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Examining the dimensionality of Circular Economy metrics using Hierarchical Clustering on Principal Components

Collin L. Yobe[1*]

[1] University of South Africa, Graduate School of Business Leadership, Cnr Janadel and, Alexandra Ave, Midrand, 1686 (South Africa)

collinyobe@gmail.com

*contact author

ORCID 0000-0001-5270-2192

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Abstract

The Circular Economy (CE) indices have become a valuable tool for supporting the development of policies that provide information that reduces environmental pressures and impacts. However, highly dimensional data identifying many CE indicators is impractical in application. This paper aims to create a composite index of the CE indicators using the Hierarchical Clustering on Principal Components (HCPC) to extract the meaning of the CE indicators, as reducing dimensionality can improve understanding of indicators and metrics. The advantage of the HCPC methodology over principal components analysis (PCA) alone involves applying objective clustering techniques to the PCA results, which results in a better cluster solution. This study analysed a dataset of 61 indicators obtained from De Pascale, Arbolino, Szopik-Depczyńska, Limosani, and Ioppolo (2021). The composite indices revealed the dimensions of industrial symbiosis (IS), CE strategies, and spatial applications of the CE and IS concepts. The bottom-up and top-down approaches for CE and IS strategies have been the main implementation approaches in different governments and regions.

Keywords: Circular Economy, Circular Economy indicators, industrial symbiosis, Hierarchical Clustering on Principal Components

1. Introduction

The circular economy (CE) is being touted as a promising solution to mitigate human activities' growing environmental and resource pressures (Bocken, De Pauw, Bakker, & Van Der Grinten, 2016). Several countries have adopted CE principles to achieve zero waste, a crucial goal for most economies as it reduces greenhouse emissions and environmental impacts from current linear waste production systems, making CE a crucial part of future strategies. A CE promotes system innovations to improve waste management resource efficiency and balance the economy, environment, and society (Kristensen & Mosgaard, 2020). The CE paradigm promotes autonomous production processes that reuse materials, generating increased interest in research and developing metrics for a circular shift. The interest in circularity indicators has led to extensive literature on CE. Currently, there are three levels of indicators for measuring the CE, i.e., micro (companies, product), meso (industrial symbiosis (IS), eco-industrial parks (EIPs)), and macro (governments, global, national, regional, city) (de Oliveira, Dantas, & Soares, 2021; De Pascale et al., 2021; Kristensen & Mosgaard, 2020; Moraga et al., 2019).

The rise of EIPs is a significant trend in the new industrial reality, aiming to promote environmental benefits and economic development through collaboration between companies (Felicio, Amaral, Esposto, & Durany, 2016). IS promotes a collective approach to competitive advantage across industries by integrating the physical exchange of materials, energy, water, and by-products into their business processes (Felicio et al., 2016; Geng, Fu, Sarkis, & Xue, 2012; Geng, Zhang, Ulgiati, & Sarkis, 2010; Jacobsen, 2006). Moreover, as such, EIPs must be able to promote IS.

The IS and CE are intricate subjects that require meticulous coordination due to the potential differences in preferences among various stakeholders. Therefore, policymakers must take a direct lead in pushing and driving IS and the CE. Through legislation, governments have managed to work towards putting CE plans into action. The Chinese government has played a significant role in the implementation of IS. They can define policy, and everyone within the country follows. CE, adopted in China to promote economic growth despite material and energy limitations, has garnered significant global interest from governments, international bodies, industrial associations, and corporations (Franklin-Johnson, Figge, & Canning, 2016). China leads the ranking of countries that have contributed most to the increasing growth rate in research, implementation, and extensive development of CE concepts in academia and politics (De Pascale et al., 2021; Geng et al., 2012). In 2008, China was the first country to adopt legislation to deploy CE strategies by enacting a specific law, confirming China's prominence (De Pascale et al., 2021; Geng et al., 2012; Moraga et al., 2019). Unlike China, the European Commission and its member countries use self-regulatory, bottom-up strategies for implementing CE strategies, which primarily rely on external factors (Cayzer, Griffiths, & Beghetto, 2017; Linder, Sarasini, & van Loon, 2017). The European Commission and member countries employ self-regulatory, bottom-up approaches to implement CE strategies, unlike China, which primarily relies on external factors.

CE is extensively researched, yet its practical application in economic initiatives remains a significant challenge. The extensive literature on CE necessitates rigorous analysis to ensure its relevance for functional purposes due to its disconnection. Several studies have come to the fore and have identified CE indicators (Argüelles, Benavides, & Fernández, 2014; de Oliveira et al., 2021; De Pascale et al., 2021; Parchomenko, Nelen, Gillabel, & Rechberger, 2019; Stanković, Janković-Milić, Marjanović, &

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Janjić, 2021). The current set of circularity metrics is criticised for failing to fully capture the multidisciplinary and systemic nature of the CE (Stanković et al., 2021). These studies critically examine the dimensionality of CE indicators used in studies, highlighting their high dimensionality and potential limitations for practitioners. It suggests that reducing dimensionality can improve understanding of indicators and metrics. The research highlights the need for further knowledge of current research work. Therefore, this paper aims to create a composite index of the CE indicators using the Hierarchical Clustering on Principal Components (HCPC) to extract the meaning of the CE indicators. A dataset of 61 indicators developed in a previous paper identified by De Pascale et al. (2021) will be analysed using the HCPC to achieve the stated aim. This approach reduces data dimensionality and enables further understanding of the already-identified CE issues—IS, spatial applications of the CE concept, and CE strategies. Based on this dataset, the exercise attempts to cluster and classify indicators and papers to provide a structure for the problem.

The rest of the document is structured as follows: Section 2 offers an extensive review of Circular Economy (CE) indicators found in previous studies, providing an understanding of the many metrics and approaches used to evaluate CE performance. In Section 3, the data sources and methodology of this study are explored. The analytical frameworks used for CE indicator analysis and classification, such as principal component analysis (PCA) and hierarchical clustering, are explained. Part 4 presents the PCA analysis and hierarchical clustering findings, thoroughly studying the principal components and clusters found, thereby illuminating the underlying patterns and trends in the CE environment. Ultimately, Section 5 summarises the results derived from the research, emphasising the critical takeaways and implications for furthering CE initiatives.

2. Review of CE indicators in research

The growing resource demand and environmental issues drive a shift towards sustainable production and consumption (Gallego-Schmid, Chen, Sharmina, & Mendoza, 2020). Contemporary sustainability literature focuses on the potential of the CE to disrupt the unsustainable production and consumption linear economy (Kristensen & Mosgaard, 2020). However, considerable effort is required to transition toward a more CE (Parchomenko et al., 2019). In transitioning to this CE economy, indices are fast becoming a valuable tool to support the development of policies in providing information and reducing environmental pressures and impacts (De Pascale et al., 2021).

There three main levels of indicators for measuring CE in the literature so far are macro (global, national, regional, city, governments), meso (IS, EIPs), and micro (single firm, product) (de Oliveira et al., 2021; De Pascale et al., 2021; Geng et al., 2012; Kayal et al., 2019; Kristensen & Mosgaard, 2020; Linder et al., 2017; Mazur-Wierzbicka, 2021; McCarthy, Kapetanaki, & Wang, 2019; Moraga et al., 2019). de Oliveira et al. (2021) present a fourth dimension, nano (products). The lack of detailed measurement and documentation of the CE's progress can hinder understanding of the subject matter, creating barriers for actors at the specific CE level. Governments, policymakers, and business practitioners need more information on CE typologies to promote their business environment towards IS.

Transitioning to a CE requires significant effort, but a widely accepted framework for monitoring progress is lacking due to the vast and diverse areas covered by different assessment methodologies (Parchomenko et al., 2019). Despite the concept's lack

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of clarity, CE focuses on defining action plans supported by specific indicators (Moraga et al., 2019). Transitioning to circular systems may not always lead to favourable alternatives, as potential environmental, economic, or social trade-offs may arise (de Oliveira et al., 2021).

Past CE research methodologies include reviews and empirical papers, with CE indicators classification, categorising and assessing existing work, with some articles developing a measurement method (de Oliveira et al., 2021; Kristensen & Mosgaard, 2020). Some of the approaches used in developing the metric for measuring CE indicators have included the (a) Principal Component Analysis and PROMETHEE (de Oliveira et al., 2021),(b) The Multiple Correspondence Analysis (MCA) (Parchomenko et al., 2019), and (c) indicators grouped by using a double classification: first according to the three spatial dimensions of sustainability –macro, micro and meso – then based on the 3R Core CE principles (De Pascale et al., 2021).

3. Data and methods

3.1 Data collection

The data for this research was obtained from De Pascale et al. (2021) through a systematic literature review, and a final list of indicators was extracted and grouped into three clusters: micro, meso, and macro. The review process involved selecting academic databases, search terms, and screening for practical purposes. Definitions and key concepts were determined, and the gathered material was summarised for future insights. The first step involved a systematic search for published CE indicator implementation studies.

The study used a methodological approach to define and select a sampling framework to review Circular Economy (CE) indicators. The framework was based on a time scale of 2000-2019 and a preliminary search of existing literature in Scopus and Web of Science databases. The results were refined using advanced search terms and keywords to identify the level of implementation of CE indicators at micro, meso, and macro spatial levels. A combination of selected keywords was chosen and compared with other CE reviews to ensure high-level significance. The keyword "Circular Economy" was selected to ensure coherence with the main topic. The academic databases were searched for spatial levels (micro, meso, and macro) and identified keywords for each level.

The classification system includes micro-level (company), meso-level (circular economy), and macro-level (city, country, region) terms, combining them to create a comprehensive understanding of the circular economy. The categories of indicator, index, assessment, evaluation, and measuring were incorporated into the literature as they are frequently used in CE studies. The study enumerated 61 articles that were used for the analysis.

3.2 Description of the Explanatory Variables

Table 1 shows the CE indicators identified by De Pascale et al. (2021). The study quantified these as categorical variables by creating lists of indicators to capture the various attributes of CE indicators. The multivariate approach implemented the Hierarchical Clustering on Principal Components (HCPC). This multivariate approach uses Principal Component Analysis (PCA) and Hierarchical Cluster Analysis (HCA) on these attributes.

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Table 1: Description of the dimensions of circular economy indicators

Attributes	**Description**
Approach:	It includes five subdivisions: Quantitative, qualitative, VBI, analytical tool, and theoretical results.
Application-level:	Refers to Product, Materials, (embodied) Energy, Components, Resource Waste (/waste streams), Product families, IS districts and networks, National, Regional, Provincial, the European Union (EU), and World Regions.
Core CE principles:	This category concerns the following Core CE principles: Reduce, Reuse, Recycle, Recover, Remanufacture, and Redesign
Sustainable Development Dimensions:	The dimensions are Environmental, Economic, and Social.
Level of CE indicators:	The spatial level applications of the circularity vary between macro - as a city, region, or nation, meso – as EIPs (eco-EIPs) and IS, and micro levels – as a single company or products using different methods and techniques.
Regions:	The study considered the following regions: the United States of America (USA), Europe, EU, Belgium, Netherlands, Italy, England/ United Kingdom (UK), India, Spain, Denmark, China, South Korea, Australia, Jordan, Japan, Switzerland, and World Regions.

Source: De Pascale et al. (2021)

3.3 Analytical techniques

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3.3.1 Multivariate Approach for Classification

- Principal Components Analysis

The study utilised Principal Component Analysis (PCA) to create typologies of CE indicators, a statistical method that reduces variables into smaller dimensions with minimal information loss (Jolliffe, 2002). PCA is a feature extraction technique that transforms an initial dataset of variables into a new uncorrelated dataset of orthogonal linear combinations (PCs). It aims to reduce the dimensionality of the data by obtaining the largest variance original variables, accounting for as much variation as possible (Jolliffe, 2002; Manly, 2005); this means that the first PC is the linear combination with the largest variance, while the second one is the linear combination with the second-largest variance, orthogonal to the first PC, etc. According to Costello and Osborne (2005), Varimax rotation simplifies the data's factor structure and makes its interpretation more straightforward and reliable. The authors argue that Varimax rotation, which produces uncorrelated factors, is superior to other rotation orthogonal methods like quartimax and equamax, as it cannot improve fundamental aspects of analysis like variance extraction. De Pascale et al. (2021) grouped the indicators using a double classification: first, according to the three spatial dimensions of sustainability – macro, micro, and meso– and then based on the 3R Core CE principles. The study mapped out dummy variables for indicators' attributes, such as level, country, analytical approach, application level, core CE principles, and sustainable development dimensions, but this approach failed to provide a clear group structure and dimensionality of the CE indicators in

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the research. Jolliffe (2002) posits that the approach to using cluster analysis is vital in cases where such a group structure is lacking. Following Vyas and Kumaranayake (2006) and Achia, Wangombe, and Khadioli (2010), PCA was applied to the dummy variables to reduce the dimensionality of the data and categorise the CE indicators into distinct dimensions (Jolliffe, 2002). The PCA scores of CE indicators initially extracted and retained were followed by Varimax rotation for the above reasons. The study used the Kaiser-Maier-Olkin (KMO) and Bartlett's sphericity tests to assess the suitability of the variables for PCA. Hair, Black, Babin, Anderson, and Tatham (2006) suggest that researchers should consider variables suitable if their KMO values exceed 0.5, and Bartlett's sphericity test yields statistical significance at $p<0.05$. PCs with Eigenvalues equal to or greater than 0.7 were retained, following Jolliffe (2002).

- Hierarchical cluster analysis

The study used Hierarchical Clustering (HCA) to classify CE indicators based on their similarity or dissimilarity. The technique uses Euclidean distance as the dissimilarity metric. The research used PCA on CE indicators' characteristics data, a hierarchical clustering method called Hierarchical Clustering on Principal Components (HCPC), to analyse the classification limits of CE indicators.

Hierarchical cluster analysis estimates the number of clusters in a dataset using Principal Component Analysis (PCA). The study uses Ward's criterion to perform hierarchical clustering on all principal components derived from PCA on the initial dataset of variables. Ward's method estimates hierarchical clusters that create equal and evenly sized clusters, with solutions estimated based on cases and variables.

Several studies, including Argüelles et al. (2014), have used HCPC and K-means clustering as candidate multivariate approaches. HCPC offers two main advantages: it applies objective clustering techniques to PCA results, resulting in a better cluster solution than factorial analysis alone, and Ward's classification enhances the robustness of the final clustering results. Garson (2009), cited in Yobe, Mudhara, and Mafongoya (2019), suggests that hierarchical clustering is the most suitable technique for data sets with less than 250 observations, indicating that datasets below this threshold are unsuitable. According to Kaur and Kaur (2013), the K-means algorithm outperforms the hierarchical algorithm on data sets with over 250 observations. However, preliminary analyses with a smaller sample size confirmed this, as the K-means clustering technique failed to adequately classify cases, leading to using the HCPC technique for multivariate classification.

4. Results

4.1 Descriptive Statistics of the Circular Economy Indicators

The dummy variables were created to measure the variation of the CE indicators accurately, enabling a quantitative analysis of their performance. Table 2 shows the descriptive statistics that measure the mean, standard deviation, minimum, and maximum. On average, the Quantitative Approach was extensively used, with a mean of 0.7458. The dominant application level is for product, and the mean value is 0.4068. The dummy variables were created to accurately measure the variation of the CE indicators, enabling a quantitative analysis of their performance.

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Table 2: Descriptive statistics of the circular economy indicators

Variable	Mean	Std. Dev.	Min	Max
Approach:				
Quantitative	0.7458	0.4392	0	1
Qualitative	0.0847	0.2809	0	1
VBI	0.0678	0.2536	0	1
Analytical tool	0.0170	0.1302	0	1
Theoretical results	0.0169	0.1302	0	1
Application-level:				
Product	0.4068	0.4954	0	1
Materials	0.1695	0.3784	0	1
(embodied) Energy	0.0678	0.2536	0	1
Components	0.0678	0.2536	0	1
Resource Waste (/ waste streams)	0.0508	0.2216	0	1
Product families	0.0169	0.1302	0	1
Industrial symbiosis districts and networks	0.1017	0.3048	0	1
National	0.0508	0.2216	0	1
Regional	0.0847	0.2809	0	1
Provincial	0.0339	0.1825	0	1
EU	0.0678	0.2536	0	1
World Regions	0.0170	0.1302	0	1
Core CE principles:				
Reduce	0.5593	0.5007	0	1
Reuse	0.6610	0.4774	0	1
Recycle	0.8136	0.3928	0	1
Recover	0.1356	0.3456	0	1
Remanufacture	0.1864	0.3928	0	1
Redesign	0.1017	0.3048	0	1
Sustainable Development Dimensions:				
Environmental	0.8983	0.3048	0	1
Economic	0.9153	0.2803	0	1
Social	0.4746	0.5036	0	1
Level of CE indicators:				
Micro-level	0.5085	0.5042	0	1
Macro-level	0.2373	0.4291	0	1
Regions:				
USA	0.0508	0.2216	0	1
Europe	0.0169	0.1302	0	1
EU	0.1017	0.3048	0	1
Belgium	0.0508	0.2216	0	1
Netherlands	0.0339	0.1825	0	1
Italy	0.0169	0.1302	0	1
England/UK	0.0339	0.1825	0	1

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Variable	Mean	Std. Dev.	Min	Max
Approach:				
India	0.0169	0.1302	0	1
Spain	0.0169	0.1302	0	1
Denmark	0.0169	0.1302	0	1
China	0.0169	0.1302	0	1
South Korea	0.0169	0.1302	0	1
Australia	0.0169	0.1302	0	1
Jordan	0.0169	0.1302	0	1
Japan	0.0169	0.1302	0	1
Switzerland	0.0169	0.1302	0	1
World Regions	0.0169	0.1302	0	1

Source: De Pascale et al. (2021)

Observations = 58. VBI is a Value-based indicator/Evaluation indicator system.

4.2 Multivariate analysis results

The results of the multivariate analysis, which employed the PCA, are presented below. Table 3 shows the level of the scree plot of the estimated PCs of CE indicators.

Table 3: Estimated PCs of circular economy indicators

Component	1	2	3	4	5	6	7	8	9	10	11	12	13	15	16
Initial eigenvalues:															
% of Variance	13.014	7.314	5.636	5.438	5.388	4.722	4.252	3.760	3.540	3.471	3.267	3.034	2.859	2.643	2.582
Cumulative %	13.014	20.328	25.964	31.402	36.790	41.512	45.764	49.524	53.064	56.535	59.801	62.835	65.694	68.337	70.980
Approach:															
Quantitative						-0.464			-0.426						
Qualitative						0.887									
Value-based indicator/Evaluation indicator system									0.824						
Analytical tool															
Theoretical results												0.910			
Core CE principles:															
Reduce	0.694													0.316	
Reuse													0.480		
Recycle								0.706							
Recover			0.731												
Remanufacture	-0.350					0.530		-0.499							
Redesign						0.604	-0.320				0.568				
Sustain. Develop. Dimensions:															
Environmental	0.448										0.356			0.358	
Economic							0.791								
Social	0.632														
Level of CE indicators:															
Micro-level	-0.857														
Macro-level	0.637														
Application-level:															
Product	-0.811														
Materials	-0.445	0.351						0.446							
Components					0.538			-0.601							
Resource Waste (/ waste streams)					0.836										
Product families					0.843										
Industrial symbiosis districts and networks													-0.524		0.453

Component	1	2	3	4	5	6	7	8	9	10	11	12	13	15	16
National				0.547						0.734					
Regional	0.549								-0.375						
Provincial									0.671						
(embodied) Energy			0.868												
Regions:															
USA		0.513		0.743											
Europe			0.769												
EU		0.342		0.441								0.636			
Belgium	-0.377													-0.309	
Netherlands														0.826	
Italy											0.847				
England/UK		0.889													
India		0.888													
Spain							-0.808								
Denmark															
China	0.694								0.315						
South Korea															
Australia													-0.846		
Jordan															0.858
Japan				0.897											
World Regions										0.911					

Source: De Pascale et al. (2021)

Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization.

The coefficients with a value of 0.3 and less were suppressed and not displayed in the estimated PC scores results.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 0.291; Bartlett's Test of Sphericity Approx. Chi-Square = 1301.698; df = 903; Sig. = 0.000.

PC 14, which explained 2.77% of the variance, was dropped from the analysis because the variation explained by the factor loadings did not make economic sense.

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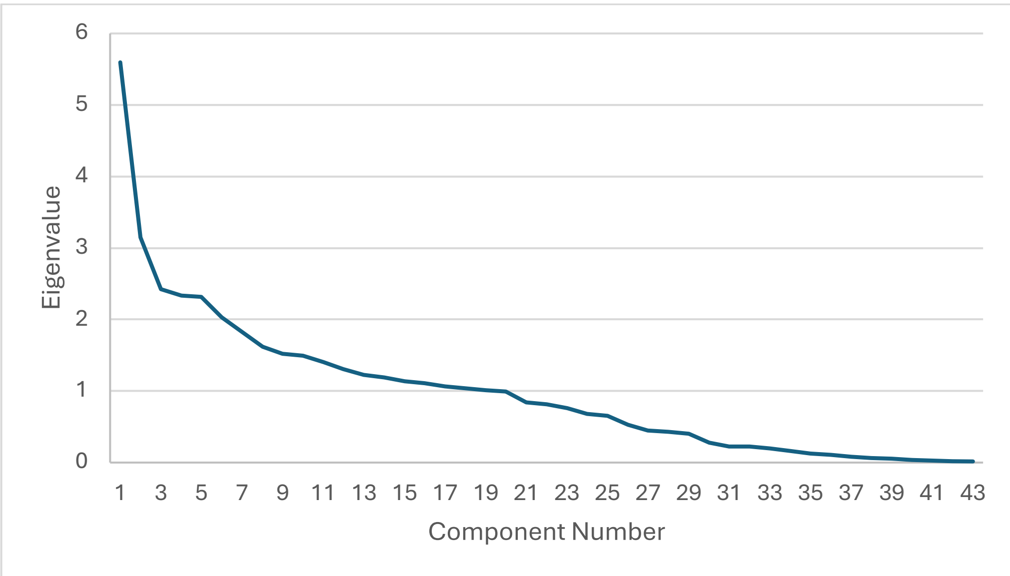
The application of PCA on the attributes of the CE indicators produced initial Eigenvalues 1.015, 19 PCs that explained a cumulative 80.941% of the variance in the dummy variables but only retained 15 PCs for the analysis Table 4. This study dropped PC 14 – which accounts for 2.77% – from the analysis because the variation it explained did not make economic sense. Therefore, the total variance explained by the PCs used in this analysis was 70.92%. The study dropped two variables – the meso-level of CE indicators and EIPs – because the rotation failed to converge in estimating the PCA's rotated component matrix.

The study utilised KMO and Bartlett's sphericity measures to assess the feasibility of incorporating 58 cases of indicators into a dataset. The KMO measure showed a 0.291 value, indicating a significant relationship between variables. Bartlett's test showed a $p<0.001$ correlation, indicating variables could be factored in. Varimax with the Kaiser normalisation rotation method improved PC interpretation.

The scree plot below shows the estimated PCs (Figure 1). The study plots Eigenvalue against PCs, with PC1 having the highest score loadings and a high Eigenvalue. PC-2 explains less variation and has a lesser Eigenvalue. The study estimates diminishing declines of Eigenvalue with other PCs, using a cut-off of PCs with an Eigenvalue of 1 and considering PCs that met this criterion.

Figure 1: Scree plot of the estimated PCs of CE indicators



Source: Author's elaboration

The first principal component (PC–1) explains 13.01% of the variance in the indicators of CE, with the estimated component loadings expressed in the following equation:

$$
\begin{aligned}
PC\text{–}1 = {} & 0.694\, Reduce\ CE\ principles - 0.350\, Remanufacture\ CE\ principles \\
& + 0.448\, Environmental\ Sustainable\ Development\ Dimensions \\
& + 0.632\, Social\ Sustainable\ Development\ Dimensions - 0.857\, Micro-level\ of\ CE\ indicators \\
& + 0.637\, Macro-level\ of\ CE\ indicators - 0.811\, Product\ Application-level \\
& - 0.445\, Materials\ Application-level + 0.549\, Regional\ Application-level - 0.377\, Belgium \\
& + 0.694\, China.
\end{aligned}
$$

In PC–1, Reduce CE principles, Social Sustainable Development Dimensions, and Macro-level CE indicators were the most dominant loadings variables. Therefore, this PC was named *Reduce CE principles*. PC–2 explains 7.314% of the variance, and the most dominant loadings were on the Materials Application-level and in the USA, EU, England/UK and India regions; this PC was thus called *Materials Application-level*. PC–3 accounts for 5.64% of the variance with dominant loadings on Recover CE principles, Energy (embodied) Application-level and the EU region and was intuitively named Energy (embodied) Application level. PC–4 was called *National Application-level* because the most significant loading for this component was the National Application Level; the other loading for this coefficient was the USA and EU regions.

The fifth component, PC–5, which accounted for 5.34% of the variation in the PC estimation, was called *Diverse Application-level* because it had loading for Application-Level variables, namely Components, Resource Waste and Product families. The sixth component, PC–6, *Recover and Redesign CE principles Qualitative Approach*, accounted for 4.72% of the variation and had significant loadings on qualitative – and negatively so on quantitative – approach, as well as Recover and Redesign CE principles. The seventh component, PC–7, was named *Sustainable Development Economic Dimension* because this PC had dominant positive loadings on the Sustainable Development Economic. The study revealed that Redesign CE principles, specifically PC-8, accounted for 3.76% of the study's variation. PC-8 had positive coefficients for Recycle and Remanufacture CE principles, positive coefficients for Materials and Components Application-level, and negative coefficients for the research approach. PC-9 had significant coefficient loadings on regional and provincial variables and China region. Hence PC–9 was called *Approach Value-based indicator/ Evaluation indicator system* and accounted for 3.54% of the variance.

PC–10, named *Application Level National and World Regions*, had dominant coefficient loadings of 0.734 Application Level National and 0.911 for the World regions, accounting for 3.47% of the variation. The next component, PC–11, accounted for 3.26% of the variation. The variables Redesign CE principles and Environmental Sustainable Development Dimensions had positive coefficient loadings of 0.568 and 0.356, respectively; this PC was called *Redesign CE principles Environmental Sustainable Development Dimensions*. PC–12 is accounted for by 3.034% of the variation and represents the dimension of the CE indicators with significant coefficient loadings on the variables for the Theoretical results approach and the EU region; this PC was thus identified as the *Theoretical results approach*. PC-13, accounting for 2.86%, showed positive coefficient loadings on Reuse CE principles, while negative coefficient loadings were observed on IS districts, networks Application-level, and Australia.

The next component, *Reduce CE principle and Environmental Sustainability Development Dimensions*, accounted for 2.64% of the variation. The component loadings of the coefficients on the variables are as follows:

$$
\begin{aligned}
PC\text{–}14 = {} & 0.316\, Reduce\ CE\ principles \\
& + 0.358\, Environmental\ Sustainability\ Development\ Dimensions - 0.309\, Belgium \\
& + 0.826\, Netherlands.
\end{aligned}
$$

The PC-16, the Application-level PC, represents coefficient loadings on IS districts and networks in the Jordan region, exhibiting minimal variation in CE indicator scores.

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4.2.1 Hierarchical clustering

The HCPC analysis uses the HCA to analyse the PCA outcome. Figure 2 displays a dendrogram representing the HCA result, with the vertical axis representing observations and clusters and the horizontal axis representing the distance between them. Similar observations are grouped based on their dissimilarity, allowing for better understanding and classification.

Figure 2 shows a hierarchical dendrogram, where PCs are extracted and arranged into new clusters along the y-axis. Each branch represents connections, and the closer they are to each other, the more related they are. For instance, PC-6 and 15 are members of one cluster from a branch that splits into two, similar to the next group comprising PCs 13, 16, 9, and 8. However, the group composed of PC-2 and PC-4 is far apart in the chart.

An imaginary cut-off point in a dendrogram creates a cluster, which becomes larger and more heterogeneous as the branching diagram moves up. This results in more variation within the cluster. For example, two variables next to each other, like PC-6 and PC-15, will be similar. Expanding the group, like one large group with PCs 6, 15, 13, 16, 9, 8, 5, 7, and 1, will result in more similar observations than grouped observations in another branch. However, there is still much variation in each group, necessitating a trade-off decision on where to make the cut-off.

The study identifies two clusters in a dendrogram, with each observation in the clusters being similar. Large clusters, with more observations, are more heterogeneous. The choice of meaningful clusters depends on the degree of change in grouping due to slight deviations. The study suggests a two-cluster solution on the dendrogram, while Figure 3 has a four-cluster solution. The ideal variation is minimally affecting solutions. The study's findings align with this rationale.

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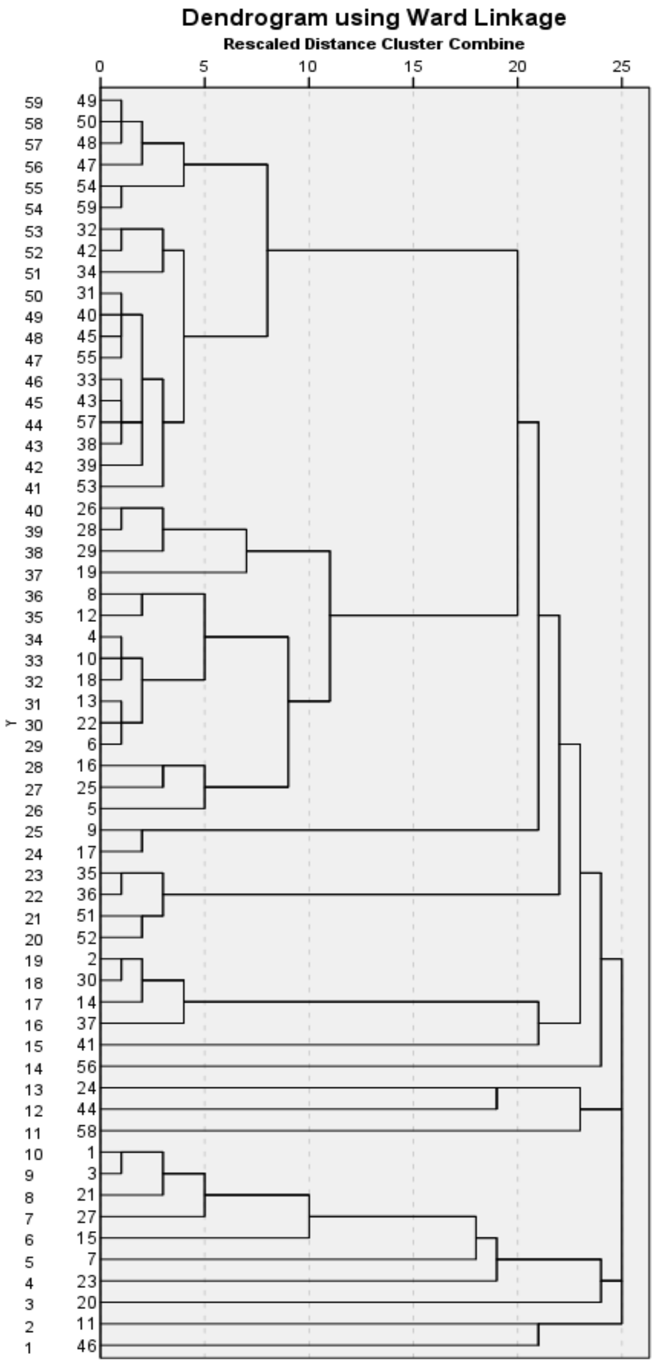
Clustering solutions by variables

Figure 2: Hierarchical clustering and initial partition solutions by variables



Source: Author's elaboration on Linkage method—Ward's method. Euclidean distance of all elements

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Table 4 shows references with their title and country for each cluster that result from the dendrogram in Figure 2. The PC-16, also known as the Application-level PC, represents coefficient loadings on IS districts and networks in the Jordan region, exhibiting minimal variation in CE indicator score (Guo-gang, 2011; Li & Su, 2012; Xiong, Dang, & Qian, 2011). Other studies in this set of results focus on industrial parks (Felicio et al., 2016; Geng, Zhang, Côté, & Fujita, 2009; Geng et al., 2010; Tiejun, 2010; Wenbo, 2011; Zhao, Guo, & Zhao, 2018), while the case studies included (Adibi, Lafhaj, Yehya, & Payet, 2017; Bovea & Pérez-Belis, 2018; Huysman, De Schaepmeester, Ragaert, Dewulf, & De Meester, 2017; Huysman et al., 2015; Sałabun, Palczewski, & Wątróbski, 2019). The countries that dominated the studies included China, EU members, Belgium, and the USA.

Table 4: List of clusters by references, article and countries

Cluster	Reference	Country
1	Das, Yedlarajiah, and Narendra (2000)	
	Lee, Lu, and Song (2014)	
	MacArthur (2015)	Europe
	Huysman et al. (2017)	Belgium; England
	Mohamed Sultan, Lou, and Mativenga (2017)	UK; EU; USA; India
	Azevedo, Godina, and Matias (2017)	
	Mesa, Esparragoza, and Maury (2018)	
	Vanegas et al. (2018)	Belgium
2		
	Nelen et al. (2014)	
	J. Y. Park and Chertow (2014)	USA
		EU
	Huysman et al. (2015)	Belgium
	Scheepens, Vogtländer, and Brezet (2016)	Netherlands
	Cayzer et al. (2017)	
	Figge, Thorpe, Givry, Canning, and Franklin-Johnson (2018); Franklin-Johnson et al. (2016)	
	van Schaik and Reuter (2016)	
	Linder et al. (2017)	
	Di Maio, Rem, Baldé, and Polder (2017)	Netherlands
	Favi, Germani, Luzi, Mandolini, and Marconi (2017)	
	Adibi et al. (2017)	
	Figge et al. (2018)	
	Marconi, Germani, Mandolini, and Favi (2019)	
	Mandolini, Favi, Germani, and Marconi (2018)	

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Cluster	Reference	Country
	Cong, Zhao, and Sutherland (2019)	
	Zwolinski, Lopez-Ontiveros, and Brissaud (2006)	
	Jacobsen (2006)	Denmark
	Karlsson and Wolf (2008)	
	Geng et al. (2010)	China
	Sałabun et al. (2019)	
	Wen and Li (2010)	China
	Geng et al. (2009)	China
	Su, Heshmati, Geng, and Yu (2013)	China
	Geng et al. (2012)	China
	Wenbo (2011)	China
	Li and Su (2012)	Beijing - China
	Wen and Li (2010)	China
	H.-S. Park and Behera (2014)	South Korea
	Pagotto and Halog (2016)	Australia
	Felicio et al. (2016)	
	Zhao et al. (2018)	China
	Tiejun (2010)	China
	Geng, Liu, Liu, Zhao, and Xue (2011)	China
	Guo-gang (2011)	China
	Faizi, Rashid, Sałabun, Zafar, and Wątróbski (2018)	China
	Chun-rong and Jun (2011)	
	Qing, Qiongqiong, and Mingyue (2011)	China
	Xiong et al. (2011)	China
	Wu, Shi, Xia, and Zhu (2014)	China
	Haas, Krausmann, Wiedenhofer, and Heinz (2015)	EU Members
	Haupt, Vadenbo, and Hellweg (2017)	Switzerland
	Tisserant et al. (2017)	World Regions
	Moraga et al. (2019)	
	Mayer et al. (2019)	EU Members
	Fregonara, Giordano, Ferrando, and Pattono (2017)	Italy
	Moriguchi (2007)	EU; USA; Japan
3	Bovea and Pérez-Belis (2018)	Spain
	Kayal et al. (2019)	Jordan
4	Smol, Kulczycka, and Avdiushchenko (2017)	EU Members

Source: Author's elaboration

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5. Discussion

Firms, governments, and regional authorities have started recognising environmental benefits and economic growth through collaboration between companies that flow directly from IS—generating better collective benefits than could have been achieved from the sum of all individual benefits combined (Bocken et al., 2016; Felicio et al., 2016; Jacobsen, 2006; Karlsson & Wolf, 2008). IS offers several benefits, including reducing waste disposal costs by converting waste into by-products for other industries, enabling innovation and process development, leading to increased profitability, and benefiting from the geographical proximity of businesses (Bocken et al., 2016; Karlsson & Wolf, 2008).

Creating a composite index can help better understand the CE indicators and measure the development of the CE guides. Applying PCA based on the above data reduced the dimensionality of the 58 – previously 61 – CE indicators in De Pascale et al. (2021) to 15 PCs, which could be classified. Table 4 shows the list of the HCPC composite indices based on the title of the articles and the regions where these studies took place. This technique provides a structural approach to navigating the multifaceted realm of circular economy indicators.

The HCPC reduced estimated PCs, resulting in terminal elements of the dendrogram from hierarchical classification. The dendrogram yielded four clusters of CE indicators, determining the group's CE performance based on specific characteristics, like countries with similar features (Stanković et al., 2021). The understanding of regional and global trends is improved by this hierarchical classification, which provides a systematic framework for identifying distinctive groupings within the CE landscape.

The areas in this first cluster include European countries (Huysman et al., 2017; McCarthy et al., 2019; Mohamed Sultan et al., 2017; Vanegas et al., 2018), the USA (Mohamed Sultan et al., 2017) and India (Mohamed Sultan et al., 2017). This first cluster displays a variation of approaches within different national contexts, spotlighting geographical concentrations of CE initiatives. Due to the need to respond to the impacts of unsustainable linear production methods, CE approaches will likely provide a compelling driver across many different governments, countries and regions. Das et al. (2000), Lee et al. (2014), and Mesa et al. (2018) in the first cluster did not focus on a particular region in their research. The first two of these studies focused on estimating the end-of-life product disassembly effort and cost and assessing product End-Of-Life performance. The last of the two studies focused on developing a sustainable circular index. The diverse research focus within this cluster illustrates the breadth of CE initiatives, spanning multiple geographical contexts and ranging from index development to product lifecycle analysis.

The following aggregation obtained after applying the HCPC, i.e. Cluster 2, shows studies in Europe (Di Maio et al., 2017; Haas et al., 2015; Huysman et al., 2015; Jacobsen, 2006; Mayer et al., 2019; Scheepens et al., 2016), the USA (J. Y. Park & Chertow, 2014), South Korea (H.-S. Park & Behera, 2014), China (Faizi et al., 2018; Geng et al., 2012; Geng et al., 2011; Geng et al., 2009; Geng et al., 2010; Guo-gang, 2011; Li & Su, 2012; Su et al., 2013; Tiejun, 2010; Wen & Li, 2010; Wenbo, 2011; Wu et al., 2014; Xiong et al., 2011; Zhao et al., 2018), Australia (Pagotto & Halog, 2016) and the World Regions (Tisserant et al., 2017). This second cluster has a broad geographical scope and implicates the variable approaches adopted by different countries and regions and the global reach of CE initiatives. Most of these primarily focused on industrial parks (Felicio et al.,

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2016; Geng et al., 2009; Geng et al., 2010; Tiejun, 2010; Wenbo, 2011; Zhao et al., 2018). Industrial parks in China are for environmental and economic growth benefits, and collaboration between companies is critical in realising this achievement; thus, it is crucial to promoting IS. According to Felicio et al. (2016), the IS in EIPs requires the implementation of intense broker involvement. Impediments to the level of symbiosis during operations usually are market changes and technological advancement. Wenbo (2011) further posits that developing CE is the only way to realise the new industrialisation, and building EIPs is an essential means of promoting CE performance. The next area of focus in this cluster that received attention from researchers is that of IS, which includes research done in China (Geng et al., 2009), Denmark (Jacobsen, 2006), South Korea (H.-S. Park & Behera, 2014) and Australia (Pagotto & Halog, 2016). The importance of collaborative efforts in promoting circular economy performance—particularly in industrialised nations—is highlighted by the focus on industrial parks as hubs for sustainability initiatives.

The cluster solution suggests a lack of coverage of CE approaches, leading to a lack of studies. These approaches may have been developed to address a specific CE problem but were never expanded to other areas. They may also be challenging to set up in regions with similar CE issues, becoming unsupported and ineffective; this could be the case with two clusters. Nonetheless, the research gaps identified in CE indicate potential areas for further research and strategic intervention to advance more comprehensive and successful circular economy initiatives.

Cluster 3 comprises two studies (Fregonara et al., 2017; Moriguchi, 2007) of the HCPC aggregates. Studies conducted in Italy, the EU, the USA, and Japan examined resource productivity indicators and environmental impact. The need to address environmental issues, such as waste reduction and pollution, is a common response to widely accepted action plans. This third cluster explores resource productivity and environmental impacts, highlighting the ongoing need to address pressing environmental issues across geographic boundaries through sustained research and policy interventions.

Cluster 4 classifies the studies focusing on circular design guidelines in Spain (Bovea & Pérez-Belis, 2018), measuring a firm's circularity in the water industry in Jordan (Kayal et al., 2019), and CE indicators concerning eco-innovation in the EU member countries (Smol et al., 2017). This final cluster focuses on particular CE initiatives, such as industrial circularity, design guidelines, and eco-innovation, and illustrates the various strategic approaches used in multiple industries and regions.Our journal adheres to the APA 7th edition style for citations and references. Please ensure that all citations in the text and the reference list comply with this format.

6. Conclusions

The study used HCPC to identify clusters in a dataset with 61 CE indicators, retaining 58 after data cleaning, utilising complementarities between clustering and principal components methods. The first stage estimation of PCA only allowed for 15 of the 16 PCs to be meaningfully interpreted. The HCPC clustering technique from four clusters provided a better cluster solution than the principal components method, identifying research dimensions such as IS, CE strategies, and spatial arrangement.

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Policy recommendations for IS and CE subjects require coordination among stakeholders with diverse agendas. Policymakers must lead the implementation of policies related to these subjects. Despite different approaches, governments and regions are adopting actions that drive the agenda forward. China has successfully used a top-down approach to policy implementation, allowing the government to prescribe policies and have everyone adopt them. This top-down approach could be a crucial lead for other countries seeking similar practices to follow. China's top-down approach could serve as a model for other countries.

The bottom-up approach to policy implementation has been successful in European countries, with governments, regions, and businesses realising the benefits of adopting such policies. These systems receive support and spread quickly, often guided by an overarching goal. The central role of government is critical in implementing regulations that fit the purpose, ensuring that well-established and beneficial systems receive support and spread quickly.

The specific impacts of top-down and bottom-up policy approaches on IS and CE projects in many geographic and cultural situations may be the subject of future research. Furthermore, examining how well various stakeholder coordination mechanisms work to implement policies will shed light on how to improve cooperation and alignment in IS and CE to achieve shared objectives. Furthermore, looking into possible synergies between top-down and bottom-up techniques may provide insightful information about optimising policy frameworks for scalability and maximum efficacy.

Understanding how to successfully negotiate the complicated terrain of corporate environmentalism can be improved by looking into these areas further, which will ultimately lead to better-informed decision-making and sustainable worldwide practices.

7. Conflict of Interest

The author has no conflict of interest to declare.

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