



Climate Neutrality of the Economy and the Green Transition

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**CIRCULAR ECONOMY DEVELOPMENT
IN EU COUNTRIES THROUGH THE LENS
OF PLASTIC RECYCLING**

Abstract

This study examines circular economy (CE) performance across 27 EU countries over 2015–2023 using indicators related to patents, resource productivity, plastic packaging waste generation, trade in recyclable raw materials, employment in CE sectors, and plastic packaging recycling. The empirical analysis combines descriptive statistics, correlation analysis, fuzzy c-means clustering, and multinomial logistic regression. The results identify three clusters of EU countries: lagging systems with weak performance across most dimensions, advanced integrated economies combining innovation and recycling capacity, and efficiency-driven recyclers that achieve comparatively strong recycling outcomes despite weaker innovation and labour-market capacity. The findings suggest that CE

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performance in the EU is not one-dimensional. Multinomial logistic regression confirms that recycling performance is the primary driver of transition from low- to intermediate-level systems, while advanced systems require broader structural integration. The findings highlight gradual, path-dependent transitions and provide evidence for differentiated policy strategies targeting both capacity building and recycling efficiency. The original contribution of this study lies in empirically distinguishing between capacity-driven and outcome-driven dimensions of CE performance and in demonstrating that intermediate circular success can emerge under structurally different national configurations, which has direct implications for differentiated EU cohesion and CE funding policy.

Key Words:

circular economy policy, circular economy, EU countries, plastic packaging waste, recycling performance, resource productivity.

JEL: Q56, O52, Q53.

3 figures, 6 tables, 64 references.

Problem Statement

The circular economy (CE) has become a strategic priority for the EU as a framework for reducing material intensity, improving resource efficiency, strengthening environmental sustainability, and enhancing long-term economic resilience (European Commission, 2018a; Geissdoerfer et al., 2017). In this context, assessing circular economy performance across EU countries is not only a matter of environmental monitoring but also an important economic question, as circular transition depends on the interaction between waste-management outcomes, innovation capacity, labour-market transformation, and integration into secondary raw material markets (PACE, 2021; Avdiushchenko & Zajac, 2019; Kamali Saraji & Torabi, 2025).

However, the empirical assessment of CE performance remains analytically challenging. Circularity at the country level is multidimensional, and high performance in one dimension does not necessarily imply broader structural ad-

vancement (Moraga et al., 2019; Fura et al., 2020; Lishchynskyy et al., 2025). In particular, strong recycling outcomes may coexist with limited innovation, weak circular employment, or low integration into secondary material flows, which makes it insufficient to interpret CE performance through isolated indicators or single aggregate rankings (PACE, 2021).

Although existing studies provide valuable benchmarking tools, they often rely on descriptive scoreboards or composite indices that flatten heterogeneous development patterns across countries (Fura et al., 2020; Kamali Saraji & Torabi, 2025). As a result, they do not fully capture whether EU countries follow a common circular transition trajectory or whether they represent distinct but partially overlapping structural configurations (Avdiushchenko, 2021; Cader et al., 2024).

Therefore, **this study aims** to identify distinct structural patterns of CE performance across EU countries and to assess whether high recycling outcomes are systematically associated with broader CE capacities. The study further seeks to explain cluster membership and to provide a differentiated interpretation of CE development in the EU.

Literature Review

The circular economy (CE) is widely understood as a systemic alternative to the traditional linear model of production and consumption, which is based on extraction, use, and disposal. In the academic literature, CE is commonly defined through strategies such as reducing, reusing, repairing, refurbishing, recycling, and recovering materials across production and consumption processes (Kirchherr et al., 2017). Similar approaches emphasise three processes: closing, slowing, and narrowing resource cycles. This means using fewer materials, extending product lifespans, and generating less waste (Geissdoerfer et al., 2017; Dominish et al., 2018; Bocken et al., 2019; Reike et al., 2018). Although definitions vary in emphasis, there is broad agreement that CE implies a structural transformation of production and consumption systems toward greater resource efficiency and value retention over time (Kirchherr et al., 2023; Ellen MacArthur Foundation, 2025).

At the national scale, CE performance can be viewed through two complementary lenses: outcomes and enabling capacities. Outcome-oriented perspectives focus on observed results of circularity – for example, how much waste is recycled or how much primary resource use is reduced (i.e. closed loops and narrowed resource flows). Capacity-oriented views emphasise the institutional, technological, and market conditions that enable circularity – such as innovation capacity, supportive policies, market infrastructure for secondary materials, and skilled labour in circular sectors (PACE, 2021).

At the macro level, CE performance is commonly structured into a limited set of recurring dimensions, typically reflecting EU monitoring practice: waste management, production and consumption patterns (resource use and efficiency), secondary raw materials (including circular material use and trade), competitiveness and innovation (investment, value added, patents), and labour-market aspects captured through employment in CE sectors (Kamali Saraji & Torabi, 2025; Avdiushchenko & Zajac, 2019; Cader et al., 2024; European Commission, 2018b). For example, the EU's own monitoring framework groups indicators into production & consumption, waste management, secondary raw materials, and competitiveness & innovation (Fura et al., 2020) – effectively covering the first four areas – and some analyses add a fifth pillar for broader resource or environmental outcomes (like resource productivity or greenhouse gas emissions) (Kamali Saraji & Torabi, 2025). This dimensional approach provides a more nuanced profile of each country's strengths and weaknesses in the circular transition.

A variety of indicator families are used to quantify countries' CE performance.

Patents as a Proxy for Innovation. Patents in the field of recycling and secondary raw materials are often seen as an indicator of innovation in the CE. They show how actively new technologies for recycling, waste management and resource efficiency are being developed (Moraga et al., 2019; Pakula et al., 2025; McMillin, 2025). In the EU monitoring framework, they are treated as an indicator of technological progress in circular solutions (European Commission, 2018c). However, patent counts capture formal innovation output rather than realised circular outcomes, and they may be shaped by cross-country differences in innovation systems, sectoral specialisation, and the uneven propensity to patent (Crescenzi et al., 2022; Crass et al., 2019; Taalbi, 2025; Lotti & Nobile, 2025; Reeb & Zhao, 2020). Thus, patents are best interpreted as an indirect measure of innovation capacity rather than direct evidence of circular performance.

Resource Productivity. Resource productivity is typically measured as GDP per unit of domestic material consumption (GDP/DMC). It is a standard indicator of material efficiency and decoupling, widely used in CE and resource-efficiency research (McCarthy et al., 2018; Eurostat, 2025b; OECD, 2024). Higher values suggest that an economy generates more value per unit of material input. However, the indicator is not a pure measure of circularity, since it may also reflect structural shifts toward services, trade patterns, or the externalisation of material-intensive production rather than genuine circular efficiency gains (Bianchi et al., 2021; Krausmann et al., 2018; Alonso-Fernández & Regueiro-Ferreira, 2021; Schandl et al., 2024; Nowaczek et al., 2023). It is therefore informative, but should be interpreted with caution.

Trade in Recyclable Raw Materials. Trade in recyclable raw materials is commonly used to capture a country's integration into secondary material markets and its participation in cross-border circular flows (Pakula et al., 2025; Moraga et al., 2019). High trade volumes may indicate that a country actively purchases or

supplies recycling materials and therefore has closer ties to the CE beyond its borders (van Beukering et al., 2014; Lingaitiene & Burinskienė, 2024; Burinskienė et al., 2025). At the same time, trade intensity may also reflect structural factors such as country size, logistics infrastructure, port functions, or limited domestic processing capacity, rather than deliberate circular-economy advancement (European Commission, 2021; Yamaguchi, 2021). For this reason, the indicator is best seen as a proxy for market integration rather than a direct measure of circular outcomes.

Recycling Rates. Recycling indicators remain central to country-level CE assessment because they capture the extent to which material loops are being closed in practice (Milanović et al., 2022; Kamali Saraji & Torabi, 2025). In particular, the recycling rate of plastic packaging waste is especially relevant in the EU context because plastic packaging is both policy-prioritised and technically challenging to recycle (Matthews et al., 2021; Picuno et al., 2021; Anwar et al., 2024; Džajić Uršič et al., 2025). Compared with broader recycling measures, it provides a more demanding test of system performance in a problematic waste stream. For this reason, it is used in this study as a focused outcome indicator of circular-economy effectiveness.

The Generation of Plastic Packaging Waste (GPPW). GPPW is used as a pressure indicator that reflects the intensity of packaging-related consumption and the scale of waste that national systems must manage (European Environment Agency, 2023; Perera et al., 2026). Because plastic packaging is short-lived, highly visible in waste streams, and central to EU environmental policy, high per capita GPPW signals stronger pressure on collection, sorting, recycling, and prevention systems (Bullock et al., 2022; Bruns et al., 2024; Torkelis et al., 2024). From an analytical perspective, this indicator complements recycling indicators, as it helps to distinguish countries that perform well in recycling even under high waste pressures from those that perform poorly even under lower pressures. In this study, the GPPW indicator is used to assess the intensity of plastic packaging consumption and the associated level of waste generation. It contextualises recycling performance and trade in secondary materials. This allows us to distinguish between systems that achieve good recycling performance despite high levels of waste generation and systems where lower waste generation coexists with weaker circularity performance.

Employment in CE Sectors. The indicator “employment in CE sectors” (and related “value added in circular sectors”) is intended to capture the socio-economic dimension of the transition – essentially, how much of the workforce is engaged in activities like recycling, repair, refurbishment, waste management, and leasing services (Eurostat, 2025e). An increasing number of circular jobs can indicate that an economy is restructuring towards circular activities, often cited as evidence of a “just transition” that creates new opportunities (Muñoz et al., 2022; Schröder, 2020). “Circular employment” is treated as a supporting indicator that signals socioeconomic engagement in CE. However, studies emphasise the need

to view it in context (scaled appropriately, and alongside outcome indicators) to discern whether it reflects true circular progression or just an artefact of economic scale.

Existing research on CE performance has generated valuable insights. Nevertheless, some limitations remain. First, many studies rely on descriptive scoreboards or composite indices that flatten multidimensional CE processes into a single ranking, thereby masking structural heterogeneity across countries. Second, performance indicators, especially recycling rates, are often analysed without sufficient attention to the factors that enable the development of more advanced CE systems. These factors include innovation, employment in circular sectors, and integration into secondary raw materials markets. Third, limited attention has been paid to the possibility that EU countries may follow different structural configurations of circular transition rather than a single linear development path.

Based on this research gap and objective, the study formulates the following hypotheses:

H1. CE performance across EU countries is multidimensional rather than one-dimensional.

H2. EU countries can be grouped into distinct but partially overlapping clusters of CE performance.

H3. High recycling performance alone is not sufficient to define an advanced CE system.

Methodology

The empirical strategy consisted of 5 stages: dataset preparation, correlation diagnostics, clustering using the fuzzy c-means algorithm to identify cross-country typologies in circular-economy performance, post-clustering analysis using multinomial logistic regression to assess the drivers of cluster membership, and multicollinearity diagnostics were performed using Variance Inflation Factors (VIF) to ensure the interpretability and stability of the estimated models.

Data preprocessing and missing value treatment. The dataset covers 27 countries from 2015 to 2023. The dataset used for the research analysis contains 243 observations. The dataset covered EU Member States and included a set of circular-economy indicators (Table 1).

Table 1

Description of factors

Factor	Measurement Characteristics	Definition and Description
Patents	Number of patents	This indicator measures the number of patent families related to recycling and secondary raw materials, identified using relevant CPC codes associated with climate change mitigation technologies in wastewater treatment and waste management (Eurostat, 2025a).
Resource Productivity	EUR per kilogram	Resource productivity is defined as the ratio of gross domestic product (GDP) to domestic material consumption (DMC) (Eurostat, 2025b).
GPPW	kg per capita	The generation of Plastic Packaging Waste indicator measures the per-capita generation of plastic packaging waste. Packaging includes all materials used for the containment, protection, handling, delivery, and presentation of goods throughout the supply chain (Eurostat, 2025c).
Trade in raw materials (TRRM)	tonne	This indicator reflects cross-border trade in recyclable raw materials, capturing the international exchange of materials suitable for recycling and secondary use (Eurostat, 2025d).
Employment	persons	Employment in CE Sectors measures employment in CE sectors, including recycling, repair and reuse, and rental and leasing activities (Eurostat, 2025e).
Recycling rate (RRPW)	Percentage (%)	The recycling rate of plastic packaging waste is defined as the share of recycled plastic packaging waste relative to the total amount generated (Eurostat, 2025f).
Recycling rate	Percentage (%)	The recycling rate of municipal waste is defined as the share of recycled municipal waste relative to the total amount of municipal waste generated. (Eurostat, 2025g).

Source: compiled by the authors.

Filling in missing values about the number of patents related to recycling and secondary raw materials is an important step. The patent dataset covers 2012-2021; 2022 and 2023 were filled in using a Compound Annual Growth Rate (CAGR) projection (Dong, 2025). For the countries that were previously mathe-

matically "Undefined" (due to a starting value of 0 in 2012), here is the calculation measured from their first non-zero year up to 2021:

Slovenia: Starting from 2013 (value: 2) to 2021 (value: 1). The 8-year CAGR is -8.30%. The number of patents was calculated at 0.92 for 2022 and 0.84 for 2023.

Bulgaria, Greece, Cyprus, Malta: Because the final value in 2021 for all of these countries is 0, the mathematical formula interprets this as a total loss (a -100% CAGR). Their future projections are permanently flatlined at 0.00 for both 2022 and 2023.

Missing values with information for the previous and subsequent years were filled with the average of the existing values. The final dataset includes 243 rows from 2015 to 2023 from 27 EU countries. Observations with missing values in other variables were removed. This listwise deletion strategy ensured that the clustering and regression stages operated on a consistent sample. Then, all indicators were normalised to remove scale-driven distortions and ensure equal contribution to the distance metric used in clustering. Min-max normalisation on the 0-1 scale was used.

Correlation analysis and normalisation. To explore pairwise linear relationships between the indicators, Pearson correlation coefficients were computed. This allowed assessment of basic covariance structure, potential redundancies among variables, and the conceptual coherence of the indicator set.

Fuzzy c-means clustering. To identify cross-country circular-economy typologies, we first estimated the Fuzzy c-means (FCM) clustering algorithm on the 2023 cross-section. This step was used to determine the reference cluster structure and find the cluster centroids for the most recent year. The obtained 2023 centroids were then retained as fixed reference points and used to calculate membership values for country-year observations in 2015–2022. Earlier observations were therefore not reclustered independently, but projected onto the 2023 cluster structure and assigned to clusters according to the maximum-membership rule. This procedure ensures temporal comparability and allows changes over time to be interpreted as movement relative to a common benchmark typology.

FCM is a soft clustering method that allows observations to belong to multiple clusters with varying membership degrees, unlike hard clustering methods such as k-means, which impose mutually exclusive assignments. Formally, FCM

assigns each country a membership degree $u_{ik} \in [0,1]$ to cluster k , subject to the

constraint $\sum_k u_{ik} = 1$. For interpretation, countries were assigned to the “winner” cluster based on the maximum membership coefficient (Bublyk et al., 2021).

Multinomial logistic regression for cluster drivers. When the clusters were created, the multidimensional logistic regression was used. It explains cluster membership using the chosen variables. To investigate which circular-economy indicators are associated with cluster membership, a multinomial logistic regression model was estimated with cluster_2 as the reference category. Positive coefficients indicate that higher values of a variable increase the probability of belonging to cluster *j* rather than cluster_2, holding all else constant; negative coefficients indicate the opposite. Statistical inference was conducted using z-tests and corresponding p-values (Agresti, 2002; Liang et al., 2020).

Multicollinearity diagnostics: Variance Inflation Factors (VIF). Before estimation, multicollinearity was evaluated using VIF for all numeric predictors. VIF measures the extent to which the variance of an estimated coefficient is inflated due to linear dependence among regressors. Higher VIF values indicate stronger multicollinearity. Across all variables, VIF values remained below conventional critical thresholds (5–10), indicating that multicollinearity did not compromise coefficient interpretability. In line with best practice (James et al., 2013), variables with VIFs exceeding 5 would have been considered for removal, but no such adjustments were necessary.

Research Results

The descriptive statistics reveal a high degree of variation across the analysed indicators, demonstrating pronounced structural differences in plastic waste management systems (Table 2).

Table 2

Descriptive statistics

	Min	Max	25% Quantile	50% Quantile (Median)	75% Quantile	Mean	St. dev
Patents	0.0	137.60	0.22	3.94	18.67	13.13	20.77
Resource productivity	0.30	7.42	1.08	1.65	2.85	2.03	1.26
GPPW	12.50	72.95	23.88	30.6	37.16	31.26	9.96
Trade in raw materials	0.0	170829.0	1492.0	11928.0	29738.0	25928.56	36949.25
Employment	6457.0	783930.0	40141.0	69339.0	134088.0	153784.33	190245.77
Recycling rate	9.10	71.43	29.5	40.3	49.9	39.00	14.87
RRPW	31.80	85.30	58.55	64.70	69.55	63.07	9.91

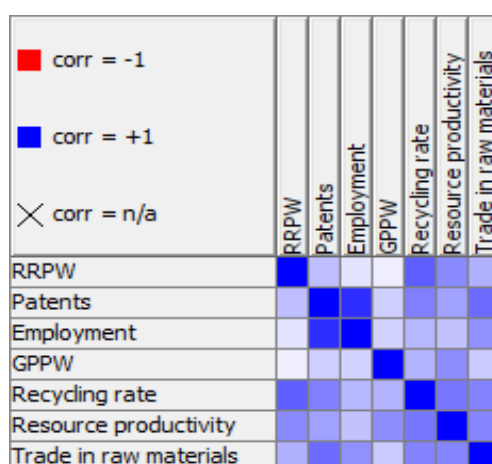
Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

Table 2 shows substantial cross-country heterogeneity in CE performance. Patents, employment, and trade in recyclable raw materials are strongly right-skewed and highly dispersed, indicating that these capacity-related dimensions are concentrated in a limited number of countries. By contrast, GPPW and the recycling rate are more evenly distributed, although recycling outcomes still vary considerably across the sample. Resource productivity shows moderate right skewness, suggesting that a smaller subset of observations achieves higher material efficiency. Overall, the descriptive statistics point to a clear contrast between highly concentrated capacity-related indicators and more balanced outcome-related indicators.

Figure 1 presents the pairwise Pearson correlation coefficients among CE-related indicators for EU countries over the 2015–2023 period. The results reveal several distinct structural relationships, indicating the presence of partially independent dimensions within the EU CE framework.

Figure 1

Correlation analysis



Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

The correlation matrix (Figure 1) reveals several meaningful relationships between the variables, highlighting structural links within plastic waste management systems.

The results indicate that innovation, economic scale, and trade intensity are closely interrelated. The recycling rate shows several moderate positive correla-

tions (resource productivity = 0.53 and trade in raw materials = 0.45). Resource productivity is associated with both higher material use ($r = 0.48$) and higher system efficiency (GPPW = 0.44). This indicates that more efficient economies and those integrated into material markets tend to achieve better recycling outcomes.

Trade in raw materials reflects its central role in the CE system. It shows consistent moderate correlations with most variables.

Waste generation exhibits weaker, less consistent relationships, suggesting that additional structural or behavioural factors drive it. The moderate correlations among recycling, productivity, and trade highlight the systemic nature of circular-economy performance, in which multiple dimensions evolve together rather than independently.

A strong positive correlation is observed between patents and employment ($r = 0.81$). It suggests that technological development and labour scale are closely connected.

Innovation is associated with both increased material flows and improved recycling performance (raw materials ($r = 0.54$) and recycling rate ($r = 0.49$)). Employment shows a moderate correlation with trade in raw materials ($r = 0.40$), suggesting that larger economies are more active in raw-material trade. However, its relationship with the recycling rate ($r = 0.27$) and resource productivity ($r = 0.23$) is relatively weak, indicating that scale alone does not ensure efficient or sustainable outcomes.

The silhouette coefficient was used to determine the optimal number of clusters. This metric evaluates both cluster cohesion and separation. The results show that the highest silhouette value is obtained for 3 clusters (0.307). This indicates the best overall balance between internal similarity and external separation among all tested solutions (Table 3).

Table 3

Silhouette coefficient

Number of clusters	Coefficient
3	0.307
4	0.290
5	0.269
6	0.298
7	0.305
8	0.264
9	0.290
10	0.228
11	0.224

Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

Table 4 reports Fuzzy c-means (FCM) memberships for three clusters in 2023. The results indicate three distinguishable but partially overlapping groups. Cluster_2 contains the largest number of countries in 2023. Cluster_1 represents a group of relatively advanced economies and Cluster_0 includes countries with weaker circular-economy profiles. Each country is characterised by a membership vector of weights, summing to one, reflecting the degree of similarity between the country's indicator profile and each cluster centroid. The winner cluster indicates the maximum membership, but the magnitude of the winning membership provides essential information on classification certainty and structural hybridity.

Table 4

Fuzzy c-means clustering by country 2023

Country	Cluster_0	Cluster_1	Cluster_2	Winner
Belgium	0.226	0.280	0.493	Cluster_2
Czechia	0.287	0.098	0.615	Cluster_2
Denmark	0.214	0.121	0.665	Cluster_2
Estonia	0.445	0.099	0.455	Cluster_2
Ireland	0.315	0.307	0.378	Cluster_2
Latvia	0.254	0.110	0.636	Cluster_2
Lithuania	0.230	0.105	0.665	Cluster_2
Luxembourg	0.275	0.265	0.460	Cluster_2
Austria	0.228	0.359	0.412	Cluster_2
Slovenia	0.211	0.139	0.650	Cluster_2
Slovakia	0.235	0.105	0.660	Cluster_2
Finland	0.337	0.231	0.432	Cluster_2
Germany	0.228	0.513	0.258	Cluster_1
Spain	0.122	0.739	0.139	Cluster_1
France	0.225	0.532	0.244	Cluster_1
Italy	0.104	0.768	0.128	Cluster_1
Netherlands	0.248	0.458	0.294	Cluster_1
Sweden	0.316	0.355	0.330	Cluster_1
Bulgaria	0.650	0.118	0.231	Cluster_0
Greece	0.728	0.090	0.182	Cluster_0
Croatia	0.512	0.117	0.372	Cluster_0
Cyprus	0.667	0.109	0.224	Cluster_0
Hungary	0.486	0.126	0.388	Cluster_0
Malta	0.560	0.150	0.289	Cluster_0
Poland	0.454	0.240	0.307	Cluster_0
Portugal	0.527	0.131	0.342	Cluster_0
Romania	0.582	0.166	0.251	Cluster_0

Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

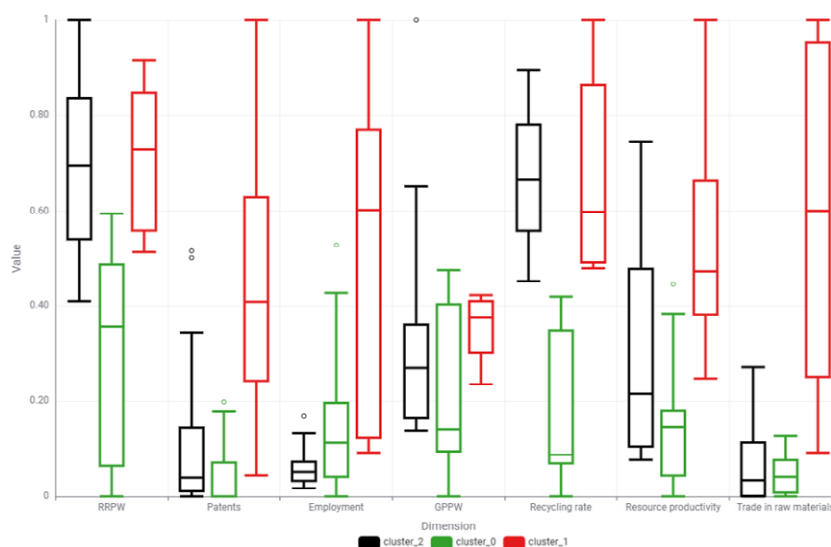
The results reveal a clear but not absolute grouping structure, with varying degrees of membership across countries.

Table 4 shows that the clustering structure across EU countries is clear, but not strictly discrete. Cluster_2 contains the largest group of countries and is associated with relatively high membership values for most assigned cases, indicating a comparatively coherent profile. Estonia and Ireland exhibit more balanced memberships across clusters, pointing to transitional characteristics. Cluster_1 includes a smaller number of countries, with especially strong membership values observed for Spain and Italy, while Sweden appears less distinctly assigned because its membership coefficients are distributed more evenly. Cluster_0 is also reasonably consistent, although Poland and Hungary display some overlap with other clusters. The results of Table 4 suggest that circular economy performance across EU countries is organised into distinguishable yet partially overlapping patterns, highlighting the value of fuzzy clustering for identifying both dominant affiliations and borderline cases.

Figure 2 presents the distribution of the selected indicators across the three clusters and highlights their structural differences.

Figure 2

Difference by cluster by factor



Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

The cluster-specific descriptive statistics demonstrate structural differences between the three groups, indicating distinct profiles of plastic waste management performance.

Cluster_0 is characterised by comparatively low median values across most indicators. Patent activity is minimal (median = 0.000), indicating almost no innovation capacity. Employment is also low (0.114), suggesting limited economic scale in the sector. Waste-related indicators show weak performance. The median recycling rate is very low (0.089), and resource productivity is also limited (0.146). Trade in raw materials is marginal (0.042). The quartile range is narrow, especially for patents and trade, confirming low variability but also uniformly weak performance. Maximum values remain relatively low compared to other clusters, indicating the absence of strong outliers. Cluster_0 should not be interpreted as a fully homogeneous group of lagging countries, but rather as a group tending toward weaker innovation, efficiency, and market integration outcomes.

Cluster_1 shows the highest median values across all indicators and appears to represent the relatively strongest performance profile. Patent activity (0.409) and employment (0.602) are higher than in other clusters, indicating strong innovation and economic scale. The median recycling rate is high (0.599), resource productivity is comparatively strong (0.473), and trade in raw materials is the highest (0.600), suggesting more developed market integration. Nevertheless, in light of the moderate silhouette coefficient, this cluster should be interpreted as representing a relatively advanced profile rather than a clearly isolated group of leaders, since some overlap with other clusters remains possible.

Cluster_2 displays a mixed profile. Innovation (patents = 0.040) and employment (0.052) are low, similar to Cluster_0. Trade is also low (0.035). Recycling performance is the highest among all clusters (median = 0.664). This indicates strong waste management outcomes despite weaker economic and innovation capacity. Resource productivity is moderate (0.215), higher than Cluster_0 but lower than Cluster_1. The quartile distribution shows that recycling rates remain consistently high (0.558–0.780 range), while other indicators remain low. This pattern may reflect a model in which stronger recycling outcomes are achieved without equally strong innovation or industrial scale. Still, because the clustering structure is only moderately separated, this profile should be seen as a dominant tendency rather than a fully distinct type.

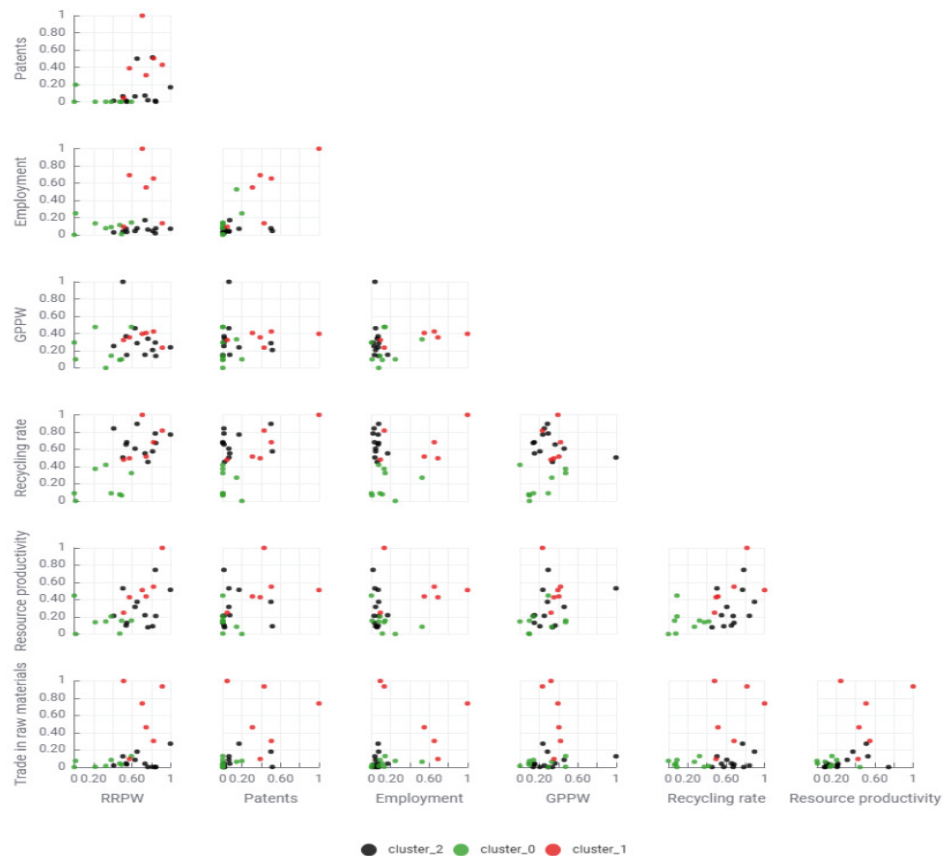
The results indicate that the three clusters capture broad differences in circular economy performance, but the moderate silhouette coefficient suggests that these differences are not absolute. Accordingly, the cluster solution is useful for identifying general performance patterns and relative country positions, while preserving the possibility of overlap and intermediate characteristics between groups.

Figure 3 visualises the pairwise projection by country by cluster. There is no complete separation between clusters because clustering was performed in a multidimensional space, while the plots show only two dimensions at a time. This

visualisation allows assessment of both cluster separation and overlap across multiple dimensions. Overlapping appears when variables do not capture the full cluster structure.

Figure 3

Deviation of the countries by cluster by variable



Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

Cluster_0 is also relatively visible. Points are concentrated near the lower-left region in most plots. Cluster_2 occupies a transitional space in the feature

space. It overlaps with Cluster_0 on economic variables and with Cluster_1 on recycling-related variables.

The fuzzy clustering results over time reveal clear transition patterns between clusters, reflecting different development trajectories in plastic waste management systems (Appendix A, Table A1).

The clustering structure is relatively stable but not fixed, as several countries gradually transitioned between profiles over time. Cluster_1 appears to be the most stable and compact group. Germany, France, Italy, and the Netherlands remained in Cluster_1 throughout the 2015–2022 period. Spain joined this group in 2016 and remained there thereafter. This indicates a highly persistent cluster core with very limited movement. Poland was the only temporary entrant, moving from Cluster_0 to Cluster_1 in 2021 and then shifting to Cluster_2 in 2022. Overall, this cluster represents a comparatively stable and clearly defined profile.

Cluster_0 shows a gradual reduction in size over time, as several countries moved out of the lowest-performing profile. In 2015, Cluster_0 contained the largest number of countries, including Bulgaria, Czechia, Estonia, Greece, Spain, Croatia, Cyprus, Latvia, Lithuania, Hungary, Malta, Poland, Portugal, Romania, and Slovakia. Over time, a number of these countries transitioned to Cluster_2. Lithuania moved from Cluster_0 to Cluster_2 in 2016 and remained there thereafter. Hungary shifted from Cluster_0 to Cluster_2 in 2018, although later classifications placed it again in Cluster_0. Latvia and Slovakia both moved from Cluster_0 to Cluster_2 in 2019 and remained there in subsequent years. Czechia transitioned from Cluster_0 to Cluster_2 in 2020 and stayed there thereafter. Poland followed a more complex path, remaining in Cluster_0 until 2020, moving to Cluster_1 in 2021, and then shifting to Cluster_2 in 2022. These transitions indicate improvements in recycling performance, even without strong increases in innovation or economic scale. They reflect policy-driven progress, such as better waste collection systems and recycling targets. Poland shows a more unstable trajectory, including temporary movement toward a higher-performing profile.

Cluster_2 appears to be the most dynamic and expansive cluster. It absorbed countries transitioning from Cluster_0 and became the dominant cluster in the later years of the sample. Belgium, Denmark, Ireland, Luxembourg, Austria, Slovenia, and Finland remained in Cluster_2 throughout the whole period. Sweden belonged to Cluster_1 in 2015, but moved to Cluster_2 in 2016 and stayed there thereafter. Lithuania joined Cluster_2 in 2016, Hungary in 2018, Latvia and Slovakia in 2019, Czechia in 2020, and Poland in 2022. This expansion suggests that Cluster_2 serves as a broad intermediate or alternative performance profile, capturing countries that improved relative to Cluster_0 but did not belong to the stable core of Cluster_1.

The transition pattern suggests three different levels of temporal stability. Cluster_1 has the strongest persistence and the clearest core membership. Cluster_0 gradually shrank as several countries moved out of it over time. Finally, Clus-

ter_2 served as the primary destination for most transitions and became the largest grouping in the later period. This means that the clusters should not be interpreted only as static cross-sectional categories, but also as reflecting movement in country profiles over time. Cluster_2 appears to represent an important transitional or mixed profile rather than a small, isolated group. Table 5 reports a multinomial logistic regression with Cluster_2 as the reference category (baseline).

Table 5

Multinomial logistic regression by clusters

Logit	Variable	Coeff.	Std. Err.	z-score	P> z
Cluster_0	Patents	-0.243	0.311	-0.784	0.433
	Resource productivity	-0.233	0.305	-0.766	0.444
	GPPW	-0.279	0.300	-0.931	0.352
	TRRM	-0.678	0.288	-2.353	0.019
	Recycling rate	0.587	0.293	2.007	0.045
	RRPW	-0.653	0.300	-2.173	0.030
	Employment	-0.766	0.290	-2.639	0.008
	Constant	0.866	0.309	2.803	0.005
Cluster_1	Patents	-0.330	0.308	-1.068	0.285
	Resource productivity	-0.262	0.305	-0.8596	0.390
	GPPW	-0.297	0.301	-0.987	0.324
	TRRM	-0.597	0.294	-2.035	0.042
	Recycling rate	-0.989	0.294	-3.362	0.001
	RRPW	-0.639	0.301	-2.120	0.034
	Employment	-0.365	0.295	-1.234	0.217
	Constant	1.722	0.342	5.040	0.000

Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

The positive, statistically significant coefficient for the recycling rate indicates that stronger recycling performance is associated with a higher likelihood of belonging to Cluster_2, while the negative, significant coefficients for employment, trade in recyclable raw materials, and plastic packaging recycling point to weaker economic scale and lower market integration. This pattern supports the interpretation of Cluster_2 as an efficiency-driven profile, characterised by comparatively strong waste-management outcomes without broader structural depth.

By contrast, the comparison between Cluster_1 and Cluster_2 suggests a different configuration. Significant negative coefficients for the recycling rate,

trade in recyclable raw materials, and plastic packaging recycling indicate that membership in Cluster_1 cannot be explained solely by these indicators. Instead, Cluster_1 appears to reflect a more integrated and system-level form of CE performance, in which no single indicator dominates. The lack of significance for patents, resource productivity, and GPPW further suggests that differences between clusters are driven less by isolated factor effects than by broader multidimensional configurations.

Variance Inflation Factors (VIFs) were calculated to assess multicollinearity among the explanatory variables (Table 6).

Table 6

Variance Inflation Factors (VIF) across all numeric variables

Factor	Variance Inflation Factors
Patents	4.56
Resource productivity	1.53
GPPW	1.33
TRRM	2.44
Recycling rate	2.40
RRPW	2.01
Employment	4.47

Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

All VIF values range from 1.33 to 4.56, indicating moderate but acceptable multicollinearity. None of the variables exceeds the chosen thresholds of 5. Multicollinearity does not impact the stability or interpretability of the regression estimates.

The model does not suffer from severe multicollinearity. The moderate VIF values for patents and employment suggest some shared structural effects, which should be considered when interpreting their individual contributions.

The findings suggest that countries' structural profiles should differentiate circular-economy policy in the EU. For Cluster_0 countries, priority should be given to basic capacity-building, including waste collection, sorting infrastructure, and regulatory compliance. For Cluster_2 countries, which have relatively good recycling performance but weaker innovation and employment capabilities, policies should focus on research development, better integration into secondary raw materials markets and skills development in the CE. For Cluster_1 countries, pol-

icy should focus on innovation, knowledge transfer, and the dissemination of best practices in the CE within the EU, as the transfer of successful development experience may support structural transformation in lower-performing systems (Freyer et al., 2021). More broadly, the results support the need for funding and monitoring frameworks that distinguish between capacity-building needs and outcome-based performance, rather than applying uniform policy expectations across all member states.

To summarise the policy implications of the cluster analysis, Table B1 (Appendix B), presents a schematic overview of the authors' proposals for strengthening the European circular economy framework. The scheme links each country profile with the main structural weaknesses identified in the study and the corresponding policy priorities.

Discussion

This study sharpens the interpretation of plastics-related recycling indicators by showing that they signal circular progress only when embedded in broader technological, socio-economic, and market capacities. This supports Moraga et al. (2019), Saidani et al. (2019), and De Pascale et al. (2021), who argue that circular economy indicators differ by scope, system level, and analytical function. The findings also align with systemic definitions of circularity (Geissdoerfer et al., 2017; Kirchherr et al., 2023).

The study complements Fura et al. (2020), Kamali Saraji and Torabi (2025), and Pakuła et al. (2025) by showing that EU circular economy differences are not only cross-country, but also structural and indicator sensitive.

Overall, the study shows that plastic recycling progress and circular economy maturity are related but not equivalent. Plastics-related indicators should therefore be interpreted within a broader capacity-based monitoring framework, rather than as isolated measures of national circular economy development, as also recommended by the OECD (2024).

Conclusions

The results indicate that CE performance in the EU during 2015–2023 is characterised by at least two partially independent dimensions: a capacity-oriented dimension encompassing innovation, trade in secondary materials, and employment, and an outcome-oriented dimension reflecting recycling performance. This distinction provides a useful analytical framework for understanding why countries may achieve similar recycling outcomes through different structural configurations.

The FCM results indicate that countries are not strictly separated into distinct groups but instead display overlapping characteristics and shared features.

The coexistence of clearly defined core members and countries with more balanced memberships suggests that performance levels evolve along a continuum of development. Some countries occupy intermediate positions, reflecting partial alignment with multiple cluster profiles.

These findings confirm that fuzzy clustering captures both heterogeneity and transitional dynamics that hard classification methods cannot fully describe.

The cluster comparison further demonstrates that CE performance is multidimensional, not only in level but also in structure. Cluster_1 shows balanced, relatively strong performance across all major dimensions and represents the most integrated circular-economy profile. Cluster_2 achieves comparatively strong recycling outcomes through an alternative pathway, combining high recycling performance with weaker innovation, employment, and trade integration. Cluster_0 remains behind on most indicators, highlighting the need for broader structural improvements. These differences provide a basis for more differentiated policy strategies across country groups.

The temporal dynamics confirm that the development of plastic waste management is evolutionary rather than abrupt. Countries typically move from low-performing systems to efficiency-driven models before reaching fully advanced circular-economy structures.

The dominance of transitions toward Cluster_2 indicates that recycling improvements are achievable without a full economic transformation, whereas reaching Cluster_1 requires broader systemic change, including innovation capacity and market integration.

The multinomial regression confirms that cluster differentiation is driven by distinct combinations of factors rather than isolated indicators. While improvements in recycling rates are sufficient to move countries from low- to intermediate-performance clusters, transitioning to advanced systems requires broader structural transformation, including the systemic integration of material flows and the development of institutional capacity.

The multicollinearity diagnostics indicate a well-specified model, where correlations among predictors are present but not excessive. The balance between independence and interrelatedness reflects the inherent complexity of plastic waste management systems, in which economic, technological, and environmental factors are inherently interconnected.

Overall, the empirical results confirm the three proposed hypotheses and show that, when assessed through plastics-related indicators, CE performance across EU countries is multidimensional, clustered, and not reducible to recycling performance alone.

This study has several limitations. First, the analysis relies on a limited set of macro-level indicators. Second, the clustering results are sensitive to indicator selection and normalisation choices. Third, patent values for 2022–2023 were estimated using a CAGR-based projection, which may introduce uncertainty into the innovation-capacity dimension. Future research should update the analysis when complete patent data become available. Finally, the regression analysis identifies statistical associations with cluster membership rather than causal relationships.

References

- Agresti, A. (2002). *Categorical data analysis*. Wiley-Interscience. <https://doi.org/10.1002/0471249688>
- Alonso-Fernández, P., & Regueiro-Ferreira, R. M. (2021). An approximation to the environmental impact of economic growth using the material flow analysis: Differences between production and consumption methods, applied to China, United Kingdom and USA (1990–2017). *Sustainability*, 13(10), Article 5489. <https://doi.org/10.3390/su13105489>
- Anwar, M. A., Suprihatin, Sasongko, N. A., Najib, M., & Pranoto, B. (2024). Challenges and prospects of multilayer plastic waste management in several countries: A systematic literature review. *Case Studies in Chemical and Environmental Engineering*, 10, Article 100911. <https://doi.org/10.1016/j.cscee.2024.100911>
- Avdiushchenko, A. (2021). Circular economy in Poland: Main achievements and future prospects. In A. Bisello, D. Vettorato, D. Ludlow, & C. Baranzelli (Eds.), *Smart and sustainable planning for cities and regions: Results of SSPCR 2019 – Open access contributions* (pp. 141–154). Springer. https://doi.org/10.1007/978-3-030-57764-3_10
- Avdiushchenko, A., & Zajac, P. (2019). Circular economy indicators as a supporting tool for European regional development policies. *Sustainability*, 11(11), Article 3025. <https://doi.org/10.3390/su11113025>
- van Beukering, P., Kuik, O., & Oosterhuis, F. (2014). The economics of recycling. In E. Worrell & M. A. Reuter (Eds.), *Handbook of recycling: State-of-the-art for practitioners, analysts, and scientists* (pp. 479–489). Elsevier. <https://doi.org/10.1016/C2011-0-07046-1>
- Bianchi, M., del Valle, I., & Tapia, C. (2021). Material productivity, socioeconomic drivers and economic structures: A panel study for European regions. *Ecological Economics*, 183, Article 106948. <https://doi.org/10.1016/j.ecolecon.2021.106948>

- Bocken, N., Strupeit, L., Whalen, K., & Nußholz, J. (2019). A review and evaluation of circular business model innovation tools. *Sustainability*, 11(8), Article 2210. <https://doi.org/10.3390/su11082210>
- Bruns, H., Borsello, A., Dupoux, M., Gaudillat, P., & Hamarat, Y. (2024). *Setting the scene for harmonised waste-sorting labels in the European Union – Insights from packaging waste data, survey findings and conceptual considerations* (JRC Science for Policy Report EUR 31960 EN). Publications Office of the European Union. <https://doi.org/10.2760/00013>
- Bublyk, M., Kowalska-Styczeń, A., Lytvyn, V., & Vysotska, V. (2021). The Ukrainian economy transformation into the circular based on fuzzy-logic cluster analysis. *Energies*, 14(18), Article 5951. <https://doi.org/10.3390/en14185951>
- Bullock, C. H., Thorball, N., Somlai, C., & Gallagher, J. (2022). *Packaging waste statistics, producer motivations and consumer behaviour* (EPA Research Report No. 426). Environmental Protection Agency. https://www.epa.ie/publications/research/circular-economy/Research_Report_426.pdf
- Burinskienė, A., Lingaitienė, O., & Byčenkaitė, G. (2025). Dynamics of trade of recycled raw materials and the connection with the circular economy. *Discover Sustainability*, 6, Article 680. <https://doi.org/10.1007/s43621-025-01502-4>
- Cader, J., Koneczna, R., & Marciniak, A. (2024). Indicators for a circular economy in a regional context: An approach based on Wielkopolska region, Poland. *Environmental Management*, 73, 293–310. <https://doi.org/10.1007/s00267-023-01887-w>
- Crass, D., Garcia Valero, F., Pitton, F., & Rammer, C. (2019). Protecting innovation through patents and trade secrets: Evidence for firms with a single innovation. *International Journal of the Economics of Business*, 26(1), 117–156. <https://doi.org/10.1080/13571516.2019.1553291>
- Crescenzi, R., Dyèvre, A., & Neffke, F. (2022). Innovation catalysts: How multinationals reshape the global geography of innovation. *Economic Geography*, 98(3), 199–227. <https://doi.org/10.1080/00130095.2022.2026766>
- De Pascale, A., Arbolino, R., Szopik-Depczyńska, K., Limosani, M., & Ioppolo, G. (2021). A systematic review for measuring circular economy: The 61 indicators. *Journal of Cleaner Production*, 281, Article 124942. <https://doi.org/10.1016/j.jclepro.2020.124942>
- Dominish, E., Retamal, M., Sharpe, S., Lane, R., Rhamdhani, M. A., Corder, G., Giurco, D., & Florin, N. (2018). "Slowing" and "narrowing" the flow of metals for consumer goods: Evaluating opportunities and barriers. *Sustainability*, 10(4), Article 1096. <https://doi.org/10.3390/su10041096>

- Dong, M. W. Y. (2025). Projecting the development of accelerator technologies using growth models and social cost benefit frameworks. *Journal of Digital Business and International Marketing*, 1(2), 109–118. <https://doi.org/10.64026/JDBIM/2025012>
- Džajić Uršič, E., Pandiloska Jurak, A., & Topić Božič, J. (2025). From policy to practice: EU circular economy legislation and Slovenia's implementation challenges – A systematic review. *Sustainability*, 17(21), Article 9408. <https://doi.org/10.3390/su17219408>
- Ellen MacArthur Foundation. (2025). What is the meaning of a circular economy and what are the main principles? <https://www.ellenmacarthurfoundation.org/topics/circular-economy-introduction/overview>
- European Commission. (2018a). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions on a monitoring framework for the circular economy* (COM(2018/29 final). Publications Office of the European Union. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52018DC0029>
- European Commission. (2018b). *Commission staff working document: Measuring progress towards the circular economy in the European Union – Key indicators for a monitoring framework* (SWD(2018) 17 final). Publications Office of the European Union. <https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52018SC0017>
- European Commission. (2018c). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: A European strategy for plastics in a circular economy* (COM(2018) 28 final). Publications Office of the European Union. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52018DC0028>
- European Commission. (2021). *Commission staff working document: Impact assessment accompanying the document Proposal for a regulation of the European Parliament and of the Council on shipments of waste and amending Regulations (EU) No 1257/2013 and (EU) No 2020/1056* (SWD(2021) 331 final). Publications Office of the European Union. <https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX%3A52021SC0331>
- European Environment Agency. (2023). *Tracking waste prevention progress: A narrative-based waste prevention monitoring framework at the EU level*. Publications Office of the European Union. <https://data.europa.eu/doi/10.2800/612143>
- Eurostat. (2025a). *Patents related to recycling and secondary raw materials* [Data set]. Retrieved October 15, 2025, from https://doi.org/10.2908/CEI_CIE020

- Eurostat. (2025b). *Resource productivity* [Data set]. Retrieved October 15, 2025, from https://doi.org/10.2908/ENV_AC_RP
- Eurostat. (2025c). *Generation of plastic packaging waste per capita* [Data set]. Retrieved October 15, 2025, from https://doi.org/10.2908/CEI_PC050
- Eurostat. (2025d). *Trade in recyclable raw materials* [Data set]. Retrieved October 15, 2025, from https://doi.org/10.2908/CEI_SRM020
- Eurostat. (2025e). *Persons employed in circular economy sectors* [Data set]. Retrieved October 15, 2025, from https://doi.org/10.2908/CEI_CIE011
- Eurostat. (2025f). *Recycling rate of packaging waste by type of packaging* [Data set]. Retrieved October 15, 2025, from https://doi.org/10.2908/CEI_WM020
- Eurostat. (2025g). *Recycling rate of municipal waste* [Data set]. Retrieved October 15, 2025, from https://doi.org/10.2908/CEI_WM011
- Freyer, E., Lishchynskyy, I., & Lyzun, M. (2021). Development of renewable energy: The experience of East Germany for Ukraine. *Journal of European Economy*, 20(3), 442–460. <https://doi.org/10.35774/jee2021.03.440>
- Fura, B., Stec, M., & Miś, T. (2020). Statistical evaluation of the level of development of circular economy in European Union member countries. *Energies*, 13(23), Article 6401. <https://doi.org/10.3390/en13236401>
- Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The circular economy – A new sustainability paradigm? *Journal of Cleaner Production*, 143, 757–768. <https://doi.org/10.1016/j.jclepro.2016.12.048>
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. Springer. <https://doi.org/10.1007/978-1-4614-7138-7>
- Kamali Saraji, M., & Torabi, M. (2025). Progress toward a circular economy: A comparative analysis of EU member states. *Sustainability*, 17(18), Article 8448. <https://doi.org/10.3390/su17188448>
- Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling*, 127, 221–232. <https://doi.org/10.1016/j.resconrec.2017.09.005>
- Kirchherr, J., Yang, N.-H. N., Schulze-Spüntrup, F., Heerink, M. J., & Hartley, K. (2023). Conceptualizing the circular economy (revisited): An analysis of 221 definitions. *Resources, Conservation & Recycling*, 194, Article 107001. <https://doi.org/10.1016/j.resconrec.2023.107001>
- Krausmann, F., Lauk, C., Haas, W., & Wiedenhofer, D. (2018). From resource extraction to outflows of wastes and emissions: The socioeconomic metabolism of the global economy, 1900–2015. *Global Environmental Change*, 52, 131–140. <https://doi.org/10.1016/j.gloenvcha.2018.07.003>

- Liang, J., Bi, G., & Zhan, C. (2020). Multinomial and ordinal Logistic regression analyses with multi-categorical variables using R. *Annals of Translational Medicine*, 8(16), Article 982. <https://doi.org/10.21037/atm-2020-57>
- Lingaitiene, O., & Burinskiene, A. (2024). Development of trade in recyclable raw materials: Transition to a circular economy. *Economies*, 12(2), Article 48. <https://doi.org/10.3390/economies12020048>
- Lishchynskyy, I., Krysovaty, A., Desyatnyuk, O., Bogacki, S., & Lyzun, M. (2025). Quantitative measurement of glocalization to assess endogenous and exogenous parameters of regional sustainability. *Sustainability*, 17(17), Article 7584. <https://doi.org/10.3390/su17177584>
- Lotti, F., & Nobile, C. (2025). *The geography of innovation: Patent insights into Europe's green and digital transitions* (Occasional Paper No. 945). Banca d'Italia. <https://doi.org/10.32057/0.QEF.2025.945>
- Matthews, C., Moran, F., & Jaiswal, A. K. (2021). A review on European Union's strategy for plastics in a circular economy and its impact on food safety. *Journal of Cleaner Production*, 283, Article 125263. <https://doi.org/10.1016/j.jclepro.2020.125263>
- McCarthy, A., Dellink, R., & Bibas, R. (2018). *The macroeconomics of the circular economy transition: A critical review of modelling approaches* (OECD Environment Working Papers No. 130). OECD Publishing. <https://doi.org/10.1787/af983f9a-en>
- McMillin, K. W. (2025). Processed meats packaging technologies and recent innovations. In *Reference module in food science*. Elsevier. <https://doi.org/10.1016/B978-0-443-34158-8.00025-6>
- Milanović, T., Savić, G., Martić, M., Milanović, M., & Petrović, N. (2022). Development of the waste management composite index using DEA method as circular economy indicator: The case of European Union countries. *Polish Journal of Environmental Studies*, 31(1), 771–784. <https://doi.org/10.15244/pjoes/139896>
- Moraga, G., Huysveld, S., Mathieux, F., Blengini, G. A., Alaerts, L., Van Acker, K., de Meester, S., & Dewulf, J. (2019). Circular economy indicators: What do they measure? *Resources, Conservation and Recycling*, 146, 452–461. <https://doi.org/10.1016/j.resconrec.2019.03.045>
- Muñoz H., M. E., Novak, M., Gil, S., Dufourmont, J., Goodwin Brown, E., Confiado, A., & Nelemans, M. (2022). Tracking a circular economy transition through jobs: Method development and application in two cities. *Frontiers in Sustainable Cities*, 3, Article 787076. <https://doi.org/10.3389/frsc.2021.787076>

- Nowaczek, A., Dziobek, E., & Kulczycka, J. (2023). Benefits and limitations of indicators for monitoring the transformation towards a circular economy in Poland. *Resources*, 12(2), Article 24. <https://doi.org/10.3390/resources12020024>
- OECD. (2024, June 26). *Monitoring progress towards a resource-efficient and circular economy*. OECD Publishing. <https://doi.org/10.1787/3b644b83-en>
- PACE. (2021, April). *Circular indicators for governments: Accelerating action in the circular economy*. https://pacecircular.org/sites/default/files/2021-04/CircularIndicatorsForGovernments_FINAL.pdf
- Pakuła, N., Łapniewska, Z., & Dutra, C. J. C. (2025). Comparative measurements of circular economy performance among European countries: Reviewing approaches and limitations. *Journal of Environmental Management*, 375(5), Article 124414. <https://doi.org/10.1016/j.jenvman.2025.124414>
- Perera, K. Y., Orhotohwo, O. L., Schutz, A., Jaiswal, A. K., & Jaiswal, S. (2026). Chapter 10 –Smart packaging for sustainability and waste reduction. In S. Jaiswal, K. Y. Perera, & A. K. Jaiswal (Eds.), *Smart and intelligent food packaging* (pp. 263–306). Academic Press. <https://doi.org/10.1016/B978-0-443-24724-8.00014-4>
- Picuno, C., Van Eygen, E., Brouwer, M. T., Kuchta, K., & Thoden van Velzen, E. U. (2021). Factors shaping the recycling systems for plastic packaging waste – A comparison between Austria, Germany and the Netherlands. *Sustainability*, 13(12), Article 6772. <https://doi.org/10.3390/su13126772>
- Reeb, D. M., & Zhao, W. (2020). Patents do not measure innovation success. *Critical Finance Review*, 9(1–2), 157–199. <https://doi.org/10.1561/104.00000087>
- Reike, D., Vermeulen, W. J. V., & Witjes, S. (2018). The circular economy: New or refurbished as CE 3.0? Exploring controversies in the conceptualization of the circular economy through a focus on history and resource value retention options. *Resources, Conservation & Recycling*, 135, 246–264. <https://doi.org/10.1016/j.resconrec.2017.08.027>
- Saidani, M., Yannou, B., Leroy, Y., Cluzel, F., & Kendall, A. (2019). A taxonomy of circular economy indicators. *Journal of Cleaner Production*, 207, 542–559. <https://doi.org/10.1016/j.jclepro.2018.10.014>
- Schandl, H., Marcos-Martinez, R., West, J., Miatto, A., Lutter, S., Lieber, M., Giljum, S., Lenzen, M., Li, M., Wang, H., Tanikawa, H., Krausmann, F., Eisenmenger, N., & Fischer-Kowalski, M. (2024). Global material flows and resource productivity: The 2024 update. *Journal of Industrial Ecology*, 28(6), 2012–2031. <https://doi.org/10.1111/jiec.13593>

-
- Schröder, P. (2020). *Promoting a just transition to an inclusive circular economy*. Chatham House. <https://www.chathamhouse.org/sites/default/files/2020-04-01-inclusive-circular-economy-schroder.pdf>
- Taalbi, J. (2025). Innovation with and without patents – An information-theoretic approach. *Scientometrics*, 130, 4879–4897. <https://doi.org/10.1007/s11192-025-05406-y>
- Torkelis, A., Dvarionienė, J., & Denafas, G. (2024). The factors influencing the recycling of plastic and composite packaging waste. *Sustainability*, 16(21), Article 9515. <https://doi.org/10.3390/su16219515>
- Yamaguchi, S. (2021). *International trade and circular economy – Policy alignment* (OECD Trade and Environment Working Papers No. 2021/02). OECD Publishing. <https://doi.org/10.1787/ae4a2176-en>

Appendix A

Table A1

Country clusters by year

Year	Countries	Cluster
2015	Bulgaria, Czechia, Estonia, Greece, Spain, Croatia, Cyprus, Latvia, Lithuania, Hungary, Malta, Poland, Portugal, Romania, Slovakia	Cluster_0
	Germany, France, Italy, Netherlands, Sweden	Cluster_1
	Belgium, Denmark, Ireland, Luxembourg, Austria, Slovenia, Finland	Cluster_2
2016	Bulgaria, Czechia, Estonia, Greece, Croatia, Cyprus, Latvia, Hungary, Malta, Poland, Portugal, Romania, Slovakia	Cluster_0
	Germany, Spain, France, Italy, Netherlands	Cluster_1
	Belgium, Denmark, Ireland, Lithuania, Luxembourg, Austria, Slovenia, Finland, Sweden	Cluster_2
2017	Bulgaria, Czechia, Estonia, Greece, Croatia, Cyprus, Latvia, Hungary, Malta, Poland, Portugal, Romania, Slovakia	Cluster_0
	Germany, Spain, France, Italy, Netherlands	Cluster_1
	Belgium, Denmark, Ireland, Lithuania, Luxembourg, Austria, Slovenia, Finland, Sweden	Cluster_2
2018	Bulgaria, Czechia, Estonia, Greece, Croatia, Cyprus, Latvia, Malta, Poland, Portugal, Romania, Slovakia	Cluster_0
	Germany, Spain, France, Italy, Netherlands	Cluster_1
	Belgium, Denmark, Ireland, Lithuania, Luxembourg, Hungary, Austria, Slovenia, Finland, Sweden	Cluster_2
2019	Bulgaria, Czechia, Estonia, Greece, Croatia, Cyprus, Hungary, Malta, Poland, Portugal, Romania	Cluster_0
	Germany, Spain, France, Italy, Netherlands	Cluster_1
	Belgium, Denmark, Ireland, Latvia, Lithuania, Luxembourg, Austria, Slovenia, Slovakia, Finland, Sweden	Cluster_2
2020	Bulgaria, Estonia, Greece, Croatia, Cyprus, Hungary, Malta, Poland, Portugal, Romania	Cluster_0
	Germany, Spain, France, Italy, Netherlands	Cluster_1
	Belgium, Czechia, Denmark, Ireland, Latvia, Lithuania, Luxembourg, Austria, Slovenia, Slovakia, Finland, Sweden	Cluster_2
2021	Bulgaria, Estonia, Greece, Croatia, Cyprus, Hungary, Malta, Portugal, Romania	Cluster_0
	Germany, Spain, France, Italy, Netherlands, Poland	Cluster_1
	Belgium, Czechia, Denmark, Ireland, Latvia, Lithuania, Luxembourg, Austria, Slovenia, Slovakia, Finland, Sweden	Cluster_2
2022	Bulgaria, Estonia, Greece, Croatia, Cyprus, Hungary, Malta, Portugal, Romania	Cluster_0
	Germany, Spain, France, Italy, Netherlands	Cluster_1
	Belgium, Czechia, Denmark, Ireland, Latvia, Lithuania, Luxembourg, Austria, Poland, Slovenia, Slovakia, Finland, Sweden	Cluster_2

Source: calculated by the authors based on data from Eurostat (2025a, 2025b, 2025c, 2025d, 2025e, 2025f, 2025g).

Appendix B

Table B1

Policy implications of the clustering results for strengthening the EU circular economy framework

Cluster profile	Main weakness	Policy priority
Cluster_0: weaker circular-economy profile	Low innovation, recycling, resource productivity, and market integration	Basic waste-management infrastructure, sorting systems, regulatory compliance, targeted cohesion funding
Cluster_1: relatively advanced integrated profile	Need to maintain systemic leadership and transfer experience	Innovation diffusion, best-practice transfer, cross-border cooperation, advanced circular technologies
Cluster_2: mixed/efficiency-driven profile	Strong recycling outcomes but weaker innovation, employment, and market integration	R&D support, circular skills, secondary raw material markets, industrial upgrading

Source: own research.

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