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Mapping socio-environmental policy integration in the European Union: A multilayer network approach

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ABSTRACT

This paper faces the relevant task of assessing the integration of European countries when dealing with three paradigmatic socio-environmental themes: Circular Economy (CE), Energy Transition (ET), and Social Justice (SJ). Specifically, we aim to explore whether a similar behavior in facing one of the considered aspects is mirrored by similarity in the others. We move from a dataset composed of five variables for CE, two for ET, and three for SJ, representing yearly data for the quinquennium 2016–2020 and European countries. We build a multilayer network based on the ten variables having countries as nodes. Each layer/variable has weighted links based on countries' similarity. Inter-layer links are created through a community detection exercise over the individual layers. This approach allows us to evaluate analogies, leading to the assessment of intra- and inter-layer policy integration. We find a relatively low level of integration at the European level and a high sensitivity to the number of detected communities, thus revealing the role of countries' heterogeneity in driving integration.

1. Introduction

Nowadays, the Circular Economy (CE) is a highly-debated and controversial topic due to its evident economic and socio-environmental implications. The transition from a linear model of production and consumption – where resources are extracted, used, and discarded – to a circular one, which emphasizes reuse, recycling, and sustainable resource management, represents a significant change (Chirumalla et al., 2024). This change has the potential to drastically reduce environmental impacts, such as waste generation and resource disruption while creating new economic opportunities, such as innovative business models and job creation (Bocken et al., 2016).

Policymakers try to face the challenge of implementing good practices for CE, which is eventually not only a country-based phenomenon but also a more general socio-environmental theme to debate. It is important to underline that CE is related to several aspects of the social and economic status of the considered countries. The identification of the complex nature of the connections between CE and relevant socio-economic variables is a challenging theme (Mies and Gold, 2021) and deserves fully devoted studies. For instance, Neves and Marques (2022) found that in the EU per capita GDP, the Gini index, and poverty, decrease circularization, while environmental regulation and environmental awareness are the main drivers for the circular economy. However, cultural attitudes towards sustainability and consumption habits can also significantly influence the adoption of circular economy principles (Kirchherr et al., 2018).

This paper enters this timely debate. We focus on assessing the connections between how countries implement CE and their approach to facing two critical issues: the management of the energy transition (ET) phase and the achievement of a satisfactory level of social justice (SJ).

Intuition suggests that CE, ET, and SJ are key elements of a unique context, that is specifically related to the ethical evolution of a country. However, reality is more heterogeneous than expected and presents issues of high complexity. As a premise, a high degree of complexity emerges from the formal contextualization of CE, ET, and SJ. Indeed, such concepts do not have straightforward definitions.

The circular economy (CE) provides a viable alternative to the existing "take, make, waste" industrial model to solve both local and global environmental problems, including resource depletion, marine plastic pollution, and maintenance of the boundaries of the planetary

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system (see e.g., Castro et al., 2022; Ellen MacArthur Foundation, 2023; Kirchherr et al., 2023; Schröder et al., 2020). The Ellen MacArthur Foundation (2016) provides one of the most widely accepted definitions of CE: "A circular economy is one that is restorative and regenerative by design and aims to keep products, components, and materials at their highest utility and value at all times, distinguishing between technical and biological cycles" (Ellen MacArthur Foundation, 2016). Regarding the other variables, ET refers to the shift from the use of fossil fuels to the use of fuels from renewable resources (see, e.g., Attílio et al., 2024, and Ghorbani et al., 2024) while SJ concerns the ability of a country to implement policies for an equitable distribution of wealth and opportunities (see e.g., Ayaz and Tatoglu, 2024; Valencia et al., 2023). Hence, there is no unique quantitative tool for measuring such concepts. It is possible to assign a level to CE, ET, and SJ in a country by evaluating many variables.

A further source of complexity is grounded on evidence that different national historical patterns are responsible for discrepancies in the interpretation and implementation of CE, ET, and SJ (see, e.g., Arsova et al., 2022; Avdiushchenko and Zając, 2019).

This research analyzes socio-environmental policy among EU countries in relation to selected variables related to Circular Economy (CE), Energy Transition (ET), and Social Justice (SJ). Focusing on the paradigmatic case of the EU countries, we provide a comprehensive analysis of the quantitative measures associated with the related pillars and obtain relevant insights on socio-environmental policy integration.

Several scholars have addressed the topic of socioeconomic policy integration in broad contexts. The monograph by Carayannis and Korres (2012) offers a wide range of studies on the topic, ranging from monetary union to social policy reform and technology policy. Interestingly, Watson et al. (2008) deals with the integration of environmental policies in the direction of waste management and analyzes the empirical case of the UK. From a more jurisdictional perspective, Scharpf (2010) presents the issue of social integration at the level of politics and law by pointing to the harmonization of the heterogeneity of the European countries. In Kaplaner et al. (2023), the authors introduce a measure of the intersectorality of a selection of legal acts in the context of the European Union for more than 40 years and for a wide set of policy sectors. The quoted paper deals with a sort of connection among sectors, but the network dimension is not represented. In general, socio-environmental integration is not presented in the literature from a complex network approach. Among the few exceptions, we mention (Oliveira-Duarte et al., 2021), where the authors discuss integration in sustainability by exploiting the methodological definition of innovation ecosystems that also involve complex networks-related quantities. We fill this gap by acknowledging the multiple dimensions of socio-economic contexts through a multilayer network approach. Furthermore, we stress that all the relevant contributions quoted above do not face explicitly the connection among CE, SJ, and ET, which is the topic we explore in the present paper.

To properly evaluate the connection between CE, ET, and SJ, we adopt a multilayer complex network approach. The multilayer network model is a powerful tool widely used to represent and analyze the organization and interactions of complex data in many sectors (De Domenico, 2023; Lei and Cheong, 2024). This model is designed to offer an accurate representation of the diverse and heterogeneous relations that may describe an entity in a network system. For example, a multilayer network provides a means of modeling many forms of relations within the same group of scientists, with layers denoting different features (like co-authorship, and affiliation to the same Institution) (Interdonato et al., 2020).

Indeed, multilayer networks have become increasingly popular for studying social systems due to their powerful ability to simultaneously account for different types of dependency (Finn, 2021). In addition, multilayer networks are widely used in the study of social sciences such as social networks (Lewis et al., 2008; Zeng et al., 2023), disease research (Halu et al., 2019), financial institutions (Poledna et al., 2015; Dai and Zhu, 2023), and waste trade networks (Poon et al., 2024). The multilayer networks can represent multiple variables and include different types of interaction among a unified set of actors that occur in multiple different contexts. They can also explain in detail the degree to which the variables considered are interdependent.

The capacity of multilayer networks to link layer-to-layer interactions also makes it possible to better represent the interdependencies between various interaction types, which are impossible to describe in single-layer networks. Therefore, the ability of multilayer networks to encode such additional information about interactions within different groups into a single framework makes them interesting tools, especially for representing social phenomena. To our knowledge, this research represents the first attempt to combine multilayer networks and community detection to examine the integration of countries for the circular economy, energy transition, and social justice.

Specifically, the use of multilayer networks allowed us to examine both intra-layer and inter-layer relationships, highlighting how EU countries act with respect to the examined variables. Furthermore, the analysis also revealed patterns at the community level, giving our research a higher level of granularity.

Here, we consider five variables associated with CE, two for ET and three for SJ. Such variables are selected according to how Eurostat identifies CE, ET, and SJ (see Section 2 for details). We have yearly data for European countries during the quinquennium 2016–2020. Thus, we build five multilayer networks on the considered years, where layers are associated with the ten variables describing the three pillars we are dealing with. The nodes of the networks are the European countries. The weights of the links in each layer represent the similarity of the considered countries in terms of the corresponding variable. The arcs inter-layers are built through a community detection procedure, so countries belonging to the same cluster in two different layers are assumed to be linked. There are various methods to detect communities in networks (Dey et al., 2022), each with different assumptions about the structure of the network and the nature of communities. Approaches include hierarchical clustering (Bandyopadhyay and Coyle, 2003) and C-means-like Banerjee et al. (2019) and Cerqueti et al. (2023). In this paper, we adopt the second approach to detect communities in the kth layer of the multilayer network, considering a Partition Around Medoids (PAM, hereafter) (Kaufman and Rousseeuw, 1990) algorithm, grouping nodes based on a similarity criterion derived from the weighted adjacency matrix.

The presence of an inter-layer link between two countries reflects the evidence that the countries are grouped in the same class for both variables. Thus, they can be seen as performing similar strategies when dealing with the phenomena described by the variables considered. In this sense, we might simply say that there is integration not only at the intra-layer level but also from an inter-layer perspective.

The results obtained from the analysis are interesting and highlight a remarkable degree of fragmentation within European countries in terms of circular economy, energy transition, and social justice. Deviations from this general result appear for specific countries and years. Interestingly, the number of communities negatively affects the level of integration. This is quite reasonable since a wide heterogeneity is associated with a less probable confluence of two countries in the same cluster.

The rest of the paper is organized as follows: Section 2 presents the employed dataset, providing details on the variables used. Section 3 outlines the methodology, with the definition of the multilayer network model, the description of the community detection procedure, and the consequent statement of the inter-layer links formation. Section 4 shows the results obtained. Finally, Section 5 offers some conclusive remarks, summarizing the key findings and their implications for socio-environmental policy in the European Union, and discussing the limitations of the study.

2. Data

Given the complexity of the main concepts explored in the present paper, we consider different types of data for describing CE, ET, and SJ.

Specifically, we take five variables for CE, i.e. recycling rate of municipal waste, circular material use rate, private investment and gross added value related to circular economy sectors, persons employed in circular economy sectors, and patents related to recycling and secondary raw materials. For ET we consider two variables: share of renewable energy in gross final energy consumption by sector and final energy consumption in households by type of fuel. Finally, SJ is captured by three variables: population reporting occurrence of crime, violence, or vandalism in their area by poverty status, corruption perception index, and perceived independence of the justice system.

Table 1 provides a description of the considered variables, along with the notation used for dealing with them. The source of the data is Eurostat,[1] which is the Official Statistical Office of the European Union and we consider a panel dataset. The temporal dimension is discrete and captures T *years* ($t = 1, \ldots, T$), while the spatial dimension is associated to N ($i = 1, \ldots, N$) *countries*. Data have been suitably treated for having a common investigation period and a common set of countries for all the considered variables. Thus, the investigation period is a quinquennium, specifically from 2016 to 2020 and the considered countries under investigation are 26. All of them belong to the European Union; they are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden. Interestingly, Luxembourg is the only country among the 27 European Union member states excluded from the considered dataset. Hence, such a country is not discussed in the present paper.

3. Methodology

This section discusses the network model adopted for carrying out the connectedness analysis and the employed methodological procedure used for exploring the intra-layer relationship, clustering network nodes (i.e. EU countries), and creating the inter-layer connections.

3.1. The multilayer network model

We assume that the K variables associated with CE, ET, and SJ dimension form K distinct layers of a multilayer network structure, related to the same set of nodes, i.e. the EU countries, $V = \{1, \ldots, i, \ldots, N\}$. As explained in Section 2, we have $K = 10$ in our empirical experiments. The variables are explained in Table 1. For each time t, we build a multilayer network with N nodes. In what follows, we describe the network at a generic time t and omit the temporal dimension from the notation for convenience.

The multilayer network is defined as

$$\mathcal{N} = (\mathcal{G}, C), \tag{1}$$

where $\mathcal{G} = \{G_k : k = 1, \ldots, K\}$ is a family of K distinct graphs, one for each kth variable in Table 1. The generic kth graph is defined as $G_k = (V, W_k)$, where $W_k = (w_k(i,j) : i, j \in V)$ is the weighted adjacency matrix of the network at the kth layer, indicating how each node (country) is connected with the others in the network. The set C collects the unweighted links between countries at different layers, so that $C = \{E_{hk}(i,j) \subseteq \{0,1\} : h, k = 1, \ldots, K; h \neq k \text{ and } i, j \in V\}$. See e.g., Boccaletti et al. (2014) and Kivelä et al. (2014) for a wide discussion on multilayer networks.

[1] https://ec.europa.eu/eurostat.

For a given layer k, we construct the weighted adjacency matrix W_k of the graph G_k by imposing a similarity criterion. Specifically, the entity of the connection between two nodes i and j is inversely related to the distance between the corresponding values of the kth variable. Therefore, the most similar two nodes are in terms of the variable k, the closer they are in the kth layer of the multilayer network (1).

In particular, we denote the values of the kth variable for country i and j by $x_k(i)$ and $x_k(j)$, respectively, and define the normalized distance $d_k : V^2 \to [0,1]$ as follows

$$d_k(i,j) = \frac{|x_k(i) - x_k(j)|}{\max\{|x_k(u) - x_k(v)| : u, v \in V\}}. \tag{2}$$

We assume that

$$w_k(i,j) = \frac{2}{d_k(i,j) + 1} - 1. \tag{3}$$

The construction of the weights in (3) leads to interesting properties. Indeed, by definition, we have that $w_k(i,j)$ decreases with respect to $d_k(i,j)$ – i.e., the higher the distance d_k between two nodes i and j, the weaker the entity of the connection between i and j. This is a standard property of some classes of weighted networks, when the weights represent the similarity of couples of nodes according to their distance. Moreover, the weight $w_k(i,j)$ ranges in $[0,1]$ for each $i, j \in V$. In this respect, the corner cases $d_k(i,j) = 0$ and $d_k(i,j) = 1$ are associated with $w_k(i,j) = 1$ and $w_k(i,j) = 0$, respectively. Therefore, corner cases capture the maximally strong link between i and j – the case of distance $d_k(i,j) = 0$ – and the absence of a link between i and j – the case of the unitary distance between i and j. We also notice that the definition in (3) is general, and the explicit definition of a distance measure d_k is not needed. This allows us to tailor the weights of the network to any selection of distance measure and reproduce the analysis presented here in a wide set of contexts and from different perspectives (on this, see e.g. the discussion in Levy et al. (2024)). In our specific case, we will refer to d_k defined in (2).

3.2. Intra-layer centrality measures

To analyze the patterns and relationships within each layer of the multilayer network model, we exploit three different centrality measures, namely strength, closeness, and clustering coefficient. These measures provide insights into the structural characteristics and roles of individual countries within the various layers of the network.

The strength of a node i in a layer k represents the weighted sum of the connections that node maintains with all other nodes in the layer. For a given node i, the strength is defined as:

$$s_k(i) = \sum_{j \in V, j \neq i} w_k(i,j), \tag{4}$$

where $w_k(i,j)$ is the weight of the connection between nodes i and j in layer k, as defined in Eq. (3). The strength measure quantifies the overall intensity of a node's connections within a layer, identifying the most "central" nodes in terms of their connectivity. This concept, which reflects the extent of a node's involvement in the network, is widely recognized in the literature as a fundamental indicator of node centrality (Dijkstra, 1959; Freeman et al., 1979; Opsahl et al., 2010).

The considered version of the closeness of a node i in a layer k represents a measure of the average distance – intended as average weight, in our case – from i to all other nodes in the layer. It indicates how easily a node can reach the other nodes in the network. Thus, closeness is defined as the inverse of the sum of weights between node i and all other nodes $j \in V$:

$$c_k(i) = \frac{1}{\sum_{j \in V, j \neq i} w_k(i,j)}. \tag{5}$$

usually, closeness is defined through distance – $d_k(i,j)$ instead of $w_k(i,j)$, in our case. This definition in (5) implies that higher weights correspond to shorter distances, and vice versa. Consequently, closeness centrality in our framework reflects the accessibility of a node based

Table 1
Notations and description of the considered variables.

Notation	Variables	Description
CE1	Recycling rate of municipal waste	The indicator measures the share of recycled municipal waste in the total municipal waste generation. Recycling includes material recycling, composting, and anaerobic digestion. The ratio is expressed in percentage (%) as both terms are measured in the same unit, namely tonnes.
CE2	Circular material use rate	The indicator measures the share of material recycled and reintegrated into the economy, thereby reducing the need for primary raw material extraction. The circular material use, or circularity rate, is defined as the ratio of circular use of materials to overall material use, which is calculated by summing aggregate domestic material consumption (DMC) and circular use. DMC is outlined in economy-wide material flow accounts, while circular use is approximated by waste recycled in domestic recovery plants, adjusted for imported and exported waste destined for recovery. A higher circularity rate indicates a greater substitution of secondary materials for primary raw materials, thus lessening the environmental impacts of extraction.
CE3	Private investment and gross added value	The indicator includes "Gross investment in tangible goods" and "Value added at factor costs" in the recycling, repair and reuse, and rental and leasing sectors. Gross investment in tangible goods represents investment exclusively in tangible assets. Value added at factor costs refers to the gross income from operating activities, net of subsidies, and indirect taxes. The single indicator is calculated as the average of the percentage rates of the two indicators. The respective percentage rates are derived by dividing the two indices, expressed in millions of euros, by the GDP of the respective nations.
CE4	Persons employed in CE sectors	The indicator expresses the percentage of "Number of persons employed" in the recycling, repair and reuse, and rental and leasing sectors relative to the total number of full-time employed individuals. The number of persons employed includes owners, partners, unpaid family workers, and individuals who work for the unit externally, such as sales representatives and maintenance personnel. Excluded from this count are personnel supplied to the unit by other enterprises and individuals serving compulsory military duty.
CE5	Patents related to recycling and secondary raw materials	The indicator measures the number of patents related to recycling and secondary raw materials. Additionally, we have a percentage calculated as the ratio of climate change mitigation technologies related to wastewater treatment or waste management to the population of the countries.
ET1	Share of renewable energy in gross final energy consumption	The indicator expressed in percentage measures the share of renewable energy consumption in gross final energy consumption according to the Renewable Energy Directive. The gross final energy consumption is the energy used by end-consumers (final energy consumption) plus grid losses and self-consumption of power plants.
ET2	Final households energy consumption	The indicator represents the final energy consumption of households in tonnes of oil equivalent per capita. It includes energy consumption for space heating, water heating, cooling, and cooking, as well as electricity used by various appliances. Self-produced electricity is included, while self-produced heat is accounted for only in active systems; passive heating systems are not included.
SJ1	Population reporting occurrence of crime, violence or vandalism	The indicator shows the share of the population who reported that they face the problem of crime, violence, or vandalism in their local area. This describes the situation where the respondent feels crime, violence, or vandalism in the area to be a problem for the household, although this perception is not necessarily based on personal experience.
SJ2	Corruption perception index	The indicator is a composite index based on a combination of surveys and assessments of corruption from 13 different sources and scores and ranks countries based on how corrupt a country's public sector is perceived to be, with a score of 0 representing the highest level of corruption and a score of 100 representing a maximally clean country.
SJ3	Perceived independence of the justice system	The indicator is designed to explore respondents' perceptions about the independence of the judiciary across EU Member States, looking specifically at the perceived independence of the courts and judges in a country. A score of 0 indicates a minimal level of perception, while a score of 1 expresses a maximum perception of independence.

on this weight-distance relationship. Nodes with higher closeness centrality are more "distant" in terms of weights, emphasizing their role in spanning across weaker connections. This interpretation deviates from the traditional use of closeness centrality, see e.g., Barrat et al. (2004) and Opsahl et al. (2008), and we clarify this distinction in our analysis.

The clustering coefficient of a node i in layer k measures the tendency of i to form tightly-knit groups with its neighbors, reflecting the local cohesion of the network. We adopt the clustering coefficient defined by Onnela et al. (2005), which is given by:

$$CC_k(i) = \frac{1}{d_i(d_i-1)} \sum_{j\neq i} \sum_{k\neq i,j} \left(w_k(i,j) w_k(i,h) w_k(j,h) \right)^{1/3}, \tag{6}$$

where d_i is the degree of node i, representing the (unweighted) number of neighbors of node i in layer k. The clustering coefficient $CC_k(i)$ quantifies the local density of connections among the neighbors of node i, where a higher value indicates a higher tendency for node i to form cohesive clusters with its neighbors.

To obtain a global measure of the clustering coefficient for the entire layer, we average the local clustering coefficients across all nodes in the network. The global clustering coefficient GCC_k is defined as:

$$GCC_k = \frac{1}{N} \sum_{i\in V} CC_k(i), \tag{7}$$

where N is the number of nodes in the layer. The global clustering coefficient measures how likely it is that nodes in layer k are grouped together in tightly connected clusters, reflecting the overall cohesion of the network.

3.3. Community detection procedure and inter-layer link formation

In the context of complex networks and for each layer k, community detection involves partitioning a set of nodes into C_k distinct communities such that nodes within the same community are more similar to each other than to nodes in different communities. The similarity between nodes is typically represented by a distance measure, and the goal is to find the community structure that minimizes intra-community distances while maximizing the distinction between communities. More precisely, for the kth layer of a multilayer network (1), we take the distance $d_k(i,j)$ as defined in Eq. (2).

To detect communities, we adopt the PAM approach rather than C-means because it is more robust to the presence of outliers (Garcia-Escudero and Gordaliza, 1999). The PAM objective function for the kth layer can be written as

$$\min_{\mathbf{U}^{(k)},\mathbf{M}^{(k)}} \sum_{l=1}^{C_k} \sum_{i=1}^{N} u_{il}^{(k)} d_k(i,\mu_k^l), \tag{8}$$

where $\mathbf{U}^{(k)} = (u_{il}^{(k)} : i = 1,\dots,N; l = 1,\dots,C_k)$ is the membership matrix for the kth layer, with entries $u_{il}^{(k)} \in \{0,1\}$, representing the assignment of nodes to communities; $u_{il}^{(k)} = 1$ if node i belongs to community l, and $u_{il}^{(k)} = 0$ otherwise. Moreover, $\mathbf{M}^{(k)} = (\mu_k^l : l = 1,\dots,C_k)$ are the prototypes of the C_k communities in the kth layer, $d_k(i,\mu_k^l)$ is the distance between node i and the lth cluster prototype μ_k^l in the kth layer.

The formulation of the objective function in (8) ensures that each node is assigned to exactly one community, and the total intra-community distance is minimized. The prototypes μ_k^l are updated iteratively, as the PAM algorithm alternates between assigning nodes to the nearest centroid and recalculating the centroids based on the current community assignments.

By solving this minimization problem, we obtain the optimal partition of nodes in the kth layer into C_k communities, represented by the membership matrix $\mathbf{U}^{(k)}$. This matrix contains all the information about the detected communities in the kth layer.

Remark on number of communities C_k selection

Instead of predefining the number of communities (clusters), we adopted an iterative approach to determine the optimal number. We evaluated different cluster configurations using the Average Silhouette Width (ASW) criterion, which is commonly adopted for number of clusters selection (Arbelaitz et al., 2013; Batool and Hennig, 2021). The ASW value ranges from −1 to 1, with higher values indicating better-defined clusters. For each possible number of clusters, we therefore compute the average silhouette width and select the number of clusters maximizing the ASW.

3.4. Inter-layer link

Given $i \in V$ and $k = 1, \dots, K$, we denote the community of the kth layer obtained with PAM (8) where one can find node i as $C^{(k)}(i)$. The outcomes of the procedure used for detecting the communities on the generic kth layer are then employed for forming the inter-layers arcs in C.

In particular, we define the existence of a link between nodes i and j in two different layers h and k if the nodes i and j belong to the same community in both layers. Specifically,

$$E_{hk}(i,j) = \begin{cases} 1 & \text{if } C^{(k)}(i) \equiv C^{(k)}(j) \text{ and } C^{(h)}(i) \equiv C^{(h)}(j), \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

Therefore, according to (9), two nodes in different layers are connected when they share a similar behavior in terms of the considered variables. By construction, the links in C are unweighted and undirected. Moreover, if node i in layer k is connected to node j in layer h, then also node i in layer h is connected to node j in layer k.

4. Results and discussion

The multilayer structure, as described in (1), consists of a set of connected layers. Each layer is a network, with its relationships across nodes. Given the data discussed in Section 2, we deal with ten different layers observed for five years. Before estimating the existing relationships between couples of layers, we analyze the main network-based characteristics of each layer for every year. Table 2 shows the values of some relevant centrality measures of each layer. In particular, we consider the average closeness centrality measure of the network (Hansen et al., 2011), the average strength (Scott and Carrington, 2011) and the Global Clustering Coefficient (GCC) (Onnela et al., 2005).

4.1. Results and discussion intra-layers

The average closeness measures how close a country is to all other countries in the network in terms of the weights ωs, see Freeman (2002). Therefore, a high value of average closeness indicates that countries are far in terms of distance and thus exhibit different behaviors for the considered variable. In this case, countries adopt likely dissimilar socio-environmental practices. Furthermore, low closeness points to contiguous areas, where some countries are well integrated into the network.

For the variable CE1, we find that the closeness centrality declined slightly over the years, from 0.1251 in 2016 to 0.1059 in 2020. This indicates that the circular economy in this dimension become more efficient in terms of integration among nodes/countries over the years. Vice-versa, the CE2 consistently has one of the highest closeness values (0.1876 in 2016, 0.1664 in 2020), albeit it shows a downward trend as well. The CE2 higher values indicates that countries are low connected in terms of CE2-related efforts compared to other CE variables. Overall, the whole set of CE-related networks shows a general decline in centrality. In particular, CE3 shows the lowest value found, and in 2020 it reached 0.0929. Even CE4 and CE5 show a decline in closeness over time, we want to point out that variable CE5 is associated with a strong decrease. Overall, the general declining closeness in CE variables may indicate increasing integration in circular economy policies across EU countries, even if CE2 maintains the highest values observed.

Considering the ET-related networks, instead, we find that ET1 shows a pretty steady closeness centrality, slightly increasing from 0.1388 in 2016 to 0.1476 in 2020, while ET2 has lower closeness than ET1, with values hovering around 0.0936–0.0985. Overall, both energy transition networks (ET1 and ET2) maintain stable or slightly rising centrality over time, indicating that the integration related to energy transition is not really achieved.

In terms of social justice, SJ1 shows a noticeable increase in closeness centrality, from 0.1069 in 2016 to 0.1419 in 2020, while SJ2 exhibits consistently high closeness centrality, starting at 0.1502 in 2016 and declining only slightly to 0.1592 in 2020, as well as SJ3 ranging from 0.1307 to 0.1395. The overall trend in social justice-related networks points to a slight enhancement in SJ2 and SJ3 while showing a strong increase in SJ1. This may suggest growing complexity or fragmentation in how social justice issues are addressed across EU countries.

In sum, the decline in closeness across most CE variables implies that EU countries may be facing challenges in pursuing integration in the circular economy, even if the integration across EU countries over the years seems to work well. The steady or slightly increasing closeness in ET variables suggests that energy transition remains an open challenge so EU countries are not really integrated, particularly referring to ET1. Finally, the overall growth in closeness for the SJ dimension indicates potential challenges in addressing social justice issues integration. Fragmentation in these networks could point to growing disparities or complexity in how social justice is handled across different countries.

The average strength reflects the average total weight of the connections of each node, summing the weights of the links with other nodes, see Barrat et al. (2004). A high average strength indicates that countries with similar values of the considered variables are strongly connected. These strong connections may represent the presence of alliances and mutual exchanges of best socio-environmental practices, supporting the widespread adoption of similar policies. Countries may have similar scores if the average strength is low, but their connections are weak.

CE1 exhibits a moderate degree centrality, ranging from 13.9436 to 14.8646, suggesting a slight increase in similarity among countries. This indicates a framework where countries implement analogous strategies, but the connections are not particularly strong compared to other variables. Similarly, CE2 shows patterns that align closely with CE1, with values fluctuating between 15.9809 in 2016 to 14.6754. Despite the degree centrality decreasing we still have a reliable level of similarity. CE3 shows a strong average degree of 16.1564 in 2016 but a lower value in 2020, namely 15.6362. This suggests that while countries are still likely implementing the same strategies, the strength of these connections is decreasing over time widening the divergences among countries on average. CE4 stands out with one of the lowest degree centrality values, fluctuating between 13.0981 and 15.3833, indicating relatively weaker connections among countries regarding this specific aspect of the circular economy. On the other hand, CE5 consistently exhibits one of the highest degree centrality values, peaking at 18.6435 in 2020. This strong centrality indicates that countries are implementing significantly similar efforts regarding CE5 efforts, likely reflecting robust collaboration and resource exchanges.

In terms of the ET variables, ET1 and ET2 maintain a stable degree centrality over time, with ET1 slightly increasing from 15.1044 in 2016 to 16.0475 in 2020, which indicates a steady and strong similarity among countries focused on energy transition. ET2, while slightly lower, remains relatively stable, with values around 15, suggesting that the overall similarity remains consistent for this network as well.

For the SJ variables, SJ1 shows a declining degree centrality, from 16.7130 in 2016 to 13.9856 in 2020, reflecting a weakening in the intensity of similarity between countries on this dimension. On the other hand, SJ2 exhibits a more stable degree centrality, with values ranging from 12.6757 to 13.2525, showing a more consistent level of connection. Similar to SJ2 last variable SJ3 shows very close behavior keeping its value around 13 over time. This suggests that while social justice issues remain connected, the intensity of similar strategic efforts may vary depending on the specific social justice variable considered.

The variation in average strength across the CE variables suggests that while countries are establishing some common strategies, the overall strength of these ties remains moderate, particularly for CE1 and CE4, indicating potential barriers to robust partnerships in the circular economy. The notable strength exhibited by CE5 highlights a crucial area of engagement, reflecting effective similarity that might lead to resource exchange among nations. Meanwhile, the stable degree centrality in the ET variables suggests that efforts towards energy transition seem to be consistently well-coordinated, supporting a unified approach among countries. In contrast, the declining average strength in the SJ variables points to potential fragmentation in the network addressing social justice issues.

Finally, we remark that the GCC measures the strength of the community structure within the network, highlighting how frequently neighboring nodes are connected, see Onnela et al. (2005). A high clustering coefficient suggests that countries with similar scores are not only connected to many other countries but also tend to be part of cohesive communities. This aspect can facilitate the diffusion of socio-environmental policies and sustainable innovations among similar countries. In contrast, a low clustering coefficient indicates that countries with similar scores do not necessarily form strong communities, thereby hindering opportunities for mutual learning and collaboration.

Looking at CE1, the GCC increases gradually from 0.5226 in 2016 to 0.5649 in 2020, reflecting a growing tendency of countries to form more tightly connected clusters over time. CE2, however, shows a slight decrease in clustering from 0.6073 to 0.5498, which may suggest increasing fragmentation in strategic policies related to this variable. For CE3, the GCC remains relatively stable, fluctuating around 0.6236 to 0.5792, indicating that while the connections among countries are somewhat cohesive, there is no significant trend towards greater or lesser clustering. This stability might reflect ongoing, yet possibly uneven, collaborative efforts among countries regarding CE3, suggesting that the networks are neither particularly strengthening nor weakening. For CE4, we observe a gradual decline in GCC from 0.4784 in 2016 to 0.5019 in 2020, suggesting that while some connections exist, there is a trend towards less cohesion over time. This decrease could reflect challenges in forming effective collaborations around circular economy initiatives, indicating a potential need for more robust frameworks to foster connectivity among countries. The layer CE5 stands out for having the highest clustering across all years, peaking at 0.7366 in 2020, indicating that countries working on CE5 form the most cohesive and interconnected clusters.

Regarding ET variables, both ET1 and ET2 maintain stable clustering values. ET1 shows a slight increase from 0.5740 in 2016 to 0.6148 in 2020, indicating growing interconnectedness among countries in this area. ET2 remains steady around 0.5747–0.6041, which suggests that the countries involved in energy transition implement similar strategies, forming relatively cohesive clusters.

For the SJ dimension, SJ1's clustering coefficient declines from 0.6480 to 0.5189, indicating a reduction in tightly knit clusters, possibly reflecting growing complexity or fragmentation in social justice issues. On the contrary, SJ2 remains relatively stable, with GCC values around 0.4806–0.4590, showing that while the clustering is not particularly high, the social justice-related strategies remain significant. Similarly to SJ2, the variable SJ3 shows relatively low GCC; however, we note positive oscillation, especially in 2019 when SJ3 reached 0.5396, suggesting some improvement in similarity among countries related to social justice initiatives.

In summary, the variations in the GCC highlight how the entity of connections within networks varies significantly across different

Table 2
Main network statistics for each layer of the multilayer structure across the years from 2016 to 2020. The table includes the average closeness centrality, the average strength centrality, and the Global Clustering Coefficient (GCC, Onnela et al. (2005)) values for each variable and year.

Variables	Years	Close	Strength	GCC
CE1	2016	0.1251	13.9436	0.5226
	2017	0.1140	14.2411	0.5376
	2018	0.1197	14.1236	0.5335
	2019	0.1084	14.5912	0.5532
	2020	0.1059	14.8646	0.5649
CE2	2016	0.1876	15.9809	0.6073
	2017	0.1774	15.3700	0.5854
	2018	0.1760	14.7762	0.5579
	2019	0.1592	14.7313	0.5633
	2020	0.1664	14.6754	0.5498
CE3	2016	0.0931	16.1564	0.6236
	2017	0.0936	15.6071	0.6002
	2018	0.0988	15.1228	0.5792
	2019	0.1025	15.0274	0.5745
	2020	0.0929	15.6362	0.6022
CE4	2016	0.1425	13.0981	0.4784
	2017	0.1228	13.6579	0.5085
	2018	0.1143	14.2627	0.5379
	2019	0.1164	15.3833	0.5888
	2020	0.1339	13.5400	0.5019
CE5	2016	0.1227	17.3107	0.6738
	2017	0.1231	17.2972	0.6726
	2018	0.1062	16.6548	0.6461
	2019	0.1166	15.2778	0.5860
	2020	0.0960	18.6435	0.7366
ET1	2016	0.1388	15.1044	0.5740
	2017	0.1441	15.0345	0.5705
	2018	0.1470	15.1743	0.5805
	2019	0.1472	15.3069	0.5837
	2020	0.1476	16.0475	0.6148
ET2	2016	0.0985	15.0301	0.5747
	2017	0.0970	15.5015	0.5956
	2018	0.0936	15.6866	0.6039
	2019	0.0948	15.6979	0.6041
	2020	0.0959	15.3340	0.5913
SJ1	2016	0.1069	16.7130	0.6480
	2017	0.1031	16.9493	0.6580
	2018	0.1093	15.2497	0.5835
	2019	0.1241	14.6197	0.5592
	2020	0.1419	13.9856	0.5189
SJ2	2016	0.1502	13.2525	0.4848
	2017	0.1505	13.1848	0.4806
	2018	0.1455	13.1728	0.4806
	2019	0.1693	12.6757	0.4540
	2020	0.1592	12.7174	0.4590
SJ3	2016	0.1307	13.2967	0.4882
	2017	0.1330	13.3742	0.4911
	2018	0.1245	13.5909	0.5045
	2019	0.1151	14.2971	0.5396
	2020	0.1395	13.2337	0.4933

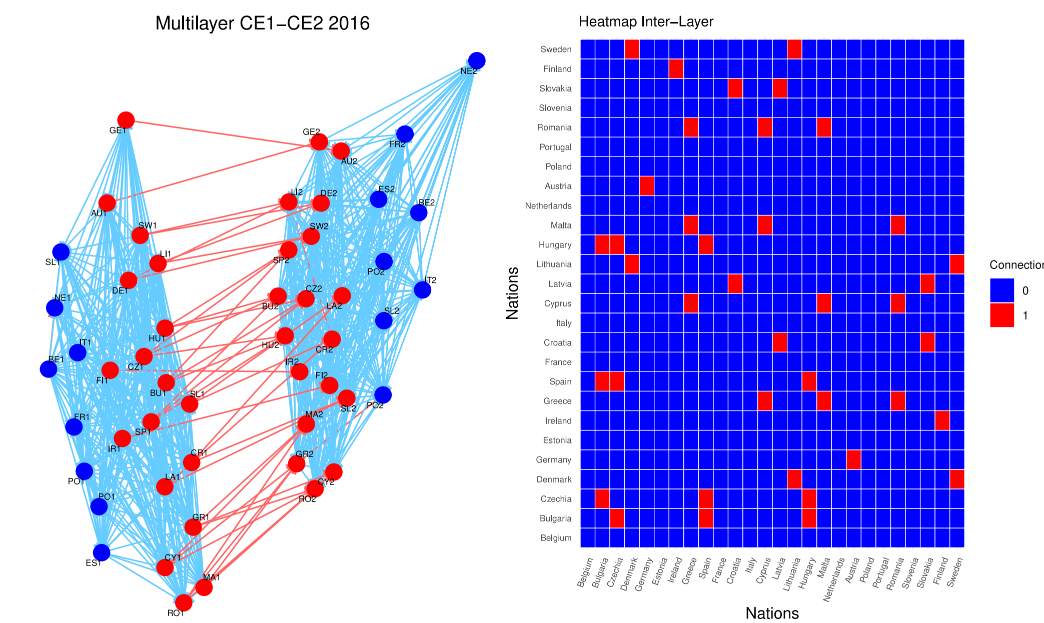

Fig. 1. The figure is composed of two panels. On the left side, we find the network, where the nodes represent EU countries, and light blue indicates the intra-layer connections, while red links highlight the inter-layer relationships. The right side displays the inter-layer connections, with red squares identifying countries that share the same cluster in both variables, while blue squares indicate countries that do not share the same cluster in either variable. Specifically the figure displays the year 2016 and variables CE1 and CE2.

domains. While some variables show increasing cohesion leading to high levels of interconnections among countries, others, such as CE2 and SJ1, indicate potential fragmentation and a weakening of the community structure. This suggests that, although efforts are being made to establish ties between nations, barriers may exist that hinder the formation of stronger and more cohesive networks, particularly in the context of social justice and the circular economy. On the other hand, a high GCC in CE5 reflects a crucial area of engagement, emphasizing significant opportunities for resource exchange and the diffusion of sustainable practices among countries.

4.2. Results and discussion inter-layers

For the definition of the multilayer adjacency, we adopt for each time the procedure based on the similarities of the communities detected at two different layers. As explained in Section 3.4, a connection between two nodes in two different layers is found if the nodes belong to the same community in both layers. Given that the estimation of the links depends on the community structures, we need to estimate what is the optimal number of communities in each layer and for each year. Table 3 shows the number of clusters identified for each variable, considering the maximization of the ASW. We notice that a low number of communities C_k indicates that the nodes, i.e. the EU countries, are overall similar in terms of the kth variable, while large values indicate higher fragmentation.

We interestingly note that the number of communities is not always stable within the different layers of the multilayer network. For example, we find that for 2016 the ET-related variables have the same number of communities, while for CE and SJ dimensions the number of communities differ by layer. In particular, for the variables related to circular economy the layer associated with CE1 is the one with the largest number of communities, while the CE4 is the layer with the lowest number of communities. For the SJ dimension, we find that SJ1 is associated with the layer with the largest number of communities, while SJ3 is the one with the highest homogeneity. These findings are somehow consistent across the years, although a few exceptions can be found. In particular, we notice that in the year 2020, the number of communities is larger for all the considered layers. This result suggests an increased fragmentation of the EU relationships in the three dimensions.

Table 3
Optimal number of clusters identified for the considered variables across the years from 2016 to 2020. The values represent the number of clusters that maximize the silhouette score, indicating the best partitioning of the data for each year and variable.

	2016	2017	2018	2019	2020
CE1	6	7	2	2	7
CE2	5	7	7	2	7
CE3	3	6	4	6	4
CE4	2	3	7	7	5
CE5	3	4	7	5	6
ET1	7	3	6	6	7
ET2	7	7	3	6	7
SJ1	7	7	5	6	7
SJ2	4	3	3	2	7
SJ3	2	2	2	2	6

We observe that the number of clusters is related to the centrality measures since the average measures shown in Table 2 describe the overall structure of the network. For instance, the closeness centrality tends to be lower (indicating more compact networks) for years, and layers are associated with a smaller number of clusters. As the number of clusters increases, closeness tends to rise, suggesting that nodes are less compact and more dispersed. Similarly, the strength centrality appears to be lower for networks with fewer clusters, indicating stronger internal connectivity within these communities, whereas a higher number of clusters is associated with increased strength, reflecting weaker or more fragmented connections. Regarding the GCC, we notice a similar pattern, where networks with fewer clusters display higher GCC values, indicating stronger triadic closures within communities. As the number of clusters grows, the GCC decreases, implying a reduction in the formation of tightly-knit triads, and hence, increased fragmentation.

In what follows, we analyze the results of the community detection phase and the consequent inter-layer formation procedure. To this aim, we discuss analogies and discrepancies in terms of the observed K variables/layers and T times. As an illustrative example, we focus on the relationships between the variables CE1 and CE2 over time. The heatmaps in Figs. 1–5 provide a preliminary idea of the global behavior of the countries with respect to the considered variable (CE1 and CE2, in this case) over the considered period.

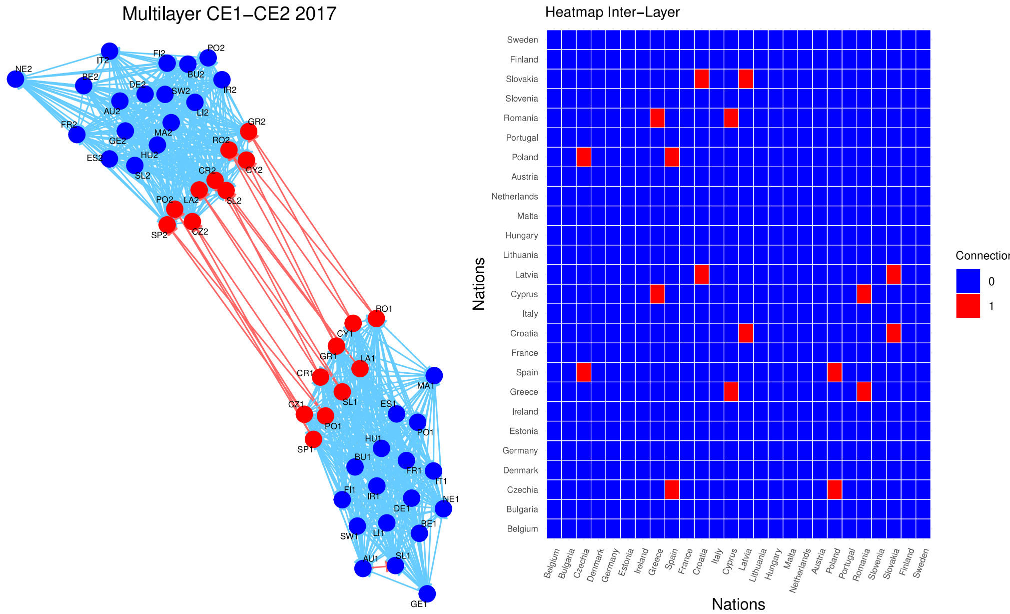

Fig. 2. As shown in Fig. 1, the figure is divided into two panels. The left panel illustrates the network, where the nodes represent EU countries. Light blue lines indicate intra-layer connections, while red lines denote inter-layer relationships. The right panel presents the inter-layer connections, with red squares highlighting countries that belong to the same cluster in both variables, whereas blue squares represent countries that do not share the same cluster in either variable. This figure specifically illustrates the year 2017 and the variables CE1 and CE2.

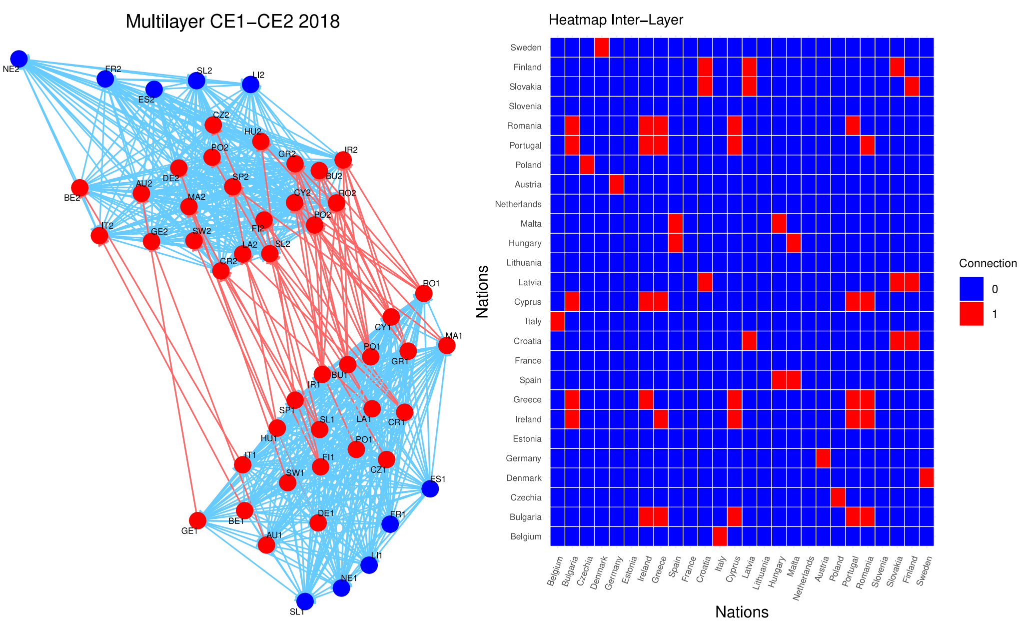

Fig. 3. As in Figs. 1 and 2, the left panel displays the network of EU countries, with light blue indicating intra-layer connections and red representing inter-layer relationships. The right panel highlights inter-layer connections, where red squares denote countries sharing the same cluster in both variables, and blue squares indicate those that do not. This figure specifically represents the year 2018 and the variables CE1 and CE2.

The blue zones are associated with couples of countries belonging to different clusters with respect to the two variables, while the red zones point to cases of countries in the same clusters. Thus, blue stands for diversity while red is related to similar behavior.

We recall that CE1 provides a measure of the share of recycled municipal waste over the entire generation of municipal waste. Differently, CE2 is the share of recycled material from waste — hence, describing the effective use of recycled waste. Similar behaviors (red cells) concerning these variables mean that the considered countries are clustered in the same class in terms of recycling waste and reuse of recycled waste. We point out that countries' similarity does not imply necessarily an analogous behavior concerning the observed variables. Indeed, two countries belong to the same cluster for both variables even when they have a high value of one indicator and a low value of the other one. In this respect, the concept of similarity should be intended in the context of similar policies for both variables, taken separately.

Importantly, results also depend on the number of clusters. Indeed, the years with a lower number of clusters are those in which more probable connections between the inter-layer nodes appear.

We notice a predominance of blue in all the years with the noticeable exception of year 2019, where there is a fair distribution of red and blue. This outcome leads to the evidence that countries that are similar in terms of CE1 are not similar when looking at CE2. The case of the highest level of common clusters of the year 2019 can be related to

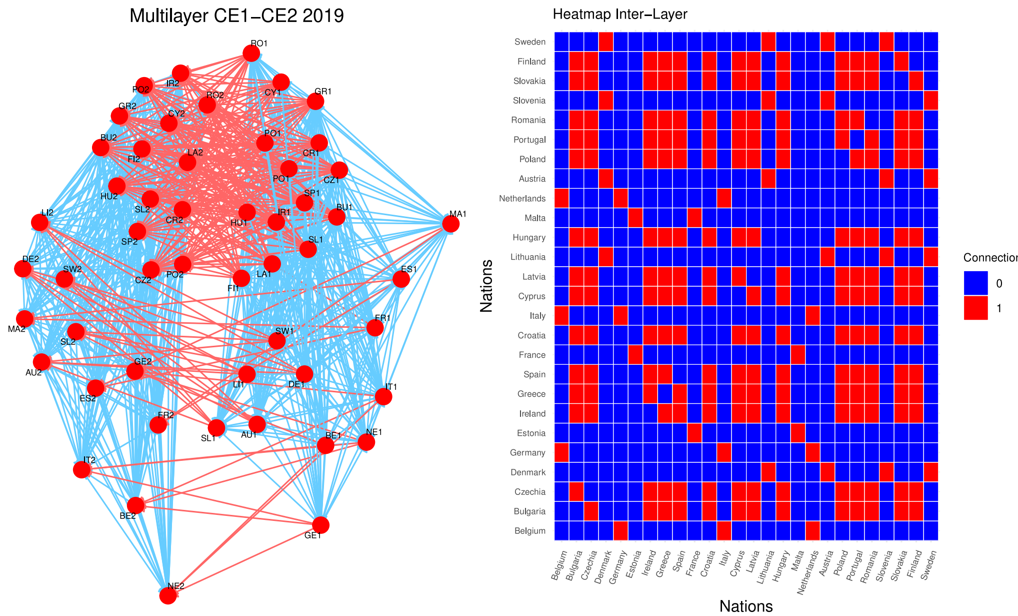

Fig. 4. Similar to Figs. 1, 2, and 3, this figure illustrates both intra-layer and inter-layer relationships. The color legend corresponds to the previous figures, and the interpretation remains consistent.

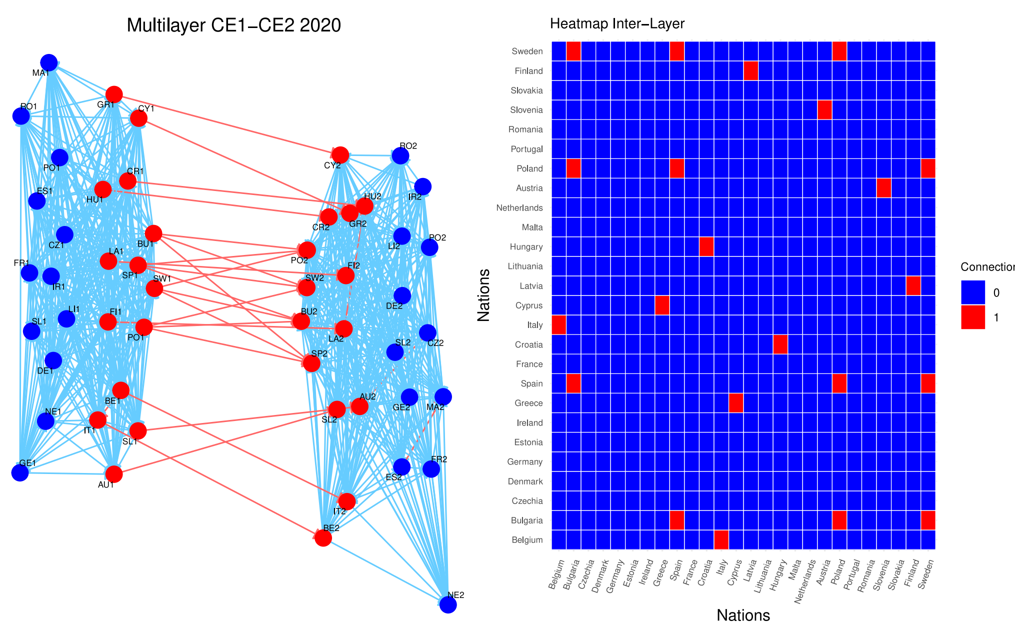

Fig. 5. Similar to Figs. 1, 2, 3, and 4 this figure illustrates both intra-layer and inter-layer relationships. In this case, the figure corresponds to the year 2020.

the First Circular Economy Action Plan implemented by the European Commission.[2] Such a plan is associated with 54 actions that have been delivered in 2019 — even if some of them are still in force after 2019.

By looking at the rows and columns of the heatmaps, one observes how individual countries belong to the same clusters for both the considered variables, hence pointing to analogies of behaviors in terms of CE1 and CE2. For instance, Estonia is always not connected with other countries except in 2019, when it behaves like France and Malta. In the highly connected year 2019, one can observe similar graphical representations for Spain, Greece, and Ireland. These three countries are connected around with the same countries in the multilayer context, so having quite common behaviors in terms of CE1 and CE2.

Individual cells describe specific cases of analogies and discrepancies. For example, Slovakia had constantly the same behavior as Latvia and Croatia from 2016 to 2019. Belgium and Italy are in the same cluster for both variables in the triennium 2018–2020.

The Appendix with the supplementary material contains the full set of heatmaps considering all the couples of variables and all the years, from 2016 to 2020, along with related comments and discussion.

In sum, the results highlight a relatively low level of integration at the European level, especially in the last year considered in the sample, given that many inter-layer connections are absent, and many clusters with different compositions can be found in terms of the single layers. In fact, the finding of a large number of clusters is evidence of the fragmentation of the EU socio-environmental policy, considering the CE, ET, and SJ dimensions.

[2] https://environment.ec.europa.eu/topics/circular-economy/first-circular-economy-action-plan_en.

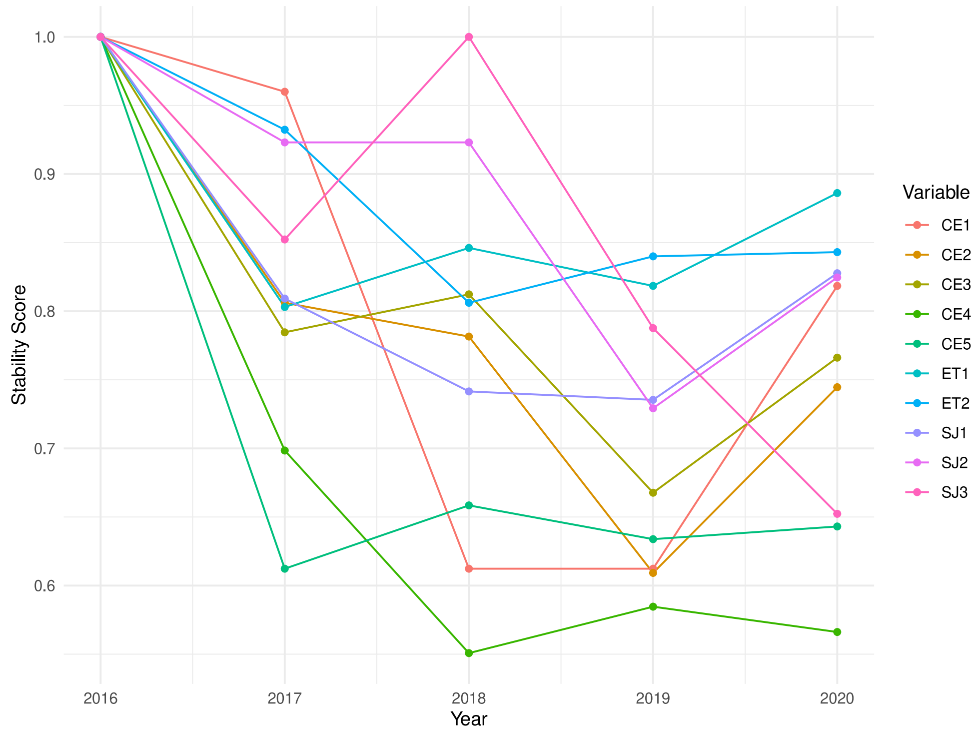

Fig. 6. Stability of the communities over the years for different variables, as listed in Table 2. The stability score is computed with the Rand Index, which measures the degree of agreement between two partitions. We consider the stability score between the partition of the year 2016 compared with all the other years. The maximum value of 1 indicates that the two communities in two years s and t are identical, while the minimum value of 0 indicates no agreement.

Finally, we evaluate the stability of the temporal evolution of the community membership for the different networks over the years. Indeed, in the presence of stable community structures, we expect to find similar inter-link relationships over the years. To address this point, we compute the stability of community memberships over time for each variable using the Rand Index (Rand, 1971). The Rand Index is a widely used measure for quantifying the similarity between two partitions of the same set, which, in our context, corresponds to the community memberships in two different years. Formally, given two partitions for two years t and s of n elements, namely $C(t)$ and $C(s)$, the Rand Index is defined as

$$\mathrm{RI}(C(t), C(s)) = \frac{a+b}{\binom{n}{2}}, \tag{10}$$

where a is the number of pairs of elements that are in the same community in both $C(t)$ and $C(s)$ b is the number of pairs of elements that are in different communities in both $C(t)$ and $C(s)$ and $\binom{n}{2}$ is the total number of pairs of elements. The Rand Index ranges from 0 to 1, where a value of 1 indicates perfect agreement between the partitions (i.e., identical community memberships across years), and a value of 0 indicates no agreement.

By computing the Rand Index for each pair of consecutive years, we have quantitatively assessed the stability of community memberships over time (see Fig. 6). We consider the year $t = 2016$ as the baseline partition and make the comparisons with all the remaining years, so that the years s are given by $s \in \{2017, 2018, 2019, 2020\}$.

In sum, the results indicate that while the number of communities fluctuates slightly, the stability of memberships across years is generally high for most of the variables. This indicates that the community structures are relatively persistent over time, even as some variations occur. However, the level of stability decreases over the observed years, meaning that the community structures differ compared to 2016 the farther we move in time. Despite this general tendency, for the majority of the networks we find a larger overlap with the 2016 during 2020 compared to 2019. The lack of perfect stability of the community structures, however, explains why different inter-layer links formation can be found between pairs of networks in the different considered years, as discussed in the web supplement to the paper.

4.3. Policy implications

One of the primary findings is that EU countries display inconsistent behaviors across different socio-environmental dimensions. For instance, CE variables – such as the share of recycled municipal waste (CE1) and the effective use of recycled materials (CE2) – show notable differences in clustering across countries, with many countries grouped together for one variable but diverging on the other. The lack of inter-layer connections, especially between CE and ET variables, suggests that countries may prioritize certain aspects of environmental policy (e.g., recycling) while neglecting others (e.g., renewable energy). To counteract this and foster virtuous behavior in EU countries, the EU should promote the development of integrated frameworks that link policies across dimensions. For example, CE policies should not be treated in isolation but should be tied to energy transition efforts, ensuring that circular economy initiatives, such as recycling and waste management, also contribute to reducing carbon emissions and increasing renewable energy use. By fostering cross-dimensional strategies, countries can more effectively address environmental goals in a holistic manner. In fact, countries with similar socio-economic and geographic characteristics could be encouraged to work together on specific environmental challenges, thereby reducing fragmentation and improving policy coherence. For example, regions that share energy infrastructures or similar economic profiles could collaborate on joint energy transition projects. This would help create synergies between countries and reduce the isolation of national policies.

The First Circular Economy Action Plan, implemented in 2019, is a notable example of how EU-level initiatives can enhance policy integration. During this year, we observed a more balanced distribution of red and blue zones, reflecting a temporary increase in the alignment of recycling-related policies across countries.

However, the return to a predominance of blue zones in 2020 indicates that this progress was not sustained, possibly due to the onset of the COVID-19 pandemic and the corresponding shift in policy priorities. The COVID-19 pandemic has had a profound impact on environmental policy coordination across the EU. In 2020, we observed a marked increase in policy fragmentation, reflected by the high number of blue zones in the heatmaps, particularly in the CE and ET dimensions. This suggests that countries shifted their focus inward to address the immediate impacts of the pandemic, rather than maintaining coordinated efforts on long-term environmental goals.

Moving forward, the EU should work to mitigate the negative effects of such disruptions by establishing mechanisms for continued policy coordination during crises. These mechanisms could include contingency plans that allow for flexible yet consistent socio-environmental policies, ensuring that member states remain committed to shared socio-environmental objectives, even in the face of economic or health crises. To maintain and build upon such successes, the EU should implement standardized regulations that set minimum socio-environmental standards across member states. These regulations could cover key areas like recycling rates, renewable energy adoption, and social justice measures related to socio-environmental policies. By creating binding legislative frameworks, the EU can ensure that countries do not deviate from collective goals, even during periods of crisis or economic instability.

Interestingly, the Social Justice (SJ) dimension exhibits relatively high levels of integration, especially between the corruption perception index (SJ2) and the perceived independence of the judicial system (SJ3). This finding is crucial, as it indicates that when countries adopt similar governance-related policies, they tend to show stronger alignment. The EU can leverage this success by using the Social Justice dimension as a blueprint for integrating other policy areas, such as CE and ET.

In general, regulators could use the proposed framework to identify areas of socio-economic disconnection or over-integration, enabling targeted interventions. Policymakers could leverage the results to monitor the impact of policy changes or external shocks and to adjust strategies accordingly. Similarly, market practitioners might find the insights valuable for assessing risk exposure or identifying opportunities within integrated socio-economic systems. By elaborating on these applications, we aim to demonstrate how the presented methodology can be effectively used to map and monitor socio-economic integration over time.

5. Conclusions and future research

In this paper, we analyzed the implementation and coordination of socio-environmental policies across European Union (EU) countries from 2016 to 2020. We focused on three key policy dimensions: Circular Economy (CE), Energy Transition (ET), and Social Justice (SJ), represented by 10 variables. The study applied a network-based approach, where nodes represented EU countries, and weighted links captured the degree of similarity between countries for each variable over time. We also constructed a multilayer network to explore the integration of socio-environmental policies across different layers (policy dimensions) by examining inter- and intra-layer connections between countries.

By computing the centrality measures for each variable and year, we assessed the extent to which countries are coordinated in their socio-environmental policies. Our findings revealed a relatively low level of policy integration at the EU level, with significant fragmentation across policy dimensions. Specifically, while there are numerous clusters of countries within each policy dimension, there was a general lack of inter-layer similarity, meaning that countries implementing the same strategies in one dimension (e.g., CE) did not in others (e.g., ET or SJ). The only dimension with relatively high levels of integration, except in 2020, is SJ.

The findings of this paper reveal significant fragmentation in the socio-environmental policies of European Union (EU) countries across CE, ET, and SJ. The absence of integration across these policy dimensions is particularly evident through the prevalence of blue zones in the heatmaps, which signal the divergence in countries' behavior between different variables. In contrast, the red zones, indicating policy alignment, are sparse and often isolated to specific years or variables. This fragmentation might be particularly problematic as it undermines the EU's collective efforts to combat socio-environmental challenges, which require integrated policy actions.

5.1. Limitations and future research

While this study provides important insights into the integration and fragmentation of socio-environmental policies across the European Union (EU), it also opens several avenues for future research.

For example, while this study covers the period from 2016 to 2020, the socio-environmental landscape, particularly in the context of the EU, is continuously evolving. Therefore future research should extend the analysis to include more recent years, capturing the post-pandemic recovery period and the impact of recent EU initiatives like the European Green Deal.

Moreover, while our current analysis focuses on national-level policies, we notice that socio-environmental challenges often have strong regional or even sub-national dimensions. Future research could explore how different regions within EU countries are aligned or fragmented in their socio-environmental efforts.

We also highlight that the observed fragmentation in socio-environmental policies may be influenced by various political and economic drivers, such as national political priorities, economic capabilities, and public opinion. Therefore, future research could investigate the extent to which these factors shape the level of policy coordination between countries.

It is surely challenging to deal with the mesoscale structure of the multilayer network. In this respect, we can notice that the ground of our analysis is the topological structure of the considered network, and surely the community structure of the multilayer network plays a relevant role in assessing the entity of EU policy integration for our specific socio-environmental context. A promising direction is the recent definition of clustering coefficient for multilayer networks as given by Bartesaghi et al. (2023). This theme should be developed with care in devoted future research.

Finally, from a purely methodological perspective, we can modify the root of the clustering exercise and deal with a fuzzy clustering procedure. In doing so, the assignments of countries to clusters are provided according to a probability law, so that each country is assigned to each cluster with a probability. The intralayer networks become complete in this case, and weighted interlayer links provide a better representation of the connections between couples of countries at different layers. Also this challenging exploration is left for future studies.

CRediT authorship contribution statement

Roy Cerqueti: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Giovanna Ferraro:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Raffaele Mattera:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Saverio Storani:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.144792.

Data availability

Data will be made available on request.

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