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Research Article

A fuzzy multicriteria group decision approach for circular business models prioritization

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Abstract

Paper aims: Presents a new group decision approach for circular business models (CBMs) prioritization based on circular economy (CE) principles and indicators.

Originality: It was not found in the literature quantitative approaches to indicate which CBMs can be prioritized towards CE implementation.

Research method: Fuzzy AHP is applied to calculate the weights of the CE principles. Fuzzy TOPSIS is used to rank the CBMs. A pilot application demonstrates the applicability of the proposed approach.

Main findings: To perform equally on all dimensions of the circularity indicators, recovery by-products have a greater impact on CE implementation. Focusing on economic indicators, Product as a Service and Recovery By-Products should receive priority. Focusing on social indicators, Product as a Service is the most recommended CBM.

Implications for theory and practice: It was identified the CBMs that are most suitable for performance improvement regarding CE implementation, according to the organization's dominant CE principles.

Keywords

Circular economy. Circular Business Models. Multi-Criteria Decision Making. Fuzzy AHP. Fuzzy TOPSIS.

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1. Introduction

The intersection between sustainability and Circular Economy (CE) lies in the fact that CE corresponds to the optimal point of sustainability, given that it offers a set of practices capable of generating more sustainable operations, making sustainability feasible in organizations (Kristoffersen et al., 2021; Rabta, 2020; Rossi et al., 2020). Indeed, sustainability can support CE implementation (Barreiro-Gen & Lozano, 2020; Kravchenko et al., 2019), acting as a driver of CE in organizations (Sehnem et al., 2019).

CE, if implemented effectively, may operate in ways where the system mimics the natural ecosystem, bringing competitive advantages (Genc et al., 2020). CE has been showing its high potential to guide organizations in the achievement of breakthrough solutions towards sustainable development (Fonseca et al., 2018). The CE concept seeks to increase resource productivity by developing ways to continuously reintroduce discarded assets in life cycles (Moktadir et al., 2018). It is an economy where stakeholders work in collaboration to maximize the value of products to create positive social and environmental impacts (Manninen et al., 2018; Bertassini et al., 2021a).

In order to guide the efforts to walk towards CE implementation, the BSI – British Standards Institution (2017) proposed six guiding principles. The task of incorporating CE concepts and principles is complex, interconnected, uncertain, and requires the company's ability to propose differentiated values and transform business models

(Pieroni et al., 2019). The business models are the main source of value creation in organizations (Suchek et al., 2021; Ferasso et al., 2020; Richardson, 2008). To be considered circular, a business model should be designed to create, deliver, and capture economic value while simultaneously contributing to environmental and social aspects (Suchek et al., 2021; Lüdeke-Freund et al., 2018). Hence, a circular business model (CBM) is defined as the logic of how an organization creates, delivers and captures value to close and slow loops (Antikainen & Valkokari, 2016; Bocken et al., 2016), and share these values with different stakeholders (Bertassini et al., 2021a).

The transition towards CE depends on the implementation of various CBMs (Husain et al., 2021), and usually the combination of various CBMs. However, there is always one business model that is predominant in the organization (e.g., if an organization has product-as-a-service as its business model, probably it will depend on product life cycle extension and/or recovery to enable the operationalization of the 'main' business model). Thus, the organization needs to choose/prioritize which CBMs will be the predominant in accordance with the organization's main strategies and goals to define the processes, activities, resources, customers, investments, revenues and other factors that are important for the implementation of the CBM. Moreover, the successful implementation of CBMs is directly dependent of the relationship between CE principles and indicators, since companies need to incorporate CE principles in their operations and culture (Bertassini et al., 2021b) and use indicators to measure how well they are performing in the CE transition (Rossi et al., 2020). The use of indicators to measure circularity performance is essential to improve and assess CBMs. However, the measurement and assessment of circularity performance are yet incipient in companies (Sassanelli et al., 2019). To address this issue, Rossi et al. (2020) developed a group of indicators, focused on the three dimensions of sustainability, which are environmental, economic, and social. In this way, to overcome the limitations of conventional indicators, the authors applied these indicators in CBMs to capture the innovations brought by CE, supporting companies to identify areas with high importance and potential for improvement, and thus to increase CE performance. Based on the CE principles and the circularity indicators, organizations may prioritize the most important CBM for its strategical goals. In this direction, only Husain et al., (2021) proposed a model to rank the most important CBMs implementation, however, they have not considerated the relationship between CE principles and circularity indicators in their model.

This relationship can only be assessed by experts with an in-depth knowledge of CE and of the organization in focus. In this direction, Keshavarz Ghorabaee et al. (2017) highlighted that human judgments contain some uncertainty and ambiguity. In this way, Computing with Words (CW) is a necessity when the accessible information is not enought precise to justify the use of numbers and points that CW encompasses a fusion of natural language and computation with fuzzy variables (Zanon et al., 2020; Zadeh, 1965). Therefore, the fuzzy set theory (FST) is one of the most efficient tools to deal with the uncertainty of evaluation processes (Caiado et al., 2021; Tavassoli et al., 2020; Keshavarz Ghorabaee et al., 2017).

In this direction, the combination of multicriteria group decision making (MCGDM) techniques with the fuzzy set theory can bring significant advantages. The fuzzy Analytic Hierarchy Process (AHP) processes pairwise comparative judgments given by the decision makers (Shete et al., 2020; Lima-Junior et al., 2014). These pairwise comparisons are adequate to deal with the subjectiveness during the weights elicitation process (Torkabadi et al., 2018; Dede et al., 2016). Another combination of a MCGDM technique with the fuzzy set theory corresponds to the fuzzy Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) technique (Mahpour, 2018). It ranks alternatives by calculating their mathematical distance both to the positive ideal solution to the negative ideal solution.

There is one study in literature that aims to rank the business models for the successful adoption of CE using fuzzy TOPSIS (Husain et al., 2021). However, to the best of the authors' knowledge, no paper was found proposing to investigate the relations between CE principles and indicators, using fuzzy MCGDM techniques to consider the inherent subjectivity of this context and to reduce research bias. Moreover, no study was found applying these techniques to calculate weights for both the CE principles and indicators, as well as using these techniques to provide recommendations to experts along with CBM feedbacks for the focus organization. Thus, this paper aims to develop a fuzzy multicriteria group decision making model for circular business models prioritization by combining the fuzzy AHP and fuzzy TOPSIS techniques for, respectively, finding the weights of each CE principles considering the specific context of the company under analysis and to build a rank of preference of CBMs according to the organization CE principles. The fuzzy MCGDM techniques were implemented in the Microsoft Excel® software and an illustrative application is presented to exemplify the use of the developed approach in practice.

The paper is organized as follows: section 2 presents the literature review regarding the circular economy construct and fuzzy MCGDM techniques; section 3 presents the proposed model; section 4 brings the results of an illustrative application; section 5 addresses discussions; and finally, section 7 draws some conclusions and suggestions for further research.

2. Literature review

CE has several definitions as presented by Kirchherr et al. (2017). The most know definition of CE points that a circular economy is an industrial system that is restorative or regenerative by intention and design, and seeks to provide multiple value-creation mechanisms which are decoupled from the consumption of finite resources (Ellen MacArthur Foundation, 2012, 2014). Considering this definition, the BSI (British Standards Institution, 2017) proposed the six principles that guide the implementation of CE concepts in companies:

1. **Systems thinking:** a holistic approach to understanding the interactions between individuals and activities within the wider system they are part of;
2. **Innovation:** continually innovate to create value by enabling the sustainable management of resources through the design of processes, products/services, and business models;
3. **Stewardship:** manage the direct and indirect impacts of their decisions and activities within the wider systems they are part of;
4. **Collaboration:** collaborate internally and externally through formal and/or informal arrangements to create mutual value;
5. **Value optimization:** keep all products, components, and materials at their highest value and utility at all times;
6. **Transparency:** organizations are open about decisions and activities that affect their ability to transition towards a more circular and sustainable mode of operation and are willing to communicate these in a clear, accurate, timely, honest, and complete manner.

These six principles comprehend, in generic terms; all the aspects that should be covered by a circular system, which can be applied in products/services, processes, business models, value chains, people, and organizational structures. Companies will only achieve a fully circular system when all the six principles are implemented (Agrawal et al., 2021; Bocken et al., 2019). One way to implement the CE principles is through the proposition of CBMs.

CBMs is considered a strategy to achieve sustainability (Geissdoerfer et al., 2017) and can be defined as "[...] the rationale of how an organization creates, delivers, and captures value with slowing, closing, or narrowing flows of the resource loops [...]" (Oghazi & Mostaghel, 2018, p. 3). According to the BSI (British Standards Institution, 2017), there are six types of CBMs:

1. **On-demand:** produces a product or provides a service only when consumer demand has been quantified and confirmed;
2. **Dematerialization:** replaces physical infrastructure and assets with digital/virtual services;
3. **Product life cycle extension/reuse:** products designed to be durable and easy to repair;
4. **Recovery of secondary raw materials/by-products:** creates products from secondary raw materials/by-products and recycling;
5. **Product as service:** delivery product performance or defines results rather than the product or service itself;
6. **Sharing economy:** collaborative consumption amongst users, either individuals or organizations.

According to Rossi et al. (2020) the use of circularity indicators to measure the performance of companies in implementing CE is essential to improve and assess the CBMs. In this way, Rossi et al. (2020) proposed a group of indicators, focused on the three dimensions of sustainability to capture the innovations brought by CE that conventional indicators do not measure. Besides, Rossi et al. (2020) also presented how each CE indicator affects the achievement of each CE principle and how each CBM affects each CE indicator. The intensity levels of the relationships was represented by the linguistic terms strong, median, and weak, as presented in Table 1, Table 2 and Table 3. These levels of intensity mean that the indicators with strong connections are very efficient to achieve CE. The indicators with median connections could help in the achievement of the requirements but in the proposition of circular solution regarding the product/service or process. The indicators with weak connections could be applied in the initial stages of the CE journey once they are useful to explore the opportunities. The data presented in

Table 1. Relationship between CE principles and material indicators proposed.

	Systems Thinking	Strong	Strong	Strong	Strong	Strong	Strong	Strong	Strong	Strong
Principles	Innovation	Weak	Strong	Strong	Weak	Weak	Strong	Strong	Strong	Strong
	Stewardship	Strong	Strong	Strong	Strong	Strong	Strong	Strong	Strong	Strong
	Collaboration	Medium	Medium	Strong	Medium	Strong	Weak	Weak	Weak	Strong
	Value Optimization	Strong	Strong	Strong	Strong	Strong	Strong	Strong	Strong	Weak
	Transparency	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Strong
Indicators	Dimension					Material				
	Control Variables	*Reduction of raw materials*	*Renewability*	*Reciclability*	*Reduction of toxic substances*	*Reuse*	*Remanufacturing*	*Refurbishment*	*Product Longevity*	*Stakeholder structure and diversity*
Circular Business Models	Product as a Service	Strong	Weak	Weak	Weak	Strong	Weak	Strong	Strong	Strong
	Sharing Economy	Strong	Medium	Medium	Medium	Strong	Medium	Medium	Medium	Medium
	Product life extension	Strong	Weak	Strong	Strong	Strong	Strong	Strong	Strong	Strong
	On-demand	Strong	Weak	Weak	Weak	Medium	Medium	Medium	Medium	Medium
	Recovery by-products	Strong	Medium	Strong	Strong	Strong	Strong	Strong	Strong	Strong
	Dematerialization	Strong	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium

Source: Rossi et al. (2020).

Table 2. Relationship between CE principles and economic indicators proposed.

	Systems Thinking	Weak	Weak	Medium
Principles	Innovation	Weak	Weak	Strong
	Stewardship	Strong	Weak	Medium
	Collaboration	Weak	Strong	Medium
	Value Optimization	Strong	Weak	Strong
	Transparency	Weak	Medium	Medium
Indicators	**Dimension**		**Economic**	
	Control Variables	***Financial results***	***Taxation or regulatory milestones***	***Circular investment***
Circular Business Models	Product as a Service	Strong	Strong	Strong
	Sharing Economy	Strong	Medium	Strong
	Product life extension	Strong	Medium	Strong
	On-demand	Strong	Weak	Weak
	Recovery by-products	Strong	Strong	Strong
	Dematerialization	Strong	Medium	Strong

Source: Rossi et al. (2020).

Table 3. Relationship between CE principles and social indicators proposed.

	Systems Thinking	Strong	Strong	Strong	Strong	Strong	Strong
Principles	Innovation	Strong	Weak	Medium	Medium	Strong	Strong
	Stewardship	Weak	Strong	Medium	Strong	Strong	Weak
	Collaboration	Strong	Weak	Strong	Weak	Strong	Strong
	Value Optimization	Weak	Strong	Strong	Weak	Weak	Strong
	Transparency	Medium	Medium	Strong	Medium	Strong	Strong
Indicators	**Dimension**						
	Control Variables	**Job creation**	**Income generated by jobs**	**Employee participation in the circular business model**	**Market characterization**	**Involvement of stakeholders in decision-making processes**	**Mindset / cultural change**
Circular Business Models	Product as a Service	Strong	Strong	Strong	Strong	Strong	Strong
	Sharing Economy	Medium	Medium	Medium	Strong	Strong	Weak
	Product life extension	Strong	Strong	Strong	Strong	Strong	Weak
	On-demand	Strong	Strong	Weak	Strong	Strong	Strong
	Recovery by-products	Strong	Strong	Strong	Strong	Strong	Weak
	Dematerialization	Medium	Medium	Strong	Strong	Strong	Weak

Source: Rossi et al. (2020).

Table 1, Table 2 and Table 3 proposed in the research of Rossi et al. (2020) is used in this study as the basis to define the relationship between CE principles and circularity indicators to prioritize the implementation of CBMs.

There are several studies in the recent literature that combines diverse fuzzy techniques considering aspects of MCDM to address CE issues and some of them can be highlighted since they are related to the fuzzy AHP and fuzzy TOPSIS techniques. Tariq et al. (2021) used the fuzzy TOPSIS to evaluate how multiple alternatives for the disposal of diapers can provide sustainable advantages in the Pakistan scenario. Mahpour (2018) applied fuzzy TOPSIS to prioritize the potential barriers to adopt circular economy in construction and demolition waste management from behavioral, technical, and legal perspectives and aggregately. Lee et al. (2021) used fuzzy AHP combined with the fuzzy TOPSIS to propose a comprehensive list of evaluation criteria to rank recycling outlets, and develop an end-of-life tire outlets selection matrix.

Lahane & Kant (2021) proposed a hybrid framework using fuzzy AHP e fuzzy VIKOR to rank solutions for mitigating the risks of circular supply chain implementation. Agrawal et al. (2021) used fuzzy TOPSIS for analysis and prioritization of roadblocks for the implementation of CE in the Indian automobile industry. Haleem et al. (2021) constructed a framework, based on the combination of fuzzy CRITIC and fuzzy TOPSIS, to determine the suppliers' ranking in the Indian automobile industry considering the CE implementation. In Chen et al. (2020), the fuzzy TOPSIS was combined with DELPHI and Best–worst method to evaluate critical barriers and pathways to implementation of e-waste formalization management systems. Nara et al. (2021) present the application of fuzzy TOPSIS to classify Industry 4.0 technologies based on sustainable development impacts. More studies using MCGDM techniques and fuzzy set theory to solve CE problems is presented in Table 4.

Table 4. Previous studies combining MCGDM techniques and Fuzzy Set Theories applied to CE context.

Authors	Proposition	Technique	Criteria
Kharola et al. (2022)	Rank the best preferred and least preferred criteria as key practices for Food Supply Chain that contribute to food waste reduction to ensure green waste management.	Best-Worst Method (BWM)	Enhancing productivity in practices Protection and infrastructure Skill and training Exposure and capacity building Environmental and circular economy involving practices
Govindan et al. (2022)	Raking CE adoption barriers in the cable and wire industry. Adoption barriers are weighted using BWM, the interdependencies among components are calculated by DEMATEL and barriers are ranked using Supermatrix Structure.	Best-Worst Method (BWM), fuzzy decision-making trial and evaluation laboratory (DEMATEL), and Supermatrix structure	Customer Financial Learning and growth Internal process
Khan & Ali (2022a)	A framework for the adoption of smart waste management in the context of CE for Pakistan. SWARA was used for allocating weights to the determined criteria; whereas, fuzzy VIKOR to rank the critical facilitators adopted from the secondary literature.	Fuzzy Stepwise Weight Assessment Ratio Analysis (SWARA) and the fuzzy Vlšekriterijumsko kompromisno rangiranje (VIKOR)	Environmental Social Economic Technical Regulatory perspectives
Kazancoglu et al. (2022)	A decision tool under uncertain and risky conditions for achieving sustainability in electronic waste (e-waste) recycling in circular economy. TODIM was used to evaluate the irrationality and risk attitudes of decision makers in a risky and uncertain environment.	TODIM	Revenue generated Part demand Disposal cost Quality risks Ergonomic risk Accident risk Crush Lifting/moving hazard Flammable Solid waste Oxidation Energy consumption
Erol et al. (2022)	An integrated decision framework to investigate the true potential of blockchain to address the CE adoption barriers.	Hesistant Fuzzy Linguistic Term Sets (HFLTS)	Transparent traceability management Improved collaboration and coordination Robust supply chain ecosystem Improved quality of life Higher level of trust Coopetition and prosumerism Sustainable behavior
Govindan (2022)	Identifies the barriers that exist with the implementation of blockchain technology in the application of the remanufacturing sector. DEMATEL is used to identify the effective and most influential barriers among common barriers.	DEMATEL	CE barriers
Shahidzadeh & Shokouhyar (2022)	Conceptual model of sustainability was proposed, discussed and analyzed to determine the relationship between reverse logistics performance and sustainability.	Hesitant fuzzy DEMATEL	Economics Environmental Social Consumer

Table 4. Continued...

Authors	Proposition	Technique	Criteria
Amiri et al. (2022)	Find the main issues and prioritize the challenges related to the adoption of circular supply chain management.	BWM and rough set	Financial and economic Rules and regulations Technology Behavioral-social Supply chain management Product specifications Market and competition
Khan & Ali (2022b)	A model to guide pharmaceutical industries to adopt circular supply chain management. F-FUCOM was used to allocating weights and prioritizing the barriers and FQFD was used to rank the enablers.	Fuzzy full consistency method (F-FUCOM) and Fuzzy quality function deployment (FQFD)	CE Barriers CE Enablers
Bertassini et al. (2022b)	An approach to assess the readiness of companies to implement a CE-oriented culture. FDM was used to identify CE culture elements and FIS was used to classify organizations in levels of readiness.	Fuzzy Delphi Methodlogy (FDM) and Fuzzy Inference Systems (FIS)	CE-oriented culture elements CE-oriented culture building blocks
Husain et al. (2021)	Rank the business models for the successful adoption of the circular economy.	Fuzzy for Order of Preference by Similarity to Ideal Solution (TOPSIS)	Partnership Activities Resources Value proposition Customer relationships Distribution Channels Client segments Cost structure Revenue flows
Pamucar et al. (2021)	A decision-making model to prioritize the possible CE concepts for the planning of urban mobility in a big city.	Fuzzy Dombi based Combined Compromise Solution (D'CoCoSo)	Economic productivity aspects Health and environment aspects Social infrastructure and cultural aspects Policy aspects Transportation aspects
Nag et al. (2021)	A theoretical framework that identifies and evaluates drivers and sub-drivers that are needed for the adoption of circular principles in product-service system business model.	Grey-Decision-Making Trial and Evaluation Laboratory (DEMATEL)	Circular Value Marketing Circular Services Circular product manufacturing Reverse flow
Karuppiah et al. (2021)	A methodological framework for evaluating the inhibitors to circular economy practices in the leather industry.	Grey-decision making trial and evaluation laboratory (DEMATEL) and fuzzy complex proportional assessment method	Organisational issues Regulatory issues Market issues Technological issues Economic issues Social issues
Gupta et al. (2021)	A framework to assess sustainability performance of manufacturing companies and to guide them in prioritizing investment in potential solutions for enhancing performance on sustainability.	BWM and CoCoSo	Industry 4.0 Sustainable and cleaner production Circular Economy
Fidan et al. (2021)	Investigate the contribution of using mechanically recycled cotton fiber instead of virgin cotton fiber.	TODIM	Washed weight Tear Tensile Cost-saving
Lee et al. (2021)	A list of evaluation criteria to rank recycling outlets, and develop and end-of-life tyre outlets selection matrix.	Fuzzy AHP and fuzzy TOPSIS	Economy Environment Social
Ali et al. (2021)	Identify and prioritize CE barriers in order of their significance.	TOPSIS	CE Barriers

Table 4. Continued...

Authors	Proposition	Technique	Criteria
Agrawal et al. (2021)	Analysis and prioritization of roadblocks for the implementation of CE in the Indian automobile industry.	TOPSIS	Technical Economic Cultural
Lahane & Kant (2021)	A framework to rank solutions for mitigating the risks of circular supply chain implementation.	Fuzzy AHP and fuzzy VIKOR	Operational and technological risks Product recovery risk Supply risks Demand risks Environmental risks Economical risks Social risks
Padilla-Rivera et al. (2021)	An approach to identify key social indicators of CE.	Fuzzy Delphi	CE indicators
Tariq et al. (2021)	Evaluate how multiple alternatives for disposal of diapers can provide sustainable advantages in the Pakistan scenario.	TOPSIS	Emissions Socio-culture Technology Cost Feasibility Energy recovery
Haleem et al. (2021)	A framework for evaluating suppliers concerning the CE implementation.	Fuzzy CRITIC and TOPSIS	Technological capability and energy consumption Economic Environment Social and regulatory support/requirement Logistics Management's respect towards CE
Bertassini et al. (2021a)	A guide for mapping stakeholders, capturing circular values and finding new CE implementation opportunities. FCM to assess the relations between captured values and CE principles	Fuzzy Cognitive Maps (FCM)	Circular captured values CE principles
Gue et al., 2020	A methodological framework for mapping causality networks for macro-level transition towards circular economy based on sector perceptions.	DEMATEL	Government support Company culture Consumer demand Social recognition Economic attractiveness Information to practitioners
Khan & Haleem (2020)	Evaluate the key strategies to accomplish CE and to develop a causal relationship among these strategies.	DEMATEL	CE strategies
Mahpour (2018)	Prioritize the potential barriers to adopt circular economy in construction and demolition waste management from behavioral, technical, and legal perspectives and aggregately.	TOPSIS	Behavioral Technical Legal
Zhao et al. (2017)	A hybrid framework for evaluating the comprehensive benefit of eco-industrial parks from the perspective of circular economy.	Grey-Delphi and fuzzy-VIKOR	Economic Social Environmental Ecology industry construction Management

Based on the review of previous studies we identified that just one study (from our set of publications) did a proposition to rank CBMs (Husain et al., 2021). However, in this study the authors defined some successful criteria to rank the CBMs (Partnership, Activities, Resources, Value proposition, Customer relationships, Distribution Channels, Client segments, Cost structure, Revenue flows) instead of using the relationship between CE principles and circularity indicators as we are proposing in the present research. The novelty of this study remains in the adoption of CE principles and circularity indicators to prioritize CBMs. Performance indicators are essential to show how well an organization is performing in CE and what could be improved. In this sense, use the circularity indicators to prioritize CBMs may help companies set the parameters such as technologies, resources, people, cultural aspects, legislations and others things that are needed for the implementation of CE in the specific context for the organization.

3. Methods

3.1. Fuzzy sets

Initially proposed by Zadeh (1965), the theories based on fuzzy sets stand out due to their ability to be combined with several multi-criteria techniques in the proposition of decision-making models that address data imprecision and uncertainty in human judgement (Deng et al., 2021; Zanon et al., 2020; Malviya et al., 2018; Kahraman et al., 2015). Linguistic variables and fuzzy numbers are used to represent decision makers' subjective assessments of the alternatives' performance and criteria weights considered in a problem (Abdullah, 2013). The linguistic variables are represented qualitatively using linguistic terms and quantitatively translated by fuzzy sets in a discourse universe using pertinence functions (Klir & Yuan, 1995).

According to Dubois (1980), for a given universe $X \to [0,1]$, a fuzzy set $\tilde{A}$ can be defined as: $\tilde{A} = \{x, \mu_A(x)\}$, $x \in X$, in which $\mu_A(x)$ is the membership degree function of the element x in $\tilde{A}$. The function $\mu_A(x)$ takes values in the interval $[0,1]$, where if $\mu_A(x) = 1$, x belongs totally to the fuzzy set $\tilde{A}$; otherwise, if $\mu_A(x) = 0$, then x does not belong to the fuzzy set $\tilde{A}$. Besides that, if $0 < \mu_A(x) < 1$, then x partially belongs to the fuzzy set $\tilde{A}$.

The triangular membership function is one of the most common shapes used to represent a fuzzy number (Klir and Yuan, 1995). Let l, m and u, be real numbers with $l < m < u$, in which m represents the point of maximum membership degree, and outside the range $[l,u]$, the degree of membership is null, then the triangular membership function $\mu_A(x)$ is represented by Equation 1.

$$\mu_A(x) = \begin{cases} 0 & for\, x < l, \\ \dfrac{x-1}{m-1} & for\, a \le x \le m, \\ \dfrac{u-x}{u-m} & for\, m \le x \le u, \\ 0 & for\, x > u. \end{cases} \tag{1}$$

Let $\tilde{Y} = (l_1, m_1, u_1)$ and $\tilde{Z} = (l_2, m_2, u_2)$ be two triangular fuzzy numbers (TFN) with $l_1 \ge 0$, $l_2 \ge 0$, and $\tilde{K}$ be a real number, then the euclidian distance ($d(\tilde{Y}, \tilde{Z})$) between two TFN is described as in Equation 2 (Wan et al., 2013).

$$d(\tilde{Y}, \tilde{Z}) = \sqrt{\frac{1}{3}\left[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right]} \tag{2}$$

To deal with hierarchical evaluations and the operations of scoring, weighting, and aggregating judgments under a fuzzy environment, the fuzzy weighted average is widely applied in several studies (Chang & Hung, 2005; Guh et al., 2008). Let $\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_n$ be a set of fuzzy numbers that represent the rates given to some alternatives $i = 1, 2, \ldots, n$ on the universes $X_1, X_2, \ldots, X_n$, and considering a set of fuzzy weighings represented by $\tilde{W}_1, \tilde{W}_2, \ldots, \tilde{W}_n$ on the universes $U_1, U_2, \ldots, U_n$, then the Fuzzy Weighted Average (FWA) is presented as in Equation 3 (Chang et al., 2006).

$$FWA = f\left(\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_n, \tilde{W}_1, \tilde{W}_2, \ldots, \tilde{W}_n\right) = \frac{\tilde{W}_1 \times \tilde{A}_1 + \tilde{W}_2 \times \tilde{A}_2 + \ldots + \tilde{W}_n \times \tilde{A}_n}{\tilde{W}_1 + \tilde{W}_2 + \ldots + \tilde{W}_n} \tag{3}$$

3.2. Fuzzy AHP

The Analytic Hierarchy Process (AHP) was proposed by Saaty (1980) and it is a MCDM that have been widely applied in several research areas, such as: engineering, business, decision sciences, environmental sciences, social sciences, economics, among others (Vieira et al., 2017; Zyoud & Fuchs-Hanusch, 2017),. The AHP is one of the most important MCDM to support decision-making problems (Wang et al., 2020; Ikram et al., 2020). In this way, the AHP can aim the experts to obtain the relative importance of a set of alternatives or criteria. However, the AHP is not fully appropriated to deal with the subjectiveness judgments of decision makers (Sultana et al., 2015). Chang (1996) proposed the fuzzy AHP, which is a technique adequate to capture the ambiguities and uncertainty present in decision makers judgments (Lima-Junior et al., 2014; Keshavarz Ghorabaee et al., 2017).

The fuzzy AHP expresses comparative judgments given by the decision makers through the use of linguistic variables (Lima-Junior et al., 2014). Let $X = \{x_1, x_2, \ldots, x_n\}$ be a set of objects and $G = \{g_1, g, \ldots, g_n\}$ a goal set. According to Chang (1996), each object must be analyzed for each goal, producing m extend the analysis for each object as shown in Equation 4:

$$M_{gi}^{1}, M_{gi}^{j}, \ldots, M_{gi}^{m}, i = 1,2,\ldots,n \tag{4}$$

where all the M_{gi}^{j} are TFNs. The value of fuzzy synthetic extent related to i th object is computed with Equation 5:

$$S_i = \sum_{j=1}^{m} M_{gi}^{1} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{i}\right]^{-1} \tag{5}$$

The $\sum_{j=1}^{m} M_{gi}^{i}$ can be calculated with the fuzzy addition operation of m extent analysis values for a particular matrix, as presented in Equation 6.

$$\sum_{j=1}^{m} M_{gi}^{i} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right) \tag{6}$$

The $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{i}\right]^{-1}$ can be computed with the following Equation 7:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{i}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} u_i}, \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} m_i}, \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m} l_i}\right) \tag{7}$$

Next, is necessary to calculate the degree of possibility of $S_2(l_2, m_2, u_2) \geq S_1(l_1, m_1, u_1)$, as Equation 8 shows.

$$V(S_2 \geq S_1) = sup_{y \geq x}\left[\min\left(\mu_{S_2}(y), \mu_{S_1}(x)\right)\right] \tag{8}$$

Since S_2 and S_1 are TFNs, Equation 8 can also be expressed as the following Equation 9.

$$V(S_2 \geq S_1) = hgt(S_1 \cap S_2) = \mu_{S_2}(d) \tag{9}$$

Where, d express the highest intersection point between μ_{S_1} and μ_{S_2}. In other words, Equation 9 can also be expressed as in Equation 10:

$$\mu_{S_2}(d) = \begin{cases} 1, & if\ m_2 \geq m_1 \\ 0, & if\ l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases} \tag{10}$$

Next, the degree of possibility for a convex fuzzy number be greater than k convex fuzzy numbers $S_1(i = 1, \ldots, k)$ should be computed by Equation 11 as follows:

$$V(S \geq S_1, S_2, \ldots, S_k) = V\left[(S \geq S_1)\, and\, (S \geq S_2)\, and \ldots and\, (S \geq S_k)\right] = \min V(S \geq S_i), i = 1,2,\ldots,k. \tag{11}$$

Finally, considering that $d'(A_i) = \min V(S_i \geq S_j)$, for $j = 1,2,\ldots, k;\ k \neq i$, the vector W' can be calculated with Equation 12:

$$W' = \left(d'(A_1), d'(A_2), \ldots, d'(A_k)\right)^T \tag{12}$$

Which can be normalized and next to be represented by Equation 13:

$$W = \left(d(A_1), d(A_2), \ldots, d(A_k)\right)^T \tag{13}$$

where W is a crisp number.

To check the consistency of the expert's judgments, after the pairwise comparisons, the consistency ratio (CR) must be calculated. For that, firstly it is necessary to defuzzify the matrix with the graded mean integration, given by Equation 14.

$$P\left(\tilde{L}\right) = L = \frac{1}{6}\left(l_1, 4l_2, l_3\right) \quad (14)$$

Next, only for the calculation of the CR reasons, consider w_j as the normalized weight of the alternative j by applying Equation 15, proposed by Saaty (2008), and the a_{ij} as the all the pairwise comparations between the alternatives, which was defuzzyfied by applying Equation 14. The ϑ_i must be calculated for each alternative with Equation 16.

$$w_i = \frac{\sum_{j=1}^{n} a_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij}} \quad (15)$$

$$\vartheta_i = \frac{\sum_{j=1}^{n} w_j a_{ij}}{w_i} \quad (16)$$

Next, the principal eigenvalue λ_{max} and the consistency index (CI), must be computed with Equation 17 and Equation 18 respectively.

$$\lambda_{max} = \frac{\sum_{i=1}^{n} \vartheta_i}{n} \quad (17)$$

$$CI = \frac{\left(\lambda_{max} - n\right)}{\left(n-1\right)} \quad (18)$$

Finally, the CR can be obtained by applying Equation 19.

$$CR = \frac{CI}{RI_n} \quad (19)$$

where, RI_n is a random index, which can be obtained in Table 5, according to the number n of alternatives. If CR < 0.1, the matrix can be considered consistent. Otherwise, the matrix is not consistent and the expert evaluations should be revised.

Table 5. Values for RI_n according to the number of alternatives (Saaty, 2008).

n	3	4	5	6	7	8	9	10
RI_n	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

3.3. Fuzzy TOPSIS

The TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) is a widely applied technique to solve MCDM problems that aim to rank the alternatives and select the best solution based on criteria and using a simple and intuitive algorithm (Montanari et al., 2021; Yadav et al., 2018; Onat et al., 2016; Wanke et al., 2015). The development of the TOPSIS algorithm is based on the idea to achieve a solution that is both as close as possible to the positive ideal solution and as far as possible from the negative ideal solution (Haleem et al., 2021; Raut et al., 2017; Shukla et al., 2017). Since its proposition by Hwang & Yoon (1981), the TOPSIS technique has become one of the most used MCDM methods with the development of different extension proposals (Çelikbilek & Tüysüz, 2020). To deal with different experts' subjective judgments, which can be imprecise and uncertain, Chen (2000) proposed the fuzzy TOPSIS. The fuzzy TOPSIS also became a very popular and successfully applied technique in several current real-world challenges from many research fields (Palczewski & Sałabun, 2019).

In the fuzzy TOPSIS, linguistic variables are used by the decision-makers to evaluate the alternatives. These linguistic variables are represented by fuzzy numbers that are used in the following steps of the TOPSIS algorithm (Nădăban et al., 2016).

Step 1:aggregate the linguistic variables provided by the decision-makers on the performance of each alternative and the weight of the criteria through Equations 20 and 21.

$$\tilde{p}_{ij} = \frac{1}{K}\left[\tilde{x}_{ij}^{1} + \tilde{x}_{ij}^{2} + \ldots + \tilde{x}_{ij}^{k}\right] \tag{20}$$

$$\tilde{w}_{j} = \frac{1}{K}\left[\tilde{w}_{j}^{1} + \tilde{w}_{j}^{2} + \ldots + \tilde{w}_{j}^{k}\right] \tag{21}$$

Where $\tilde{x}_{ij}^{k}$ is a fuzzy element that represents the judgment of decision-maker $k = (1,2,\ldots,K)$ for the performance of the alternative i = (1, 2, ..., n) related to the criterion $j = (1,2,\ldots,m)$. $\tilde{w}_{j}^{k}$ is the fuzzy element that represents the judgment of decision-maker k for the weight of the criterion j.

Step 2: create a decision matrix $\tilde{D}$ to represent all the performances $\tilde{p}_{ij}\,(\mathrm{i} = 1, 2\ldots,\ \mathrm{n};\ \mathrm{j} = 1, 2,\ \ldots,\ \mathrm{m})$ of the alternative $A_i\,(i = 1,2\ldots,n)$ according to each criterion $C_j\,(j = 1,2,\ldots,m)$ as represented in Equation 22. In addition, a vector of criterion weights $\tilde{W} = \tilde{w}_j\,(j = 1,2,\ldots m)$ is defined by Equation 23.

$$\tilde{D} = \begin{matrix} & C_1 & C_2 & \ldots & C_m \\ A_1 & \tilde{p}_{11} & \tilde{p}_{12} & \cdots & \tilde{p}_{1m} \\ A_2 & \tilde{p}_{21} & \tilde{p}_{22} & \cdots & \tilde{p}_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_n & \tilde{p}_{n1} & \tilde{p}_{n2} & \cdots & \tilde{p}_{nm} \end{matrix} \tag{22}$$

$$\tilde{W} = \left[\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_m\right] \tag{23}$$

Step 3: normalize the matrix $\tilde{D}$ using a linear transformation scale represented by the Equations 24 to 26 to get the matrix $\tilde{R}$.

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{n \times m} \tag{24}$$

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^{+}}, \frac{m_{ij}}{u_j^{+}}, \frac{u_{ij}}{u_j^{+}}\right), u_j^{+} = \max_i u_{ij} \ |\mathit{benefits\ criteria} \tag{25}$$

$$\tilde{r}_{ij} = \left(\frac{l_j^{-}}{u_{ij}}, \frac{l_j^{-}}{m_{ij}}, \frac{l_j^{-}}{l_{ij}}\right), l_j^{-} = \min_i l_{ij} \ |\mathit{costs\ criteria} \tag{26}$$

Step 4: multiply the elements $\tilde{r}_{ij}$ in matrix $\tilde{R}$ by the weights $\tilde{w}_j$ to obtain the matrix $\tilde{V}$ as shown in Equations 27 and 28.

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{n \times m} \tag{27}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_j \tag{28}$$

Step 5: Define the Fuzzy Positive Ideal Solution - FPIS (F^{+}), and the Fuzzy Negative Ideal Solution – FNIS (F^{-}) as presented in Equations 29 and 30, in which $\tilde{v}_j^{+} = \max_i\left\{\tilde{v}_{ij}\right\}$ and $\tilde{v}_j^{-} = \min_i\left\{\tilde{v}_{ij}\right\},\ j = 1,2,\ldots,m.$

$$F^{+} = \left(\tilde{v}_1^{+}, \tilde{v}_2^{+}, \ldots, \tilde{v}_m^{+}\right) \tag{29}$$

$$F^{-} = \left(\tilde{v}_1^{-}, \tilde{v}_2^{-}, \ldots, \tilde{v}_m^{-}\right) \tag{30}$$

Step 6: Calculate de distance S_i^{+} between the values of FPIS (F^{+}) and the scores of the alternative A_i in the $\tilde{V}$ matrix using Equations 31 and 32. The same procedure should be performed for the calculus of the distance S_i^{-} between the values of FNIS (F^{-}) and the scores of the $\tilde{V}$ matrix. For this purpose, the Euclidian distance between two triangular fuzzy numbers presented in Equation 2 is used.

$$S_i^{+} = \sum_{j=1}^{m} d\left(\tilde{v}_{ij}, \tilde{v}_j^{+}\right), \forall i = 1,2,\ldots,n. \tag{31}$$

$$S_i^{-} = \sum_{j=1}^{m} d\left(\tilde{v}_{ij}, \tilde{v}_j^{-}\right), \forall i = 1,2,\ldots,n. \tag{32}$$

Step 7: Compute the closeness coefficient CC_i for each alternative A_i using Equation 33. Then, based on the CC_i results, a ranking of the alternatives A_i is created in decreasing order. The closer the coefficient is to 1, the better is the overall performance of the alternative.

$$CC_i = \frac{S_i^{-}}{S_i^{+} + S_i^{-}}, \forall i = 1,2,\ldots,n. \tag{33}$$

3.4. Proposed model for CBMs prioritization

Several approaches can be found in literature that proposes the hybridization of different MCDM techniques, since each MCDM is appropriate for different purposes or requires different types of information (Büyüközkan & Göçer, 2021; Büyüközkan & Güler, 2021; Ortiz-Barrios & Alfaro-Saiz, 2020; Ortiz-Barrios et al., 2020). The proposed model uses the hybridization of fuzzy AHP and fuzzy TOPSIS techniques, since both techniques are necessary for different purposes. The fuzzy AHP is commonly used to determine the relative weights of decision criteria, as can be seen in several studies (Büyüközkan & Güler, 2021; Ortiz-Barrios & Alfaro-Saiz, 2020; Ortiz-Barrios et al., 2020). In addition, the fuzzy TOPSIS is an adequate technique to find an alternative's priority rank (Montanari et al., 2021). Despite of fuzzy AHP is also often used to rank alternatives, it was not appropriate to use it to rank the alternatives, since the available inputs of relationship between CE indicator and CBM (Table 1, Table 2 and Table 3) are not pairwise comparisons.

As can be seen in Figure 1, the proposed decision making model is composed of four steps. Step 1 consists of the parametrization of the fuzzy numbers as detailed in section 3 and the selection of the CE principles. In this way, it is necessary to define the linguistic terms and the correspondent fuzzy sets to the judgments

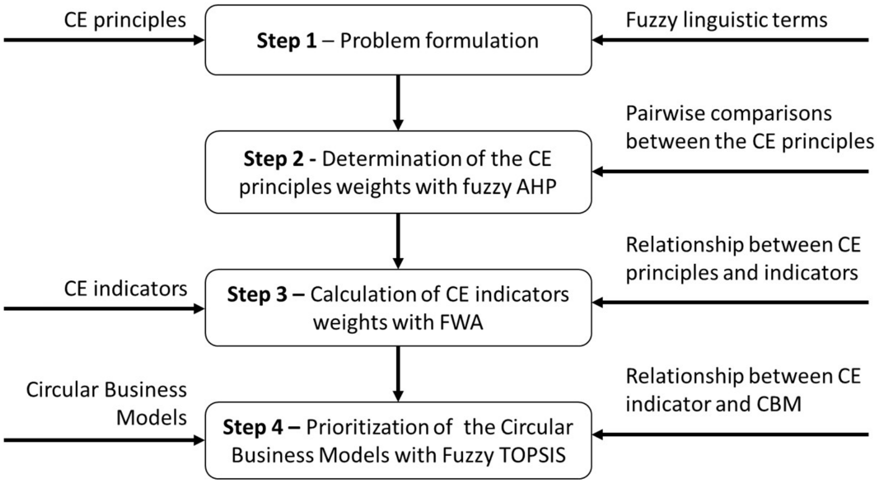

Figure 1. Proposed model for CBM prioritization.

related to the pairwise comparisons between the preference orders of the CE principles. In addition, it is necessary to define the fuzzy sets related to the linguistic term which represents the intensity level of the relationship between the CE principles, the CE indicators, and CBM. An example of linguistic terms and the correspondent fuzzy sets can be seen in Table 6 and 7.

Table 6. Fuzzy linguistic terms for the pairwise comparisons.

Fuzzy Linguistic Terms	Triangular Fuzzy Number
Extremely more important (EI)	(7, 9, 9)
Much more important (MMI)	(3, 5, 7)
More important (MI)	(1, 3, 5)
A little more important (LMI)	(1, 1, 3)
Equally important (EI)	(1, 1, 1)

Table 7. Fuzzy linguistic terms to represent the intensity level of the relationship.

Fuzzy Linguistic Terms	Triangular Fuzzy Number
Strong	(5, 9, 9)
Medium	(1, 5, 9)
Weak	(1, 1, 5)

In Step 2, the experts should evaluate the preference relations between the CE principles, presented in section 2, using the linguistic terms defined in Step 1. Note that, since the experts' assessments are independent, the consistency ratio (CR) should be checked for each one of them. Therefore, it is necessary to apply Equations 14 to 19 to calculate the CR of each decision maker set of assessments. If CR < 0.1, the assessments are considered consistent, otherwise, the decision makers with a CR ≥ 0.1 must review their assessments. Then, the expert's assessments can be aggregated using the arithmetic mean (Lima-Junior et al., 2014):

Following the fuzzy AHP procedure, it is necessary to compute the values of the fuzzy synthetic extent, by applying Equations 5 and 7. Next, the degrees of possibility of the fuzzy values must be calculated with Equations 9 and 10. Finally, the CE principles weight vector W can be calculated using Equation 12, which should be normalized.

To begin Step 3, firstly it is necessary to select the adequate CE indicators for the organization since not all of them can be applied for all organizations. Next, is necessary to calculate the weights of the CE indicators, by using the fuzzy weighted averaging (FWA) aggregation operator, to aggregate the intensity level of the relationship of each CE principle for all CE indicators. Therefore, by applying Equation 3, using the weights of the CE principles, computed in Step 2, and the level of the relationship between the CE principles and the CE indicators, the CE indicators weights can be calculated. Note that the intensity level of the relationship of each CE principle for all CE indicators should be assessed by the DMs.

Finally, with fuzzy TOPSIS technique, it is possible to prioritize the mentioned CBMs in Section 2. In this way, Step 4 uses the CE indicators weights, calculated in Step 3, and the intensity level of the relationship between the CE indicators and the CBMs, which also have to be assessed by the DMs. The $\tilde{p}_{ij}$ index, from Equation 20, is composed by the level of the intensity of the relationship between the CE indicators and the CBMs. The $\widetilde{K}_j$ value corresponds to the normalized CE indicators weights, which can be computed by defuzzifying the CE indicators weights computed in Step 3 with Equation 14 and normalizing them.

Following the fuzzy TOPSIS procedure, the intensity level of the relationship between the CE indicators and the CBMs converted in TFNs. Next, the decision matrix must be normalized with Equations 24 to 26. Using Equation 28, the normalized decision matrix has to be multiplied using the CE indicators weights.

Now, the Fuzzy Positive Ideal Solution FPIS (F^{+}) and the Fuzzy Negative Ideal Solution FNIS (F^{-}) must be computed with Equation 29 and Equation 30. The distance between the intensity values and the FPIS $\left(D_i^{+}\right)$ and the distance between the intensity values and Fuzzy Negative Ideal Solution FNIS (D_i^{-}) can be computed by Equation 31 and Equation 32. Finally, by applying Equation 33, it is possible to compute the closeness coefficient CC_i of each CBM. The output is a rank of priority of CBMs, according to the organization's principles.

4. Results

In order to illustrate the step-by-step of the model proposed in section 4, a manufacturer from the automotive industry supply chain was chosen for an illustrative application. This organization aims to implement CE to become more sustainable. However, to initiate the transition towards CE, the organization needs to decide which CBM is more suitable for its context and is more valuable to put resources. Therefore, to select the most suitable CBM based on the CE principles, four organization's specialists in sustainability and CE were selected to judge the relative importance of the CE principles.

In Step 1, all the CE principles were selected, Table 6 and Table 7 show the fuzzy linguistic terms and the TFNs for the pairwise comparisons and to represent the intensity level of the relationship, respectively. Note that the linguistic terms used to represent the intensity level of the relationship between the CE principles, the CE indicators, and the CBM, were defined based on the study of Rossi et al. (2020), as can be seen in the Table 1, Table 2 and Table 3.

Following Step 2 of the proposed model, the linguistic pairwise comparisons between the CE principles of each DM were converted to TFN and the CR of each DM matrix, computed with Equations 14 to 19, are shown in Table 8. The DMs pairwise comparisons converted to TFN and their respective CR can be seen in the Supplementary Material (Table S1).

Table 8. Expert's pairwise comparisons between CE principles.

	System Thinking	Innovation	Stewardship	Collaboration	Value Optimization	Transparency
DM1						
System Thinking	EI	EI	EI	LMI	LMI	MI
Innovation	1 / EI	EI	EI	LMI	LMI	MI
Stewardship	1 / EI	1 / EI	EI	LMI	LMI	MI
Collaboration	1 / LMI	1 / LMI	1 / LMI	EI	EI	LMI
Value Optimization	1 / LMI	1 / LMI	1 / LMI	1 / EI	EI	LMI
Transparency	1 / MI	1 / MI	1 / MI	1 / LMI	1 / LMI	EI
DM2						
System Thinking	EI	EI	EI	LMI	LMI	MI
Innovation	1 / EI	EI	EI	LMI	LMI	MI
Stewardship	1 / EI	1 / EI	EI	EI	MI	LMI
Collaboration	1 / LMI	1 / LMI	1 / EI	EI	EI	LMI
Value Optimization	1 / LMI	1 / LMI	1 / MI	1 / EI	EI	LMI
Transparency	1 / MI	1 / LMI	1 / LMI	1 / LMI	1 / LMI	EI
DM3						
System Thinking	EI	EI	EI	EI	LMI	MI
Innovation	1 / EI	EI	LMI	LMI	LMI	MI
Stewardship	1 / EI	1 / LMI	EI	LMI	LMI	MI
Collaboration	1 / EI	1 / LMI	1 / LMI	EI	LMI	LMI
Value Optimization	1 / LMI	1 / LMI	1 / LMI	1 / LMI	EI	EI
Transparency	1 / MI	1 / MI	1 / MI	1 / LMI	1 / EI	EI
DM4						
System Thinking	EI	EI	LMI	LMI	LMI	MI
Innovation	1 / EI	EI	EI	LMI	LMI	MI
Stewardship	1 / LMI	1 / EI	EI	EI	EI	MI
Collaboration	1 / LMI	1 / LMI	1 / EI	EI	EI	MI
Value Optimization	1 / LMI	1 / LMI	1 / EI	1 / EI	EI	LMI
Transparency	1 / MI	1 / MI	1 / MI	1 / MI	1 / LMI	EI

Since, the CR's of DM1, DM2, DM3 and DM4 are respectively, 0.070, 0.083, 0.077 and 0.067, all the CR are lower than 0.1, and therefore, the decisions matrices can be aggregated with arithmetic mean, considering that all DMs have the same weight. The aggregated decision matrix is presented in Table 9.

Next, the values of the fuzzy synthetic extent can be computed applying Equations 5 to 7, for example:

$$S_{C1} = (6.0, 8.0, 14.0) \otimes \left(\frac{1}{63.5}, \frac{1}{40.33}, \frac{1}{28.57} \right) = (0.094, 0.198, 0.490)$$

The degrees of the possibility of the fuzzy values can be calculated with Equations 9 and Equation 10. Now, the CE principles weight vector W' can be computed by applying Equation 12, assuming that:

Table 9. Aggregated decision matrix of the CE principles pairwise comparisons.

	System Thinking	Innovation	Stewardship	Collaboration	Value Optimization	Transparency
System Thinking	(1.0, 1.0, 1.0)	(1.0, 1.0, 1.0)	(1.0, 1.0, 1.5)	(1.0, 1.0, 2.5)	(1.0, 1.0, 3.0)	(1.0, 3.0, 5.0)
Innovation	(1.0, 1.0, 1.0)	(1.0, 1.0, 1.0)	(1.0, 1.0, 1.5)	(1.0, 1.0, 3.0)	(1.0, 1.0, 3.0)	(1.0, 3.0, 5.0)
Stewardship	(0.83, 1.0, 1.0)	(0.83, 1.0, 1.0)	(1.0, 1.0, 1.0)	(1.0, 1.0, 3.0)	(1.0, 1.5, 3.0)	(1.0, 2.5, 4.5)
Collaboration	(0.5, 1.0, 1.0)	(0.33, 1.0, 1.0)	(0.67, 1.0, 1.0)	(1.0, 1.0, 2.0)	(1.0, 1.0, 1.5)	(1.0, 1.5, 3.5)
Value Optimization	(0.33, 1.0, 1.0)	(0.33, 1.0, 1.0)	(0.47, 0.83, 1.0)	(0.83, 1.0, 1.0)	(1.0, 1.0, 1.0)	(1.0, 1.0, 2.5)
Transparency	(0.2, 0.33, 1.0)	(0.2, 0.33, 1.0)	(0.23, 0.50, 1.0)	(0.30, 0.83, 3.0)	(0.5, 1.0, 3.0)	(1.0, 1.0, 1.0)

$$d'(C_1) = V(S_{C1} \geq S_{C2}, S_{C3}, S_{C4}, S_{C5}, S_{C6}) = \min(1.000, 1.000, 0.856, 0.758, 0.538) = 0.538$$

$$d'(C_2) = V(S_{C2} \geq S_{C1}, S_{C3}, S_{C4}, S_{C5}, S_{C6}) = \min(1.000, 1.000, 0.856, 0.758, 0.538) = 0.538$$

$$d'(C_3) = V(S_{C3} \geq S_{C1}, S_{C2}, S_{C4}, S_{C5}, S_{C6}) = \min(1.000, 1.000, 0.856, 0.758, 0.549) = 0.549$$

$$d'(C_4) = V(S_{C4} \geq S_{C1}, S_{C2}, S_{C3}, S_{C5}, S_{C6}) = \min(1.000, 1.000, 1.000, 0.920, 0.691) = 0.691$$

$$d'(C_5) = V(S_{C5} \geq S_{C1}, S_{C2}, S_{C3}, S_{C4}, S_{C6}) = \min(1.000, 1.000, 1.000, 1.000, 0.764) = 0.764$$

$$d'(C_6) = V(S_{C6} \geq , S_{C1}, S_{C2}, S_{C3}, S_{C4}, S_{C5}) = \min(1.000, 1.000, 1.000, 1.000, 1.000) = 1.000$$

Then,

$$W' = (0.538, 0.538, 0.549, 0.691, 0.764, 1.000)$$

Finally, the W' was normalized to $(0.132, 0.132, 0.135, 0.169, 0.187, 0.245)$, which represents the final CE principles weights vector .

For Step 3, all DMs agreed to use the intensity level of relationship between the CE indicators and the CE principles presented in the Table 1, Table 2 and Table 3, which were converted to their respective TFN, as shown in Table S2 (from the supplementary material). Next, the CE indicators weights were calculated through the FWA, from Equation 10, using the weights of the CE principles, obtained in step 2, and their respective intensity level of relationship with the CE indicators.

For example, the indicator reduction of raw materials has a strong relationship with the principle systems thinking, a weak relationship with innovation, a strong relationship with stewardship, a median relationship with collaboration, a strong relationship with value optimization, and a median relationship with transparency. The TFN associated with these intensity levels of relationship, shown in Table S3 (from the supplementary material), were multiplied with their related principle weight. Therefore, the weight $\widetilde{K}_j$ of the reduction of raw materials, the indicator is given by:

$$\widetilde{K}_1 = (0.132) * (5,9,9) + (0.132) * (1,1,5) + (0.135) * (5,9,9) + (0.169)$$
$$* (1,5,9) + (0.187) * (5,9,9) + (0.245) * (1,5,9) = (2.81,\ 6.29,\ 8.47)$$

The weights of all CE indicators are presented in the supplementary material (Table S3). Next, the CE indicators weights were defuzzyfied with Equation 21, for example:

$$P(\tilde{L}) = L = (2.81 + (4 * 6.29) + 8.47) = 6.07$$

The defuzzyfied CE indicators weights should be normalized. In this case:

$$\tilde{N}(L) = \frac{6.07}{110.53} = 0.0549$$

The defuzzyfied values and the normalized CE indicators weights are also shown in the supplementary material (Table S3).

Likewise in Step 3, the DMs agreed to consider the intensity level of the relationship between the CE indicators and the CBMs presented in Table 1, Table 2 and Table 3, which were converted to TFNs (Table S4). For example, the relationship between the indicator Reduction of Raw materials and the CBM Product as service is strong. Therefore, the respective TFN for this relationship is (5, 9, 9). Following Equation 24 and Equation 25, the decision matrix was normalized considering $u_j^+ = 9$. For instance, (5, 9, 9) is normalized to (0.555, 1.000, 1.000). The normalized values of the intensity level of the relationship between the CE indicators and CBMs can be found in the supplementary material (Table S5). With Equation 28, the normalized decision matrix was multiplied by the CE indicators weights, obtained in Step 3. Therefore, following the same example of the relationship between the indicator Reduction of Raw materials and the CBM Product as service:

$$\tilde{v}_{11} = \tilde{r}_{11} \times \tilde{w}_1 = (0.555, 1.000, 1.000) \times 0.0549 = (0.0305, 0.0549, 0.0549)$$

The weighted normalized decision matrix can be seen in the supplementary material (Table S6).

The FPIS (F^+) and the FNIS (F^-) values were defined following Equation 29 and Equation 30, the D_i^+ and the D_i^- values were calculated with Equation 31 and Equation 32, respectively. Finally, to obtain the CBM priority ranking, the closeness coefficient CC_i of each CBM was computed following Equation 33, as shown in Table 10. All FPIS (F^+), FNIS (F^-), D_i^+ and D_i^- values are presented in the supplementary material (Table S7, Table S8 and Table S9).

Table 10. Circular Business Models closeness coefficient CC_i and rank.

Circular Business Model	CC_i	Rank
Recovery by-products	0.6740	1_{st}
Product life extension	0.6489	2_{nd}
Product as service	0.5969	3_{rd}
Sharing economy	0.5222	4_{th}
Dematerialization	0.5240	5_{th}
On-demand	0.4794	6_{th}

5. Discussion and sensitivity analysis

5.1. Regarding the obtained results

Table 7 presents the performance of the CBMs and the respective ranking considering the influence of all the three dimensions of indicators. The main purpose of this ranking is to show that to achieve greater performance in the proposed circularity indicators, CBMs should be prioritized as the presented classification. The best CBM ranked indicated that Recovery by-products is the most suitable CBM for improving the circularity of an organization when all the indicators of the three dimensions (economic, social, and material) are selected. Product life extension was classified as the second and Product as a service as the third. These three CBMs are closely related to each other.

Recovery by-products means that other products will be created from secondary raw materials and/or end-of-life materials (British Standards Institution, 2017; Ellen MacArthur Foundation, 2012). A lot of organizations emerged to apply this business model to deal with the existing waste. Applying this kind of CBM means that resources in the product remain available for consumption and that no virgin materials need to be mined (Prosman & Sacchi, 2018; Vegter et al., 2020). Moreover, the performance objective is to recover a product, so that is available for subsequent consumption, making it possible to use less materials, water, and energy (Vegter et al., 2020). Recovery by-products helps in the extension of product life and in closing the loop when Product as a Service CBM is applied (Arponen et al., 2018).

Product life extension seeks to design products to be more durable and to circulate in the system aiming to keep value. Product life extension is the key to reducing rapid and excessive consumption of Product as a service (Chen et al., 2020). It is also the main purpose to create durable products to slow material and energy flows (Milios, 2021). For companies and stakeholders, it is important to create and capture value via extending product lifetime in their business models (Hopkinson et al., 2020). Recovery by-products and Product life extension are directly connected to Product as a service, since the first two CBM are essential for the planning and implementation of successful Product as a service system.

Product as a service is based on the idea of a performance economy, where ownership-based business models are replaced with pay-per-use models to reduce production and fulfill CE requirements (British Standards Institution, 2017; Chen et al., 2020). Product as a service incorporates strategies such as leasing, renting, and pay-per-use which help manufacturers and product owners handle the whole life cycle of products and decide when they should be repaired, recycled, or remanufactured (Arponen et al., 2018; British Standards Institution, 2017; Chen et al., 2020).

Those CBM were classified as the third that most impacts on the achievement of a good circular performance because they incorporates the majority of the specific indicators of the three dimensions of CE indicators. Those CBM when correctly implemented in the automobile sector have the potential to reduce operating expenses, make companies participate in secondary sales, increase gross profits, generate and increase revenue, and reduce input material costs (Arponen et al., 2018).

5.2. Regarding the managerial and practical implications

This paper is relevant for practitioners since, based on the analysis and tests conducted, it was possible to identify the CBMs that are most suitable for the improvement of performance regarding CE implementation. The ranking of the CBMs concerning the CE principles and the circularity indicators indicate that organizations have some paths to follow in the transition towards CE. The choice will depend on the main strategic goals of the organization. If the organization aims to have equal performance on the three dimensions of circularity indicators, it should choose Recovery by-products as its initial CBM. If the focus is on economic indicators, the organization could choose between Products as a Service or Recovery by-products. If the focus is on social indicators the decision is to implement Product as a service. In case of the intention is to improve the material indicators, the decision is to implement Recovery by-products. Hence, this research contributes to managers and practitioners by operationalizing forms to connect CBMs ans CE indicators systematically.

It is worth saying that a combination of different CBMs could be used to make the business stronger and to fulfill some aspects of the value proposition that sometimes could not be fulfilled using only one CBM. Also, it should be highlighted that the choice of the CE indicators can vary depending on the organizational context. Therefore, the model must be applied selecting only the relevant CE indicators, and then, the company can obtain the appropriate CBM ranking.

5.3. Regarding contributions to theory

CE can support organizations to develop sustainable solutions, maximizing the collaboration between stakeholders to create positive social and environmental impacts. The CBMs are strategies used to achieve sustainability. However, it was not found in the literature quantitative approaches to indicate which CBMs can be prioritized towards CE implementation.

In contrast with similar papers, and in a wide search through the literature, to the best of our knowledge, just the study of Husain et al. (2021) similarly addresses CBMs, as it can be seen in Table 5. However, Husain et al. (2021) do not analyze the relationship between CE principles and circularity indicators as we propose in the present research. The authors only seek to rank the CBMs with pre-defined criteria. Hence, the use of CE principles and circularity indicators to rank CBMs remains innovative in this study. Performance indicators are critical for determining how well a business is performing in CE and where improvements may be made. In this regard, using circularity indicators to prioritize CBMs may assist firms in establishing the parameters like as technology, resources, people, cultural elements, regulations, and other things that are required for CE implementation.

5.4. Sensitivity analysis

Sensitivity analysis is usually performed to check the robustness of the current search structure by considering the sources of uncertainty within a multi-criteria analysis (Maliene et al., 2018). In the application of the Fuzzy TOPSIS technique, sensitivity analysis contributes to understanding the influence of varying input data on the final ranking of alternatives (Kumar & Barman, 2021). Thus, several studies dealing with a variety of criteria and applying Fuzzy TOPSIS seek to change the weights of the decision-making criteria to assess their influence on the final solution (Awasthi et al., 2011; Dwivedi et al., 2018; Kumar & Barman, 2021).

In this way tests were conducted to understand the influence of the indicators' weights on the prioritization of the CBMs according to each dimension of indicators. To perform these tests, each dimension of indicator had its weight considered as integral while the other dimensions of indicators had their weights set to zero. Table 11 presents the performance of the CBMs and the respective ranking for each test carried out.

Table 11. Performance of each CBM when isolating each dimension of indicators.

Circular Business Models	Dimension of the analyzed indicators					
	Material		Economic		Social	
	Coe	Rank	Coe	Rank	Coe	Rank
Product as service	0.4277	5	0.7350	1	0.7070	1
Sharing economy	0.5191	3	0.6152	3	0.4570	6
Product life extension	0.6379	2	0.6152	3	0.5713	2
On-demand	0.4216	6	0.2807	6	0.5713	4
Recovery by-products	0.6859	1	0.7350	1	0.5713	2
Dematerialization	0.5033	4	0.6152	3	0.5220	5

The best CBM ranked according to each dimension of indicators indicates that Product as a service is the most suitable CBM in the economic and social dimension and Recovery by-products is the most suitable CBM for the material and economic dimension. Both CBM are complementary to each other since Recovery by-product is part of the Product as a service (Arponen et al., 2018). Moreover, Recovery by-products has a major focus on value optimization of materials while Product as a service has its major focus in creates new kinds of business structures.

In order to understand the influence of the principles' weights on the prioritization of the CBMs, tests were conducted by setting each principle with its weight considered as integral while the other principles had their weights set to zero. Table 12 presents the performance of the CBMs and the respective resulting ranking.

Table 12. Performance of each CBM when with integral weight in each criterion.

Circular Business Models	System Thinking		Innovation		Stewardship		Collaboration		Value Optimization		Transparency	
	Coe	Rank	Coe	Rank	Coe	Rank	Coe	Rank	Coe	Rank	Coe	Rank
Product as service	0.555	3	0.532	3	0.530	4	0.549	3	0.539	3	0.541	3
Sharing economy	0.518	4	0.510	4	0.534	3	0.517	4	0.523	4	0.511	5
Product life extension	0.643	2	0.634	2	0.653	2	0.611	2	0.636	2	0.622	2
On-demand	0.484	5	0.463	5	0.466	6	0.446	5	0.460	5	0.457	6
Recovery by-products	0.671	1	0.667	1	0.684	1	0.662	1	0.668	1	0.663	1
Dematerialization	0.518	4	0.516	4	0.528	5	0.517	4	0.523	4	0.518	4

It's relevant to note that although some variations in the rankings could be noted from the changes in the weights, the order of the CBMs remains unaltered. This happens because all CE indicators were selected in the performed test, which makes them all assume similar weights. This indicates the robustness of the proposed decision model and consistency in the execution of the soft computing techniques.

As it can also be observed in Table 12, the ranking of CBM consists of the Recovery by-products first, followed by Product life extension, Product as a service, sharing economy, and On-demand. In this direction, it should be emphasized that, in real case applications, each organization should select only the principles that apply to its reality, as commented in section 4. The company of the illustrative application did not especified which indicator's dimension should be focused, which justifies the rank obtained in Table 10.

6. Conclusions

This paper presented a new approach to support CBMs prioritization based on fuzzy multicriteria group decision making. The proposed model combines the fuzzy AHP technique for weighting the CE principles, which is used to find the weights of the CE indicators, with the fuzzy TOPSIS technique to find the priority order of the CBMs. An illustrative application was conducted to evaluate the CBM prioritization of a manufacturer of the automotive industry supply chain, according to four organization's experts in sustainability and CE.

This paper brings a novelty in the analysis of the CBMs that should be applied to foster the transition towards the CE in combination with the use of circularity indicators to measure organizational performance. To the best of the authors' knowledge, no previous article proposes such analysis using fuzzy techniques. Thus, this paper brings new insights for the research field proposing a more analytical way to look at the CBMs and showing the importance of the implementation of CBMs combined with circularity indicators.

A major contribution of the presented work is the proposal of the first approach to CBM prioritization, which was developed based on two of the main elements of the CE: CE principles and CE indicators. Therefore, this article can be used to a guide future research on the proposition of other approaches to CBM prioritization. For further researches, it is suggested to explore other group decision making approaches, such as consensus reaching process techniques. Also, since this paper presented an illustrative application, it is suggested to compare the results of the proposed model application in real-world companies from different sectors.

As a suggestion for future studies, it can be cited the consideration of the interretaltions between CBMs to obtain the final ranking. The adoption of CE is possible through a combination of different CBMs (Husain et al., 2021), being that always will be a predominant one and other CBMs that are complementar. In this sense, it is important to identify how the different CBMs are related and complementar to each other. For this purpose, different techniques can be used, such as the DEMATEL and the Fuzzy Cognitive Maps.

Another suggestion for future studies is the use of more advanced linguistic representations of fuzzy sets. For instance, Hesitant Fuzzy Sets, Dual Hesitant Fuzzy Sets and Double Hierarchy Hesitant Fuzzy Linguistic Terms Sets are fuzzy generalizations that allow to collect more complex evaluations composed of sentences of judgments. In this way, such generalizations are able to handle higher levels of imprecision and hesitation in the decision makers' evaluations. As a final direction for future research, other MCDM techiniques, such as combined compromise solution (CoCoSo) and Complex Proportional Assessment (COPRAS) which can be applied to prioritize CBMs.

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Supplementary Material

Supplementary material accompanies this paper.

Table S1. Expert's pairwise comparisons between CE principles converted in TFN and their CR.
Table S2. Intensity level of relationship between CE principles and indicator converted in TFN.
Table S3. CE indicators weights, defuzzyfied weights and normalized weights.
Table S4. Intensity level of relationship between the CE indicators and CBMs converted in TFNs.
Table S5. Normalized intensity level of relationship between the CE indicators and CBMs.
Table S6. Weighted intensity level of relationship between the CE indicators and CBMs.
Table S7. Fuzzy Positive Ideal Solutions and Fuzzy Negative Ideal Solutions.
Table S8. Distance between the intensity values and Fuzzy Positive Ideal Solution.
Table S9. Distance between the intensity values and Fuzzy Negative Ideal Solution.

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