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CLOSING THE LOOP: INDUSRY 4.0 AND OPEN INNOVATION FOR CIRCULAR ECONOMY TRANSITION

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Abstract. In response to the need for digital and circular transformations in Europe, this study examines how the integration of Industry 4.0 (I4.0) and open innovation (OI) is facilitating the shift towards a circular economy (CE) by mitigating environmental impact and enhancing regional competitiveness. Using panel data for 27 European Union member states, hierarchical cluster analysis reveals four distinct transition paths among EU countries: 1: balanced transition (Bulgaria, Belgium, Czechia, Denmark, Croatia, Austria and Slovakia belong to this cluster), 2: open innovation focused (Estonia, Ireland, Greece, Cyprus, Luxembourg, Hungary, Malta), 3: circular economy and Industry 4.0 leaders (belong Germany, France, Latvia, Lithuania, Poland, Romania, Sweden), 4: growing circular potential (Spain, Italy, Netherlands, Portugal, Slovenia, Finland). These groupings diverge from traditional economic or R&D league tables, suggesting that the combination of different long-term policies shapes digital-circular synergies. The findings highlight the need to modify digital manufacturing roadmaps to address specific circular bottlenecks (e.g., open innovation in Cluster 2, growing circular potential in Cluster 4). For policymakers, the findings emphasize that coupling Industry 4.0 incentives with OI policies can facilitate faster, more inclusive circular transitions across the EU.

Keywords: Industry 4.0, innovation, open innovation, circular economy, European Union, hierarchical clustering.

JEL Classification: O14, O33, L6, O1, O2, O3, O4.

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1. Introduction

Recent research has highlighted the importance of exploring whether Industry 4.0 technologies and open innovation practices can facilitate the transition of firms and nations to a circular economy. Evidence shows that sharing knowledge across organizational borders and adopting new digital tools can improve the circular economy (Calabrese et al., 2024; Jesus et al., 2025; Kim & Park, 2024). At the regional level, Pakuła et al. (2025) observe that European countries are weaving the principles of circular economy into industry, public institutions, and society. While Skare et al., (2024a) examine how advances in infrastructure and production support sustainable outcomes in the EU. In a recent research, Soto (2025) points out that nations need to revise their CE frameworks and try to emphasize open innovation. Together, these studies emphasized that there is a need to examine Industry 4.0 more closely and open innovation work together to advance circularity.

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However, the scholarly discourse still leaves unresolved the macro-level adoption of I4.0 technologies and open innovation for circularity (Li, 2025; Usas et al., 2025; Arion et al., 2023). These emerging technologies and open innovation facilitate traceability and the attainment of a circular economy by enhancing transparency, accountability, and material recycling (Jesus & Jugend, 2023; Strazzullo, 2024; Kamble & Gunasekaran, 2023; Leskovec et al., 2025). Policymakers and state institutions stressed upon that Europe faces challenges related to biodiversity degradation, resource consumption, the consequences of climate change, and environmental risks.

The recent studies unlocked long-term economic benefits on Industry 4.0 technology and open innovation on circular economy (Behl et al., 2023; de Sousa Jabbour et al., 2022; de Silva & Sehnem, 2025; Yin et al., 2025), societal benefits for sustainable future (Sasso et al., 2025; Wamane, 2025). The present academic discourse centers on internal-external open innovation and digital technology on the circularity for enhancing business processes, customization, servitization and manufacturing processes (Neri et al., 2023; Dorrego-Viera et al., 2025; Primario et al., 2024), adopting sustainable methods for lessen environmental impacts (Strazzullo et al., 2025), transformation towards CE (Yang et al., 2023). These studies help to understand link between Industry 4.0 and CE through open innovation, given the importance of the collaborative model. Most research on the CE concentrates on the firm level, analyzing how Industry 4.0 technologies and open-innovation practices help individual companies reduce waste and recirculate resources (Piedra-Muñoz et al., 2025; Rossi & Srai, 2025; Yin et al., 2025; Dorrego-Viera et al., 2025; Jesus et al., 2025; Sgambaro et al., 2025). Prior studies discussed Industry 4.0 with sustainability from companies' perspectives at the micro-level (Tiwari et al. 2025; Perçin, et al., 2025; Datta et al., 2025). In similar fashion, some of the scholars highlighted the advantages of Industry 4.0 and open innovation and industrial ecosystems at the meso-level by analyzing industry-level transitions towards circularity (Harala et al., 2023) and eco-innovation in the EU countries (Cattani et al., 2025; Kasztelan et al., 2025; Triguero et al., 2022).

What is still missing is a macro-level view. Existing country-level work rarely examines how the combined uptake of I4.0 technologies and open innovation affects national CE outcomes (Lopes et al., 2021; Soto, 2025; Tokar et al., 2025; Vokoun & Dvouletý, 2025). This gap limits our understanding of how well nations can turn their digital capabilities and open innovation into less waste and higher resource efficiency (Usas et al., 2025). Therefore, recent calls urge researchers to link technology adoption and open innovation to CE indicators in cross-country analyses (D'Adamo et al., 2024: Jiao et al., 2025; Smol et al., 2025). Closing this gap will clarify the extent to which I4.0 and open innovation together drive the circular transition across Europe. Recent, research on I4.0 is under-scoring the macro level, particularly regarding innovative perspectives from European nations (Soto, 2025). Notably, digital tools combining by open innovation strategy considered as a potentially fruitful strategy for changing economic paradigm from linear to circular (Jesus & Jugend, 2023; Neligan et al., 2023). Notably, recent studies encouraged to address major challenges by investing Industry 4.0 and open innovation (Barrett & Dooley, 2025; Wegener et al., 2025; Aiello et al., 2025). By doing so, the need to transition to a sustainable circular economy is emphasized, as well as importance of open innovation and digital technologies. In line with these challenges, this research addresses the following research questions:

RQ1. *How does Industry 4.0 influence on circular economy in EU economies?*

RQ2. *What is the role of open innovation on circular economy in EU economies?*

By answering these questions, this study makes two contributions to research and policy on the circular economy. First, we step beyond firm-level (micro-level) studies and look at the country level (macro level). Using data for all 27 EU members (2013–2023), we build two new indexes—one that tracks Industry 4.0 readiness and another that tracks circular economy. These indexes enable us to examine how digital technology and circular outcomes evolve together over time. Second, we examined open innovation to get better understanding on collaboration technological innovation among diverse countries by using data from OECD database. Prior studies stressed open innovation is driver for circularity if countries adopt their policies on timely manner for a sustainable future (Kim & Park, 2024; Vokoun & Dvouletý, 2025). This analysis allows us to provide comprehensive reflection on adoption of Industry 4.0 and open innovation among EU countries for their transition towards CE. The four-cluster typology was developed to provide with a clear benchmarking tool and give policymakers evaluation for accelerating Europe's circular transition.

The remainder of this paper is organized as follows. The introduction shows needs for research and its main research questions. The literature review discussed relationship between Industry 4.0 and circular economy and open innovation with circular economy. The methodology describes source of data and process to analyze the data. Then, presents the empirical results; and provides an in-depth analysis of those findings. The concluding section outlines the study's limitations, suggests directions for future research, and discusses its theoretical contributions and managerial implications.

2. Literature review

2.1. Industry 4.0 enhance circular economy

There has been a rapid expansion in research linking Industry I4.0 to the circular economy (Piyathanavong et al., 2024; Soto, 2025). Most authors agree that digital tools in industry help to keep materials in use, reduce waste and lower carbon emissions (Kurniawan et al., 2023; Kim & Park, 2024). Three technological streams—artificial intelligence (AI), information and communication technology (ICT) connectivity, and nanotechnology—are central to this link (Balsalobre-Lorente et al., 2023; Sanchez-Garcia et al., 2024,). AI and machine learning applications transform real-time data into predictive maintenance schedules, demand forecasts and quality controls that minimize waste and extend product life (Yang et al., 2023). ICT infrastructures, such as cloud platforms, the Internet of Things and cyber-physical systems, create a digital backbone for tracking components, managing reverse logistics and enabling product-as-a-service models that keep assets in circulation for longer (Li et al., 2025). At the material level, nanotechnology—often combined with additive manufacturing—enables lighter, more durable and more recyclable designs, thereby lowering the demand for raw materials and supporting high-quality recycling loops (Spaltini et al., 2021). Together, these AI-driven analytics, ICT-enabled connectivity and nanotech-based material innovations form the core of Industry 4.0 contribution to closing resource cycles and reducing the environmental

footprint of production (Awan et al., 2022). We discuss the impact of these technologies in more detail further on.

The role of AI in CE. As a core pillar of I4.0, AI accelerates complex decision-making processes and enhances digital capabilities within both the public and private sectors, establishing itself as a pivotal catalyst for circularity (Roberts et al., 2024). Studies show that AI can support every stage of the CE loop, from product design and smarter operations to waste sorting (Ellen MacArthur Foundation, 2019; Lanzalonga et al., 2024). Recognizing this potential, the EU's AI strategy promotes the development of "trustworthy" systems that enhance competitiveness while advancing circular economy goals (European Commission, 2024a, 2024b). In brief, AI provides public and private institutions with the intelligence required to design better products, implement cleaner processes.

ICT's role in CE. ICT technologies such as blockchain, 5G networks and the Internet of Things create a mixed picture for circularity, producing 1.5–3.2% of total emissions (UN Trade and Development [UNCTAD], 2024). However, shared ICT standards can make these systems interoperable, widen market access, and offer consumers a broader choice of products, thereby laying the groundwork for resource-efficient solutions (European Commission, 2025a). When integrated into smart grids, reverse logistics platforms or product-sharing apps, ICT tools can streamline material flows and reduce indirect greenhouse gas emissions, thereby supporting transition to CE.

Nanotechnology's role in CE. Nanomaterials can make products lighter and stronger while also making them easier to recycle, thereby reducing both resource use and waste. They also enable scarce elements to be substituted or recovered, thereby helping to close material loops and reduce environmental pressure (Hansen et al., 2022). A primary objective of nanotechnology is to make materials stronger, more useful, and more recyclable (Dixit et al., 2023; Manikandan et al., 2023). Nanotechnology became crucial for improving resource efficiency while reducing waste.

Industry 4.0 relies on intelligent automation, advance materials and connectivity, so its development is closely linked to the number of patents for AI, ICT and nanotechnology, as well as the number of researchers who transform these innovations into smart manufacturing solutions. Accordingly, counts of such patents and the number of researchers can serve as practical predictors of Industry 4.0 development.

Drawing from the insights of the literature review, we propose the following hypotheses:

H1: *Artificial Intelligence patents exert a positive and significant impact on the advancement of the circular economy.*

H2: *ICT patents exert a positive and significant impact on the advancement of the circular economy.*

H3: *Nanotechnology patents exert a positive and statistically significant impact on the advancement of the circular economy.*

H4: *The number of researchers per million inhabitants has a positive impact on the advancement of the circular economy.*

2.2. Open innovation promotes circular economy

Open innovation is described as a dispersed kind of innovation on deliberately administered information transfers across organisational limits (Chesbrough & Bogers, 2014). Collaborative efforts between enterprises, academic institutions, and research labs form "knowledge and innovation communities," which in turn create novel services and even new businesses (European Commission, 2025a). The changing production processes from linear to circular necessitates collaboration across different sectors within networks (Köhler et al., 2022). Cross-sectorial collaboration and knowledge sharing an important for countries to bring novelty into their public and private sectors. There is little known about the open innovation and circular economy (Tokar et al., 2025; Vokoun & Dvouletý, 2025; Jesus & Jugend, 2023). Previous study revealed shift from traditional organisational learning to "learning by porting" represented a technological advancement for the open innovation strategy's cumulative component (Kodama, 2018). Notably, open innovation emphasizes issues that can enhance societal welfare and modernize industries and markets. They are initiated in regions where it is evident that the integration of EU, national, and regional research and development efforts can provide successful outcomes (European Commission, 2025a). These studies show open innovation is underexplored and indicating the need for further analysis at macro-level in EU countries. As shown above, although the literature linking open innovation and the circular economy is limited, policies involving diverse actors can undoubtedly enhance circular economy practices. Accordingly, based on the above, we propose the following hypothesis:

H5: *Open innovation exhibits a positive and statistically significant impact on the advancement of the circular economy.*

3. Research methods

To examine the impact of Industry 4.0 and open innovation on national progress towards a circular economy, we constructed a panel covering all 27 EU member states. Industry 4.0 is measured by a composite index of AI, ICT, and nanotechnology patents, as well as the number of researchers per thousand employees. Circular economy is measured by an index combining the circular material-use rate, e-waste generation, production-phase greenhouse-gas emissions, and overall competitiveness. Open innovation is measured by the percentage of international co-inventions.

As the dependent variable (the circular economy index) is likely to be affected by its own previous values, and as the main regressors may be endogenous, we estimate a dynamic panel model using the system GMM estimator proposed by Arellano and Bond (1991) and refined by Blundell et al. (2001). System-GMM uses internal instruments derived from lagged levels and differences, making it more reliable than ordinary least squares or fixed-effects estimators, which can be biased and inconsistent in this setting (Baltagi, 2008). We also applied Method of moment quantile regression (MMQR) which allowed us to overcome the endogeneity risk. Following using Principal component analysis (PCA), to enhance our outcomes, the indicators were diminished and amalgamated utilizing the PCA statistical procedure as suggested by Booysen (2002). Similarly, it accepts a dataset comprising numerous variables

as input and generates a reduced dataset in a lower-dimensional subspace, containing fewer variables. It is frequently employed in exploratory data analysis for constructing predictive models, as well as in data pretreatment for dimensionality reduction (IBM, 2023). Finally, we used hierarchical cluster analysis (HCA) for grouping countries as suggested by previous studies (Claudio-Quiroga & Poza, 2024; Zomer et al., 2024).

3.1. Data description

This research used the data of 27 nations of Europe for the period [2013–2023]. The data were obtained from Eurostat database (Eurostat, 2025), OECD database (Organization for Economic Cooperation and Development [OECD], n.d.) and World bank database (World Bank, n.d.). The countries selected for this estimation are from *Belgium*; *Bulgaria*; *Czechia*; *Denmark*; *Germany*; *Estonia*; *Ireland*; *Greece*; *Spain*; *France*; *Croatia*; *Italy*; *Cyprus*; *Latvia*; *Lithuania*; *Luxembourg*; *Hungary*; *Malta*; *Netherlands*; *Austria*; *Poland*; *Portugal*; *Romania*; *Slovenia*; *Slovakia*; *Finland and Sweden*.

The variables of interest are decomposed into three analytical dimensions: CE, OI, and I4.0. The *first dimension* relates to CE and includes four variables that reflect the four core goals of a circular economy—recirculation, waste prevention, climate protection, and economic resilience. We track EU countries progress with four macro indicators (1) the Circular Material Use rate (CMR), shows the proportion of secondary raw materials in total domestic material consumption, indicating how far an economy has moved from linear extraction to closed-loop use (Eurostat, 2024; Eurostat n.d.). (2) Waste from Electrical and Electronic Equipment (WEEE) is the flagship waste-prevention metric because electrical and electronic equipment is the fastest-growing solid waste stream, with well-defined collection targets under the WEEE Directive. (European Parliament, 2024). (3) Greenhouse Gas emissions from production activities (GHG) quantify the climate impact of manufacturing activity and align with EU net-zero targets (United Nations [UN], 2022). (4) Competitiveness measured by private investment and gross value added in circular economy sectors (denoted as COMP), ensures that the analysis is aligned with the EU mandate that circularity should enhance, rather than hinder, economic vitality (European Commission, 2025b).

The *second-dimension* presents OI, measured by the percentage of co-inventions in each country. Co-inventions illustrate that patent statistics and indicators are effective for monitoring innovation in environmentally-related technology. They enable the evaluation of nations' innovation efficacy and the formulation of governmental environmental and innovation strategies. This dataset provides information on the proportions of co-inventions and the rates of inventors' partnerships across the OECD region and beyond, specifically in environmentally-related technologies, based on the inventors' countries of residency (OECD, 2025a).

The *third dimension*, related to I4.0, includes four key variables: the number of Artificial Intelligence patents (AI), the number of Information and Communication Technology patents (ICT), the number of Nanotechnology patents (NANO), and the number of researchers per million persons (RES). We measured I4.0 by using these four variables: (1) AI patents are at the heart of I4.0 strategy, AI patents maximise the vast amount of data generated on the manufacturing floor, within business units, and from partners and third parties. Artificial

intelligence can automate and visualize commercial processes (OECD, 2025b). (2) ICT patents evaluate product "servitization," indicating the significant interdependence between products and services in contemporary society. In the current setting, the services linked to products are seen as the most significant component of their overall worth (Inaba & Squicciarini, 2017). (3) Nanotechnology patents encompass entities with a minimum of one functional element with a geometrical size below 100 nanometers in one or more dimensions, capable of producing physical, chemical, or biological phenomena inherent to that scale. It encompasses apparatus and techniques for regulated analysis, manipulation, processing, manufacture, or measurement with precision under 100 nanometers (Friedrichs & van Beuzekom, 2018). (4) The number of researchers per million persons (RES) represents the intellectual capacity and correlates with the quantity of patents and scientific publications, so indicating the significance of intellectual capital in advancing nations (OECD, 2015). Countries with a greater number of researchers are more inclined to invest in sustainable development and renewable energy (OECD, 2025c). The description of these variables is explicitly mentioned in Tables 1 and 2.

Table 1. Data description

Variable	Definition	Criterion	Strategic purpose	Source
CMR	Circular material use rate	Circular Economy	Promotes efficient resource use and waste reduction	Eurostat database
OI	Open Innovation	Open Innovation	Encourages cross-border collaboration and knowledge diffusion	OECD statistics
AI	Artificial Intelligence patents	Industry 4.0	Reflects technological advancement and innovation capacity	OECD statistics
ICT	Information and Communication Technologies patents	Industry 4.0	Indicates digital transformation and smart infrastructure development	OECD statistics
NANO	Nano patents	Industry 4.0	Supports high-tech innovation and advanced material development	OECD statistics
RES	Number of researchers per million persons	Industry 4.0	Reflects investment in human capital and R&D capabilities	World Bank Database
GDP	Real Gross Domestic Product	Control Variable	Measures overall economic performance and growth	Eurostat database
WEEE	E-waste	Circular Economy	Indicates electronic consumption patterns and recycling needs	Eurostat database
RPR	Resource Productivity	Control Variable	Measures economic efficiency of resource use	Eurostat database
GHG	Greenhouse gases emissions from production activities	Circular Economy	Assesses environmental impact and sustainability performance	Eurostat database
COMP	Competitiveness (Private investment and gross added value related to circular economy sectors)	Circular Economy	Reflects market orientation toward sustainable and circular practices	Eurostat database

3.2. Econometric estimation: application of GMM and MMQR

For model estimation, given the presence of causality between variables, we adopted a dynamic econometric approach to mitigate the endogeneity issues that often arise in static models. We employed the Generalized Method of Moment System (GMM-System) and Quantile regression via method of moments which allow us to overcome the endogeneity risk. GMM offers significant advantages: it accounts for country-specific heterogeneity and addresses potential endogeneity-issues commonly encountered when analyzing dynamic relationships.

Two widely used estimators in this context are the difference GMM estimator (Arellano & Bond, 1991) and the system GMM estimator (Blundell & Bond, 1998). The difference GMM relies on first-differencing the data and using lagged levels as instruments. In contrast, the system GMM enhances efficiency by combining the equation in levels with the equation in first differences, using lagged differences as instruments for the level equation.

In our analysis, we choose the GMM-system estimator for three main reasons. First, it allows for a larger set of instruments, which significantly improves estimation efficiency, as highlighted by Blundell and Bond (1998). Second, unlike the difference GMM, the system GMM retains fixed effects, which are essential in analyzing well-being outcomes. Third, compared to methods such as Ordinary Least Squares, Fixed Effects, or Random Effects, GMM does not require strong distributional assumptions (e.g., normality) and can accommodate unspecified forms of heteroscedasticity. The equations of our model are specified as follows (Eqs. (1)–(4)):

$$\ln cmr_{it} = \beta_0 + \alpha \ln cmr_{it-1} + \beta_1 \ln oi_{it} + \beta_2 \ln ai_{it} + \beta_3 \ln ict_{it} + \beta_4 \ln nano_{it} + \beta_5 \ln gdp_{it} + \beta_6 \ln res_{it} + \beta_7 \ln rpr_{it} + \varepsilon_{it}; \quad (1)$$

$$\ln weee_{it} = \beta_0 + \alpha \ln weee_{it-1} + \beta_1 \ln oi_{it} + \beta_2 \ln ai_{it} + \beta_3 \ln ict_{it} + \beta_4 \ln nano_{it} + \beta_6 \ln res_{it} + \beta_7 \ln rpr_{it} + \varepsilon_{it}; \quad (2)$$

$$\ln ghg_{it} = \beta_0 + \alpha \ln ghg_{it-1} + \beta_1 \ln oi_{it} + \beta_2 \ln ai_{it} + \beta_3 \ln ict_{it} + \beta_4 \ln nano_{it} + \beta_5 \ln gdp_{it} + \beta_6 \ln res_{it} + \beta_7 \ln rpr_{it} + \varepsilon_{it}; \quad (3)$$

$$\ln comp_{it} = \beta_0 + \alpha \ln comp_{it-1} + \beta_1 \ln oi_{it} + \beta_2 \ln ai_{it} + \beta_3 \ln ict_{it} + \beta_4 \ln nano_{it} + \beta_5 \ln gdp_{it} + \beta_6 \ln res_{it} + \beta_7 \ln rpr_{it} + \varepsilon_{it}. \quad (4)$$

Table 2. List of abbreviations

ln*cmr*	*Ln*(*Circular material use rate*)
ln*weee*	*Ln*(*E-waste*)
ln*ghg*	*Ln*(*Greenhouse gases emissions from production activities*)
ln*comp*	*Ln*(*Competitiveness*) (*Private investment and gross added value related to circular economy sectors*)
ln*oi*	*Ln*(*Open Innovation*)
ln*ai*	*Ln*(*Artificial Intelligence patents*)
ln*ict*	*Ln*(*Information and Communication Technologies patents*)
ln*nano*	*Ln*(*Nano patents*)
ln*gdp*	*Ln*(*Real Gross Domestic Product*)
ln*res*	*Ln*(*Number of researchers per million persons*)
ln*rpr*	*Ln*(*Resource Productivity*)

As a robustness check for our System GMM estimates, we apply the bias-corrected Least Squares Dummy Variable estimator (bias-corrected LSDV) introduced by Kiviet (1995) and adapted for unbalanced panels by Bruno (2005a, 2005b). The System GMM estimator, while effective in addressing endogeneity, may be subject to finite-sample bias and instrument proliferation when the cross-sectional dimension is small. Monte Carlo evidence suggests that the bias-corrected LSDV estimator provides more reliable inference in such settings, as it yields a lower Root Mean Square Error (RMSE) compared to conventional GMM estimators when the number of cross-sectional units is limited.

Also, the Method of moment quantile regression (MMQR) performed. The aim of this technique is to assess the heterogeneous effect of Industry 4.0 technologies on circular economy indicators. Hence, Machado and Silva (2019) introduced an advanced version of quantile regression based on the Method of Moments (MM-QR), which uses moment conditions derived from quantile restrictions. According to the authors, quantile regression with individual effects lacks moment conditions, making it more difficult to derive standard errors and perform valid inference in complex settings. In contrast, MM-QR introduces moment conditions enabling the use of standard GMM inference tools and thus improving the reliability of inference. Additionally, MM-QR naturally extends to panel data by incorporating moment conditions that account for individual fixed effects, heterogeneity, and endogeneity. This method enables the estimation of conditional quantiles by jointly modelling the location and scale functions. The method can also accommodate instrumental variables and other structural components due to its GMM-based formulation, making it especially suitable for applied research involving complex data structures.

MM-QR method estimates the conditional quantiles of a dependent variable *Y*, if the conditional distribution of *Y*, given a k-dimensional vector of covariates X, follows a location-scale model. The variable *Y* is specified as follows (Eq. (5)):

$$Y_{it} = \alpha_i + X'_{it}\beta + \left(\delta_i + Z'_{it}\gamma\right)U_{it}. \tag{5}$$

$P\left\{\delta_i + Z'_{it}\gamma > 0\right\} = 1$ is the probability. (α; β; δ; γ)′ are parameters to be estimated. $\left(\alpha_i,\ \delta_i\right)$, $i = 1,...,n$ denotes the individual *i* fixed effects.

3.3. Principal component analysis

Principal Component Analysis (PCA) is a statistical method utilized to reduce the dimensionality of datasets including linked variables (Berrittella, 2025). We utilized PCA to diminish the dimensionality of the data by converting the original covariates into a reduced set of uncorrelated variables known as principal components. These components are linear combinations of the original variables that encapsulate the most variance in the data. If considering the variables X_1; X_2, ..., X_i, a PCA of variables can generate new ones, called principal components (PC_1; PC_2, ..., PC_i). The values of the principal components are calculated as follows (Eqs. (6)–(7)):

$$PC_1 = W_1X_1 + W_2X_2; \tag{6}$$

$$PC_2 = W_3X_1 + W_4X_2. \tag{7}$$

W_i denotes the regression coefficient of the principal components (PC_i) of the variables. It is important to point out that whilst the quantity of primary components matches the number of original variables, only a subset has been chosen. The scree plot and eigenvalues are used to determine the appropriate number of components. The primary aim is to consolidate the variables into two composite indices that reflect circular economy and Industry 4.0 attributes.

4. Empirical findings

4.1. Panel unit roots test

Proceeding to the stationarity assessment, due to the existence of cross-sectional dependence (CSD) among individuals, it is essential to conduct second-generation panel unit root tests. These tests are beneficial as they address the issue of CSD. Consequently, we submitted applications for two assessments: the Maddala and Wu (1999) test and the CIPS test by Pesaran (2007). The results are reported in Table 3 below.

Table 3. Panel unit roots results

	Maddala and Wu (1999)		Pesaran (2007)	
	I (0)	I (1)	I (0)	I (1)
ln*cmr*	258.615***	209.239***	–12.648***	–10.657***
ln*weee*	126.185***	285.607***	–5.747***	–11.035***
ln*ghg*	54.162**	319.167***	–3.839**	–11.432***
ln*comp*	91.662***	206.974***	–7.053***	–12.977***
ln*oi*	129.897***	259.057***	–5.199**	–11.518***
ln*ai*	99.531***	203.279***	–8.972***	–11.589***
ln*ict*	75.488***	194.298***	–7.680***	–14.390***
ln*nano*	93.522***	216.062***	–3.440***	–9.734***
ln*gdp*	165.831**	440.586***	–7.542**	–12.361
ln*res*	44.828***	192.674***	–6.735***	–12.294***
ln*rpr*	133.932***	443.075***	–3.644***	–9.091***

Notes: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. The results of two tests reveal that all the majority of variables are I (0) stationary at level at 1% threshold, but in their first difference, all the variables are stationary at 1% threshold.

4.2. Result of causality tests

The presence of a cointegration vector among the variables indicates causality in at least one direction. Consequently, prior to advancing with the estimation, it is crucial to investigate the potential endogeneity problem—namely, the likelihood of reverse causality from the dependent variable to the independent variables. To address this, we apply one Granger non-causality test: the Juodis et al. (2021), Granger non-causality test, known as JKS test (see Tables 4–5).

Table 4. Granger non-causality test

	Model1	Model2	Model3	Model4
H0: x does not Granger-cause y. **H1:** x does Granger-cause y for at least one panel (id).				
ln*oi*	–0.0108 (0.041)	0.008 (0.011)	–0.004 (0.045)	–0.169 (0.206)
ln*ai*	0.073** (0.025)	0.0142** (0.006)	–0.017 (0.025)	–0.65943*** (0.214)
ln*ict*	0.013 (0.012)	0.0047 (0.003)	–0.0180 (0.012)	0.0841 (0.131)
ln*nano*	0.082* (0.045)	0.035*** (0.012)	.0033 (0.043)	–1.304*** (0.342)
ln*gdp*	0.0189 (0.033)	0.0064 (0.008)	–0.2093*** (0.039)	0.409** (0.177)
ln*res*	0.0040 (0.037)	0.0116 (0.010)	0.0503 (0.046)	1.323*** (0.203)
ln*rpr*	0.812*** (0.243)	0.081 (0.056)	–1.139*** (0.022)	3.895*** (1.231)

Notes: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Values in parentheses indicate the standard error.

Table 5. Granger non-causality test

	Model1	Model2	Model3	Model4
H0: y does not Granger-cause x. **H1: y does Granger-cause x for at least one panel (id).**				
ln*oi*	0.052 (0.094)	–0.211 (0.323)	0.088 (0.082)	0.0085 (0.017)
ln*ai*	0.290 (0.197)	0.42024 (0.596)	0.621*** (0.151)	–.015 (0.053)
ln*ict*	0.294 (0.384)	3.752*** (1.18)	1.638*** (0.299)	–0.434*** (0.129)
ln*nano*	–0.010 (0.109)	0.8344** (0.326)	0.292*** (0.844)	–0.056** (0.028)
ln*gdp*	0.283** (0.124)	0.360 (0.405)	0.637*** (0.119)	–0.026 (0.0226)
ln*res*	–0.067 (0.108)	0.247 (0.364)	0.506*** (0.101)	–0.056*** (0.021)
ln*rpr*	0.027 (0.022)	–0.0470 (0.064)	0.028* (0.016)	–0.0108*** (0.003)

Notes: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Values in parentheses indicate the standard error.

4.3. Result of GMM model

The estimation findings are in Table 6. The Sargan/Hansen test for over-identifying limitations is not significant at conventional levels (p-values are large), indicating that the instruments are valid across all models. In addition, the Arellano-Bond AR (2) test for second-order auto-correlation fails to reject the null hypothesis. These results validate our estimates' robustness and the system GMM approach's validity.

Table 6. Estimation results of the GMM-SYS method

	Model1(Y = *lncmr*)	Model2 (Y = *lnweee*)	Model3 (Y = *lnghg*)	Model4 (Y = *lncomp*)
l.ln*cmr*	–0.217* (0.13)			
l.ln*weee*		–0.496** (0.22)		
l.ln*ghg*			–0.382*** (0.06)	
l.ln*comp*				0.521*** (0.11)
ln*oi*	0.146* (0.08)	–0.033* (0.02)	0.199*** (0.08)	–0.751* (0.45)
ln*ai*	0.334* (0.17)	–0.018 (0.03)	0.093 (0.07)	–1.241** (0.62)
ln*ict*	0.018 (0.09)	0.003 (0.02)	0.014 (0.05)	0.679*** (0.21)
ln*nano*	–0.683*** (0.22)	0.074 (0.06)	–0.805*** (0.22)	2.509*** (0.96)
ln*gdp*	–0.995*** (0.25)	0.218* (0.12)	0.130 (0.14)	–0.728 (0.97)
ln*res*	0.059 (0.25)	–0.159** (0.08)	0.254** (0.13)	2.218* (1.33)
ln*rpr*	8.553*** (1.45)	–1.186** (0.59)	1.843** (0.81)	–3.639 (5.55)
constant	–7.741*** (2.45)	8.579*** (1.38)	5.393*** (1.45)	–1.465 (9.48)
AR (1)	0.000	0.002	0.000	0.008
AR (2)	0.212	0.491	0.151	0.540
SARGAN	0.180	0.436	0.470	0.687
Instruments	14	23	17	13
N	286	264	265	275

Notes: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Values in parentheses indicate the standard error.

4.4. Robustness check

To ensure the robustness of our findings, we adopt a complementary strategy. We are going to use an alternative estimation technique. We will apply the bias-corrected Least Squares Dummy Variable (LSDV) estimator proposed by Kiviet (1995) and extended to unbalanced

panels by Bruno (2005a, 2005b). This approach allows us to confirm the baseline regressions by changing the estimation technique. While System GMM is designed to address endogeneity, its performance can be compromised in samples with a small cross-sectional dimension (N = 27), leading to concerns about finite-sample bias and the proliferation of instruments. Monte Carlo evidence suggests that the LSDV bias-corrected estimator often outperforms standard GMM estimators particularly when the number of individuals is limited. The bias-corrected LSDV estimator addresses this by approximating the small-sample bias of the fixed effects estimator and removing it, thereby providing a reliable benchmark against which the consistency of the GMM estimates can be evaluated. This method corrects for the dynamic panel bias without relying on the potentially problematic instrument sets required by GMM, offering an alternative identification strategy.

Table 7. Robustness check results for bias-corrected LSDV estimator

	Model1(Y = *lncmr*)	Model2 (Y = *lnweee*)	Model3 (Y = *lnghg*)	Model4 (Y = *lncomp*)
L.ln*cmr*	0.105* (0.05)			
L.ln*weee*		0.200*** (0.07)		
L.ln*ghg*			0.131** (0.06)	
L.ln*comp*				0.84** (0.03)
ln*oi*	0.049 (0.09)	0.033 (0.03)	0.043 (0.12)	0.542* (0.32)
ln*ai*	0.001* (0.04)	–0.024 (0.02)	0.050 (0.05)	–0.276* (0.14)
ln*ict*	–0.023 (0.03)	–0.001 (0.01)	–0.085** (0.03)	0.888*** (0.09)
ln*nano*	0.226*** (0.07)	0.018 (0.03)	–0.089 (0.08)	0.165 (0.23)
ln*gdp*	–0.265*** (0.05)	0.032 (0.02)	0.407*** (0.07)	–1.437*** (0.18)
ln*res*	0.144*** (0.05)	0.003 (0.02)	0.099 (0.07)	0.352* (0.18)
ln*rpr*	2.794*** (0.34)	–0.280** (0.12)	–0.814** (0.41)	8.922*** (1.16)

Table 7 presents the results of the robustness and validity checks conducted using the bias-corrected LSDV dynamic panel data estimator. The findings confirm the reliability of the estimates obtained from the System GMM model. The results indicate a positive impact of open innovation on the circular material use rate. AI patents also exhibit a positive and statistically significant effect on the circular material use rate, while showing a negative impact on competitiveness. ICT patents and the number of researchers positively influence competitiveness. In contrast, resource productivity exerts a negative and significant impact on the circular material use rate.

4.5. Result of Method of Moments Quantile Regression (MM-QR)

Moving now to the Quantile Regression via the Method of Moments. This method was selected due to its advantages, namely its ability to account for outliers and the fact that it does not rely on any distributional assumptions. The panel quantile regression results are revealed for 10th, 25th, 50th, 75th and 90th percentiles of the conditional dependent variable. In the first model (Table 8), we find that nanotechnology patents have a positive and statistically significant effect on the circular material use rate from the 10th to the 75th quantile. In contrast, real GDP exhibits a negative and significant coefficient across all quantiles at the 1% level of significance. This result can be explained by the fact that in high-growth economies, the focus is often on industrial expansion, which is initially associated with increased environmental pressure. A similar interpretation applies to the resource productivity rate, which indicates that economies generating more value per unit of natural resource consumed tend to be more efficient in reusing materials. Surprisingly, artificial intelligence patents, open innovation, and ICT patents do not show any significant impact on the circular material use rate. This outcome suggests that, despite their theoretical potential to enhance circular practices, the practical implementation of advanced technologies and open innovation in this domain may still be limited or indirect. Furthermore, the diffusion of such technologies into sectors directly involved in circular activities may still be in its early stages.

Table 8. MM-QR results for model 1 (*lncmr* as dependent variable)

	Location	Scale	Q10	Q25	Q50	Q75	Q90
ln*oi*	–0.018 (0.03)	–0.017 (0.02)	0.012 (0.03)	–0.005 (0.03)	–0.016 (0.03)	–0.030 (0.03)	–0.045 (0.05)
ln*ai*	0.020 (0.03)	0.012 (0.02)	0.040 (0.03)	0.012 (0.03)	0.019 (0.03)	0.029 (0.03)	0.039 (0.05)
ln*ict*	–0.015 (0.02)	–0.004 (0.01)	–0.008 (0.02)	–0.012 (0.02)	–0.015 (0.02)	–0.018 (0.02)	–0.022 (0.03)
ln*nano*	0.163*** (0.05)	–0.067* (0.03)	0.278*** (0.06)	0.211*** (0.05)	0.170*** (0.05)	0.114* (0.06)	0.053 (0.09)
ln*gdp*	–0.267*** (0.05)	–0.010 (0.03)	–0.249*** (0.06)	–0.259*** (0.05)	–0.266*** (0.05)	–0.274*** (0.06)	–0.283*** (0.08)
ln*res*	0.166*** (0.04)	0.032 (0.02)	0.110** (0.04)	0.142*** (0.03)	0.162*** (0.03)	0.189*** (0.04)	0.218*** (0.06)
ln*rpr*	2.672*** (0.26)	0.168 (0.18)	2.382*** (0.33)	2.550*** (0.25)	2.654*** (0.26)	2.796*** (0.33)	2.948*** (0.46)
constant	–2.689*** (0.47)	–0.191 (0.32)	–2.359*** (0.59)	–2.550*** (0.45)	–2.668*** (0.46)	–2.829*** (0.59)	–3.002*** (0.81)

Notes: ***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Values in parentheses indicate the standard error.

4.6. Multivariate analysis

Our decision to conduct a multivariate analysis is justified by the presence of four indicators related to the circular economy (namely CMR, WEEE, GHG, and COMP), as well as four others representing Industry 4.0 (specifically AI, NANO, ICT, and RES). Therefore, we follow a two-step

approach. First, we employed Principal Component Analysis (PCA) to construct two composite indexes: one pertaining to the circular economy and another related to Industry 4.0. Next, we conducted a cluster analysis based on the three indexes representing the circular economy, Industry 4.0, and open innovation. This allowed us to group countries into homogeneous clusters according to their overall performance in these three strategic areas. These facilities us to examine the specific focus of each cluster. As mentioned previously, the objective of cluster analysis is to create groups of observations that are highly homogeneous internally and distinctly heterogeneous from one another. Beyond simply creating clusters based on similarity, this method also provides insight into the reasons that explain why these groups have emerged. For this step, we utilized the data from the year 2023. Additionally, given the different units of measurement (e.g., patent counts vs. percentages), the selected variables were standardised prior to conducting the PCA.

4.6.1. Principal component analysis

4.6.1.1. Industry 4.0 Index

Regarding the Industry 4.0 index, we adopted a multidimensional approach in which each sub-element corresponds to a specific dimension of Industry 4.0. The selected variables include the number of patents in artificial intelligence, ICT, and nanotechnology, as well as the number of researchers per million inhabitants. These four components are combined to construct the Industry 4.0 index (see Figure 1). The eigenvalues and the cumulative proportion of variance explained by the selected principal components are presented in Appendix, Table A1.

4.6.1.2. Circular economy index

The circular economy emphasizes prolonging product lifespans, reducing waste, and safeguarding the environment. In this part we selected four key dimensions of circular economy to create the CE index (Figure 2). The results of the principal component analysis, including the eigenvalues and the cumulative proportion of variance explained, are reported in Appendix, Table A2.

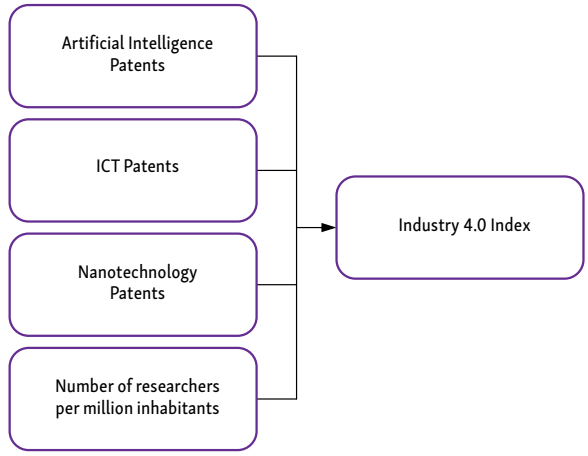


Figure 1. Construction of Industry 4.0 Index

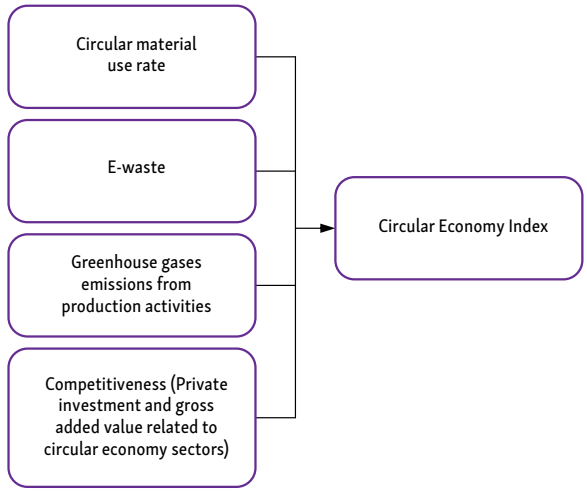


Figure 2. Construction of circular economy index

Table 9. Scores of Industry 4.0 and circular economy

Country	Circular economy index	Industry 4.0 index
Belgium	0.348	–0.083
Bulgaria	–0.494	–0.465
Czechia	–0.335	–0.445
Denmark	–0.172	–0.135
Germany	4.071	4.354
Estonia	–0.514	–0.431
Ireland	–0.432	–0.308
Greece	–0.523	–0.404
Spain	0.345	0.079
France	2.087	1.691
Croatia	–0.503	–0.465
Italy	0.645	0.016
Cyprus	–0.535	–0.475
Latvia	–0.516	–0.476
Lithuania	–0.489	–0.455
Luxembourg	–0.420	–0.438
Hungary	–0.410	–0.317
Malta	–0.534	–0.361
Netherlands	0.768	0.890
Austria	0.088	–0.245
Poland	–0.043	–0.299
Portugal	–0.335	–0.308
Romania	–0.407	–0.398
Slovenia	–0.529	–0.477
Slovakia	–0.479	–0.450
Finland	–0.428	–0.180
Sweden	–0.254	0.584

The table above (Table 9) shows the scores of each index per country for the year 2023. Germany has the highest values for both the circular economy index and Industry 4.0, followed by France, while Cyprus has the lowest value for the circular economy index, and Slovenia has the lowest value for Industry 4.0.

Figure 3 shows the time trends of the composite indexes from 2013 to 2022. The circular economy index demonstrated a substantial growth, while the growth of the Industry 4.0 index, although notable, was relatively smaller in comparison.

4.6.2. Cluster analysis

Cluster analysis is a multivariate statistical approach for classifying samples, variables, observations, etc. into relatively homogeneous groups of cases, or variables, based on selected characteristics (Rubio-Andrés & Abril, 2024). At this stage of analysis, the group of countries had been aggregated into homogeneous groups (i.e. clusters) using the composite index of circular economy and the composite index of Industry 4.0 and the open innovation. We applied hierarchical approach and K-means analysis (non-hierarchical approach). In the hierarchical approach we worked on Ward's algorithm. Then, we used dendrogram to check the ideal number of clusters. Since we used quantitative and standardized data, the Ward's algorithm seems the best to be selected with squared Euclidean distance. The Ward's dendrogram results (Figure 4) indicate that the sample is grouped into two distinct clusters.

At this step of analysis, the group of countries will be aggregated into homogeneous groups (i.e., clusters) using the composite index of circular economy and the composite index of Industry 4.0 and the open innovation. We applied hierarchical approach and K-means analysis (non-hierarchical approach). In the hierarchical approach we will work Ward's algorithm.

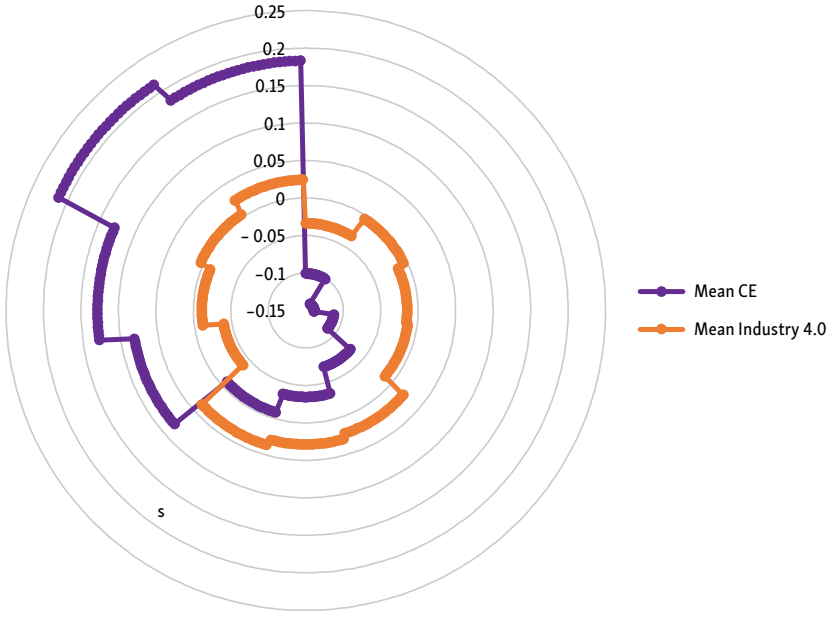


Figure 3. Trends for the composite indexes during the period [2013–2022]

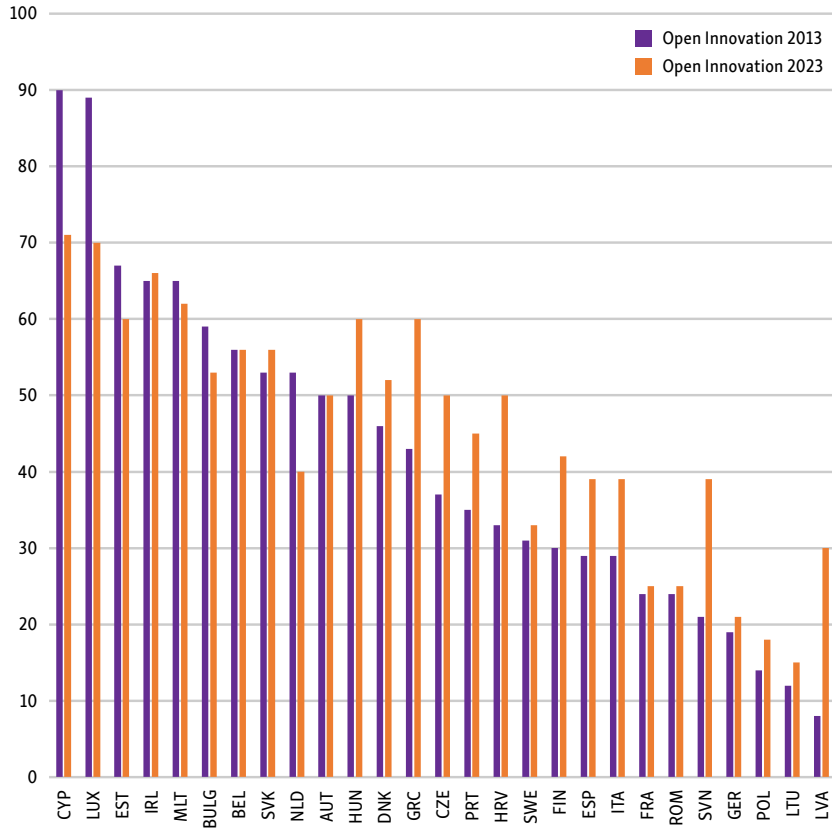


Figure 4. Mean of open innovation by European countries (2013 vs 2023)

Then, we will use dendrogram to check the ideal number of clusters. Since we use quantitative and standardized data, the Ward's algorithm seems the best to be selected with squared Euclidean distance the Ward's dendrogram results (Figure 5) indicate that the sample is grouped into four distinct clusters. They exhibit a high degree of internal homogeneity, while displaying substantial heterogeneity between clusters.

Figure 6 below presents the distribution of observations across the four identified clusters. Each cluster contains a relatively equal number of countries, with Clusters 1 comprising 7 countries (25.93 % of the sample), while Cluster 4 includes 6 countries (22.22%). The cumulative percentages confirm that all 27 observations (100%) are accounted for. This balanced distribution suggests that the clustering process produced well-divided groups, enabling a meaningful comparison of characteristics across clusters.

Figure 7 presents the classification of open innovation values by cluster for the years 2013 and 2023. The general observation highlights a notable degree of heterogeneity in the levels of open innovation across clusters. As previously indicated, Cluster 2, which is referred to as the "Open Innovation Focused" group, exhibits the highest levels of open innovation in both years, followed by Cluster 1. In contrast, countries in Cluster 3, labelled the "Circular Economy and Industry 4.0 Leaders", demonstrate comparatively weaker performance in terms of open innovation.

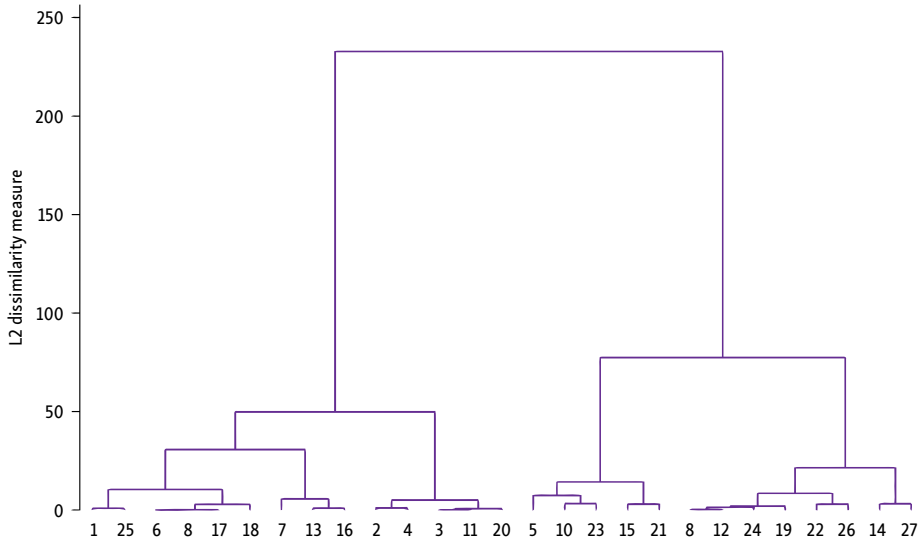


Figure 5. Dendrogram for ward's method

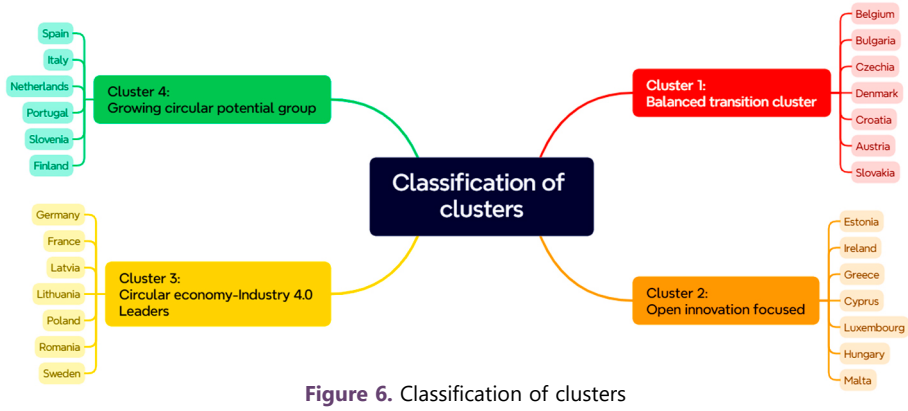


Figure 6. Classification of clusters

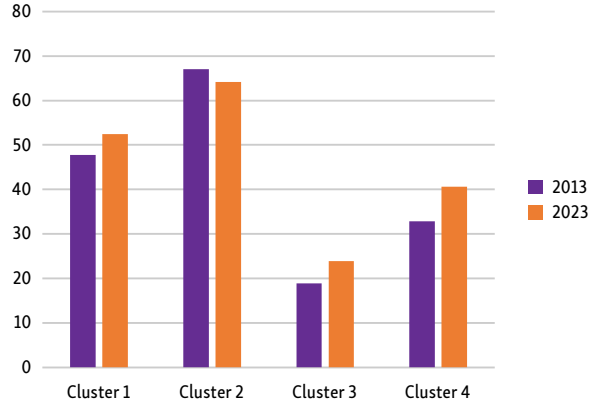


Figure 7. Classification of open innovation values by cluster for the years 2013 and 2023

5. Generalization

5.1. Generalization of findings

The data reveals on link between circular economy and I4.0 as well as open innovation. Our results are aligned with prior studies (Claudio-Quiroga & Poza, 2024; Pintilie, 2021), in addition, our study identified an enhancement in circular economy in Europe from 2014 to 2021. In this regard, the case of the EU, recycling rates are shown to positively influence all the indices examined, underscoring their critical role in promoting circular and innovation-driven transitions. The EU is presently undergoing two transitions such as circular economy and the digital revolution could assist the EU in tackling its foremost challenge: establishing a sustainable, green economy that remains competitive globally (European Policy Centre, 2020).

Regarding (RQ1) how does Industry 4.0 influence CE in EU countries, (H1) the main findings of this research show that Industry 4.0 (AI patents) has significant impact on circular economy (CMR), AI technologies significantly contribute to more efficient resource management and support the integration of secondary raw materials. AI enables optimization of recycling systems, which enhances material recovery. Therefore, we can say that this technological advancement improves closed-loop systems, aligning with the goals of the circular economy. This finding is aligned with previous research by Popović et al. (2022), who emphasized that AI adoption is positively associated with higher circular material use rates, particularly when paired with resource efficiency and economic readiness.

Moreover, (H2) this research demonstrates a strong positive relationship between Industry 4.0 (ICT patents) and circular economy (competitiveness) indicating that innovations in ICT play a critical role in enhancing economic performance within circular sectors. Additionally, the integration of ICT applications in circular business models—such as product-as-a-service, smart recycling, and digital marketplaces—drives value creation and increases gross value added in circular industries. Regarding the greenhouse gas (GHG) emissions, we found a negative relationship between ICT patents and GHG emissions from production, highlighting a potential environmental trade-off. This could be explained by the fact that ICT development is strongly aligned with low-carbon and sustainable practices in our sample. Promoting energy-efficient ICT design, green data centers, and responsible e-waste management are essential strategies to mitigate these adverse environmental effects while sustaining the competitiveness benefits. Our results are in line with previous studies (Cecere & Martinelli, 2017; Quttainah & Ayadi, 2024) who show how digital innovation, including ICT, enables circular practices such as reuse, remanufacturing, and material efficiency.

(H3), we also found Industry 4.0 (nanotechnology patents) positively influence circular economy (competitiveness). This finding is consistent with those of Ghasemi et al., (2015). Nanotechnologies enable the development of advanced materials and product designs that enhance durability, minimize resource intensity, and promote innovation—factors that drive industrial efficiency and attract economic activity. Likewise, we found a negative and significant nexus between, nanotechnology patents and greenhouse gas emissions from production.

(H4), when looking at the ratio of researchers, the findings reveal a favourable and highly substantial impact on the circular economy. This could be because of the importance of research in creating new materials, technologies, and processes that enhance material flow

recycling and reuse. This finding is aligned with prior study (Ghannouchi, 2023), it highlighted to promote national development and competitiveness on a global scale, it stresses the importance of investing in human capital and knowledge generation for CE transition. The positive association between resource productivity rate and circular material use means that as European countries become more efficient in using resources, they also tend to increase the share of secondary materials (recycled or reused materials) in their total material consumption. Our results align with findings of prior studies (Bao & Lu, 2023; Soto, 2025; Xu & Wang, 2025). Also, the negative impact of resource productivity (RPR) on e-waste shows that more efficient use of resources reduces e-waste volumes. This outcome emphasizes the role of efficient systems in minimizing waste. Furthermore, RPR shows a positive relationship with competitiveness in circular economy activities. This supports the view that resource efficiency not only benefits environmental outcomes but also drives innovation, profitability, and sustainable industrial growth (Skare et al., 2024b).

Real GDP exhibits a negative relationship with the circular material use rate, suggesting that higher levels of economic growth may hinder the adoption of circular practices. This finding also clarifies why our four country clusters differ from standard GDP or R&D rankings: it is the long-term policy mix that aligns digital technologies with circular-economy goals, not economic size alone, that drives digital-circular synergies. GDP growth is often driven by traditional, energy-intensive industries—such as fossil fuels, electricity production, and heavy manufacturing rather than clean and circular activities. Our results align with these studies (Khan & Haleem, 2021; Xu & Wang, 2025), these authors reported that economic growth contributes to increased emissions and environmental degradation, both of which hinder the implementation of circular economy measures.

The first cluster focuses on balance transition. This cluster reflects countries (Bulgaria, Belgium, Czechia, Denmark, Croatia, Austria and Slovakia) making solid, balanced progress across all dimensions, without excelling in any one area. They may be in a policy transition phase. The second cluster based on open innovation focused as it is these countries are (Estonia, Ireland, Greece, Cyprus, Luxembourg, Hungary, Malta) advanced in terms of collaboration in technology, but it is still lack in circular economy and Industry 4.0 characteristics. This suggests an opportunity for policymakers to better link innovation policy with sustainability goals. For firms, the existing innovation ecosystem could be leveraged to construct new circular business models, provided that enabling digital infrastructure is improved. However, the cluster 3 is on circular economy-industry 4.0 leaders (Germany, France, Latvia, Lithuania, Poland, Romania, Sweden) as it has the highest value of circular economy components and Industry 4.0 but it is lack regarding the open innovation. Regarding Cluster 4, it focused on growing circular potential group, as it is slightly stronger in the Circular Economy Index than in the other two indices (Spain, Italy, Netherlands, Portugal, Slovenia, Finland). We can say that these countries are in a transition phase where innovation strategies are beginning to support circular goals.

Regarding the second research question (RQ2) and hypothesis (H5), our research revealed open innovation has significant effect on the circular economy (circular material use rate), as it promotes exchange of knowledge, collaboration, and the diffusion of environmentally friendly technologies. This finding corresponds with the result by Jesus et al. (2025) they

worked on a survey of 163 Brazilian firms, they found that open innovation practices (e.g., collaboration, co-creation) directly support CE implementation. Also, Perotti et al. (2025) shows that open innovation enables firms to access essential resources and knowledge to implement CE practices, especially green product/process innovation. Similarly, another study found open innovation is vital for innovation performance at country level as they explored in Austria, Switzerland and Germany (Inauen & Schenker-Wicki, 2011). We suggest open innovation platforms, firms can adopt best practices in material recovery, product redesign, and industrial symbiosis, thereby enhancing the inclusion of secondary raw resources into manufacturing cycles. However, despite these environmental benefits, we found a negative relationship between open innovation and competitiveness in circular activities. This could be explained to the high coordination costs, intellectual property risks, and limited immediate returns associated with open innovation strategies, particularly in emerging circular economy markets.

5.2. Theoretical contributions

This research has four notable contributions. Firstly, this research developed a multidimensional Industry 4.0 readiness Index and Circular Economy Index in European countries by providing a broader perspective than earlier studies (Claudio-Quiroga & Poza, 2024; Castelo-Branco et al., 2023). Secondly, we contribute by tracking data from 2013 to 2023, as this research captures the impact of significant policy shifts, such the Circular Economy Action Plan 2015, and European Green Deal 2019. This reflects European countries are following this transformative model of circularity into their businesses and societal domains. Thirdly, our research advances understanding by exploring open innovation towards circular economy at macro-level by providing insights on EU countries. Fourth, it advances the methodology by combining system-GMM, moment-quantile regression, and hierarchical clustering to address endogeneity, heterogeneity, and country grouping within a single framework. Finally, this research advances our understanding on European countries by adopting policy intiatives on technological, regulation, governance and finance for circular economy transition.

5.3. Practical implications

This research provides an important guideline for practical implications. First, the result show Industry 4.0 is main driving force for CE transition. Second, our finding show first cluster is about balanced transition. For policymakers, this result suggests a need to maintain balanced policy support. For companies, this balanced environment may offer stable ground for experimenting with integrated circular-digital strategies for these countries e.g., Belgium, Bulgaria, Czechia, Denmark, Croatia, Austria and Slovakia. Third, the result reveals second cluster is on open innovation focused. This suggests an opportunity for policymakers to better link innovation policy with sustainability goals. For firms, the existing innovation ecosystem could be leveraged to construct new circular business models, provided that enabling digital infrastructure is improved. This could also include capacity-building programs, pilot projects, or regional hubs for innovation for Estonia, Ireland, Greece, Cyprus, Luxembourg, Hungary and Malta. Fourth, our data show cluster 3 mainly about circular economy-industry 4.0 leaders.

This finding could point to a more centralized or tech-driven approach, with less collaborative innovation. Policymakers in this group might consider fostering more public-private and cross-sector partnerships. Companies should seek more collaborative innovation platforms to sustain long-term competitiveness for Germany, France, Latvia, Lithuania, Poland, Romania and Sweden. Finally, the results demonstrate cluster 4 growing circular potential group in Spain, Italy, Netherlands, Portugal, Slovenia and Finland. This result suggests that policy-makers could accelerate this shift through targeted digitalization programs for incentives for collaborative innovation. Companies in this group could find emerging opportunities for circular innovation, particularly in materials reuse, waste valorisation, and product-as-a-service models.

5.4. Limitations and future directions

This study has few limitations and provides potential avenues for future investigation. First, we used few indicators on Industry 4.0 and circular economy. There are currently not many indicators available for cross-national comparison However, as open data expands, more indicators could be included in the future, enabling greater precision. In particular, our use of researchers per million inhabitants relies on a population-size-adjusted measure of scientific capacity, which captures workforce density but not the broader resource environment in which research takes place. Future studies should complement population-size indicators with additional measures such as public research expenditure as a percentage of GDP, education spending as a percentage of GDP, and more granular R&D funding data. This would help disentangle the effects of human capital from those of financial investment and institutional support, and clarify whether circular economy outcomes respond more strongly to researcher density, funding intensity, or the interaction between the two. Likewise, our patent-based indicators reflect invention quantity rather than invention quality or actual adoption; future research may integrate forward citations, international patent families, or technology-uptake proxies to capture innovation depth and diffusion. Circular economy indicators also vary in measurement precision across countries, which introduces potential comparability limitations that future studies could address through harmonized or composite CE metrics.

Second, we focused on digital and circular transitions. Future researchers may explore multi-system innovations and socio-technical systems, e.g., by focusing on electric vehicles, smart cities, wearable technology, and circular business models at sectors, industries, or segments of a value chain. Sector-specific analyses would help reveal industry heterogeneity, pathway dependencies, and potential rebound effects associated with digitalization and resource use.

Finally, we explored EU countries only by analysing digital technologies, open innovation for circularity. Future studies may explore the Global South in the context of Industry 4.0 and the circular economy, particularly at the micro and meso levels (i.e., companies and industries). These economies are not only at an earlier stage of circularity and digitalization but also account for over half of the world's population and are experiencing rapid economic growth. Understanding their transition paths is crucial for shaping inclusive and sustainable global strategies.

6. Conclusions

The results also reveal that the relationship between innovation and environmental performance is multidimensional. Although advances in AI and ICT strengthen competitiveness in circular sectors, the negative association between real GDP and the rate of circular material use suggests that traditional growth patterns can conflict with circularity objectives. This underscores a structural tension in EU economies: economic expansion driven by linear, resource-intensive industries may hinder circular progress unless accompanied by deliberate policy alignment that reorients growth toward cleaner and digitally enabled sectors. Clustering analysis further illustrates that Member States follow distinct transition pathways, depending on their technological readiness, circular performance, and openness to collaboration. These heterogeneous patterns underscore the need for tailored policy mixes that bridge digital innovation systems with circular economy strategies.

The findings show that open innovation plays a constructive, yet complex role in supporting the circular economy. Significantly increases the use of secondary materials, confirming that knowledge sharing, collaborative experimentation, and the diffusion of environmentally orientated technologies are crucial for accelerating circular practices. However, the negative association between open innovation and competitiveness within circular industries suggests that the benefits of openness may not be immediately reflected in market performance. Coordination costs, intellectual-property concerns, and limited short-term returns can constrain firms' ability to convert collaborative innovation into competitive advantage. This highlights the importance of governance structures, absorptive capacity, and supportive innovation frameworks to ensure that collaborative approaches translate into both environmental and economic gains.

In general, this research provides strong evidence that the twin transitions in Europe—digital and circular—are increasingly intertwined. Industry 4.0 technologies improve resource efficiency, reduce environmental impacts, and stimulate new business models, while open innovation fosters the exchange of knowledge necessary to scaling circular solutions. However, these transitions do not progress automatically; they depend on sustained research capacity, coherent long-term policy strategies, and the ability of firms and institutions to integrate digital tools into circular practices. By clarifying the mechanisms through which technological and collaborative innovation shape circular outcomes, this study contributes to a better understanding of how the EU can advance toward a competitive, low-carbon and resource-efficient economic model.

Data availability statement

All data used for analysis are publicly available on the Eurostat Website, OECD Website and World Bank website.

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Zuhair Abbas: Conceptualization, Writing original draft, Data Curation, Investigation. Rasa Smaliukienė: Writing-review & editing, Supervision, Resources, Project administration. Imen Ghannouchi: Software, Methodology, Formal Analysis, Visualization, Validation.

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APPENDIX

Table A1. PCA of Industry 4.0 index

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.97119	2.12531	0.7428	0.7428
Comp2	0.845876	0.679611	0.2115	0.9543
Comp3	0.166265	0.149596	0.0416	0.9958
Comp4	0.0166685	0.0	0.0042	1.0000

Table A2. PCA of circular economy index

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.65864	0.653499	0.4147	0.4147
Comp2	1.00514	0.148528	0.2513	0.6659
Comp3	0.856609	0.376991	0.2142	0.8801
Comp4	0.479618	0.0	0.1199	1.0000