THE EU's PROBABILISTIC DEPENDENCY STRUCTURE TOWARDS THE GOAL OF A CIRCULAR ECONOMY

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Abstract
This paper explores the interdependencies among key circular economy (CE) indicators across the European Union using data from the EUROSTAT Monitoring Framework. The dataset spans the years 2012–2021 and includes information from 27 EU member states, covering thematic areas such as production and consumption, competitiveness and innovation, and global sustainability and resilience. A Bayesian network is employed to learn the probabilistic structure among seven selected indicators, revealing conditional relationships that characterize the dynamics of the EU's circular economy. Scenario analysis shows that increased consumption levels are associated with higher material use and waste generation, alongside a notable rise in patent activity related to recycling—suggesting that environmental pressure may stimulate innovation. These findings highlight the value of understanding indicator interdependencies to support evidence-based policymaking and guide the EU's transition toward a more circular and resilient economy.

Key words:*Circular Economy,Bayesian networks, Probabilistic dependency, CE indicators, EUROSTAT, European Union*

Introduction

The EU's aim to achieve a circular economy over a linear one requires transformative actions targeting countries' policy frameworks, governance structures, and operational practices. These actions must prioritize sustainability, resource efficiency, and innovation across all sectors. Key steps include implementing regulations to support circular business models, enhancing local government capacities for waste management and recycling, and fostering public-private partnerships for sustainable development. However, these actions depend heavily on the economic resilience of the participating countries which in turn depend on the continuous availability of resources for production. This challenge underscores a long-overlooked truth: humanity has only recently come to fully recognize that natural resources are, in fact, finite.

The concept of the circular economy (CE) originated from Boulding's (1966) call for a shift from unlimited resource use to a closed-loop system, recognizing the planet's finite resources. Pearce and Turner (1989) later formalized this idea by introducing the term "circular economy," promoting a circular model over a traditional linear one to enhance economic resilience. Since then, as pointed out by Cinicioglu and Korkmaz Tümer (2024) interest in CE has grown significantly. On that, Merli *et al*. (2018) document the rise in CE-related publications and offer a comprehensive review of the field. Much of this research has been concentrated in Europe and China, where CE has been adopted as public policy. Europe has advanced the agenda through frameworks like the European Green Deal (European Commission, 2019), while China embedded CE into national laws such as the Circular

Economy Promotion Law. Winans *et al.* (2017) emphasize the importance of supportive policies for standardized recycling to encourage industry adoption.

This paper explores the probabilistic dependency structure of EU member states using datasets from the EUROSTAT database, focusing on production & consumption, competitiveness& innovation and global sustainability & resilience. To analyze these relationships, the study employs Bayesian networks, a powerful probabilistic graphical modeling tool that reveals conditional dependencies among the set of selected circular economy indicators. The insights gained from this approach will shed light on the interplay between resource dependency, self-sufficiency, and eco-innovation, offering valuable implications for policymaking and institutional reforms necessary for achieving a circular economy.

The remainder of this paper is structured as follows: In the next section, we present our methodology which will be used as the main tool of our analysis. This is followed by an introduction to the set of indicators obtained from Eurostat database, along with a description of the data cleaning procedures applied on the data set. The subsequent section is devoted on the construction of the Bayesian network and the analysis conducted on it. This includes an exploration of the dependency structure, as well as scenario analysis on it, which provides insights into the interdependencies among EU countries with respect to the circularity indicators. Finally, we conclude the paper by summarizing the key findings and implications.

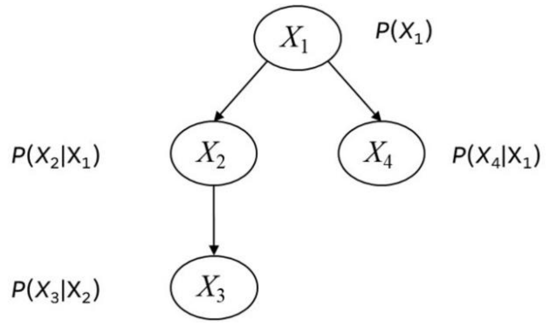
Methodology: Bayesian Networks

Bayesian networks are acyclic probabilistic graphical networks in which variables are represented through nodes and the probabilistic dependencies between the variables are represented through directed arcs. In a Bayesian network (BN) if there is an arc between two variables then the variable from which the arc is pointed is called as the parent variable of the node to which the arc is pointed. Each variable in a Bayesian network $X_1, \ldots, X_N$ follows a probability distribution conditioned on its parent variables and the joint probability distribution of the network is formed by the product of these conditional probability distributions as it is shown in Equation 1 below. Each variable in a Bayesian network is conditionally independent given its parents.

$$P(X_1, \ldots, X_N) = \prod_{i=1}^{N} P(X_i \mid Pa(X_i)) \qquad (1)$$

Below in Figure 1 a small Bayesian network with four variables X_1, X_2, X_3 and X_4 which follow the probability distributions $P(X_1)$, $P(X_2|X_1)$, $P(X_4|X_1)$ and $P(X_3|X_2)$ are represented. In this small Bayesian network X_1 is the parent variable of X_2 and X_4, X_3 is the child variable of X_2 and X_4 is the child variable of X_1. Notice that in the small BN X_1 stands without any parents with its marginal distribution and therefore is called as to root variable of the network.In BNs there is no limit regarding the parent variables and children that a variable can take. Once an observation(s) for the state(s) of the variables is observed, the BN is updated accordingly, representing the posterior probabilities of the variables in the network. As represented in Figure 1 given below the variables X_3 and X_4 do not possess any children. One of the most important advantages of Bayesian network is that it allows us to use the backpropagation algorithm which ensures that an observation downstream in the network will result in an updating process upstream in the network.

Figure 1. A Bayesian network representation with four variables



The chain rule that is represented in Equation 1 ensures that Bayesian networks are acylic graphical networks in the sense that if you follow the direction of arcs beginning from one node you cannot close the cycle and cannot end up in your starting node. Another aspect regarding the Bayesian network is that it possesses two different layers, one is the graphical network structure which is represented through the graph and the other is the computational background where the conditional probability distributions of the variables are represented which constitute the parameters of the variables. Consequently, the inference process in Bayesian networks relies on continual application of the Bayesian updating rule. The graphical interface of Bayesian network provides an intuitive appeal and understanding to the audience outside the field and the computational background and inference process ensures the correct demonstration of the joint probability distribution represented by the set of variables in the network.

Bayesian networks are first introduced by Pearl (1985) which later became an important part of artificial intelligence, and its use spread to many different application areas from healthcare, risk assessment, medicine, targeted advertising, competitiveness and innovation, finance, Maritime industry and numerous more. Some examples are as follows: Cinicioglu *et al.* (2024) provide a benchmark procedure for the evaluation of the sovereign risk of countries using Bayesian networks which involves a comprehensive analysis involving several steps conducted comprehensive analysis involving conducted on the BNs for each of the 3-month intervals of the COVID-19 pandemic. Their study illustrates the use of artificial intelligence methods to understand the working mechanism of economic systems. Kyrimi *et al.* (2025) advocate the use of BNs as a healthcare governance tool since it allows for counterfactual reasoning which can be used to assess what would have happened if treatments other than those occurred has been selected. Animah *et al.* (2024) provides a comprehensive literature review on Bayesian network applications in maritime industry emphasizing that uncertainty-related tasks such as accident investigation, reliability prediction and port sustainability are key priorities of the industry, making Bayesian networks a convenient and reliable method for analysis. Cinicioglu *et al.* (2017) explores the interaction between competitiveness and innovation using Bayesian networks and Cinicioglu *et al.* (2012) analyses the competitiveness of automative industry using Bayesian networks.

As demonstrated, there exists a broad range of application areas for the use of Bayesian networks. This wide variety exemplified above can be further expanded to include even more domains. The reasons are as follows: The intuitive appeal of Bayesian networks makes it a convenient tool accessible to a wider audience. Additionally, their strong computational foundation and ability to update in light of new evidence allow for accurate inference. Moreover, scenario analysis conducted on Bayesian networks enables the researcher to explore the answers of what-if questions, drawing insights from the updated network after incorporating new evidence(s). Another key advantage is their ability to represent and explore multiple input and output variables, unlike regression analysis, which is limited to a single output variable. This capability significantly enhances their prediction power. Lastly, Bayesian networks support counterfactual reasoning and backward propagation further strengthening their analytical and decision-making capabilities. In the following section, we describe the data set obtained from the EUROSTAT database which will be used for learning the Bayesian network for analysis.

Data Set: EU Circularity Indicators

The Circular economy Action plan was launched in 2020 as a key initiative under the European Green Deal and its goal is set as to transform the EU into a leader in sustainability and resource efficiency. The European Commission's Monitoring Framework, designed to keep track toward a circular economy, collects data of European countries across five thematic sections of production & consumption, waste management, secondary raw materials, competitiveness and innovation and global sustainability and resilience. These thematic sections encompass a total of eleven statistical indicators, some of which also feature sub-indicators. Seven different sub indicators from the EUROSTAT database are selected in this work to infer the probabilistic dependency structure in EU regarding the selected circularity indicators. For that purpose, using the data set obtained from EUROSTAT database between the years of 2012-2021 containing the data of 27 European countries the corresponding Bayesian network will be learned. The list of the countries is provided in Table 1 below which were selected on the basis of availability of data for the time frame considered. The list of the sub indicators selected for analysis are provided in Table 2 following along with their codes as used in the EUROSTAT database.

Table 1. The list of countries included in the data set used to learn the Bayesian network

Belgium (BE)	Estonia (EE)	Hungary (HU)	Malta (MT)	Slovenia (SI)
Bulgaria (BG)	Greece (EL)	Ireland (IE)	Netherlands (NL)	Slovakia (SK)
Cyprus (CY)	Spain (ES)	Italy (IT)	Poland (PL)	United Kingdom (UK)
Czech Republic (CY)	Finland (FI)	Lithuania (LT)	Portugal (PT)	
Germany (DE)	France (FR)	Luxemburg (LU)	Romania (RO)	
Denmark (DK)	Crotia (HR)	Latvia (LU)	Sweden (SE)	

Table 2. The list of countries included in the data set

Thematic section	Online data code	Indicator name	Sub indicator code	Corresponding sub indicator
Production & Consumption (cei_pc)	pc020	Material footprint	A, T_HAB, TOTAL, RMC	Annual total raw material consumption per inhabitant
	pc050	Generation of plastic packaging waste per capita	A,W150102,GEN,KG_HAB	Annual generation of plastic packaging in kilograms per inhabitant
Competitiveness & Innovation (cei_cie)	cie012	Private investment and gross added value related to CE sectors	A, GVA, PC_GDP	Gross value added on CE per capita
	cie012		A, INV, PC_GDP	Private investment in CE per capita
	cie_020	Patents related to recycling and secondary raw materials	A,Y02W,P_MHAB	Annual number of patents related to waste management per million inhabitants
Global Sustainability and Resilience (cei_gsr)	cei_gsr_010	Consumption footprint	A_SWS_P_HAB	Annual single weighted score per inhabitant
	cei_gsr030	Material import dependency	A_TOTAL_PC	Ratio of imports over direct material inputs

According to the EUROSTAT database, the set of variables used for this study are defined as follows:

Material Footprint (pc020): This indicator measures the global demand for raw materials (biomass, metal ores, non-metallic minerals, and fossil energy materials) that results from consumption and investments by households, governments, and businesses within the EU.

Generation of Plastic Packaging Waste per Capita (pc050): This indicator tracks the amount of plastic waste produced per person, specifically focusing on packaging materials. Packaging, in this context, refers to any material used to contain, protect, handle, deliver, or present goods throughout their lifecycle, from raw material to consumer. It also includes non-returnable packaging items.

Private Investment and Gross Added Value Related to Circular Economy Sectors (cie012): This indicator assesses the financial investments and value added by private sectors that are directly involved in circular economy activities. It reflects the economic contributions from industries focused on sustainability, recycling, and the reuse of materials.

Patents Related to Recycling and Secondary Raw Materials (cie_020): This indicator counts the number of patents issued that are related to recycling technologies and secondary raw materials. These patents are categorized using the Cooperative Patent Classification (CPC), focusing on innovations that improve recycling processes or create new uses for secondary raw materials.

Consumption Footprint (cei_gsr_010): The consumption footprint measures the environmental impacts of consumption in the EU and its member states. It combines data on how intensely products are consumed with the environmental effects of producing these goods, helping to assess the overall sustainability of consumption patterns.

Material Import Dependency (cei_gsr_030): This indicator calculates the EU's reliance on imported materials by comparing the volume of material imports to direct material inputs (DMI). It is expressed as a percentage, highlighting how much the EU depends on external sources for its raw materials.

The data set obtained from EUROSTAT database constitutes 10 years of annual data for the twenty seven countries listed in Table 1. This data set is transformed into a form where a country's data for each year corresponds to a line, resulting in 270 observations for the seven variables given in Table 2. Since the variables used in this study use different range of values all the variables are discretized using hierarchical discretization technique. Hierarchical discretization is an unsupervised method that begins with one bin per record and merges bins with the smallest mean differences until the desired number of states is reached (Cinicioglu *et al*., 2024). Accordingly, each variable is discretized with five states where the state beginning $s1\_$ refers to the lowest values for that variable and the state beginning as $s5$ refers to the state referring to the highest values of that variable. In the following section the discretized data set will be utilized for learning the BN.

Bayesian Network Analysis:

Exploring Dependency Structures via Bayesian Network

Using the discretized data set described in the previous section we will learn the corresponding Bayesian network demonstrating the dependency structure between the circular economy indicators selected. For learning the structure of the Bayesian network from the data, Bayesian search algorithm is employed which uses the hill-climbing structure with random starts. The Bayesian search algorithm identifies the most probable Bayesian Network (BN) structure *G* given the data *D* by maximizing the log-likelihood scoring function shown below. In this context, n denotes the number of variables in the BN, q_i represents the number of configurations of the$i$*th* variable's parent set, and r_i indicates the number of categories (or states) of the i*th* variable (Bouckaert, 1995). The terms N_{ijk} and N_{ij} correspond to the number of instances in the dataset *D*, where N_{ij} is the marginal count over the states *k* of the variable.

$$LL\,(G \mid D) = \sum_{i=1}^{n}\ \sum_{j=1}^{q_i}\sum_{k=1}^{r_i} N_{ijk} \log\left(\frac{N_{ijk}}{N_{ij}}\right) \qquad (2)$$

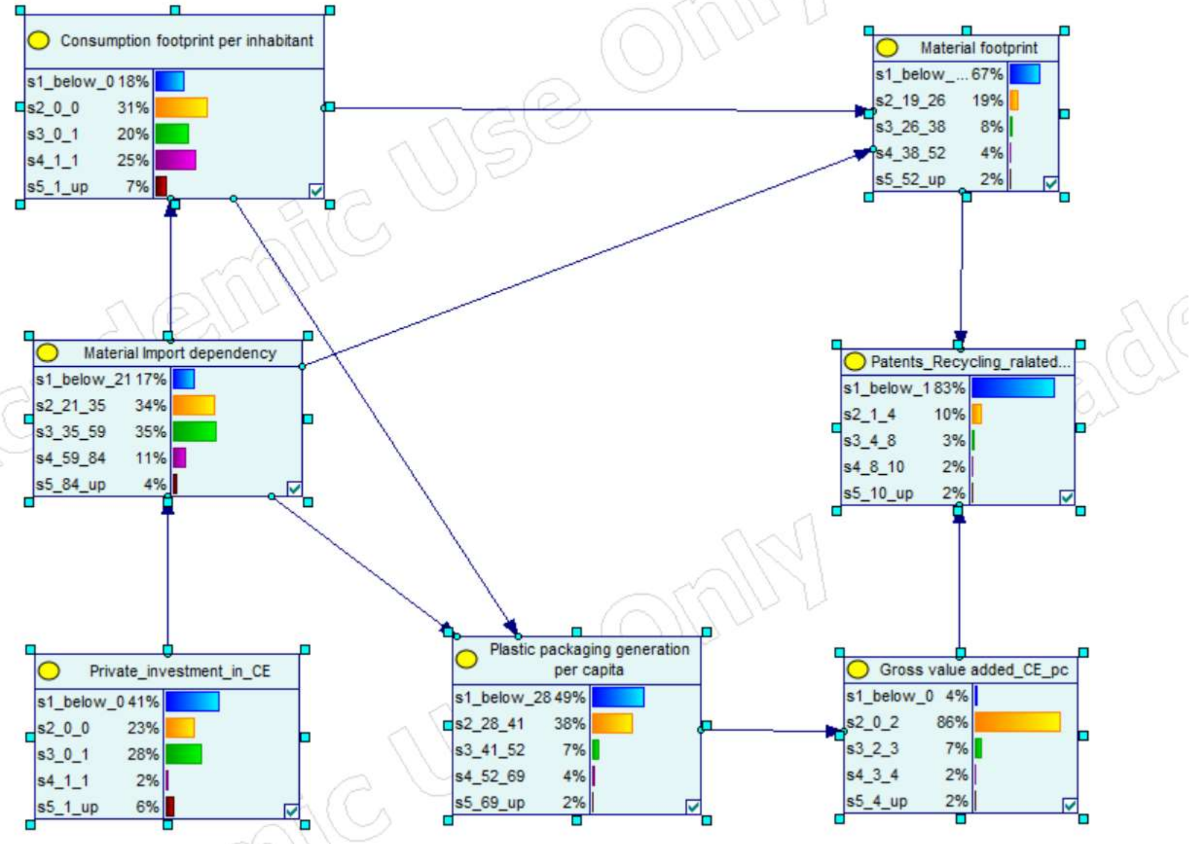
Once the structure learning of the Bayesian Network (BN) is completed, the parameters of the variables are estimated using the Expectation-Maximization (EM) algorithm (Dempster *et al*., 1977; Lauritzen, 1995). This algorithm follows an iterative process to estimate the conditional probability tables of the variables, aiming to maximize the likelihood of the observed data given the network model.

Figure 2 below illustrates the Bayesian network structure learned directly from the dataset. Each node in the network represents a variable, and alongside these nodes, marginal probabilities for each distinct state are displayed, providing clear insight into the distribution and trends of each variable across the data. For example, consider the node labeled "Patents related to Recycling," which reflects the annual count of patents filed per million inhabitants in relation to waste management and recycling technologies. Observing the probabilities, we note that state $s1$, representing the lowest category (below a value of 1), holds a substantial marginal probability of 83%. This significant finding indicates that, across most European countries examined during the ten-year span covered by the data, innovation and patent activity in recycling-related technologies remain strikingly limited. Given the context where a higher number of patents would indicate more robust innovative efforts and potential advancement towards circular economy goals, the observed concentration in the lowest patent state clearly highlights a notable gap in scientific and technological developments. Consequently, this analysis reveals a somewhat concerning stagnation in research outputs and innovation, suggesting that the current trajectory of scientific effort dedicated to advancing circular economy practices may not yet be sufficient to meet the ambitious targets envisioned by policy frameworks and sustainability initiatives.

Moreover, as illustrated in Figure 2 below, which shows the Bayesian network structure learned from the data, we observe a direct dependency between “Material import dependency” and both “Material footprint” and “Plastic packaging per capita”. Specifically, “Material import dependency” acts as a parent node to the other two variables. While in a Bayesian network the use of the chain rule and the assumption of conditional independence allows the influence of a variable to extend beyond its immediate children, the presence of an arc between two nodes always indicates a strong dependency structure. In this case, the arcs from “Material import dependency” to the other two variables confirm a substantial direct influence. More generally, wherever an arc is present between two variables in the network, it signals that a significant statistical dependency exists between them.

Another noteworthy observation concerns the variable “Consumption footprint,” which measures the sustainability of consumption by combining product use intensity with the environmental impact of production across EU member states. As illustrated in Figure 2, the marginal probabilities associated with this variable reveal a high degree of variation across its different states, encompassing low, medium, and high consumption profiles. This pattern stands in contrast to most other variables in the Bayesian network, which tend to exhibit one or two dominant states characterized by significantly higher marginal probabilities. Notably, two other variables—“Material import dependency” and “Private investment in the Circular Economy”—also exhibit broader variation across states, though less pronounced than that of “Consumption footprint.” This wider distribution suggests diverse structural conditions and policy environments across EU countries, as well as significant heterogeneity in consumption-related environmental pressures. It also reflects the longitudinal nature of the dataset, which spans a 10-year period during which consumption patterns and related indicators may have shifted considerably. In the following subsection scenario analysis will be conducted which will further shed light in the dependency structure and explain how the realization of different scenarios is changing our inferences regarding the set of variables.

Figure 2. The Bayesian network structure showing the probabilistic dependencies and marginal probabilities of the variables



Scenario Analysis

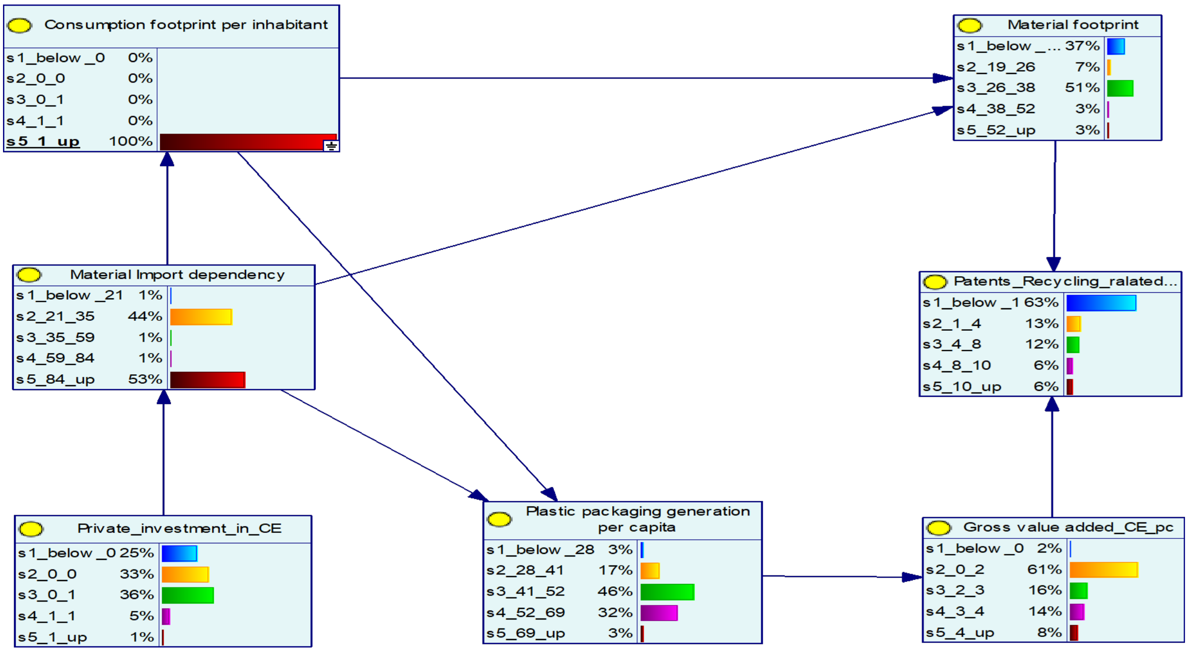
As the next step in our analysis, we apply the evidence propagation functionality of Bayesian networks to perform scenario analysis. This approach involves setting one or more variables to a specific state—effectively assigning a probability of 1 to that state—and then examining how this observation influences the posterior probabilities of other variables throughout the network.

In Figure 3, the variable "Consumption footprint per inhabitant" is observed in its fifth state *s*5, representing the highest level of consumption. By comparing the updated posterior marginal probabilities in Figure 3 with the baseline probabilities presented in Figure 2 (prior to the evidence), we observe a substantial increase in the likelihood of higher states for both "Plastic packaging waste per capita" and "Material footprint." This result aligns with expectations: as consumption intensifies, both plastic waste generation and material usage tend to rise accordingly.

However, more nuanced insights emerge when examining the response of two other variables—"Material import dependency" and "Patents related to recycling." Following the observation of high consumption (*s*5), the posterior probabilities for both variables shift towards higher states. This suggests a potential causal chain where increased consumption leads to greater reliance on imported materials, likely due to the depletion or insufficiency of domestic resources. Simultaneously, the rise in the state associated with patent activity implies that as environmental pressure from consumption intensifies, greater scientific and technological efforts are directed toward recycling and waste management solutions.

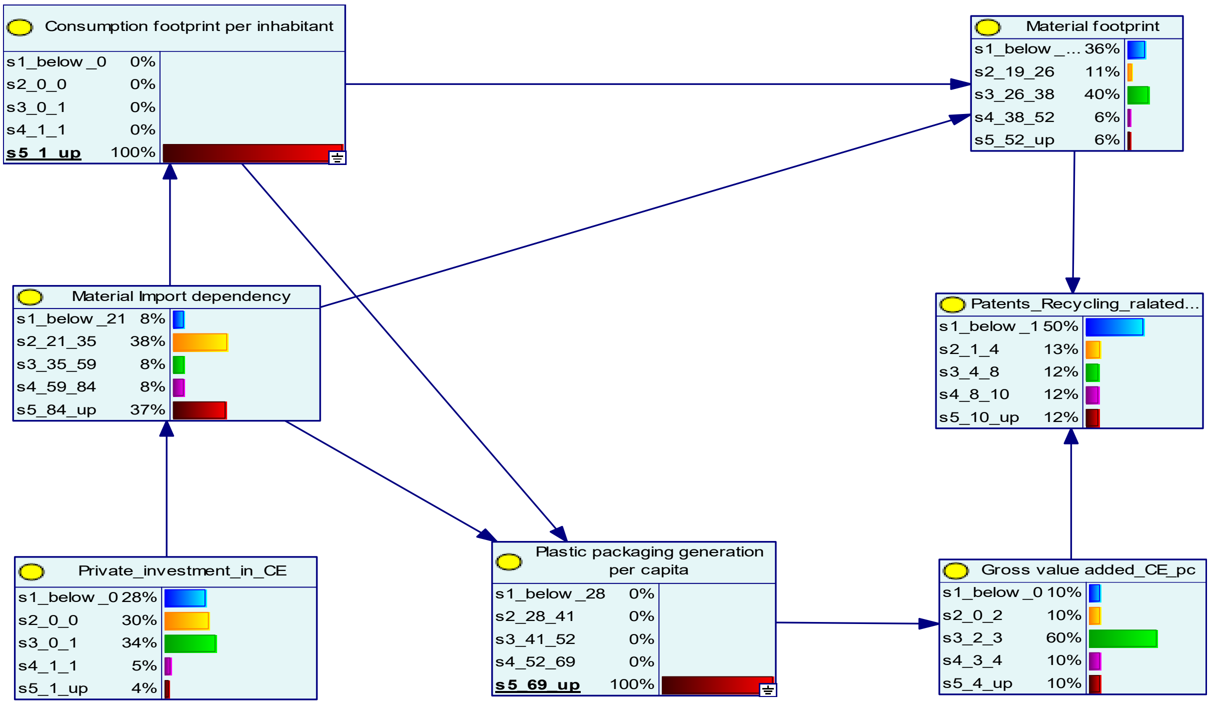
It is important to note, however, that this observed relationship might also reflect structural patterns in which countries with the highest consumption levels are concurrently those investing the most in circular economy research and innovation. Therefore, while the scenario analysis supports intuitive dependencies, it also highlights the potential influence of underlying economic and policy environments that shape both consumption behavior and CE-related advancements.

Figure 3. The updated BN after observing the evidence for *P* (Consumption footprint per inhabitant = s5|Material Import Dependency)



As the next step of the analysis, we extend our investigation by incorporating additional evidence: namely, that "Plastic packaging generation per capita" is in its fifth state (*s*5), representing the highest level of plastic packaging use which is represented in Figure 4 below. At this stage, both observations—"Consumption Footprint per inhabitant" and "Plastic packaging generation per capita"—are simultaneously set to their fifth state (*s*5), indicating the highest levels for each. Upon entering this evidence, the updated posterior probabilities in the Bayesian network reveal slight improvements in the probabilities of higher-value states for the variables "Patents related to CE" and "Gross value-added CE". These two indicators reflect positive developments in the context of the circular economy, where higher values represent a more favorable position. Consequently, one may interpret this result to suggest that increased environmental waste can potentially trigger a counter-response by accelerating progress toward circular economy solutions. As represented through these scenario analyses conducted Bayesian networks represent a favorable tool in terms of the policy analyses. In the following section, we summarize our research and conclude.

Figure 4. The updated BN after observing the evidences for
***P* (Consumption footprint per inhabitant = s5|Material Import Dependency) &*P* (Plastic packaging generation per capita= s5 |Material Import Dependency, Consumption footprint per inhabitant = s5)**



Conclusions

The fast depletion of natural resources and the substantial increase in the amount of waste generated over the years is the result of the reckless consumption pattern that humankind has followed over the last century. As a response to the resource-intensive and environmentally harmful patterns of consumption and production, the circular economy has emerged as a significant and rapidly growing concept. Launched alongside the 2015 UN Agenda for Sustainable Development, the EU's Circular Economy Action Plan and European Green Deal aim to promote sustainable growth, improve resource efficiency, and reach climate neutrality by 2050. On the other hand, for impactful consideration and implementation of circular economy, it is important to apply the right set of Circular economy indicators to assess the current state and guide progress effectively. Moreover, it is also very important to observe the dependency structure between the set of CE indicators used for identification purposes. Understanding how changes in one or more circular economy (CE) indicators affect others is essential for effective policy analysis and responsible legislation. In this study, we use seven CE indicators from the EU Monitoring Framework published by Eurostat, covering the thematic areas of production and consumption, competitiveness and innovation, and global sustainability and resilience. Our analysis shows that "Consumption footprint" varies significantly across EU countries, reflecting diverse environmental pressures. Scenario analysis reveals that higher consumption levels increase plastic waste, material use, and import dependency, while also correlating with greater innovation in recycling. These findings suggest that rising environmental impact may drive circular economy advancements, highlighting the value of Bayesian networks for policy analysis.

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