Enhancing the Circular Economy in the European Union with Machine Learning

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Abstract. *For the European Union, the 2030 Agenda represents a comprehensive framework that aims to achieve objectives such as sustainable development, promoting economic growth, social inclusion, and environmental protection by the year 2030. One of the main strategies of the European Union's Agenda 2030 is to implement a circular economy (CE) with the aim of supporting elements such as sustainable development, emphasizing resource efficiency, waste reduction, and a shift towards renewable materials. One of the most important tools that can help the circular economy achieve its objectives is Machine Learning (ML). Machine Learning can transform the economy by driving innovation, improving efficiency, and enabling data-driven decision-making across industries.*

Circular economy and machine learning intersect by leveraging data-driven insights to optimize resource use, improve recycling processes, and enhance product life cycles for greater sustainability.

The research paper's purpose is to highlight the role that the use of ML can have in the implementation of the principles and approaches specific to the circular economy. The paper describes the specific aspects of the circular economy, types of Machine Learning algorithms and the support that ML can offer EC. A data analysis using a specific ML algorithm is also performed. However, it is important to note that the research is limited by the choice of specific methods and datasets, without extending the analysis to various economic sectors or to the political and social influences that may affect the integration of these technologies. The research also does not address the possible ethical and security challenges associated with the use of machine learning algorithms in the circular economy.

Keywords: circular economy, machine learning, European Union, artificial intelligence.

Introduction

Within the European Union (EU) framework, one of the main commitments promised to be achieved is represented by the United Nations 2030 Agenda for Sustainable Development (Alpopi et al., 2022). This agenda includes several topics like 17 Sustainable Development Goals (SDGs), a specific action plan to achieve SDGs, Green Deal (adopted in 2019) (CEES, 2023; Ruiz et al., 2023; Mogos et al., 2023), global cooperation and engagement, etc. In addition to these topics, the

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priorities of the European Commission for the period 2019-2024 are also added, the period in which aspects such as (EC 2023 - https://commission.europa.eu/strategy-and-policy/priorities-2019-2024_en) were pursued: a Europe fit for the digital age, an economy that works for people, a stronger Europe in the world, promoting our European way of life, a new push for European democracy.

The agenda also represents a global framework to promote prosperity while protecting the planet. The EU has integrated these goals into its own policies and strategies, aligning them with its vision for a sustainable future (Angheluta et al., 2019). The 17 objectives have determined the main directions regarding strategies and policies to build a sustainable future, largely in terms of used resources. An example in which the use of resources can be optimized is the consumption of resources intended for the export and import of products of various types.

A key element in achieving these goals is the approach based on the circular economy (CE). CE represents a sustainable economic model that aims to use the available resources as efficiently as possible and at the same time to minimize the degree of waste (Buzoianu, et al., 2024). This economic model proposes, as its name suggests, a circular approach (Rădulescu et al., 2022). This basically represents a circuit in which all the elements used (primary resources, materials used and products obtained) must be used, refurbished, remanufactured, and recycled for as long as possible (Burlacu, Bran et al., 2022).

An important element used in the fulfillment of these objectives set by the EC is represented by the field of Artificial Intelligence (AI). AI represents an interdisciplinary field that encompasses several subfields and applications. The most important areas of AI are designed and implemented to simulate and in many cases to replicate human-like cognitive functions. Examples of these functions are learning, decision-making, language understanding, problem-solving, and perception.

Machine Learning (ML) is part of AI that deals with the design and implementation of algorithms that allow computers to learn from and make decisions based on data sets. Decision-making will be based solely on data analysis, without any explicit mention of this. Currently, it can be said that ML is the part of AI that is experiencing the fastest development. Given the context imposed by the development of the circular economy, it can be stated that ML represents a tool of major importance to achieve its objectives (Radulescu et al., 2018).

The main objective of this paper is to identify the main characteristics of CE and correlate them with ML properties. Through this association, solutions can be identified for specific CE actions that can lead to the achievement of objectives to the greatest extent. The degree of novelty of the author's approach consists in using ML for several specific CE actions. The author also proposes an example of analysis using ML for high-tech products exported by EU countries. The purpose of this analysis is to group EU countries based on their exports of high-tech products and to identify patterns in the data, taking into account the quantities exported and a 10-year time period (2013-2022).

The research questions that the authors answer in this article: (Q1): What are the main characteristics of EC and how they are correlated with the approaches offered by ML? (Q2): how ML could be used by applying specific algorithms to analyze the export of high-tech products over a 10-year period (2013-2022) by grouping the EU countries based on this information?

To obtain the answer to the second research question (Q2), data from the Eurostat website (Eurostat 2024 - https://ec.europa.eu/eurostat) were used. The dataset was previously processed and analyzed within the Weka software (Weka 2024) for which it uses specific ML algorithms, respectively for data mining.

Literature review

The working framework of the 2030 Agenda includes a set of 17 Sustainable Development Goals (SDGs) that must be fulfilled by the year 2030. Among the aspects targeted by them we can mention (EC, 2024; Lella et al., 2024; Mogos et al., 2024; Kulkarni et al., 2022; Mogos et al., 2021): education, responsible consumption and production, clean water and energy, industry and innovation, poverty, hunger, health, sustainable cities, climate action, etc.

Among the 17 objectives, the SDG no.12 – "Responsible Consumption and Production" targets in particular sustainable production, consumption, and waste management. These elements represent specific characteristics of the circular economy action plan (CEAP) (EEE, 2024; Papamichael et al., 2023; Katsanakis et al., 2023; Voulgaridis et al., 2022). Among the key areas of the CEAP it could be mentioned (Fig. 1):

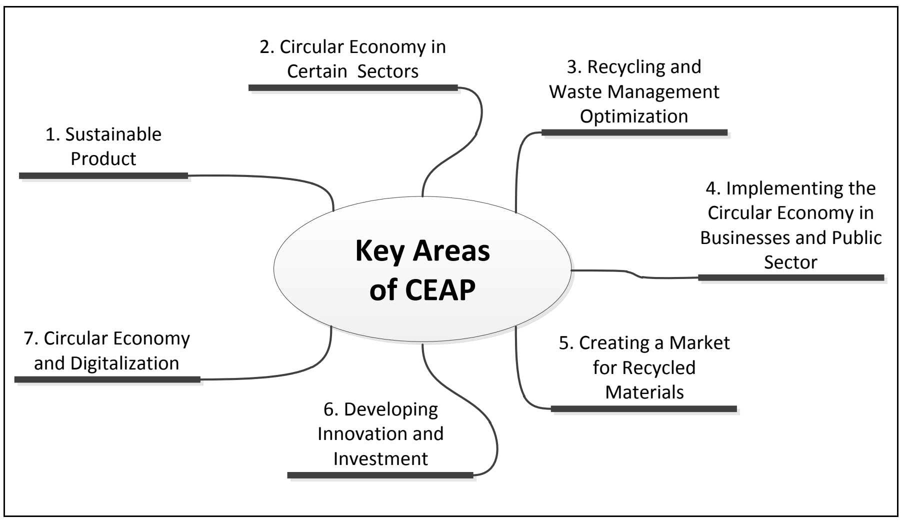

Figure 1. Key areas of Circular Economy Action Plan

Source: Authors' own research.

Sustainable Product: The plan highlights the importance of eco-design, ensuring that products are created with sustainability as a priority. This involves designing products to be easier to repair/reuse/recycle or upgrade. New EU eco-design regulations for sustainable products will ensure that items introduced to the EU market adhere to strict environmental standards and support the transition to a CE.

- Circular Economy in Key Sectors: The CEAP targets sectors with the highest potential for circularity, such as electronics, plastics (Plastic Strategy was introduced, strategy which aims to reduce single-use plastics and boost recycling rates), textiles (Textile Strategy was proposed, strategy which addresses issues of fast fashion, promote the use of sustainable materials, and enhance textile recycling efforts), construction (incorporation of recycled materials in construction and promoting the building designs that are easily disassembled and reused) and food.
- Recycling and Waste Management Optimization: The EU new approaches aim to increase recycling rates and reduce landfilling by promoting better waste collection, sorting, and processing systems.
- Implementing Circular Economy in Business and Public Sector: The businesses are encouraged to adopt circular business models and sustainable procurement practices. These

must prioritize circularity in both public and private sectors. Also, the CE must be integrated into EU trade agreements and international policies.

- Creating a Market for Recycling Materials: A key challenge in the transition to a CE is ensuring that there is created a demand for recycled materials and reused/refurbished products. The EU aims to establish standards for recycled materials and promote markets for secondary raw materials.
- Developing Innovation and Investment: Through programs like Horizon Europe, EU provides funding in order to foster research and innovation. the main areas that will benefit from them are areas like green and recycling technologies, and circular business models. One of the main goal of the European Investment Bank (EIB) is to support investments in CE projects.
- Circular Economy and Digitalization: Through programs like Horizon Europe, EU provides funding in order to foster research and innovation. the main areas that will benefit from them are areas like green and recycling technologies, and circular business models. One of the main goal of the European Investment Bank (EIB) is to support investments in CE projects.

Machine Learning (ML), as part of AI, allows systems to learn from data, identify patterns, and make decisions without being explicitly programmed. ML specific algorithms enable electronic devices to learn from past experiences (comprised in data) and improve over time. The main algorithms types are: Supervised Learning, Unsupervised Learning, and Reinforcement Learning (Ashish P., 2018; Zhou et al., 2023). As can be seen in Table 1, many fields can benefit from the use of ML, the multitude of specific algorithms trying to provide solutions for many real-life problems.

Table 1. Machine Learning – Algorithms Type

Main algorithm type	Specific algorithms	Example of applications
A. Supervised Learning	Convolutional Neural Networks (CNNs)	Image Classification
	Logistic Regression, Naive Bayes	Spam Email Detection
	Support Vector Machines (SVMs) or Random Forests	Medical Diagnosis
	Linear Regression	Predicting House Prices
B. Unsupervised learning	K-Means Clustering, Hierarchical Clustering	Customer Segmentation
	Collaborative Filtering, Autoencoders	Recommendation Systems
	Principal Component Analysis (PCA)	Dimensionality Reduction
	Isolation Forest, DBSCAN	Anomaly Detection
C. Semi-Supervised Learning	Combines A and B category.	Image Labeling, Speech Recognition, Text Classification
D. Reinforcement Learning	Q-Learning, Deep Q-Networks (DQN)	Robotics
	AlphaGo, Proximal Policy Optimization (PPO)	Game Playing
	Combines Reinforcement Learning with Deep learning	Autonomous Vehicles

Main algorithm type	Specific algorithms	Example of applications
E. Self-Supervised Learning	BERT or GPT models	Natural Language Processing (NLP)
	Learning useful representations of images without direct supervision	Computer Vision
F. Transfer Learning	like a CNN trained on a large dataset of general images	Medical Imaging
	using a model trained on a large text corpus (like BERT)	Sentiment Analysis
	Speech-to-Text models	Voice Assistants
G. Deep Learning	Convolutional Neural Networks (CNNs)	Computer Vision
	Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks).	Speech Recognition
	Transformer models like GPT or BERT	Natural Language Processing
	Generative Adversarial Networks (GANs)	Generative Models
H. Ensemble Learning	Random Forests, Gradient Boosting Machines (GBM)	Credit Scoring
	Boosting or Stacking methods	Stock Market Prediction
	XGBoost	Medical Diagnosis

A term associated with ML is data mining (DM). Many ML algorithms are considered to be of the data mining type because they allow the extraction of patterns from the data and provide insights, smartly substantiating decisions and automatic predictions. An example of DM are the cluster algorithms.

Circular Economy and Machine Learning

Considering the characteristics of the circular economy, ML can play a particularly important role in applying its principles. The main identified aspects of CE that can be improved and optimized by using ML are mentioned below. For each aspect, a direction is mentioned that, through the use of ML, can lead to improved results. These aspects are:

a) optimize the use of resources: using ML can improve the production process, thus minimizing the waste and energy consumption. This could also aim at optimizing the supply chain to reduce the excess of materials used.
b) supply chain transparency: use ML to enhance transparency in supply chains, allowing companies to track materials' origins and ensure sustainable sourcing. In this way, attention can be directed to truly sustainable sources.
c) material recovery: use ML and computer vision to sort several types of recyclable materials more efficiently. Automated systems can identify and separate different types of materials for recycling, improving in this way the recovery rates.
d) perform predictive maintenance for products: using ML, it is possible to predict more accurately when a device or equipment will no longer function at normal parameters (fail to work). This predictive maintenance can extend the life of the products and implicitly reduce waste through periodic spot repairs instead of replacing the equipment or parts altogether.
e) analysis of the product lifecycle: use the ML tools to analyze the lifecycle of products, assessing environmental impact of these and suggesting improvements and optimization in design for longevity and recyclability process.

f) product design centered on disassembly: ML can offer or create algorithms that help designers model products to create designs that take into account an easier disassembly and recycling, ensuring that components can be reused or repurposed for other products.
g) insights of the consumer behavior: use ML to analyze consumer data and choices in order to identify trends in sustainable product preferences, helping companies adjust their offerings and product variety to align with CE principles.
h) transform waste into resource: implement ML-based solutions that aims to identify and analyze waste sources, finding innovative ways to transform waste materials into valuable resources that will be used in another context.
i) energy management: ML can offer solutions in order to optimize energy usage in production facilities. This can be done by predicting demand and adjusting operations accordingly, supporting energy efficiency.
j) feedback loops: build systems that collect data regarding the product performance and recycling rates (for the product as a whole or some of its components), using ML to create feedback loops that inform and improve future design and production processes.

In this section, the answer to research question Q1 is provided: "*What are the main characteristics of EC and how they are correlated with the approaches offered by ML?*"

In order to minimize waste and energy consumption, the optimization of resources in the field of transport represents one of the aspects that can be improved. A large part of the daily transports are aimed at the export and import of goods. In order to exemplify the use of ML, a clustering process for data aimed at the export of high-tech products for EU countries is carried out.

Methodology

In this section, the methodology used to carry out the clustering process is described, process which refers to the grouping of EU countries from the point of view of exports of high tech products. The analysis is carried out over a period of 10 years, covering the period 2013-2022.

To perform this analysis, the CRISP-DM methodology was used. This methodology includes 6 stages, namely Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation and Deployment (Schröer et al., 2021).

Business Understanding phase focuses on identifying and understanding business objectives and converting them into ML and data mining problems that can be solved with the help of specific algorithms. Specific activities: defining the business problem and objectives, determining the goals of the project and how to evaluate the achieved success, defining the context of the problem and the potential of the data, transposing the business objectives into the ML and data mining problem.

The second phase, data understanding, aims to identify and understand the data needed and used in the analysis. Usually this stage involves collecting data from several sources and exploring them to identify issues, patterns, and relationships that may inform further analysis. Specific activities: collecting data, checking their quality (missing values, outliers, errors, etc.), exploring data, identifying the relationships between attributes and checking if they are suitable for analysis.

The third stage, data preparation, involves taking actions on the data, actions such as: data cleaning, processing and transformation into a suitable form for modeling. This stage is the most time-consuming because real-life data is often incomplete, inconsistent, or requires extensive preprocessing. Specific activities: clean the data, selection of relevant elements/attributes (algorithms can be applied to determine the information input for each attribute), data normalization and scaling (when necessary), in order to develop the model, the data is divided into training, testing, and validation sets.

In the fourth stage, the modeling stage, specific algorithms are applied to the data prepared in order to build the models necessary to solve the business problem. After testing several modeling techniques, the one that offers the best results will be chosen. Specific activities: the best modeling technique is chosen (e.g., clustering, classification, etc.), training models are used and parameters are adjusted, models are evaluated using specific metrics, several modeling techniques are applied until the best model for the problem.

In the fifth phase, evaluation, it is verified that the built model corresponds to the business objectives and is ready to be applied. Specific activities: model evaluation on test data, checking the results that they are in agreement with the business objectives, identifying the limitations of the model, determining if the model still needs improvements.

The sixth stage, deployment, the model is used in the real world. Specific activities: the use of the model within an environment (e.g., platform, system, etc.), the performance of the model is monitored, the results are analyzed, and decisions are made based on the results provided by the model.

For the realized analysis, the data were collected from Eurostat (Eurostat, 2024). The data set includes information on the exports of high-tech products made by EU countries for the period 2013-2022. The values are expressed in percentages. The results were obtained following the successive application of the Simple-K Means algorithm. This algorithm is a clustering technique that has the goal of creating partitions within the data set based on a predefined number of distinct groups (k) by minimizing the variance within each cluster. During the process, cluster centroids are updated based on the mean of assigned points.

Results and discussions

The data set shows the share of exports of all high technology products in total exports. High technology products are defined according to SITC Rev.4 (SITC Rev.4, 2024 as the sum of the following products: Aerospace, Computers-office machines, Electronics -telecommunications, Pharmacy, Scientific instruments, Electrical machinery, Chemistry, Non-electrical machinery, Armament. The total exports for the EU do not include the intra-EU trade.

About the data set: the last data update was in 31/01/2024, time period is annual for 10 years (2013-2022), unit of measure: percentage.

The EU countries comprised in the analysis: Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden. In Table 2 there are mentioned the export values at the EU level for the 10 years (2013-2022). Overall, a constant increase can be observed between 2013-2019 and a slight decrease in 2019 – 2020 period (Fig. 2).

Table 2. High Tech Exports

Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
European Union - 27 countries (Percentage)	14,63	14,83	16,04	16,48	16,68	16,89	17,9	17,7	17,65	17,32

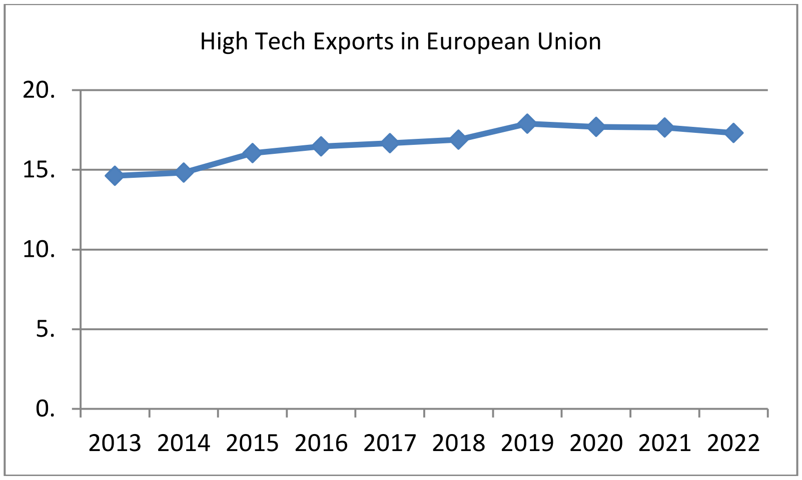

Fig. 2 High-Tech Exports in EU for 2013-2022 periods

Source: Eurostat, 2024.

Applying the Simple K-Means clustering algorithm, 3 clusters were obtained. Information about these 3 clusters is given in Table 3.

Table 3. Cluster centroids

Attribute	**Cluster 0** (8 countries – 30%)	**Cluster 1** (16 countries – 59%)	**Cluster 2** (3 countries – 11%)
Country (the most significant for the cluster)	Austria	Belgium	France
Year_2013	15.92	7.08	23.26
Year_2014	15.72	6.68	23.45
Year_2015	16.14	7.57	23.42
Year_2016	15.67	7.60	22.88
Year_2017	14.29	7.75	25.86
Year_2018	14.19	7.71	26.46
Year_2019	15.42	7.65	27.91
Year_2020	15.27	8.42	30.26
Year_2021	14.25	8.17	28.55
Year_2022	13.67	7.83	30.24

Considering the distribution into clusters, the following can be mentioned:

- in the first cluster (cluster 0) countries were distributed that have the value of exports in the range of 13-15%, these countries are: Austria, Czech Republic, Estonia, Germany, Hungary, Luxembourg, Netherlands, and Sweden. The most representative country for this cluster is Austria.
- in the second cluster (cluster 1) countries were distributed that have the value of exports in the range of 6-8%, these countries are: Belgium, Bulgaria, Croatia, Republic of Cyprus, Denmark, Finland, Greece, Italy, Latvia, Lithuania, Poland, Portugal, Romania, Slovakia, Slovenia, Spain. The most representative country for this cluster is Belgium.

- in the third cluster (cluster 2) countries were distributed that have the value of exports in the range of 22-30%, these countries are: France, Ireland, Malta. The most representative country for this cluster is France.

Following the results obtained, an answer is given to research question number 2, respectively: (Q2): how ML could be used by applying specific algorithms to analyze the export of high-tech products over a 10-year period (2013-2022) by grouping the EU countries based on this information?

Conclusion

Although important progress has been made in aligning policies on the SDGs within the EU, there are still some challenges to overcome. These challenges consist in particular in: identifying an optimal balance between achieving the Green Deal objectives and development policies, identifying EU actions to provide support for sustainable development in countries where it is most needed, and integrating the SDGs into development policies, especially for countries with less developed economies.

The circular economy finds in ML a powerful tool that offers important support in terms of achieving its objectives. The mentioned ideas regarding the use of ML for CE can contribute significantly to the goals of a CE, promoting sustainability while leveraging the power of ML. Due to its characteristics, ML can easily identify solutions for a longer use of products, their recycling, the reuse of components, and ways of reconditioning to offer a new life to products. From this point of view, the export of high-tech products (and not only) will be able to focus much better on the components, products, and elements that are truly necessary. The analysis performed using ML aims to exemplify its use in identifying countries with similar export levels for high-tech products.

The limitations of the research are determined by the exclusive focus on the intersection of the circular economy and Machine Learning, without including a detailed analysis of other relevant technologies that can support the implementation of circular economy principles. Also, the data analysis performed uses a specific set of machine learning algorithms, which may limit the generalizability of the results to the entire economy. Another important aspect is that the research does not consider the impact of socio-economic or political externalities in the application of machine learning technologies in the circular economy.

As future research directions, several elements that are closely related to the circular economy can be taken into account in the analysis. In this way, by applying specific ML algorithms, correlations can be identified that can help achieve the CE objectives.

References

Alpopi, C., Burcea, Ș. G., Popescu, R. I., & Burlacu, S. (2022). Evaluation of Romania's Progress in Achieving SDG 11: Sustainable Cities and Communities. *Applied Research in Administrative Sciences, 3(2), 76-87.*

Angheluta, S. P., Burlacu, S., Diaconu, A., & Curea, C. S. (2019). The Energy from Renewable Sources in the European Union: Achieving the Goals. *European Journal of Sustainable Development, 8(5), 57.*

Ashish P. (2018), Machine Learning Algorithm Overview, https://medium.com/ml-research-lab/machine-learning-algorithm-overview-5816a2e6303)

Burlacu, S., Bran, F., Rădulescu, C. V., & Bodislav, D. A. (2022). The circular economy-Romania's paradigm from the perspective of EU principles and directions for 2050. In *Proceedings of the International Conference on Business Excellence* (Vol. 16, No. 1, pp. 278-284).

Buzoianu, O. A. C., Iacob, O., Mateescu, V. M., & Burlacu, S. (2024). Balancing Economic, Environmental, and Technological Systems for Sustainable Agricultural Development in Romania. *European Journal of Sustainable Development*, *13*(4), 153-153.

CEES (2023). Accessed October 2024, https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en

EC (2023). Accessed November 2024, https://commission.europa.eu/strategy-and-policy/priorities-2019-2024_en

EC (2024). Accessed November 2024, https://commission.europa.eu/strategy-and-policy/sustainable-development-goals_en

EEE (2024). Accessed October 2024, https://environment.ec.europa.eu/strategy/circular-economy-action-plan_en

Eurostat (2024). Accessed November 2024, https://ec.europa.eu/eurostat

https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an_5.pdf

https://ecsdev.org/ojs/index.php/ejsd/article/view/1238

https://journals.plos.org/sustainabilitytransformation/article?id=10.1371/journal.pstr.0000020

https://www.sciencedirect.com/science/article/pii/S138912862200490X

https://www.sciencedirect.com/science/article/pii/S1470160X24007052

https://www.sciencedirect.com/science/article/pii/S1877050921002416

https://www.sciencedirect.com/science/article/pii/S2352554123003649

Katsanakis N., Ibn-Mohammed T., Moradlou H., Godsell J. (2023). Circular economy strategies for life cycle management of returnable transport items, Sustainable Production and Consumption, Volume 43, 2023, Pages 333-348, ISSN 2352-5509, https://www.sciencedirect.com/science/article/pii/S2352550923002683

Kulkarni S, Hof A, Ambrósio G, Edelenbosch O, Köberle AC, van Rijn J, Detlef van Vuuren. (2022). Investment needs to achieve SDGs: An overview. PLOS Sustain Transformation 1(7),

Lella L., Oses-Eraso N., Stamos I. (2024). Pioneering a sustainable development goals monitoring framework for European regions, Ecological Indicators, Volume 166, 2024, ISSN 1470-160X,

Mogos R.I., Negescu-Oancea D.M., Burlacu S., Troaca V.A. (2021). Climate Change and Health Protection in European Union, in European Journal of Sustainable Development, Vol. 10, No. 3 (2021), IDS Number: Xa7tp, WOS: 000720844500008, ISBN 2239-5938, 12 pagini,

Mogoș R.I., Crețu R. F., Dinu M. & Gomboș C. I. (2024). Circular Economy and Recycling of Electronic Products in the European Union, eISSN: 2558-9652, Language: English, Published Online: Jul 03, 2024, Page range: 898 – 912, DOI: https://doi.org/10.2478/picbe-2024-0078, published by Sciendo

Mogoș R.I., Petrescu I., Chiotan R.A., Crețu R.C., Troacă V.A., Mogoș P.L. (2023). Greenhouse gas emissions and Green Deal in the European Union. Front. Environ. Sci. 11:1141473. doi: 10.3389/fenvs.2023.1141473

Papamichael I., Voukkali I., Loizia P., Stylianou M., Economou F., Vardopoulos I., Klontza E., Lekkas D., Zorpas A. (2023). Measuring Circularity: Tools for monitoring a smooth transition to Circular Economy, Sustainable Chemistry and Pharmacy, Volume 36, 2023, 101330, ISSN 2352-5541, https://doi.org/10.1016/j.scp.2023.101330,

Radulescu, C. V., Bodislav, D. A., & Burlacu, S. (2018). Demographic Explosion and IT Governance in Public Institutions. *Managerial Challenges of the Contemporary Society. Proceedings*, *11*(1), 18.

Rădulescu, C. V., Bran, F., Bodislav, D. A., & Burlacu, S. (2022). Circular Economy in Infographics. In *Proceedings of the International Conference on Business Excellence* (Vol. 16, No. 1, pp. 420-426).

Ruiz J., Martin-Moreno J.M., Perez R. (2023). Mid-term policy considerations of the EU green deal, Energy Strategy Reviews, Volume 50, 2023, 101239, ISSN 2211-467X, https://www.sciencedirect.com/science/article/pii/S2211467X2300189X

Schröer C., Kruse F., Gómez J.M. (2021). A Systematic Literature Review on Applying CRISP-DM Process Model, Procedia Computer Science, Volume 181, 2021, Pages 526-534, ISSN 1877-0509,

SITC Rev.4 - Standard International Trade Classification, Revision 4, (2024). Eurostat indicators on High-tech industry and Knowledge – intensive services, Annex 5 – High-tech aggregation by SITC Rev.4,

Voulgaridis K., Lagkas T., Angelopoulos C.M., Nikoletseas S. (2022). IoT and digital circular economy: Principles, applications, and challenges, Computer Networks, Volume 219, 2022, 109456, ISSN 1389-1286,

Weka (2024). Accessed October 2024, https://ml.cms.waikato.ac.nz/weka

Zhou S.L., Shah A.A., Leung P.K., Zhu X., Liao Q. (2023). A comprehensive review of the applications of machine learning for HVAC, DeCarbon, Volume 2, 2023, ISSN 2949-8813, https://www.sciencedirect.com/science/article/pii/S2949881323000239