass. The environmental performance and circularity of CleanTechBlock is assessed for different end-of-life (EoL) scenarios, including reuse, closed- and open-loop recycling. The ECI-MCDA approach has demonstrated its efficacy in handling divergent results between circularity and environmental performance, identifying an alternative that addresses both perspectives. Additionally, the proposed approach shows the potential to support decision-making to improve circularity and environmental performance, thereby promoting the eco-design of products.

1. Introduction

The concept of a circular economy (CE) is receiving increasing attention as an alternative to the take-make-dispose system; however, decisions about CE are often simply based on beliefs or metrics that do not explicitly assess environmental performance (Haupt and Hellweg, 2019). Although CE is a widespread topic in the literature, measuring the circularity of a product is still a topic in progress, requiring the development of new and more adequate metrics. Several circularity indicators (C-indicators) have been developed, each focusing on different approaches and interpretations (Saidani et al., 2019b). The literature commonly classifies C-indicators into micro (products, companies, or organizations), meso (eco-industrial parks), and macro (regions, cities, countries, or global economy) levels. However, due to the ongoing debate on C-indicators and the lack of consensus on how to measure circularity (Brändström and Saidani, 2022) or how to select appropriate metrics, multi-indicator frameworks for assessing CE were developed (Niero and Kalbar, 2019). Many authors suggested that C-indicators should not be used individually, as they provide a limited perspective on environmental performance and can potentially conceal burden shifting resulting from increasing energy consumption or polluting emissions (Rigamonti and Mancini, 2021).

Life Cycle Assessment (LCA) is a widely used methodology to assess and quantify the environmental impacts of products (or services). C-indicators and Life Cycle Impact Assessment (LCIA) can reveal different perspectives. In some particular situations, improving the circularity performance might result in a negative environmental impact over the entire life cycle (Saidani et al., 2019a), since CE focuses on product and/or material recirculation and environmental impacts are not assessed. For instance, improvements in resource use efficiency (closed loop) might lead to a rebound effect, wherein production and consumption levels increase, offsetting the environmental benefits (Helander et al., 2019). In addition, the energy used for recycling might result in the release of more greenhouse gases than when obtaining the material from conventional sources (Geissdoerfer et al., 2017).

Although LCA is the most widely used methodology to evaluate CE

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strategies (Corona et al., 2019; Elia et al., 2017; Harris et al., 2021; Sassanelli et al., 2019), combining C-indicators and LCA perspectives has been insufficiently exploited. LCA results have been compared with C-indicators, but trade-offs between circularity and environmental assessment are often at stake affecting the interpretation of results (Rigamonti and Mancini, 2021). Some studies combined LCIA with Material Circular Indicators (MCI). Lonca et al. (2018) revealed trade-offs between the environmental and circular perspectives for the end-of-life of tires showing that extending lifetime through retreading and introducing recycled material improves the MCI of a tire but does not necessarily improve impacts on human health and ecosystems. Glogic et al. (2021) proposed a numerical and visual approach to compare normalized MCI scores with LCIA and discussed possible trade-offs between the results of MCI and LCA applied to alkaline batteries. Mantalovas and di Mino (2020) developed an indicator combining LCA results and MCI, adjusted for asphalt mixtures. Saidani et al. (2019a) developed a framework to link economic profitability, circular economy, and environmental performance in the design phase of products through an optimization model. To our knowledge, Niero & Kalbar (2019) is the only study that coupled two C-indicators with LCIA via the TOPSIS method of Multiple Criteria Decision Analysis (MCDA) for beer packaging. MCDA methods consider a set of alternatives to be evaluated according to a set of multiple, conflicting, and incommensurate criteria for selection, ranking, or rating purposes (Roy, 1991).

The systematic literature review linking MCDA and CE aspects by dos Santos Gonçalves and Campos (2022) highlighted the growth of MCDA studies addressing environmental and management problems for sustainability assessment. Associating MCDA with C-indicators provides the decision-maker (DM) with insights to define appropriate strategies and practices for companies, and contributes to develop new tools to support the transition from a linear to a circular economy. LCA and MCDA are robust decision-making methods commonly employed together for sustainability assessment. Regarding their applications, MCDA can be used to aid in interpreting LCA results by analysing trade-offs among the impact categories. MCDA can attribute significance to impact categories in LCIA (Zanghelini et al., 2018). For instance, Deshpande et al. (2020) evaluated different EoL scenarios (landfilling, incineration, and recycling inland and export) for plastic from fishing gear and ropes in Norway. The authors assessed the environmental impacts through LCA and the results were coupled with Multi-Attribute Value Theory (MAVT) MCDA method. The results revealed that recycling inland is the most sustainable EoL management strategy followed by incineration. Amir-udin et al. (2022) compared recycling technologies for PET bottles and combined LCA with the Analytical Hierarchy Process (AHP) method. Müller-Carneiro et al. (2023) highlighted that MAVT (as well as AHP) is a fully compensatory method, which means that a poor evaluation on one criterion can be offset by very good performance on another criterion. Additionally, the normalization is essential to compare criteria with different measurement units (Vafaei et al., 2016). In contrast, Electre methods are not fully compensatory and elicit more information about the DM's preference, allowing to refuse compensation of very poor performance on some criteria, and they can deal with all types of scales without requiring normalization (Dias, 2021).

Considering the lack of studies that have explored the combination of LCIA and circularity indicators, addressing the differences between them, this article proposes a novel approach (hereafter called ECI-MCDA) that considers both Environmental LCIA and Circularity Indicators (ECI) via MCDA to guide the DM to select the best CE strategy, advancing the state-of-art by using Electre methods. The MCDA methods Electre I and Electre TRI are used in this work, the former being a simpler method to identify a single preferred alternative (or a reduced subset of alternatives deemed incomparable) and the latter being a more sophisticated method to sort the alternatives into predefined ordered classes. As additional contributions to the literature, the proposed approach includes a clustering analysis stage to inform the choice of C-indicators and, considering that several circularity indicators have been created, the clustering methods can be used to assist the DM in selecting groups of indicators that cover different perspectives. Additionally, this paper conducts a robustness analysis (Dias et al., 2002) to evaluate the influence of the MCDA parameters on the results. The ECI-MCDA approach was applied to a novel building block (CleanTechBlock, CTB) composed of a foam glass core as insulation material and clay brick shells as structural components (Rodrigues et al., 2023), which was evaluated for different EoL scenarios.

This article is organized in six sections, including this introduction. Section 2 introduces the ECI-MCDA approach. Section 3 describes the application of the approach to the CTB. Section 4 presents the results of the application. Section 5 discusses the results and Section 6 draws the conclusions.

2. The ECI-MCDA approach

This section presents the proposed approach combining environmental and C-indicators through MCDA methods (ECI-MCDA), which is outlined in Fig. 1. This approach aims to provide a more holistic assessment of a product circularity and environmental performance. The approach is applied to a case study detailed in Section 3. The ECI-MCDA approach includes six steps: I) Building up the life cycle model (goal and scope definition, and Life Cycle Inventory); II) Calculation of environmental impact indicators using LCIA; III) Selection and Calculation of C-indicators using clustering methods according to the CE strategies; IV) Multi-criteria Decision Analysis: Construction of the outranking relation for Electre I and Electre TRI methods, as well as the set of parameters and assumptions established for both the environmental and C-indicators; V) Combination of LCIA and C-indicators results via Electre I and Electre TRI; and VI) Robustness analysis, to evaluate the reliability of the results and the influence of the MCDA parameters on the results and conclusions. The ECI-MCDA approach is an iterative process where the steps are interrelated, allowing going back to adjust the data whenever the succeeding steps require it.

2.1. *Step I – life cycle model, including i) goal and scope definition and ii) life cycle inventory*

The first step consists of defining the goal and scope of the analysis and implementing the Life Cycle Inventory (LCI, data collection of inputs and outputs). This step is based on the two initial phases of the LCA methodology (ISO 14044, 2006, ISO14040, 2006) to build up the life cycle model of the application. It includes the definition of the system boundaries (e.g., cradle to grave) and functional unit (FU), the reference for comparing different alternatives. The alternatives of the application, scenarios, and selection of circular strategies to be assessed are also defined in this step. This step provides data for both the LCA and C-indicators steps (steps II and III), ensuring that the set of C-indicators selected (Step III) aligns with the goal and scope of the LCA. For instance, if the LCA is applied to a product, C-indicators at the micro level must be selected. Nonetheless, some C-indicators can require additional data (e.g., costs, product lifetime, refurbished product lifetime).

2.2. *Step II – environmental impact indicators*

The Life Cycle Impact Assessment (LCIA) involves associating emissions and resources used with specific environmental impact categories to calculate environmental indicators using factors from impact assessment models. This step is the third phase of the LCA methodology, and the LCIA method could be recommended by the European Commission to measure the environmental footprint (European Commission, 2021). An LCA software is typically used to implement the LC model and calculate environmental indicators (e.g., Simapro).

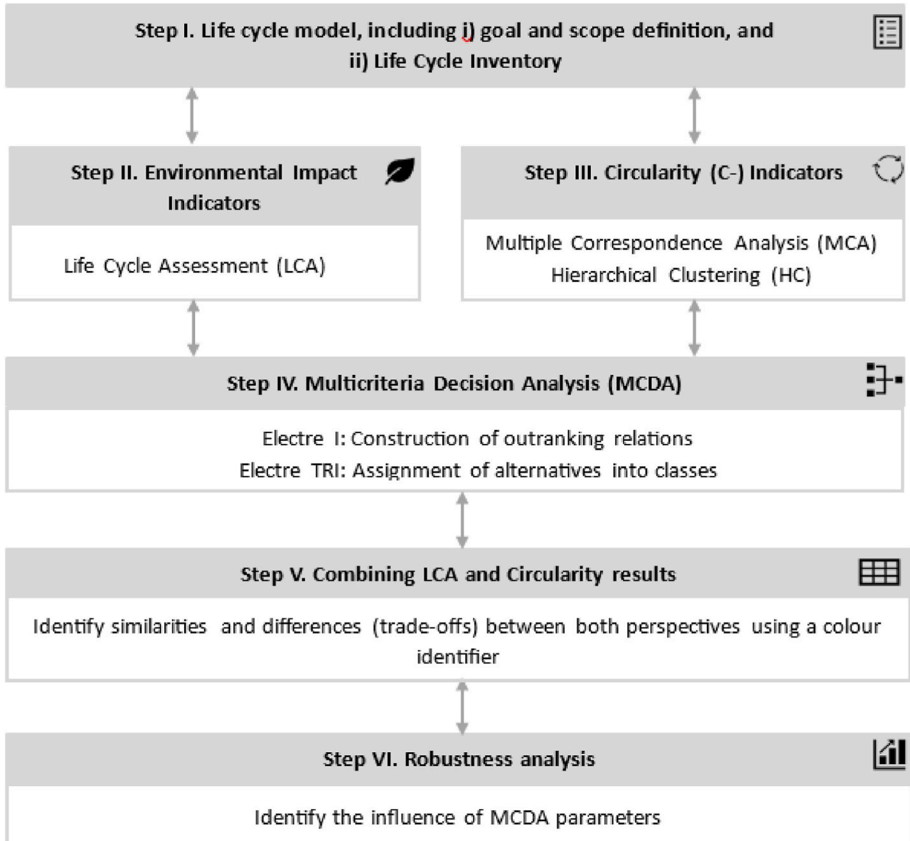

Fig. 1. ECI-MCDA approach.

2.3. Step III – circularity (C-) indicators

Step III describes the selection of C-indicators using the clustering methods Multiple Correspondence Analysis (MCA) and Hierarchical Clustering (HC). MCA is a statistical method to study the associations between qualitative variables, which represents data as "clouds" of points in a multidimensional space and observes the relative position between the variables along the dimensions (Costa et al., 2013). The dimensions represent the highest percentage of inertia or variance, indicating the dispersion of the data along the axes (Rodriguez-Sabate et al., 2017). MCA aims to identify a limited number of dimensions that account for the majority of the variability. The results of the association among the data are displayed on a biplot graph. MCA can be complemented with HC to provide an effective way to analyse the C-indicators. MCA can be used to identify relationships among the C-indicators and their common characteristics, and HC identifies clusters through a dendrogram representation, where the horizontal axis represents the (Euclidean) distance calculated between a pair of scores at a time in the similarity matrix (Yim and Ramdeen, 2015). The dendrogram is a tree diagram that shows the similarity between the data sets and helps determine the number of clusters and which variables belong to each group. Determining the clusters requires choosing a cut-off line. Yim & Ramdeen (2015) pointed out the absence of a strict rule to choose the cut-off and suggested drawing a line that eliminates the long or distant branches. From each cluster, the C-indicators are selected, ensuring the inclusion of at least three indicators, which is the minimum number of criteria typically considered in the Electre method (Figueira et al., 2013).

The inputs are the same for both methods. Statistical software can assist in performing the analysis (e.g., IBM SSPS). The first step is to define the criteria and characteristics for the association. The DM identifies the level at which the case study should be carried out, whether it is micro (products, companies, or organizations), meso (eco-industrial parks), or macro (regions, cities, countries, or global economy). Subsequently, the DM compiles a list of indicators corresponding to the level identified. While there is not a dedicated database, several studies in the literature have listed and classified C-indicators (Kristensen and Mosgaard, 2020; Parchomenko et al., 2019; Saidani et al., 2019b). Once the indicators are compiled, the next step is to classify them based on the CE strategies identified in each indicator. The DM creates a matrix, in which the rows refer to the metrics and the columns refer to the circular strategies. These inputs are qualitative: each element is a "yes" or a "no", depending on whether the strategy is associated with the metric or not. The analysis can be refined with additional data or adjustments to the characterization of the indicators. As more data is included, the representation of variability and diversity improves, leading to a more accurate cluster identification; however, this can represent a challenge when interpreting the associations.

2.4. Step IV – MCDA

Phase IV presents the construction of the outranking relation for Electre I (Section 2.4.1) and Electre TRI (Section 2.4.2). MCDA methods provide insightful decision support in complex problems in which a set of alternatives is evaluated by multiple, conflicting and incommensurate criteria. MCDA methods can be used for identifying the most preferred alternative, ranking alternatives, or assigning alternatives to predefined ordered classes. The MCDA Electre family of methods builds and exploits an outranking relation based on pairwise comparisons of alternatives (Roy, 1991). The alternative *a* outranks alternative *b* (denoted *aSb*) if *a* is at least as good as *b*. The outranking relation holds when a sufficient majority of the criteria agree with it and no criterion strongly disagrees. The Electre methods were chosen due to their relevant characteristics to our problem: the criteria can have scales expressed in different measurement units (costs, meters, etc.), without the need to normalize the data since no operations leading to a synthesis value (e.g., weighted sums) are done. These methods have a non-compensatory nature, enabling them to penalize weak performance in some criteria and can deal with imprecise data (Figueira et al., 2016; Govindan and Jepsen, 2016). For the ECI-MCDA approach, Electre I and Electre TRI can be alternative methods, but they can also be complementary. Whereas Electre I provides more detailed information about how each alternative compares against each other, Electre TRI provides insights on how to improve the baseline scenario, allowing the DM to refine the parameters according to their preferences. The outranking results of both methods can be presented in a tabular format.

2.4.1. Construction of the outranking relation for electre I

Electre I defines an outranking relation on a set of alternatives, denoted $A=\{a_1, \ldots a_m\}$, based on a set of criteria denoted $G=\{g_1(.), \ldots, g_n(.)\}$ (Figueira et al., 2013). Given a pair of alternatives (a_1,a_2), let $\Delta j(a_1,a_2)$ denote the advantage of a_1 over a_2 in criterion g_j. The outranking relation is based on two conditions, the concordance and (non)discordance. The concordance index is the sum of weights of the criteria that agree with the assertion "a_1 outranks a_2" (meaning at least as good as, i.e., agreement means $\Delta j(a_1,a_2) \geq 0$). The concordance threshold (c) represents the majority level required to support the outranking conclusion a_1Sa_2:

$$c(a_1, a_2) = \sum_{j:\Delta_j(a_1,a_2)\geq 0} k_j \geq c$$

where k_j denotes the criterion weights (set between 0 and 1, and adding up to 1).

The (non)discordance condition requires that a_1 cannot be worse than a_2 by a difference greater than the criterion's veto threshold v_j:

$$\Delta_j(a_1, a_2) \geq -v_j, \forall_j$$

Thus, v_j is the maximum acceptable difference between a_1 and a_2 (unfavourable to a_1) that would veto the outranking conclusion a_1Sa_2. If both conditions are satisfied, then one concludes that a_1Sa_2. If a_1 outranks a_2 but not the reverse, then a_1 is preferred to a_2 (and vice-versa). If they outrank each other, they are considered indifferent (sufficiently similar to not declare a winner). If neither alternative outranks the other one, they are considered incomparable (too different to declare a winner without making questionable trade-offs).

The outranking results can be presented as a table (alternatives × alternatives), e.g. using different colours to distinguish which relation applies to each pair. In this work, alternatives that outrank are identified by green cells, the red cells indicate being outranked, the yellow cells denote incomparability (when both alternatives do not outrank each other) and the blue cells represent indifference between alternatives (when both alternatives outrank each other).

2.4.2. Construction of the outranking relation for electre TRI

Electre TRI is a method that sorts the alternatives according to predefined ordered classes (e.g., "bad", "good", "excellent") (this description is based on Dias (2021) and Dias & Mousseau (2003)). The performance of each alternative in $A=\{a_1, \ldots a_m\}$ is compared with each one of the boundaries (profiles) in $B = \{b_1, \ldots, b_{k-1}\}$ that define a set of k predefined classes $(C_1, \ldots, C_k)$. If an alternative a_i under evaluation does not outrank the alternative bounding the first class, it is placed in this worst class, C_1. If a_i is sufficiently good for a_1Sb_1, but not good enough for a_1Sb_2, it is sorted into C_2, etc. The alternative must outrank b_{k-1} to reach the top class C_k.

The concordance index C_j indicates how much the jth criterion agrees with a_iSb_h on a scale between 0 (does not agree) and 1 (fully agrees):

$$C_j(a_i, b_h) = \begin{cases} 0, & \text{if } \Delta_j(a_i, b_h) < -p_j \\ \dfrac{\Delta_j(a_i, b_h) + p_j}{p_j - q_j}, & \text{if } -p_j \leq \Delta_j(a_i, b_h) < -q_j \\ 1, & \text{if } \Delta_j(a_i, b_h) \geq -q_j \end{cases}$$

The parameters q_j and p_j represent the indifference and preference thresholds for the j^{th} criterion, respectively. These parameters allow for imprecision in performances to assess the outranking relation, hence concordance is no longer binary (i.e., just yes/no).

The global concordance index quantifies the importance of the criteria that are in favour of a_iSb_h, considering criterion weights (k_j):

$$C(a_i, b_h) = \sum_{j=1}^{n} c_j(a_i, b_h) \times k_j$$

The discordance index indicates how much the j^{th} criterion disagrees with a_iSb_h in a scale ranging from 0 (does not oppose) to 1 (fully opposes):

$$d_j(a_i, b_h) = \begin{cases} 0, & \text{if } \Delta_j(a_i, b_h) \geq -p_j \\ \dfrac{-\Delta_j(a_i, b_h) - p_j}{v_j - p_j}, & \text{if } -v_j \leq \Delta_j(a_i, b_h) < -p_j \\ 1, & \text{if } \Delta_j(a_i, b_h) \leq -v_j \end{cases}$$

The credibility index $\sigma(a_i,b_h)$ is composed by the concordance $C_j(a_i, b_h)$ and discordance $d_j(a_i,b_h)$ indices (Mousseau and Dias, 2004). The credibility is null if the discordance is maximum (which cannot be compensated by other criteria).

$$\sigma(a_i, b_h) = C(a_i, b_h) \times \left(1 - \max_{j\in\{1,\ldots,n\}} d_j(a_i, b_h)\right)$$

The assertion a_iSb_h is valid if the credibility index $\sigma(a_i,b_h)$ is equal or greater than the cutting level (λ), which represents the required majority level:

$$\sigma(a_i, b_h) \geq \lambda$$

The results can be presented as a table (alternatives × classes). In this work, the assignment of an alternative to a class is identified by green cells, and red cells represent that the alternative is not sorted into the class.

2.5. Step V – combining LCA and circularity results

Step V combines LCIA and C-indicators results of Electre I and Electre TRI. The tabular results from step IV are compared in a new table with the outcomes of the comparative analysis. Similarities and differences between the results obtained in step IV are identified by colours. Therefore, when LCIA and C-indicators lead to same results the scenarios keep their previous colours. In contrast, scenarios with opposite results (when a trade-off is identified) are coloured orange.

2.6. Step VI – robustness analysis

Setting the parameters for Electre I and TRI can be a challenging task (Dias et al., 2002), and the specific values selected can always be questioned. The parameters that most influence the results are the weights, the cutting level (Electre TRI), the concordance threshold (Electre I), and the veto threshold. The robustness analysis aims to evaluate the reliability of the results by identifying how the parameters influence the conclusions. To evaluate the robustness of the results, different combinations of weights and concordance thresholds/cutting levels were tested. The robustness analysis informs the DM on how the changes in the parameters can affect the results.

3. Application: multifunctional building sandwich-block (CleanTechBlock)

3.1. Life cycle model, including i) goal and scope definition, and ii) life cycle inventory (step I)

A life-cycle model was developed to evaluate the environmental impacts of the novel building sandwich-block (CTB) composed of a foam glass core (92% recycled glass), serving as insulation material, and two layers of clay brick shells (Rodrigues et al., 2023). The aim is to assess the environmental and circularity performance of different EoL scenarios, including circular strategies such as reuse, closed- and open-loop recycling. The functional unit selected is one unit of CTB (50 cm of length and 10 cm of height). Each unit (block) includes one layer of foam glass with 38 cm of thickness (1.85 kg) and two layers of clay brick shells (one interior and one exterior), each 4 cm thick each (4 kg each). The foam glass has a thermal conductivity (λ) of 0.037 W/mK with a density of 100 kg/m^3. Detailed information regarding the life cycle inventory, as well as an illustrative drawing of the CTB, is documented in (Rodrigues et al., 2023). A cradle-to-grave model was considered to assess six alternative EoL scenarios based on circular strategies (open- and closed-loop recycling and reuse). The materials and production inventory were adapted from Rodrigues et al. (2023) and Kellenberger et al. (2007). The EoL phase assessed includes the transportation to an EoL treatment plant (recycling or landfill) or a manufacturer (reuse), the energy required to produce aggregates by crushing brick/foam glass, and the burdens from virgin material. Table 1 provides a summary of the different EoL scenarios addressed. All scenarios assume a recovery rate of 90% for foam glass and 70% for brick. The first scenario (SC1) represents the linear model in which all waste is landfilled. In scenarios SC2a/b, only the foam glass is recovered. In SC2a, 90% of foam glass is recycled as a primary aggregate in road pavement. In SC2b, within the 90% of foam glass recovered, 30% is re-incorporated into the production as raw material and the remaining 60% is used as aggregate. For SC3a/b and SC4, 70% of the brick is also recovered to be used as aggregate in concrete production. Only in SC4 is foam glass re-used as insulation without undergoing the recycling process.

3.2. Environmental impact indicators (step II)

The impact categories assessed were selected based on the European standard EN 15804+A2:2019 for the construction sector. In 2019, the European Committee for Standardization revised EN 15804, requiring the use of 10 main environmental impact categories (Table 2), based on

Table 1
End-of-life scenarios.

	End-of-life		
	Foam Glass Recovered	Brick Recycling	Landfill
Scenario 1 – Landfill	–	–	100%
Scenario 2a – Open-loop recycling (foam glass)	90% aggregate	–	10% foam glass 100% brick
Scenario 2b – Open- and closed-loop recycling (foam glass)	30% returns to manufacture 60% aggregate	–	10% foam glass 100% brick
Scenario 3a – Open-loop recycling (foam glass and brick)	90% aggregate	70% aggregate	10% foam glass 30% brick
Scenario 3b – Open- and closed-loop recycling (foam glass and brick)	30% returns to manufacture 60% aggregate	70% aggregate	10% foam glass 30% brick
Scenario 4 – Reuse (foam glass)	30% reuse 60% aggregate	70% aggregate	10% foam glass 30% brick

Table 2
Selected environmental impact categories.

Impact Categories	Units
Climate change (CC)	kg CO_2 eq
Ozone depletion (OD)	kg CFC-11 eq
Acidification (A)	mol H+ eq
Eutrophication, freshwater (Ef)	kg P eq
Eutrophication, marine (Em)	kg N eq
Eutrophication, terrestrial (Et)	mol N eq
Photochemical ozone formation (POF)	kg NMVOC eq
Resource use, fossils (RUf)	MJ
Resource use, minerals, and metals (RUm)	kg Sb eq
Water use (WU)	m^3 depriv.

the recommendations of the most recent guidance for developing Product Environmental Category Rules (PEFCR) published by the European Commission for conducting Product Environmental Footprint (PEF) studies (Fazio et al., 2018; Zampori and Pant, 2019). LCIA results are calculated using the Environmental Footprint (EF) 3.0 method (European Commission, 2021) for the 10 selected categories, which are then combined via MCDA methods as detailed in section 3.4.1.

3.3. C-indicators (step III)

C-indicators have been developed based on CE strategies to measure and monitor progress (Kristensen and Mosgaard, 2020), supporting practitioners, decision makers, and policy makers (Saidani et al., 2019b). Table 3 details the C-indicators at micro-level selected for this study. The C-indicators MCI, PCI, CI, REV CEIP, and CPI were selected based on their use in practice and in comparative studies (Bracquené et al., 2020; Brändström and Saidani, 2022; Glogic et al., 2021; Haupt and Hellweg, 2019; Linder et al., 2020; Walker et al., 2018). Additionally, CC and Agro were chosen for their online accessibility and straightforward application. The MRS indicator is included in the cradle-to-cradle product certification program (Vercoulen et al., 2014). The CEI and LI indicators were selected due to their attributes: CEI measures circularity through economic value and LI through material retention.

The main CE strategies are related to the Rs framework (Jawahir and Bradley, 2016), from 3Rs to 10Rs (de Pascale et al., 2021; Kirchherr et al., 2017; Zhang et al., 2022). Table 4 presents the classification of CE strategies proposed by Potting et al. (2017). It is a well-defined and comprehensive set of strategies that aims at representing the core principles for CE and is used as a framework in academia and industry (Kovačič Lukman et al., 2022). Strategies with high circularity maintain the product in the chain for a long period, reducing resource consumption and waste generation by increasing manufacturing efficiency and making product use more intensive. Table 5 presents the classification of the C-indicators (Table 3) according to CE strategies (Table 4) based on the literature as well as on the classifications proposed by de Pascale et al. (2021) and Kristensen & Mosgaard (2020). It can be noted that each indicator focuses on one (e.g., CI) to five (e.g., LI) strategies. Recycling is the most common CE strategy used to calculate circularity, followed by reduce and reuse. Refuse, rethink, and repurpose are not addressed by the circularity indicators identified in this work. MCA and HC were applied using the IBM SPSS v27 statistical software. The classification presented in Table 5 is the input data to the SSPS software for performing MCA and HC.

3.4. MCDA (step IV) and combining results (step V)

3.4.1. Set of parameters to combine LCIA with Electre I and Electre TRI

For Electre I and TRI, the alternatives are the scenarios (Table 1), and criteria are the impact categories (Table 6) to be minimized. The veto threshold (v_j) was defined in relative terms. If the impact of a_i exceeds the impact of b_h by 50% or more on any criterion, then the outranking

Table 3
Selected circularity indicators at the micro level.

Circularity Indicators	Abbreviations	Description	Units	Reference
Agrocirclewins	Agro	Online tool based on internal and external input and output of mass flow or energy. Circularity is measured by the mass or energy circulated inside a system.	Percentage	Barros et al. (2023)
Circularity Calculator	CC	Online tool for product designers. The circularity is calculated through the inputs of the amount of recycled content, reuse, remanufactured, refurbished, and recycled material for closed loops.	Percentage	de Pauw et al. (2022)
Circular Economy Index	CEI	Ratio of the material produced by the recycler economic value by the material value entering the recycling facility. Requires market price.	Ratio	Di Maio and Rem (2015)
Circular Economy Performance Indicator	CPI	Ratio between the potential environmental savings achieved by recycling the product over the environmental burdens of virgin production followed by disposal.	Ratio	Huysman et al. (2017)
Circular Economy Indicator Prototype	CEIP	Based on 15 questions divided into five lifecycle stages (design, manufacturing, commercialisation, use and end of use). The questions have predefined answers with different scores.	Percentage	Cayzer et al. (2017)
Circularity Index	CI	Multiplication of the rate of recovered EoL material by total material demand and the energy needed for material recovery relative to the energy required for primary material production from virgin ore.	Ratio	Cullen (2017)
Longevity Indicator	LI	Amount of time a resource is kept in use, considering initial lifetime, earned refurbished and recycled lifetime.	Months	Franklin-Johnson et al. (2016)
Material Circularity Indicator	MCI	Formula combines the mass of raw material used in manufacture, the mass of unrecoverable waste attributed to the product, and a utility factor that accounts for the length and intensity of the product's use.	Ratio	Ellen MacArthur Foundation (2015)
Material Reutilization Score	MRS	Formula combines the fraction of recycled or rapidly renewable content in a product with the fraction of material in a recyclable, biodegradable, or compostable product.	Ratio	Vercoulen et al. (2014)
Product Circularity Indicator	PCI	Based on the MCI indicator, with some differences as the addition of waste from manufacturing and post-use.	Ratio	Bracquené et al. (2020)
Retained Environmental Value	REV	Impact of the displaced product or material following any value retention process (after deduction of the impact for recycling, remanufacturing, etc.) to the impact of the original product.	Percentage	Haupt and Hellweg (2019)
Recycling Rates	RRs	Ratio between recycled materials and waste generated after use.	Percentage	Haupt et al. (2017)

Table 4
Circular economy strategies according to the 10Rs.

	Strategies	Concepts
Circular economy ↑	Refuse	Make product redundant by abandoning its function or by offering the same function with a radically different product.
	Rethink	Make product use more intensive: sharing or multi-functional products.
	Reduce	Consume fewer natural resources.
	Reuse	Reintroduction of the product for the same purpose without any modification and with minimal maintenance.
	Repair	Product that can be used with its original function after repair and maintenance.
	Refurbish	Restore an old product and update it.
	Remanufacture	Use parts of a discarded product in a new product with a different function.
	Repurpose	Use products or parts in a new product with a different function.
	Recycle	Process for converting materials into new materials of higher (upcycling) or lower (downcycling) quality.
Linear economy	Recover	Energy recovery through incineration.

Source: Potting et al. (2017).

relation $a_i S b_h$ is vetoed. The weights (k_j) were obtained from the PEF weighting recommendations (Table 6). The weights are standardized by the PEF by identifying the most relevant impact categories and in the PEF studies the weighting step is mandatory (Sala et al., 2018, Zampori and Pant, 2019). The concordance threshold (c) and the cutting level (λ) that represent the required majority level to warrant an outranking are set to 65%; thus, for instance, the coalition of the impact categories CG, RUf, RUm, and WU, with a total weight of 63% is not sufficient to

Table 5
Circular economy strategies identified for each C-indicator.

Circularity Indicators	Reduce	Reuse	Repair	Refurbish	Remanufacture	Recycle	Recover
Agro	x	x				x	
CC	x	x		x	x	x	
CEI	x					x	x
CPI	x					x	x
CEIP	x	x				x	
CI						x	
LI		x	x	x	x	x	
MCI	x	x				x	x
MRS	x					x	
PCI	x	x				x	x
REV	x	x	x		x	x	
RRs						x	

Table 6
Environmental impact categories definition and weightings.

Impact Categories	Units	Weighting (%)
Climate change (CC)	kg CO_2 eq	29.21
Ozone depletion (OD)	kg CFC-11 eq	8.71
Acidification (A)	mol H+ eq	8.61
Eutrophication, freshwater (Ef)	kg P eq	3.90
Eutrophication, marine (Em)	kg N eq	4.06
Eutrophication, terrestrial (Et)	mol N eq	5.14
Photochemical ozone formation (POF)	kg NMVOC eq	6.57
Resource use, fossils (RUf)	MJ	11.51
Resource use, minerals, and metals (RUm)	kg Sb eq	10.43
Water use (WU)	m^3 depriv.	11.85

Source: adapted from Sala et al. (2018).

support the outranking relation.

Electre TRI uses additional parameters. Four classes were established: "much worse", higher environmental impact (C_1), "slightly worse" (C_2), "slightly better" (C_3) and "much better" representing reduced environmental impact (C_4). The linear scenario (SC1) was used as the boundary b_2. The boundaries b_1 and b_3 were set as b_2 plus 25% and minus 25% respectively. For all criteria the indifference threshold (q_j) was set as zero, and the preference threshold (p_j) was set at 10% of the impact of the alternative being compared.

3.4.2. *Set of parameters to combine C-indicators with Electre I and Electre TRI*

To use Electre I and TRI with C-indicators, the alternatives are the scenarios, and the C-indicators are the criteria to be maximized. The weight of each C-indicator was determined by summing weights defined for the CE strategies it encompasses (Table 5). The weights for these CE strategies were distributed linearly following a hierarchy from the strategy considered to be the most circular to the strategy considered to be the least circular (Table 7). For example, in Table 5 the CE strategies that characterized MCI were reduce, reuse, recycle, and recover. In Table 7, the weights corresponding to the MCI CE strategies are 25%, 21%, 6%, and 3%, respectively. The sum of the corresponding weights is equal to 55%. Similar calculations are performed for the chosen indicators. Finally, the weights are rescaled so that their sum is 100%.

Table 7
Weights attributed to the CE strategies.

Circular economy	CE strategies	Weights (%)
	Reduce	25
	Reuse	21
	Repair	18
	Refurbish	15
	Remanufacture	12
	Recycle	6
Linear economy	Recover	3

Again, a veto will occur if the difference between the alternatives is greater than 50% of the alternative to be outranked. The concordance threshold (c) and the cutting level (λ) were set to 65%, so at least two criteria are needed to establish the outranking relation. In Electre TRI, four classes were considered: "much worse" (C_1), "slightly worse" (C_2), "slightly better" (C_3) and "much better" circularity (C_4). The boundaries, indifference and preference thresholds were set in the way already described in section 3.4.1.

3.5. *Robustness analysis (step VI)*

A total of 10,000 iterations were simulated with randomly defined weights, concordance threshold (Electre I) and cutting level (Electre TRI) using uniform distributions. The simulation results are presented as percentages, indicating the frequency with which each alternative outranks the other (Electre I) or the profiles (Electre TRI) for the different iterations.

4. Results

This section presents the results of the ECI-MCDA approach applied to a novel building block considering six EoL scenarios (Table 1): LCIA results for the 10 selected environmental impact categories (Section 4.1); Selection and Calculation of C-indicators (Section 4.2); LCIA results combined via Electre I and Electre TRI (Section 4.3.1); C-indicators combined via Electre I and Electre TRI (Section 4.3.2); Combination of LCIA results and C-indicators via Electre I and Electre TRI (Section 4.4); and robustness analysis (Section 4.5).

4.1. *Life cycle impact assessment*

The LCIA results (Table 8) show that CE strategies lead to lower environmental burdens, as more materials are recovered. The linear scenario (SC1) has higher impacts than the others, although SC2a has the same results in four categories (OD, Ef, Et and RUf). Scenario SC3a presents the lowest environmental impacts in seven categories (OD, A, Em, Et, POF, RUf, RUm). The CE strategies adopted in the EoL scenarios lead to a reduction of environmental impacts by recovering and treating more materials compared to the linear scenario.

4.2. *C-indicators*

This section presents the results concerning the selection of the C-indicators to be used as assessment criteria in the MCDA, aiming at using a diverse and comprehensive range of perspectives while keeping their number as small as possible and avoiding redundancies. For the selected application, although selecting C-indicators directly from Table 5 to encompass all circular strategies could be straightforward, the choice of one among the possible combinations is not as evident, due to the various ways indicators can be grouped. Figs. 2 and 3 present the results

Table 8
Cradle-to-grave life cycle impact assessment results for the CTB (to be minimized).

End-of-life scenarios	CC	OD	A	Ef	Em	Et	POF	RUf	RUm	WU
	kg CO_2 eq	kg CFC-11 eq	mol H+ eq	kg P eq	kg N eq	mol N eq	kg NMVOC eq	MJ	kg Sb eq	m3 depriv.
SC1	10.3	1.63E-06	3.80E-02	3.24E-03	1.09E-02	1.08E-01	3.28E-02	1.39E+02	2.41E-04	1.79
SC2a	10.2	1.63E-06	3.78E-02	3.24E-03	1.08E-02	1.08E-01	3.26E-02	1.39E+02	2.39E-04	1.77
SC2b	10.1	1.62E-06	3.68E-02	2.72E-03	1.04E-02	1.05E-01	3.22E-02	1.38E+02	2.25E-04	1.53
SC3a	10.2	1.10E-06	2.74E-02	2.97E-03	7.82E-03	7.50E-02	2.28E-02	1.02E+02	1.36E-04	1.57
SC3b	9.98	1.60E-06	3.62E-02	2.70E-03	1.01E-02	1.03E-01	3.15E-02	1.36E+02	2.19E-04	1.47
SC4	9.09	1.54E-06	3.20E-02	2.38E-03	9.22E-03	9.30E-02	2.88E-02	1.24E+02	2.10E-04	1.34

Climate change (CC); Ozone depletion (OD); Acidification (A); Eutrophication, freshwater (Ef); Eutrophication, marine (Em); Eutrophication, terrestrial (Et); Photochemical formation (POF); Resource use, fossils (RUf); Resource use, minerals and metals (RUm); Water use (WU).

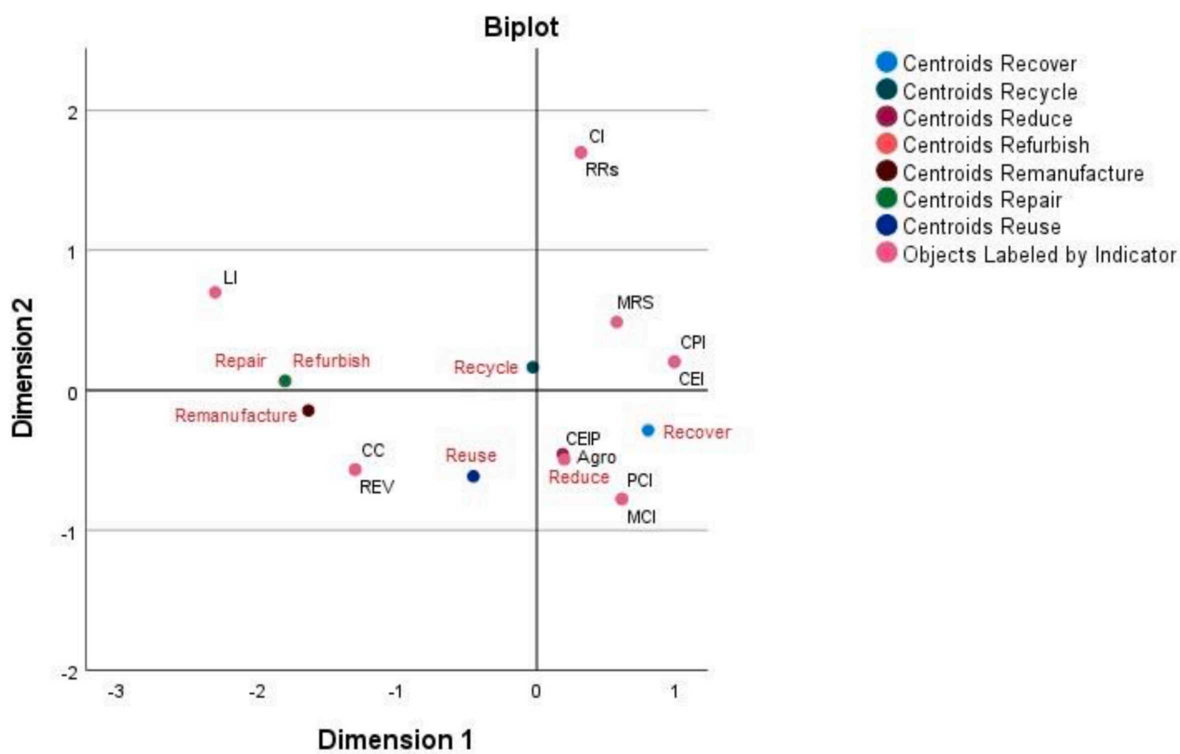

Fig. 2. Relationship between C-indicators (black font) and circular economy strategies (red font) in MCA results.

of MCA and HC, respectively. Fig. 2 presents the C-indicators and CE strategies in a biplot graph generated by SPSS. The horizontal axis explains 41.4% of the variance and the vertical axis explains 21.5%. The proximity of the points indicates a higher association between the variables. In this case, for each C-indicator (Table 3) and each CE strategy (Table 4), the dataset indicates whether the strategy corresponds to the metric or not. The indicators close to each other in the graph represent similarity in their categorization (e.g., CEIP, MCI, Agrocirclewins). The pairs MCI and PCI, CEI and CPI, and CEIP and Agro are characterized by the same CE strategies and, therefore, share the same coordinates. The REV and CC indicators also share the same coordinates, even though the strategies do not coincide, which is possible since the two axes do not explain 100% of the variation. CE strategies such as refurbishing, repair, and remanufacturing are highly associated, which means that they tend to appear together among the C-indicators evaluated. Strategies close to the centre of the graph, such as recycling, are the most frequent in the indicators. The farther a category is from the origin, the less frequent it is and the greater is the characterization of the indicator produced by the category. Indicators distant from the rest are characterized by fewer strategies (e.g., RRs and CI are characterized only by recycling).

Fig. 3 Depicts the dendrogram. The clustering method employed is the Ward Linkage, which focuses on minimizing the variance within each cluster. The red line represents the cut-off line, which determines the number of clusters. In the absence of a specific rule for its placement, it was considered that a minimum of three indicators should be chosen, since the Electre method requires at least three criteria. Fig. 3 presents the three clusters identified: one formed by CEI, CPI, MRS, CI and RRs, another by MCI, PCI, Agro and CEIP, and a third by REV, CC and LI. If more clusters were selected, cluster {CEI, CPI, MRS, CI, RRs} would be split in two: {CEI, CPI, MRS} and {CI, RRs}. However, CI and RRs are focused on recycling strategy only, which is already well covered by the other indicators. Therefore, keeping only three clusters was considered to be preferable.

Selecting one C-indicator from each cluster is sufficient to cover the entire MCA graph. The criterion for selecting the indicators is to choose the indicator from each cluster that covers a broader range of circular strategies. In cases where indicators within the same cluster share the same strategies, the selection is based on some differentiating factor. The selection of C-indicators from each cluster was based on those that cover more circular strategies. Therefore, from cluster 1, among the C-indicators CEI and CPI, the former is selected because it measures circularity through economic value. In cluster 2, MCI and PCI encompass the strategy of recover, which is not included in CEIP and Agro. The application of PCI is more complex, while MCI offers a more comprehensive

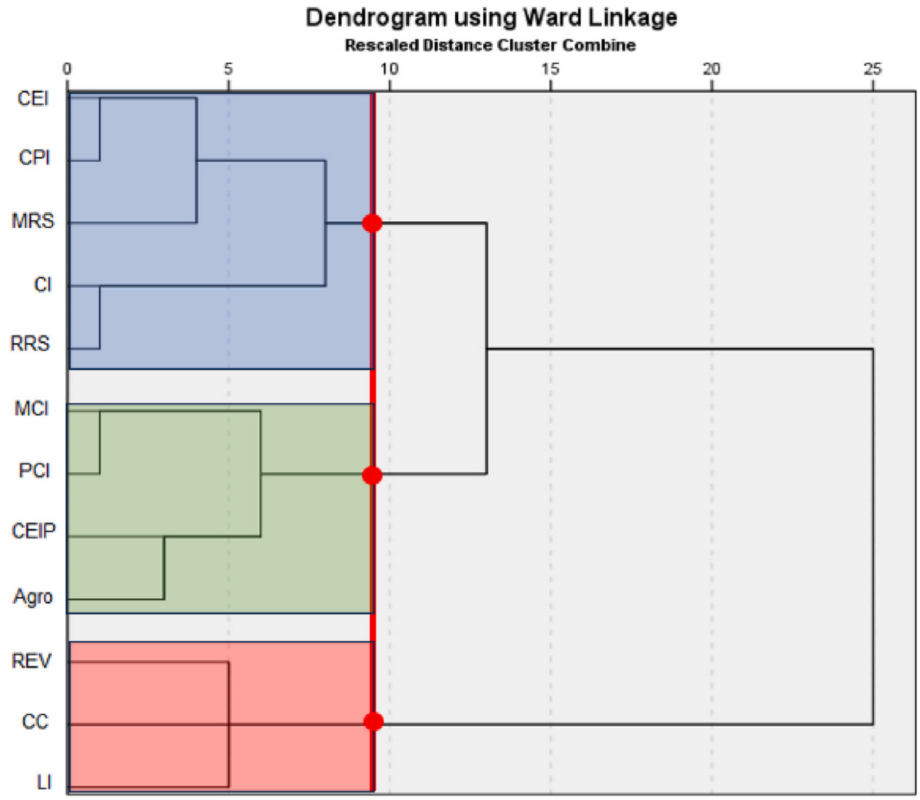

Fig. 3. Identification of the three clusters. In red is the cut-off life, which defines the number of clusters.

assessment. Finally, from the cluster 3, LI includes all three strategies, repair, refurbish and remanufacture, which are not presented together in the other C-indicators. Furthermore, LI is the only indicator that measures circularity through resource conservation.

Fig. 4 depicts the clusters in the MCA biplot graph. Cluster 1 includes indicators characterized by reduce, recycle, and recover. In cluster 2, the indicators are characterized by the recycle strategy. Cluster 3 focuses on the 4Rs (reduce, recycle, reuse, and recover). Cluster 4 includes the

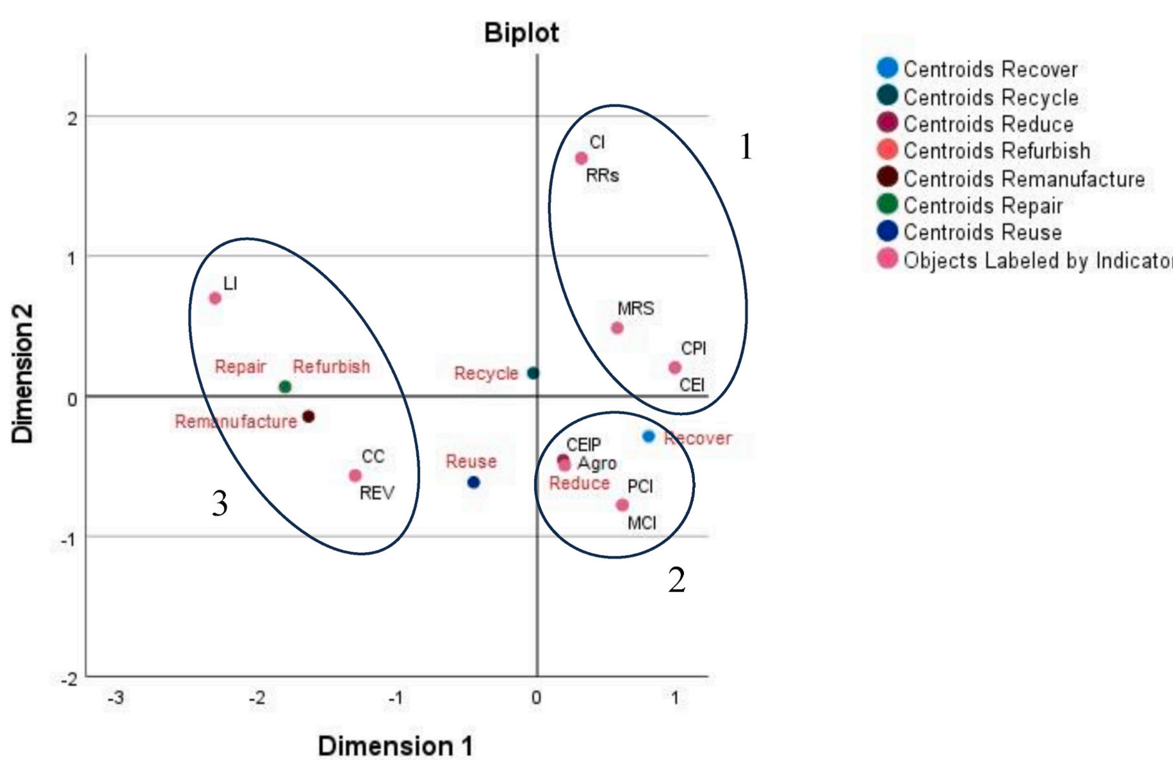

Fig. 4. Clusters representation in the MCA biplot graphic.

indicators that address remanufacture, repair, and refurbishment strategies, as well as recycling and reuse. Considering the weights associated with each strategy (cf. Section 3.4.2), the final weights for MCI, LI and CEI to be used in Electre were set to 34.3%, 51.3% and 14.3%, respectively.

After selecting the C-indicators, the level of circularity is calculated. The inputs to calculate the circularity of MCI and LI are a fraction of the mass of the product being collected for recycling and reuse at the end of its use phase. For the CTB, an efficiency of 90% of the recycling process and a lifespan of 80 years were considered. To calculate the MCI of the CTB, a raw material fraction of 92% from recycled sources was considered. For the CEI parameters, data were collected from two companies that provide waste management, treatment, recycling, and recovery services. The price of treatment of bricks and insulation material was 25 €/t and 145 €/t, respectively. The price considered for the material before recycling was 17 €/t for slightly mixed material (various plastics, cement bags, textile waste, insulation materials, etc.).

Table 9 presents the results of the C-indicators calculation for each scenario. The MCI depends on the level of linear flow (raw material consumption and waste generation) and the utility factor. Since the utility factor remains constant across all alternatives, the linear flow explains the difference in the results. SC1 has the lowest circularity due to the high amount of waste, whereas SC4 attains the highest circularity because the MCI assumes no waste generation when a product is reused for its intended purpose. For the LI indicator, SC1, SC2a and SC2b display lower circularity. The recycling waste rates generated in SC2a and SC2b are similar and very small, resulting in the same circularity as SC1. SC4 has the highest circularity for LI, because of the reused strategy. The CEI indicator measures the value of materials produced by the recycler and the value of materials entering the recycling facility. Therefore, SC1 does not demonstrate circularity as all materials are disposed of in landfill. Since foam glass and brick have the same recycling rates, the outcomes are identical for some scenarios such as the SC2a and SC2b pairs and the SC3a and SC3b scenarios. These indicators assess different strategies, but circularity is measured by the amount of material recovered, which leads to less waste and greater circularity. Hence, circularity increases from the first to the last scenario, thanks to the increase in material recovery, although different EoL scenarios were evaluated. Comparing the results of C-indicators with those from LCIA, the results differ because SC3a has lower environmental burdens whereas SC4 is the best alternative from a circularity perspective.

4.3. MCDA

4.3.1. Electre I and Electre TRI combined with LCIA

The Electre I outranking relation between the different scenarios is depicted in Fig. 5. SC4 and SC3a stand out as the only scenarios not outranked by any other one. The LCIA results had identified SC3a as the scenario with the lowest environmental impacts in most of the impact categories. However, these categories correspond to criteria (OD, A, Em, Et, POF, RUf and RUm) that together account for 55% of the total PEF weighting. Thus, these weights do not attain the 65% majority required to warrant outranking alternatives SC2b, SC3b, and SC4.

Fig. 6 presents the results of the LCIA combined with Electre TRI. All alternatives outrank b_2 (profile to reach C_3). The global concordance was

Table 9
C-indicators result for each scenario (to be maximized).

Scenarios	MCI	LI	CEI
SC1	0.48	960	0
SC2a	0.53	960	7.50
SC2b	0.53	960	7.50
SC3a	0.67	964	8.70
SC3b	0.67	994	8.70
SC4	0.69	1028	8.70

unanimous, leading to the classification of all scenarios in C_3. Although scenario SC3a was close to reaching C_4 if the cutting level was lower, seven out of the ten criteria favoured outranking, but the weight coalition (55%) was insufficient.

4.3.2. Electre I and Electre TRI combined with C-indicators

The results of Electre I show that SC4 outranks all scenarios (Fig. 7). SC4 has greater circularity than the other scenarios because it is the only scenario that reuses foam glass as insulation. The reuse strategy considered in the indicators implies that the product does not undergo any process, resulting in no material losses. Additionally, reuse extends the material lifespan. The blue cells indicate indifference between SC2a and SC2b, i.e., both scenarios outrank each other.

The results of Electre TRI are depicted in Fig. 8. The first scenario (SC1) does not outrank boundary b_1, remaining in C_1 (the worst class). The other scenarios reach the third class (C_3). If the cutting level was just a simple majority of 50%, scenarios SC3a, SC3b and SC4 would reach C_4.

4.4. Combining LCIA results with C- indicators via MCDA

The combination of LCIA results and C-indicators through Electre I and Electre TRI offers an effective way to communicate which alternatives are preferable in Electre I and Electre TRI. Figs. 9 and 10 present the results of Electre I and Electre TRI, respectively. Figs. 9c and 10c present the results of the combination between LCIA (Figs. 9a and 10a) and C-indicators (Figs. 9b and 10b), identifying the similarities and differences between them: common results for LCIA and C-indicators keep their colour. In contrast, scenarios with different results are coloured orange.

Fig. 9a and b indicate SC4 as the most favourable alternative regarding environmental impact and circularity for Electre I. The results combined in Fig. 9c reveal that the main differences observed are due to the incomparability associated with SC3a. As stated in section 3.1, SC3a has fewer environmental burdens, highlighting the influence of the parameters selected to perform the Electre I analysis (an aspect addressed in the robustness analysis section below).

Fig. 10 shows that the results of the LCIA and C-indicators are nearly identical, except for scenario SC1.

4.5. Robustness analysis

Figs. 11 and 12 show the results of simulating the weights and the concordance threshold for Electre I, while Figs. 13 and 14 show the results of simulating the weights and the cutting level for Electre TRI. The percentages indicate the frequency over the 10,000 simulations that each alternative outranks the other (Electre I) or is sorted into a particular class (Electre TRI).

Fig. 11 shows that all scenarios offer robust conclusions, except SC3a. In 100% of the simulations, scenarios SC1, SC2a, SC2b, SC3b and SC4 presented the same outranking result while SC3a's outranking ability depends on the combination of parameter values, showing different outranking frequencies (100%, 81% and 40%). To assess the influence of weights and the concordance threshold, additional simulations were conducted by separately varying only the weights or the threshold. Compared to the results presented in Fig. 11, keeping the PEF weights constant and varying the concordance threshold between 0.50 and 1 reduces the frequency of SC3a outranking SC2a from 81% to 22%, and for SC2b, SC3b and SC4 this frequency decreases from 40% to 22%. Keeping the concordance threshold constant at 65% and varying the weights, the frequency of SC3a outranking SC2b, SC3b and SC4 increases from 40% to 72%, and SC3a outranks SC2b in 100% of the simulations. Therefore, comparing the results in Fig. 11 with those in Fig. 5 (fixed parameters), the incomparability condition regarding SC3a with SC2b, SC3b, and SC4, occurred due to the fixed weights.

Regarding the C-indicators, the results presented in Fig. 12 are consistent with those in Fig. 7 (fixed parameters), identifying SC4 as the

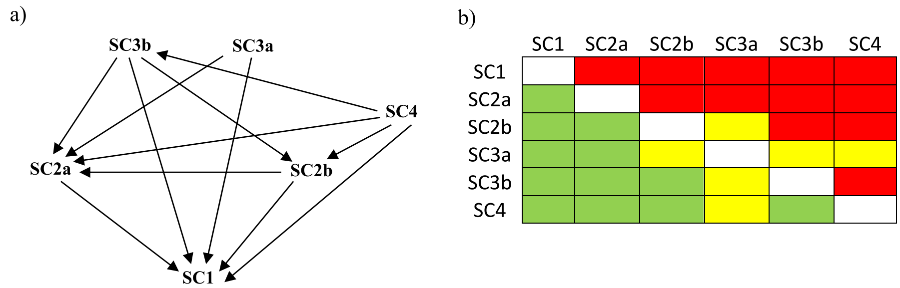

Fig. 5. (a) Scenarios outranking (arrows mean "at least as good as"); (b) Outranking relation in tabular format. Green cells indicate scenarios that outrank, the red cells indicate being outranked, and the yellow cells are denoted as incomparable scenarios (when both scenarios do not outrank each other).

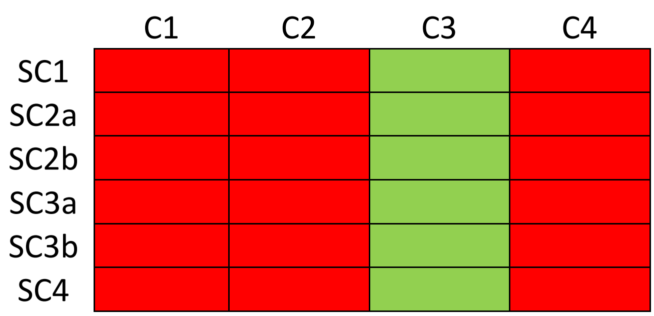

Fig. 6. Classification of scenarios in Electre TRI for LCIA. The four classes are labelled as: "much worse" (C_1), representing the class with higher environmental impact, "slightly worse" (C_2), "slightly better" (C_3) and "much better" (C_4) indicating a reduced environmental impact.

best alternative. When varying the weights and keeping the concordance threshold, the frequency that SC1 outranks SC2a, SC2b increases from 4% to 5% and the same occurs for the frequency that SC3a and SC3b outranks SC4. The frequency of SC3b outranking SC3a also increases from 37% to 54%. When only the concordance threshold varies between 0.5 and 1, the simulations point out that SC3a and SC3b do not outrank SC4, and SC3b does not outrank SC3a since they are worse on criterion LI, which has a large weight.

The robustness analysis of LCIA combined with Electre TRI (Fig. 13) provides more information than the results obtained with fixed parameters (Fig. 6). In Fig. 6, all scenarios are sorted into C_3, and the simulation indicates that SC3a can be also sorted into C_4 depending on the combination of parameters. By only varying the cutting level from 0.5 to 1, SC3a is sorted into C_4 in 10% of the simulations only if $\lambda \leq 0.55$, because when the parameters were fixed the credibility between SC3a and SC3b was 55%, which was less than the 65% required to outrank b_3 (the profile to reach C_4). However, when only the weights vary, SC3a reaches C_4 in 72% of the simulations.

The robustness analysis of C-indicators combined with Electre TRI is shown in Fig. 14. When only the cutting level varies, all scenarios, except SC1, are always sorted into C_3, the same result obtained with fixed parameters. However, when only the weights vary, SC1 is kept into C_1, and the other scenarios are classified in C_3 and C_4, as displayed in Fig. 14 but with different percentages. SC2a and SC2b are sorted into C_4 in 5% of the simulations, while SC3a, SC3b and SC4 reach C4 in 54% of the simulations.

5. Discussion

The application presented in this article to demonstrate the proposed ECI-MCDA approach identified significant trade-offs between the environmental and the circularity indicators results. Scenario SC3a (Open-loop recycling: foam glass and brick) has fewer environmental impacts, whereas SC4 (Reuse of foam glass) results in more circularity. The combination of C-indicators and LCIA via MCDA provides a more comprehensive decision-making framework, that allows the DM to set his/her preferences and values from both circularity and environmental perspectives, leading to the selection of alternatives with both aspects.

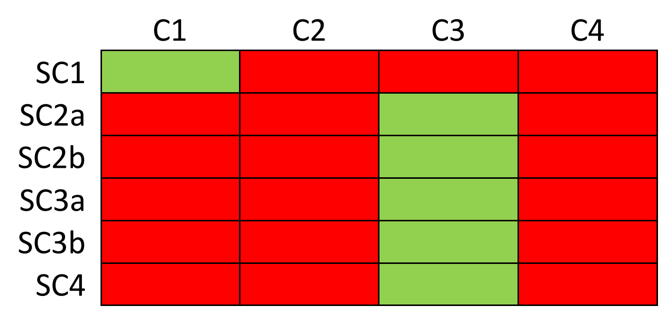

Fig. 8. Classification of scenarios in Electre TRI for C-indicators. The four classes are labelled as: "much worse" (C_1), "slightly worse" (C_2), "slightly better" (C_3) and "much better" circularity (C_4).

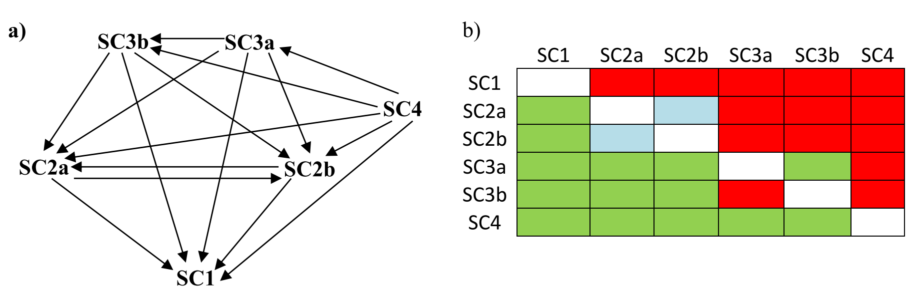

Fig. 7. a) Scenarios outranking (arrows mean "at least as good as"); b) Outranking in tabular format. Outranking relation. Green cells indicate scenarios that outrank, the red cells being outranked, and the blue cells are denoted as indifferent scenarios (when both scenarios outrank each other).

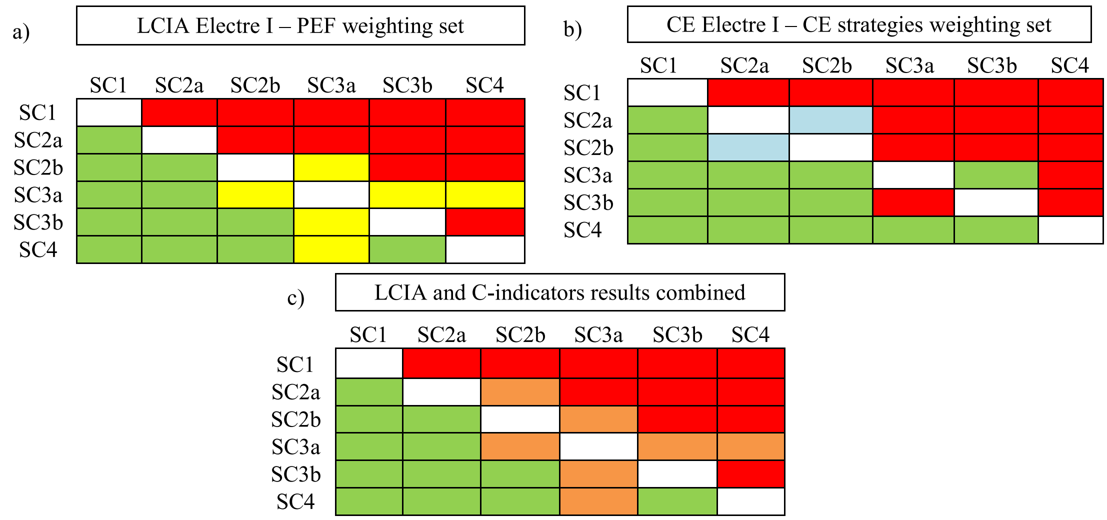

Fig. 9. LCIA and C-indicators results combined via Electre I.

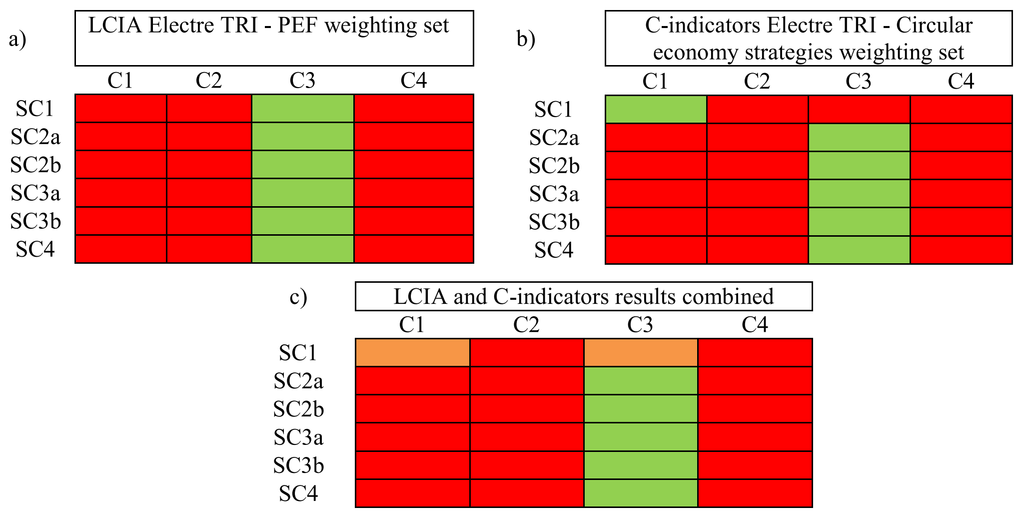

Fig. 10. LCIA and C-indicators results combined via Electre TRI.

	SC1	SC2a	SC2b	SC3a	SC3b	SC4
SC1		0	0	0	0	0
SC2a	100%		0	0	0	0
SC2b	100%	100%		0	0	0
SC3a	100%	81%	40%		40%	40%
SC3b	100%	100%	100%	0		0
SC4	100%	100%	100%	0	100%	

Fig. 11. Outranking frequency for LCIA combined with Electre I for weights and concordance threshold simulations. Green cells indicate the scenario outranks more frequently than it is outranked; the red cells indicate the opposite.

	SC1	SC2a	SC2b	SC3a	SC3b	SC4
SC1		4%	4%	0	0	0
SC2a	100%		100%	0	0	0
SC2b	100%	100%		0	0	0
SC3a	100%	100%	100%		100%	4%
SC3b	100%	100%	100%	37%		4%
SC4	100%	100%	100%	100%	100%	

Fig. 12. Outranking frequency for C-indicators combined with Electre I for weights and concordance threshold simulations. Green cells indicate the scenario outranks more frequently than it is outranked, the red cells indicate the opposite.

Electre I allowed to select SC4 with better performance. In Electre TRI, the classification of the scenarios did not allow for the selection of a specific scenario, which means that the differences between the performance of the scenarios were not significant to establish a clear preference. For instance, if the number of classes were increased, the scenarios could be better discriminated, but the changes in the set of parameters would require more precise and reliable data, which could lead to overfitting of the model. Moreover, further discrimination between the alternatives is provided by the robustness analysis to offer sound decision support.

MCDA and LCA have been employed collaboratively as decision support tools by CE practitioners. Including the C-indicators in combination with MCDA and LCIA can offer to companies a tool to design strategies in the transition to a more CE, as they aim is to monitor the circular progress of products and are a means of communication with consumers and suppliers (Jerome et al., 2022). Additionally, the

	C1	C2	C3	C4
SC1	0%	0%	100%	0%
SC2a	0%	0%	100%	0%
SC2b	0%	0%	100%	0%
SC3a	0%	0%	59%	41%
SC3b	0%	0%	100%	0%
SC4	0%	0%	100%	0%

Fig. 13. Frequency in which the scenarios are sorted in each class for LCIA combined with Electre TRI for weights and concordance threshold simulations.

	C1	C2	C3	C4
SC1	100%	0%	0%	0%
SC2a	0%	0%	96%	4%
SC2b	0%	0%	96%	4%
SC3a	0%	0%	63%	37%
SC3b	0%	0%	63%	37%
SC4	0%	0%	63%	37%

Fig. 14. Frequency in which the scenarios are sorted into each class for C-indicators combined with Electre TRI for weights and concordance threshold simulations.

C-indicators can provide different insights about how circularity could be improved strategies at the early stages of the life cycle of a product (Saidani et al., 2020). However, such approach is time consuming in all its stages and requires managing the uncertainties due to the significant resources and data quality required for LCA and the subjectivity of the DMs to set the MCDA parameters.

The proposed ECI-MCDA approach has demonstrated to be effective in dealing with potential trade-offs between circularity and environmental performance that have been pointed out in the literature (Harris et al., 2021) as a challenge to the decision-making process when choosing an action or strategies to be aligned with both perspectives. Additionally, ECI-MCDA also deals with the subjectivity of DM's preferences by performing robustness analysis to evaluate the reliability of the results and the influence of the MCDA parameters on the results. The ECI-MCDA approach can be applied to different contexts, using the same or a different set of LCIA and circularity indicators. In particular, whenever new circularity indicators appear in the future, the MCA and clustering can be redone to reappraise the choice of indicators to be used.

6. Conclusions

Due to their distinct perspectives, LCIA results and C-indicators can lead to different conclusions for the same product application. CE focuses on maintaining resources and products within the economy, while LCA examines the environmental life cycle impacts of a product. Most previous research has assessed LCA or circularity indicators separately, therefore missing the opportunity to have a richer and more comprehensive picture.

The objective of this article is to propose an application-driven approach (ECI-MCDA) to combine environmental impact and circularity indicators via MCDA to identify the differences between them and guide the decision maker to select the best alternative considering environmental and circular perspectives. Therefore, advancing the state-of-art of combining environmental and circularity indicators via MCDA, non-compensatory methods of the Electre family were proposed, aiming at limiting trade-offs, i.e. the compensation of very poor performance on one indicator by better performances on other indicators. The Electre I and Electre TRI methods offer two different perspectives: the former makes a relative assessment of all scenarios against each other; the latter assesses how each innovation improves (or not) the system currently implemented. Additionally, a clustering analysis was performed to inform the choice of indicators, and a robustness analysis stage evaluated the influence of the Electre parameters on the results thus offering sounder decision support. The ECI-MCDA approach developed in this article was applied to a novel building block (CleanTechBlock) composed of a foam glass core as insulation material and clay brick shells, which was evaluated under different EoL scenarios.

Evaluating the stand-alone LCIA and C-indicators results, SC3a (open-loop recycling: foam glass and brick) presents fewer environmental impacts in most categories, whereas SC4 (reuse of foam glass) is the most favourable scenario in terms of circularity. Interestingly, the LCIA and C-indicators results for Electre I were never contradictory. If a scenario was preferred under one perspective, the same occurred under the other perspective, or the other perspective did not provide a clear preference (indicating indifference or incomparability). The Electre TRI results for the LCIA and C-indicators differed for only one scenario.

Combining the indicators through MCDA indicated SC4 as the best alternative from circular and environmental perspectives for Electre I, whereas for Electre TRI their classification was the same. The robustness analysis explored an extensive range of possibilities (10,000 simulations) by varying the weights, the concordance threshold, and the cutting level associated with the outranking relation. Combining LCA with Electre I and Electre TRI revealed that SC3a was the most sensitive scenario. Regarding C-indicators, the results were robust for Electre I and TRI. The robustness analysis showed that some scenarios could reach the highest class. Varying the weights in Electre I and Electre TRI increase the possibility of having a strong coalition that allows the scenarios to outrank others. Conversely, varying the cutting level or the concordance threshold changes the level required for scenarios to reach the highest classes. The simulations offer a more comprehensive understanding of the results obtained with distinct decision maker's preferences, highlighting which conclusions are robust. By combining LCA and circularity indicators, the decision maker can identify the environmental benefits and trade-offs associated with implementing CE strategies.

This article is limited by its application to a single product and by using a specific MCDA type of method. In future studies, it would be valuable to assess additional case studies involving different CE strategies that provide practical insights into combining C-indicators and LCA via MCDA methods. Future studies can also compare different types of MCDA methods to assess the different insights they might provide and their adequacy to distinct decision support settings.

CRediT authorship contribution statement

Erika Barrak: Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Carla Rodrigues:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Carlos Henggeler Antunes:** Writing – review & editing, Funding acquisition, Conceptualization. **Fausto Freire:** Writing – review & editing, Supervision, Conceptualization. **Luis C. Dias:** Writing – review & editing, 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.

Data availability

Data will be made available on request.

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