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Abstract: In line with the EU's goal of climate neutrality by 2050 set out in the green deal, the European Commission has proposed a new action plan for the circular economy development. The goal is to identify specific indicators able to provide a measure of circularity at a macro level. The objective of this study is to contribute to this effort by determining the most relevant criteria that business and academic experts can use to identify additional sub-criteria for the degree of circularity of the economy at a macro level. To this end, the study considers four macro indicators and 15 sub-indicators taken from the Eurostat circularity indicators database. The fuzzy AHP analysis has been used to rank indicators and sub-indicators. The proposed study highlights that the main criteria, exhibiting a vast potential to influence the circular economy, are the indicators 'competitiveness and innovation' for academic respondents and 'secondary raw materials' for business respondents, while patents related to recycling and secondary raw materials are the most significant sub-indicators.

Keywords: circular economy; fuzzy AHP; environmental indicators; circularity assessment.

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1 Introduction

The paradigm of the circular economy (hereinafter CE) enhances the principle of material efficiency through a rational and appropriate use of resources during all phases of the production cycle minimising, as well, the waste production. The overall goal is overcoming the take-make-dispose model in which materials are collected, transformed into products that at the end of their life are discarded as waste (Murray et al., 2017). To do this, it becomes important to shift to a restorative and regenerative economy allowing the recycling and recovering of many materials instead of being produced by primary extraction (Braungart et al., 2007; Ghisellini et al., 2016; Lieder and Rashid, 2016).

Conversely, CE focuses on more specific topics such as industrial symbiosis, clean and efficient production eco-efficiency, eco-efficient design (Blomsma, 2018; Zhao et al., 2020; Pardo Martinez, 2013; Selinšek et al., 2021).

Furthermore, the adoption of the CE could incentivise different solutions to the environmental issues of the industrial production system addressing a waste-free production value. For instance, it is possible to mention:

1 The eco-design of the products that has the main objective to extend the durability of items creating modular and decomposable parts for a correct management of downstream waste.

2 The replacement of virgin raw materials with secondary raw materials and biomaterials.

3 The control and management of return flows of end-of-life products for a sustainable supply chain (Agyemang et al., 2019; Rossi et al., 2016).

Therefore, the transition to the CE will also contribute to achieve different goals set out in the 2030 agenda for sustainable development, as SDGs six on energy, eight on economic growth, 11 on sustainable cities, 12 on sustainable consumption and production, or 13 on climate change.

For this reason, the EU has extensively discussed the different role played by CE in the economy, such as in planning new labour policies and finding indicators to measure and monitor progress toward achieving CE.

In the first case, the promotion and implementation of measures that address new professional retraining and training of workers, can create new jobs, namely green jobs, that use environmentally sustainable solutions and production techniques such as reuse of materials, renewable energy, green building, redevelopment of old industrial plants, or increase the degree of digitalisation through Industry 4.0 (IISD, 2020; Bach and Sulíková, 2021; Mirolyubova and Voronchikhina, 2022). Considering the second case, related to indicators to measure CE, the European Commission has issued the action plan on the CE, which states "the need for a control panel to strengthen and verify the progress towards the CE, and in the meantime minimise the bureaucracy" (European Commission, 2015).

For this reason, it has become strategically important to identify specific indicators able to provide a measure of circularity, also adopting public procurement as strategic lever for reducing environmental impact (Davtyan and Piotrowicz, 2021). Specifically, indicators must include several aspects such as decoupling resource use and environmental impact, improving resource efficiency and minimising waste production for recreating new lines of business (EASAC, 2016). These considerations suggest that it is very difficult to summarise indicators that can measure CE both in economic sector and performance organisation. The problem is that, while some aspects – such as the amount of renewable materials or the amount of reused elements – are easily measurable, other benefits, such as the extension of the useful life of a product, or of all sharing activities, are less tangible. There is, however, no agreed global vision of how a company or the economic sector can truly close the loop. The issue of metrics in the CE is highly topical and quite complex. However, several organisations and companies have developed metrics to measure circularity not only on a micro level but also on a macro level. Among the most relevant are the Ellen MacArthur Foundation's work whose goal is to support companies in their transition to CE systems, regardless of sector, structure and size or the circularity gap report of circle economy (Circle Economy, 2021), which measures the circularity of entire countries. Furthermore, back in 2018 the International Organisation for Standardisation (ISO), which is globally responsible for setting technical standards, created a technical committee dedicated to the CE. The technical committee in question, ISO/TC 323, aims to cover all individual aspects of the CE, including public procurement, production and distribution, end-of-life, as well as broader areas such as behavioural change in society, evaluation and, again, the creation of a circular footprint or circularity index.

There is still a lack of research literature to identify the progress towards CE at macro level and to help policy makers' judgments. To this end, the main research question has been: What indicators can be selected to facilitate the CE at macro level and what are the most relevant indicators to be used for addressing the CE at macro level? This research seeks to answer to the following question: how to create a hierarchy among the various CE indicators for helping practitioner communities to determine which productive economic areas have the greatest impact on a country's circularity and, on which macro indicators to target economic incentives and legislative policy to encourage a country's transition to a higher rate of circularity. To fulfil this objective, Eurostat circularity indicators at macro level have been used, grouped into four macro-indicators and into 15 sub-indicators. The macro-indicators are the following:

1 production and consumption

2 waste management

3 secondary materials

4 competitiveness and innovation.

Therefore, the fuzzy AHP analysis has been used to rank indicators and sub-indicators, highlighting point of view both of academic and business. Some recent studies at macro have developed CE indices based on Eurostat indicators. Comparing with the current literature on CE at the macro level, it appears that Mitrović and Veselinov (2018) elaborated the circular economy index (CEI) of 11 indicators divided into three groups of sub-indices:

1 sustainable resource management

2 social behaviour

3 business operations and developed through data envelopment analysis.

Using the catastrophe progression method to estimate CE competitiveness, Karman and Pawłowski (2022) proposed a composite index called circular economy competitiveness index (CECI), consisting of 30 indicators grouped into four pillars:

1 resource management

2 societal behaviour

3 business operations

4 innovativeness.

Although Garcia-Bernabeu et al. (2020) recognise that there is no composite CE indicator that shows the overall overview of the CE country's performance, they proposed a monitoring CE framework and a CE composite index with 17 indicators based on TOPSIS that reveals three sustainability perspectives: weak, strong, and limited. These studies have grouped similar indicators based on Eurostat databases and have created a hierarchic index with appropriate weighting. Our study follows a similar logic, but the novelty of our contribution that fills the research gap is the use of the fuzzy AHP methodology with expert opinions to analyse individual indicators. More specifically, we use the opinion of academics and business representatives who have experience and expertise in CE performance and measurement indicators, making the analysis different from the previous research, based on expert-based guidance for prioritising the most relevant indicators for the transition from a linear to a CE. No previous study has adopted this methodological approach for this type of analysis.

The rest of the paper is arranged as follows. Section 2 illustrates the literature review on existing circularity indicators. Section 3 explains the logical steps of fuzzy AHP methodology. Section 4 discusses the results by CE indicators and sub-indicators. Finally, the main findings and concluding remarks are reported.

2 Outlook of existing circularity indicators

In what follows we expound the main indicators at macro level used to analyse the progress into CE. For the sake of clarity, the literature review is discussed in each sub-section of the paper.

Most existing literature has focused on the development of indicators to measure the circularity at micro level (such as a product or firm), meso level (such as industrial parks) and macro (such as a region or country). This growing interest in the circular indicator depends mainly on the need to identify the characteristics and quantity of the resources used (matter, energy, water, and air/emissions) in an input-output process to assess the level of efficiency of their management. Bailey et al. (2008) highlight the importance of the input–output cycling metrics to estimate the percentage of both direct and indirect flows that are recycled in a system. Figge et al. (2018) propose and develop indicators for both circularity and longevity to contribute to the sustainability of an organisation. Saidani et al. (2019), Parchomenko et al. (2019) and De Pascale et al. (2021) analyse and scrutinise the different circular indicators which can incentivise the use of virgin resource and increase eco-efficiency. Sassanelli et al. (2019) make a systematic literature review of CE performance and confirm that circular models can be measured taking care of different aspects. Other studies have focused on the creation of a framework according to

CE policies. For instance, Moraga et al. (2019) group different CE indicators in a ladder classifying them as strategies to: "preserve the function of products, preserve the product itself through lifetime; preserve the product's components through the reuse, preserve the materials through recycling and down cycling; preserve the embodied energy through energy recovery, and measure the linear economy as the reference scenario." Pauliuk (2018) proposes a dashboard of existing and new CE performance indicators at an organisational and product system level with the BSI standard.

Another strand of literature provides macro-level indicators to assess circularity within an economic system. Especially, in the EU, different organisations have suggested a set of indicators for the measurement of CE. In this context, the indicators that deserve attention are those developed by:

1 The International Resource Panel (IRP)

2 The Ellen Mac Arthur Foundation

3 Eurostat.

International Resource Panel (UNEP, 2017) proposed the report 'resource efficiency: potential and economic implications' which defines two categories of indicators. The first one quantifies resources based on a physical unit; the second one measures the efficiency of the level of conversion of resources into products destined for the market.

The Ellen MacArthur Foundation (2022) promotes the material circularity indicator (MCI). The MCI is composed of ten indicators, divided into two categories: the first group analyses the circularity of the company: the second group does not directly measure circularity (for this reason, it is not included in Table 1) but is divided into risk indicators (price and volatility of raw materials, supply, scarcity, or legislative) or impact indicators, such as CO_2 emissions and water consumption on circular system.

Eurostat (2022) developed four main indicators and 15 sub-indicators which represent the official monitoring tool of the EU through key indicators that include the main and most representative aspects of the CE.

Another study on the metrics of CE that deserves to be mentioned is the global circularity metric (Circle Economy, 2021) which measures the circularity of the global economy of a particular year, by calculating the part of non-virgin raw materials on the total of raw materials used.

The global circularity metric is a single indicator able to calculate the overall circularity of the reference system: the resource efficiency scoreboard which is based on statistics data from Eurostat and the European Environment Agency (EEA) and other EU/international sources. The first report was issued in 2014 and the first full version of the Scoreboard in 2015. However, the data continues to be updated annually. It is developed by using a three-tiered approach which combines 32 different indicators:

1 An overall lead indicator for 'resource productivity'.

2 A second tier 'dashboard' of complementary macro indicators for materials, land, water, and carbon.

3 A third tier of theme-specific indicators to measure progress towards key thematic objectives, and the actions and milestones set out in the roadmap.

Table 1 Framework of CE indicators at macro level

Indicator	*Description*	*Organisation and researchers*
a Material flow analysis		
Direct material flow	Raw materials (excluding water and air) taken from the natural environment to be used in economy	
Materials import	Imports in physical weight	
Material exports	Exports in physical weight	
Direct input material	Sum of domestic withdraw and material imports	UNEP (2017) l
Consumption of domestic material	It is the input direct material from which material exports are subtracted	
b Equivalent raw material		
Imports of equivalent raw material	Amount of imported raw materials	
Export of raw material equivalent	Amount of exported raw materials	
Raw material input	Sum of domestic levies and imports of raw materials	
Raw material consumption	Difference between raw material inputs and raw material exports	
Natural resource		
Technical efficiency	Raw materials transformed into a usable product	
Resource productivity	Relation between an output measured in economic terms and the input from which it is derived	
Resource intensity	Relation between emission and resources	
Resource efficiency	Environmental impact of material extraction	
Economic efficiency	Economic value of input and output	
Virgin raw material	Percentage of raw material recycled in a product	
Non recoverable waste	Percentage of waste that is reused, recycled, incinerated, or land filled	Ellen MacArthur Foundation (2022)
Linear flow index	Percentage of material that has a linear trend in the process (virgin material in input, non-recyclable waste in output)	
Usage index	Useful life of the product both in terms of time and intensity of use	
Production and consumption		
Self-sufficiency for raw material	Share of raw materials including critical raw material used in the EU and produced within it	
Generation of municipal waste per capita	Share of municipal waste disposed	Eurostat (2022)

Note: *Split in other sub indicators.

Table 1 Framework of CE indicators at macro level (continued)

Indicator	*Description*	*Organisation and researchers*
Production and consumption		
Generation of waste excluding major mineral waste per GDP	Comparison of waste generated to GDP for calculating the waste intensity	
Generation of waste excluding major mineral wastes per domestic material consumption.	Indicator that monitors the efficiency of EU material consumption by comparing the tons of waste generated to domestic material consumption (DMC).	
Waste management		
Recycling rate of all waste excluding major mineral waste	Waste recycling, excluding the main mineral residues	
Recycling rate for packaging waste by type of packaging	Recycling of all packaging, wooden packaging, plastic packaging, etc.	
Recycling rate of e-waste	Percentage of recycled electronic waste	
Recycling of bio-waste	Percentage of municipal waste over the total population	
Recovery rate of construction and demolition waste.	Percentage of demolition waste prepared for recycling	
Secondary raw material		
Contribution of recycled materials to raw materials demand end-of-life recycling input rates	Share of recycled material used in the economy	
Circular material use rate	Share of material recovered and fed back into the economy – thus saving extraction of primary raw materials	
Trade in recyclable raw materials	Intra EU trade of selected recyclable raw materials	
Competitiveness and innovation		
Private investments, jobs and gross value added related to circular economy sectors	Investment in tangible goods	
Patents related to recycling and secondary raw materials.	Number of patents related to waste management and recycling	

Note: *Split in other sub indicators.

Table 1 Framework of CE indicators at macro level (continued)

Indicator	*Description*	*Organisation and researchers*
Circular economy index		
Sustainable resource management index (SRMI)	SRM1 – resource productivity (Euro PPS per kg)	Mitrović and Veselinov (2018)
	SRM2 – recycling rate of municipal waste (%)	
	SRM3 – recycling rate of e-waste (%)	
	SRM4 – circular material use rate (%)	
Societal behaviour index (SBI)	SB1 generation of municipal waste per capita (Kg per capita)	
	SB2 – citizens who have been chosen alternatives to buying new products	
	SB3 – repair of computers and personal and household goods	
	SB4 – repair of computers and personal and household goods	
Business operations index (BOI)	BO1 – share of enterprises that facilitated recycling of products after use	
	BO2 – Enterprises that extended product life through more durable products, by innovating	
	BO3 – Enterprises that recycled waste, water or materials for own use or sale within the enterprises by innovating	
CE competitiveness index		
Social behaviour	Waste household*	Karman and Pawłowski (2022)
	Energy and material consumption households*	
Business operation	Energy and material consumption industry*	
	Waste industry*	
Resource management	Recycling*	
	Recycling specific waste (e-waste, bio-waste, plastic)*	
	Recovery*	
	Circularity*	
Innovativeness	Eco innovation index*	
	Investment*	
	Green economy*	

Note: *Split in other sub indicators.

The Organisation for Economic Cooperation and Development, (OECD, 2021) elaborated the inventory of circular economy indicators. The indicators were gathered from 29 CE studies applied at national and local level with the general goal to track the progress of existing CE strategies.

The inventory is characterised by five main categories (economy and business-environment, governance, infrastructure technologies and jobs) and for each indicator 33 sub-categories are hierarchised according to specific sectors. The inventory is regularly updated given the progress made by countries, regions, and cities in developing CE action and related measurement frameworks. Infrastructure, food, mobility, consumer goods, services, health, and communications are analysed. Table 1 reports the most important CE dashboard indicators at macro level developed by organisations and researchers.

Some European countries are developing their own models. In Italy as well, it is possible to cite ENEL (2021) which developed the *CirculAbility* model, which measures circularity based on five pillars: sustainable inputs, sharing, product as a service, product life extension and end-of-life. The model defines a single circularity index, calculated from two components: flow circularity, which considers all material and energy components at the stages of: input (if renewable, from recycling, from reuse, etc.); output (to recycle, to reuse, to landfill).

3 Methodological framework and data

To define the indicators of highest impact on circularity performance, we use the fuzzy analytic hierarchy process (fuzzy AHP, henceforth), an extension to the original AHP method proposed by Saaty (1980) and successively developed by other researchers (Wang and Chin, 2011; Alonso and Lamata, 2006). Fuzzy AHP allows to effectively prioritise objects assessed through linguistic judgements, which are in general fuzzy and vague. Fuzzy sets have been used in many domains with incomplete or imprecise information.

Among the reasons for the fuzziness in the preference relation are time pressure, lack of knowledge, limited expertise of the decision maker, etc. (Zhao et al., 2013). As Chang (1996) summarises, the first task of the fuzzy AHP is to determine the relative importance of factors via pairwise comparison.

Fuzzy AHP is a popular method widely employed in multi-criteria decision making; in particular, it allows to determine the weights of criteria and priorities of alternatives in a structured way based on pairwise comparison (Liu et al., 2020). In recent years, this approach has been applied in some studies related to environmental policies, sustainability, and social strategies (Ma et al., 2019; Petrini et al., 2016; Padilla-Rivera et al., 2021; Rossi et al., 2013; Aguilar-Rivera, 2019; Ogundoyin and Kamil, 2020). There are also few case studies of application of fuzzy methods in the sustainability area or in the CE at macro level. Menichini and Rosati (2014) use the fuzzy AHP methodology to support decision makers to effectively propose a hierarchy between the global reporting initiative (GRI) indicators showing which are the most significant in the corporate social responsibility report assessment. Shuangliang (2021) adopts a fuzzy-based multi-criteria decision analysis for achieving green economic efficiency in China prioritising ten criteria and 48 sub-criteria in the context of environmental regulations. Padilla-Rivera et al. (2021) through qualitative (Delphi) and quantitative (fuzzy logic) tools identify which are the most significant social indicators for achieving CE. Patel et al. (2021) analysed CE implementation enablers through fuzzy MICMAC approach highlighting and categorising the dependency on the best key enabler indicators. The results identified a cluster of indicators with a strong hierarchical structure supporting CE.

Sagnak et al. (2021) proposed a framework to identify the best location of sustainable collection centres for e-waste. Fuzzy best-worst method ranked the best selecting the most appropriate indicators (as collection centre, collection cost, greenhouse gas emission, energy cost, tax, and investment cost). Although it is the most frequently adopted approach in the literature, the method proposed by Saaty (Liu et al., 2020) does not fully capture the relevance of qualitative aspects since its discrete scale is not able to reflect the human thinking style. Indeed, when expert preferences are suffering from uncertainty and imprecision, it is not very meaningful to use definite and precise numbers to depict linguistic judgments (Kwong and Bai, 2002). To address ambiguity, triangular fuzzy numbers (TFNs) and AHP are integrated in the fuzzy AHP approach to overcome decision making problems with respect to subjective evaluations.

Fuzzy AHP converts linguistic judgments into TFNs arranged in fuzzy pairwise comparison matrices. These matrices are then computed to obtain the relative weights of the elements and the ranking of the alternatives. Several methods are introduced to handle the comparison matrices (Buckley, 1985; Chang, 1996; Csutora and Buckley, 2001; Wang and Chin, 2011) and, among them, the method suggested by Chang (1996) is widely used because it allows to easily compute relative weights. According to this approach, fuzzy numbers have a triangular membership function and simple operation laws.

The triangular fuzzy number is denoted by (l, m, u) triad, where $l \leq m \leq u$, m stands for the modal value, and l and u stand respectively for the lower and upper value of the support of M, which is the set of elements $\{x \in R \mid < l < m < u\}$. The values l and u represent the fuzziness of the decision, the greater u – l, the fuzzier the degree of judgement. Under the fuzzy methodology, the fundamental pairwise comparison is performed as in the classical case, but the scores are not 'crisp' scores ('hard' numbers), fuzzy values are used instead. The pairwise comparisons a_{ij} are expressed as TFNs. TFNs are organised in a fuzzy AHP matrix (FAHP).

If multiple experts participate in the process, the values for the matrix are the averages from the scores of the individual experts. In our study, we use the TFN values of Chang (1996). To fulfil the final steps of the process, the FAHP must be converted to a 'crisp' form, (which corresponds to an AHP matrix) to determine the degree to which the input belongs to each of the appropriate fuzzy sets. After the transition to a crisp form, the rest of the calculations is performed as in the classical case with AHP matrices.

In our analysis we apply the approach of Calabrese et al. (2013) who extend the most popular and widely used fuzzy AHP method of Chang (1996), and aim to overcome the main weakness of Chang's method, the possibility for zero weights.

The process can be summarised as follows:

Step 1 In the first step we use the main indicators and sub-indicators elaborated by Eurostat to construct the decision hierarchy, in three levels, 'goal' (the top level), 'criteria' and 'alternatives'.

Step 2 The experts make pairwise comparisons using linguistic terms for each pair of indicators within each level of the hierarchy, based on their knowledge and the comparisons are organised in a matrix, which is square and symmetric. The resulting pairwise comparison matrix, is 'fuzzificated' by converting the linguistic terms of each expert's opinion into fuzzy numbers using a triangular fuzzy number, TFN. The fuzzy scale used for the conversion of linguistic terms into a triangular fuzzy set, the fuzzy AHP comparison matrix, is built with upper, middle, and lower levels in synthesised pair-wise judgments for alternatives. The fuzzy pairwise comparison matrix for all experts' opinions is combined into a form of single decision matrix.

Step 3 The final steps are to check the consistency of the combined pairwise matrix obtained in the previous steps, to confirm whether the opinions of all experts regarding the circularity criteria identified are consistent and to calculate the weights of each indicator in the hierarchy.

Decision makers must arrange the goal of the decision process into subdivisions, in a tree form – a hierarchy, consisting of a goal, criteria and alternative levels. Each item of the hierarchy can be further divided in more detail.

So, knowing that the preference of the i^{th} alternative over the j^{th} alternative is denoted by a_{ij}, in pairwise comparisons the preferences must be reciprocal, $a_{ij} = 1 / a_{ji}$, for each $i, j \in \{1, 2, I\, n\}$. Pairwise comparisons are consistent if a_{ij}. a_{jk}; for all i, j, k.

The preferences are further arranged in a pair wise comparison matrix $A_{n\times n}(a_{ij})$:

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & 1 & \vdots \\ a_{n1} & \cdots & \cdots & 1 \end{bmatrix}$$

If the matrix A is consistent and reciprocal, it has a maximal eigenvalue $\lambda_{\max} = n$ and $rank(A) = 1$.

This matrix is fuzzificated to obtain the FAHP matrix

$$\tilde{A}(\tilde{a}_{ij})n\times n = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) & \cdots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & \cdots & \cdots & (1,1,1) \end{bmatrix}$$

where

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = \widetilde{a^{-1}}_{ji} = \left(\frac{1}{u_{ji}}, \frac{1}{m_{ji}}, \frac{1}{l_{ji}}\right), \quad i, j = 1, \ldots n; i \neq j$$

As a result of a high number of comparisons within the AHP, the issue of the consistency of the judgements has received particular attention. To measure inconsistency, several indexes have been proposed (Koczkodaj et al., 2017; Mazurek, 2018).

From pair wise comparisons and AHP we derive a vector of weights of compared objects (priority vector w). The vector w exists, where $a_{ij} = \dfrac{w_i}{w_j}$, for all i, j, when A is consistent. Several methods can be employed to obtain the vector w. The first approach is the Saaty's eigenvalue method (Liu et al., 2020) which shows that:

$Aw = \lambda_{\max} w$ where $\lambda_{\max}$ is the largest (positive) eigenvalue of A.

Another procedure to derive vector *w* is the geometric mean method known as the least squares method (Crawford and Williams, 1985). According to this approach, vector *w* can be expressed as follows:

$$w = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}}$$

Thus, both methods provide the same result when the matrix *A* is consistent. To check the consistency of the matrix *A*, two different indices are available, namely the consistency index CI (Liu et al., 2020) and the consistency ratio CR (Saaty, 2004).

$$CI = \frac{\lambda_{\max} - 1}{n - 1}$$

$$CR = \frac{CR}{RI}$$

where *RI* is the random inconsistency, that is an average value obtained by Monte Carlo simulations of *CI*. According to the eigenvalue method, *CR* is considered sufficiently consistent if it exhibits a value less than or equal to 0.1. However, this value can be slightly adjusted according to the preferences of the researcher and the specifics of the concrete study.

To complete and strengthen our analysis, we also compute the row inconsistency index (RIC) suggested by Mazurek (2018). The row inconsistency index is as follows:

$$RIC = 1 - \frac{2\sum_{i=1}^{n-1}\sum_{j>i}^{n}\cos\phi_{ij}}{n(n-1)}$$

where $\cos\phi_{ij} = \frac{r_i \cdot r_j}{|r_i| \cdot |r_j|}$, and $r_i.r_j$ denotes the dot product.

For the calculation of weights using the method of Calabrese et al. (2013), first the row sums of the FAHP matrix are calculated,

$$RS_l = \sum_{J=1}^{n}\left(\widetilde{a_{lJ}}\right) = \left(\sum_{J=1}^{n} l_{lJ}, \widetilde{\sum_{J=1}^{n}} m_{lJ}, \sum_{J=1}^{n} u_{lJ}\right) \quad l = 1 \ldots n$$

and later these row sums are normalised and are the base for the weights,

$$\widetilde{S_l} = \frac{\widetilde{RS_l}}{\sum_{j=1}^{n} RS_J} \; j = 1, \ldots n.$$

In a final step, these normalised row sums are compared using their degree of possibility and the relative crisp weight is calculated (see Calabrese et al., 2013 for details).

To assess which indicator has a greater importance for the circularity performance we exploit information taken from a survey conducted on two cohorts of experts, originating from the academic's environment and from the business both involved in the transition of

CE. Following the usual practice (see Calabrese et al., 2013; Rajak and Shaw, 2019), we have considered two small groups of experts in our survey. Our business respondents are from Italy, and the academic ones come from universities in Italy and Bulgaria.

As mentioned above, the macro-indicators and the 15 sub-indicators are taken from the Eurostat CE database (see Table 1), we build a three-level hierarchy. Specifically, respondents are asked how important is production and consumption; waste management; secondary raw materials and competitiveness and innovation from the point of view of CE, in order to evaluate the importance of the Eurostat indicators with respect to the higher level of the hierarchy, with the help of linguistic judgements on a six-level scale (we present here also the correspondent triangular fuzzy numbers, TFNs, and their reciprocal values):

1 just equal (1, 1, 1, reciprocal 1, 1, 1)

2 equally important (2/3, 1, 3/2, reciprocal 2/3, 1, 3/2)

3 weakly more (1, 3/2, 2, reciprocal 1, 2/3, 1)

4 moderately more (3/2, 2, 5/2, reciprocal 2/5, 1/2, 2/3)

5 strongly more (2, 5/2, 3, reciprocal 1/3, 2/5, 1/2)

6 extremely more (5/2, 3, 7/2, reciprocal 2/7, 1/3, 2/5) (Chang, 1996; Calabrese et al., 2013).

We asked our experts to make pair wise comparisons for all items in the hierarchy, level by level, and with the linguistic judgements obtained we organise the judgements in five matrices – one for the levels 1–2 ('goal' – 'criteria'), and four for the levels 2–3 ('criteria'–'alternatives').

In our study we first asked our respondents to fill an online questionnaire to make their pair wise comparisons. Next, we converted the linguistic terms to TFNs to make for each group of experts five fuzzy pair wise comparison matrices, one for levels 1–2 and four for levels 2–3, a total of ten matrices. These fuzzy matrices were defuzzificated to calculate their consistency, we found that all are consistent (results from the tests are in Table 4) and continued with the calculation of the weights of individual indicators. For the calculation of weights, we applied two competing methods – the relative row sums (see Calabrese et al., 2013 for details), and the geometric mean method known as the least squares method (Crawford and Williams, 1985). Both methods give very close results, we present the data in Tables 5–8.

Table 2 Critical values of random index

Dimension	*1*	*2*	*3*	*4*	*5*	*6*
Saaty (1980)				0.89		
Xu and Wang (2013)	0	0	0.52	0.89	1.12	1.26
Alonso and Lamata (2006)	-	-	0.5247	0.8815	1.1086	1.2479
Lambda max (Alonso and Lamata, 2006)	-	-	4.0486	6.6531	9.4383	12.2394

Hereinafter are the results obtained by employing the fuzzy AHP. As stated above, we use two different approaches to identify the weight of each sub-criterion on CE, specifically, we employ and compare the crisp sums method and the geometric means procedure. Firstly, we analyse the consistency indexes through a comparative analysis with different authors:

We use these values to check the correctness and the consistency of data. Once verified the data consistency we perform the fuzzy analysis. Table 3 shows the different coefficient indexes (consistent index (CI); consistent ratio (CR); RIC-row inconsistent coefficient (RIC); Lambda) split for academic and business answers.

Since the inconsistency index has a low value, we can proceed to fuzzification using the geometric mean method and the crisp sum method.

Table 3 Different coefficient indexes

Typology of indicators	*N. indicator*	*CI[a]*	*CR*	*RIC*	*Lambda*	*CI[b]*	*CR*	*RIC*	*Lambda*
	s		*a*	*a*	*a*		*b*	*b*	*b*
CEI	4	0.007	0.008	0.010	4.020	0.150	0.170	0.100	4.460
Production	4	0.049	0.056	0.018	4.150	0.040	0.040	0.002	4.110
Waste management	6	0.075	0.059	0.089	6.370	0.080	0.060	0.060	6.400
secondary raw material	3	0.019	0.036	0.006	3.040	0.100	0.190	0.010	3.200
Competitiveness and innovation	2	0.030	-	0.000	-	0.100	-	0.003	-

Note: Coefficient estimates performed by the authors. a: academic; b: business.

4 The results of CE indicators

In this section, the findings of 4 CE indicators and 15 sub-indicators have been analysed and ranked using the fuzzy AHP method. In each table are reported the results both with geometric mean method and crisp sums method split between academic and business respondents. In detail, in columns 3 and 5 weight is obtained with defuzzification to crisp values after calculation of the row sums. Columns 2 and 4 display the weight estimated applying the geometric mean method (the least squares method). If the matrix is consistent, both methods give similar results.

Table 4 Estimation results: circular economy macro-indicators

	Geometric mean method[a]	*Crisp sums method[a]*	*Geometric mean method[b]*	*Crisp sums method[b]*
Production and consumption	0.22	0.23	0.17	0.16
Waste management	0.25	0.26	0.21	0.22
Secondary raw materials	0.24	0.25	0.31	0.33
Competitiveness and innovations	0.30	0.31	0.31	0.30

Note: [a]Academic respondents; [b]business respondents.

The results in Table 4 show that the main macro-indicators with a vast potential to influence CE are the indicator ‘competitiveness and innovation’ for academic and ‘secondary raw materials’ for business respondents. In this case there is a small divergence in the expert’s opinion. The macro indicators competitiveness and innovation are the most relevant CE indicators with a weight of 0.30 (for academic) and 0.31 (for business) to achieve CE goal, and the secondary raw material indicator obtained a high weight (0.31–0.33) from business whereas 0.24–0.25 from academic respondents. The main reason is that the business sector prefers working on reducing barriers on trading *secondary raw materials*, such as clarifying rules on the definition of waste, or defining EU quality standards for certain materials (such as plastics) that if solved will foster CE transition.

The waste management is the third indicator in terms of magnitude with a weight of 0.24–0.25 from academic researchers and 0.21–0.22 from businesses. Finally, production and consumption are the least significant CE indicators with 0.22–0.23 (for academic) and 0.16–0.17 (for business). Overall, the results present that all these criteria seem to strongly affect the CE performance.

4.1 The results of CE sub-indicators

In the above section we provided information on the CE sub-indicators, specifically, we analysed and ranked them employing the fuzzy AHP method. Table 5 shows the final prioritising order with respect to *production* that is the first sub criterion observed.

According to the analysis related to the area *production* the sub-indicator generation of waste excluding major mineral waste per domestic material consumption has the higher weight equal to 0.32-0.33 (for academic) and 0.29 (for business) followed by generation of waste excluding major mineral waste per GDP unit with a weight of 0.28–0.29 (for academic) and 0.27 (for business) and generation of municipal waste per capita of 0.21–0.22 (for academic) and 0.25 (for business). The main reason of this ranking is attributable to the importance in finding a solution for reducing *ex ante* waste production acting directly on different sectors as in mining sector as Tayebi-Khorami et al. (2019) pointed out, for promoting the cradle-to-cradle approach.

Table 5 Estimation results: production sub-indicators

	Geometric mean method[a]	*Crisp sums method*[a]	*Geometric mean method*[b]	*Crisp sums method*[b]
EU self-sufficiency for raw materials	0.19	0.19	0.19	0.2
Generation of municipal waste per capita	0.21	0.22	0.25	0.25
Generation of waste excluding major mineral wastes per GDP unit	0.28	0.29	0.27	0.27
Generation of waste excluding major mineral wastes per domestic material consumption	0.32	0.33	0.29	0.29

Notes: *a*: academic respondents; *b*: business respondents.

Our findings are consistent with a part of literature which states the emergent need to develop techniques for a best waste management, both aiming to reduce environmental impact by increasing the shelf life of products and reuse waste to make new goods thus minimising the waste production (Silva and Morais, 2021; Cohen and Gil, 2021). Furthermore, the EU self-sufficiency for raw materials is recognised as less important in the realisation of CE also because it is far away from the dependency on raw materials (European Commission, 2017).

Table 6 contains the weight and ranking of CE sub-indicator with respect to waste management.

Table 6 Estimation results: waste management sub-indicators

	Geometric mean method[a]	*Crisp sums method*[a]	*Geometric mean method*[b]	*Crisp sums method*[b]
Recycling rate of municipal waste	0.13	0.13	0.11	0.1
Recycling rate of all waste excluding major mineral waste	0.12	0.13	0.13	0.13
Recycling rate of packaging waste by type of packaging	0.16	0.18	0.13	0.14
Recycling rate of e-waste	0.19	0.19	0.15	0.16
Recycling of biowaste	0.22	0.23	0.2	0.21
Recovery rate of construction and demolition waste	0.19	0.19	0.28	0.27

Notes: [a]Academic respondents; [b]business respondents.

In the area *waste management*, we have a divergence in the opinion of academic and business respondents. The *recovery rate of construction and demolition waste* (CDW) has a significant rate with 0.19 (for academic) and 0.28 (for business) accompanied by the recycling of biowaste with 0.22–0.23 (for academic) and 0.20–0.21 (for business). The relevance of CDW in the achievement of CE is probably due to the high volume of CDW that is worldwide produced, and its adequate management can contribute to achieving the CE strategies (Wu et al., 2019; Ruiz et al., 2020). The biowaste is also seen as a priority in the CE strategies because biowaste can be transformed into value-added materials such as bioethanol, bioplastics and its implementation can also minimise food waste (Kee et al., 2021). On the contrary, the other sub-indicators show a lower weight, therefore, they are not considered as vital for the achieving or transition to CE. Table 7 displays the weight and ranking of CE sub-indicators with secondary raw materials.

For the area *secondary raw materials* trade in recyclable raw materials is the most significant indicator with a weight of 0.37–0.38 (for academic) and 0.43 (for business) whereas the circular material use achieves the second highest weight of 0.33–0.34 (for academic) and 0.34 0.35 (for business) followed by the contribution of recycled material to raw materials (0.29–0.30 and 0.22 respectively). The importance of trade in recyclability is remarkable, it is considered as a factor that can drive towards the CE transition since it involves national and local government institutions to overcome export restrictions by avoiding trade barriers. Our results are in line with those obtained by Tan et al. (2021), in their study the authors highlight the importance of implementing the trade of metal scrap to affect positively CE strategies. Table 8 shows the weight and the ranking of competitiveness and innovation.

Table 7 Estimation results: secondary raw materials sub-indicators

	Geometric mean method[a]	*Crisp sums method*[a]	*Geometric mean method*[b]	*Crisp sums method*[b]
Contribution of recycled materials to raw materials demand – end-of-life recycling input rates	0.29	0.30	0.22	0.22
Circular material use rate	0.33	0.34	0.34	0.35
Trade in recyclable raw materials	0.37	0.38	0.43	0.43

Notes: [a]Academic respondents; [b]business respondents.

Table 8 Estimation results: competitiveness and Innovation sub-indicators

	Geometric mean method[a]	*Crisp sums method*[a]	*Geometric mean method*[b]	*Crisp sums method*[b]
Private investments, jobs and gross value added related to circular economy sectors	0.45	0.45	0.36	0.35
Patents related to recycling and secondary raw materials	0.55	0.55	0.64	0.65

Notes: [a]Academic respondents; [b]business respondents.

For the area *competitiveness* and *innovation*, patents related to recycling and secondary raw materials have a greater weight with 0.55 (academic) and 0.64–0.65 (business) with respect to the private investment jobs and gross value added. The number of patents is considered a proxy for innovation activities and can be used to assess technological progress in a specific industrial sector and for this reason could be an asset in the transition to CE.

4.2 Results of overall CE sub-indicators

This sub-section determines the overall ranking of CE sub-indicators. The findings reveal that patents related to recycling and secondary raw materials are the most significant sub-indicators among all 15 CE sub-indicators, in fact it has the highest value both from academic and business experts. Other important sub-indicators are generation of waste, excluding major mineral waste per domestic material, recycling of biowaste, recovery rate of construction and trade in recyclable raw materials. In conclusion, the results show that these sub indicators are considered as very crucial for the transition and development of the CE.

5 Concluding remarks

This study relies on a fuzzy-based multi-criteria decision by means of the fuzzy AHP analysis using a TFN scale to evaluate and prioritise four main indicators and 15 sub-indicators of CE indicators elaborated by Eurostat through fuzzy AHP approach for comparing academic and business opinions and propose suggestions to decision and policy makers towards the transition to CE. The empirical results of the Fuzzy AHP show that competitiveness and innovation are the most important macro indicators for academic respondents and secondary raw materials are the most important macro indicators for business respondents to move towards a CE. The importance of competitiveness and innovation reflects the changes that lead to a system able to develop new products and services and redesign a new value chain of products. Conversely, the secondary raw material is the best macro indicator identified by businesses to address CE because it represents a more affordable challenge to the transition to CE. The most relevant sub-indicators both for academia and business are the following:

1 generation of waste excluding major mineral wastes per domestic material consumption

2 recycling biowaste, recovery rate of construction and demolition waste

3 trade in recyclable raw materials

4 patents related to recycling

5 secondary raw materials.

The final ranking of sub-indicators shows that patents related to recycling and secondary raw materials are the most significant in the overall sub-indicators.

The scientific value added of our results is represented by the fact that with the methodological fuzzy AHP it is possible to extend its applicability within each country of the European Union, developing an additional assessment in each country's circularity, both competitiveness potential and investment priorities. In particular, the main advantage of our study is that we overcome the issues of availability of data for constructing CE indices. In addition, the integration of the two groups of experts (business and academia) that allows us to prioritise the most relevant indicators for the transition of CE at macro-level from a practical point of view.

It is clear that our evidence must be interpreted considering some limitations. One limitation of the research is related to the fact that our study does not consider any EU country separately, which could be useful in understanding countries' different attitudes towards the CE.

Furthermore, our study does not consider social dimensions in CE design. Social CE indicators, as eradicating poverty, food security, or equal opportunity, are becoming new priorities for CE experts in each EU country. Health and safety are also a matter of concern for CE experts because the transition to a CE could bring implications for the stated priorities of human health (Padilla-Rivera et al., 2021). These implications may affect the health and safety of European citizens both positively and negatively. The CE could also promote supportive environments and resilient communities to the extent that this translates into improved well-being and quality of life.

This study confirms the circularity path as a trend in EU countries. Other studies carried out on CE at the macro level above cited contribute to implement the methodological framework by developing a CE composite index and by introducing other indicators for highlighting the factors influencing competitiveness as well. We adopt the methodological fuzzy AHP approach based on Eurostat indicators both for contributing on the most important indicators affecting the progress towards the CE and for verifying whether the Eurostat metrics are relevant and accurate for evaluating the most crucial actions and strategies on CE. Future studies must be based on considering other CE indicators and sub indicators at macro level to suggest a better systematic view of the CE development, to add potential normative applications for the decision-makers or to indicate standardised and more comprehensive evaluation of CE indicators at macro level.

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