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The circular economy (CE) paradigm has recently gained increasing attention in both academic and policy circles. The existing literature has stressed that the transition to the CE paradigm implies innovation that aims to change consumption and production behaviors and technologies. Empirical studies have focused on the drivers and effects of the adoption and generation of CE innovations, based on survey and patent data, respectively. However, identifying and tracking CE innovations through patents has been challenging due to the lack of a domain-specific classification system. Existing methods are often insufficient to capture the diversity and complexity of CE technologies. This paper introduces a replicable methodology for identifying and analyzing CE patents, combining large language models (LLMs), a fine-tuned transformer classifier, and unsupervised topic modeling techniques. Applying this approach to European patent data uncovered sectoral and geographical patterns in CE innovation, highlighting key technological trends aligned with CE principles. The findings point to widespread and growing engagement with circular strategies, particularly reuse and recycling. The study provides a flexible tool for CE mapping and offers actionable insights for researchers, policymakers, and practitioners interested in innovation-led sustainability transitions.

1 Introduction

In recent decades, the debate about circular economy (CE) has gained momentum, as it represents a promising alternative to the traditional linear model of ”take, make, and dispose” [Barros et al., 2020]. Increasing environmental concerns, supportive global policies, technological advancements and emerging business opportunities are the main factors driving this growing interest, as the world faces resource depletion, waste accumulation and climate change [Geissdoerfer et al., 2017, Nikolaou et al., 2021].

CE can be defined as an industrial system intentionally designed to be restorative or regenerative, focusing on renewable energy use, elimination of toxic chemicals that hinder reuse, and waste reduction through innovative design in materials, products, systems, and business models [Ellen MacArthur Foundation, 2013]. Unlike linear models that prioritize resource consumption, it highlights the crucial role of environmental sustainability by improving resource management [Yuan et al., 2006] and allowing the decoupling of economic growth from resource consumption [Bocken et al., 2016, Wijkman and Berglund, 2017, Kjaer et al., 2019].

Exploring CE through the lens of innovation economics offers valuable insight into how transformative innovations can drive economic development while ensuring environmental sustainability and resource efficiency [Stankevičienė and Nikanorova, 2020]. Building on Schumpeter's theory of economic development, which identifies innovation as the main force behind economic progress and global competitiveness [Schumpeter, 2017], integrating CE principles into the eco-innovation economic framework could provide a theoretical basis for understanding the economic mechanisms and incentives that promote the development of circular solutions [de Jesus and Mendonça, 2018, Grafström and Aasma, 2021]. This approach is particularly relevant in contexts where environmental sustainability has become a critical policy imperative [Hobson and Lynch, 2016, Fratini et al., 2019, Campbell-Johnston et al., 2020].

Given the relevance of innovation in the transition to CE, empirical research has increasingly investigated the determinants and effects of both the adoption [Ren and Albrecht, 2023, Antonioli et al., 2022a,b, Quatraro and Ricci, 2023, Segarra-Blasco et al., 2024] and the generation [Fusillo et al., 2024, Valero-Gil and Scarpellini, 2024, Rainville et al., 2025] of CE innovations. However, the precise identification and tracking of CE innovations through patents has remained challenging due to the absence of a domain-specific classification. Existing methods based on keyword retrieval or Cooperative Patent Classification (CPC) and International Patent Classification (IPC) have limitations in capturing the full complexity and diversity of CE technologies. Keyword retrieval methods face challenges due to the inherent heterogeneity of CE technologies, which span a wide range of sectors and processes, making them difficult to define within a single framework [Burger et al., 2019]: keywords can be too broad or vague, leading to the inclusion of irrelevant patents, or too narrow, excluding key innovations that align with CE principles but use non-standard terminology [Hambarde and Proença, 2023]. CPC or IPC classification, which categorizes patents based on technical domains, is not designed for emerging fields such as CE [Nikolova-Minkova, 2023, Eurostat, 2022, Fusillo et al., 2024, Caldarola et al., 2024]. The patent class more closely related to

CE topics, the Y02W, deals with "Climate change mitigation technologies related to wastewater treatment or waste management", but it does not include different aspects related to CE, such as optimization practices, resource efficiency, and design for reuse or remanufacturing.

This paper addresses these gaps by proposing a novel methodology that combines LLMs, a fine-tuned transformer model, and topic modelling techniques to identify and classify CE-related patents accurately. Specifically, the goal is to answer two interrelated research questions.

1. *How can advanced NLP and GenAI methods improve the identification and classification of CE patents beyond the conceptual and coverage limitations of existing keyword- and CPC-based approaches*

2. *What trends emerge from the distribution of identified CE patents across sectors, technological fields, and geographical regions?*

By addressing these questions, this study contributes to the innovation economics literature by providing an empirically grounded approach to analyzing technological change within the CE. This paper combines methodological precision with substantive inquiry: on one hand, it proposes a reproducible classification framework tailored to CE, and on the other, applies it to uncover the main technological directions of CE innovation across time, regions, and sectors.
Our approach combines the contextual reasoning capabilities of LLMs with the scalability of transformer-based classifiers. By integrating recent advances in NLP with CE-specific conceptual frameworks, the contribution of this paper is twofold: (1) it proposes a reproducible method for identifying CE innovation across technological and sectoral boundaries, and (2) it generates a structured classification that supports empirical mapping and policy-relevant monitoring of CE trends. In doing so, we provide a scalable and adaptive alternative to keyword filtering and narrow taxonomy-based methods. This framework is designed to enhance the accuracy of CE patent identification and enable a more meaningful exploration of sectoral and technological trends shaping the CE transition. Furthermore, the pipeline's modular structure makes it adaptable to various data sources and model architectures. Each component can be updated or replaced as new models and datasets become available, ensuring the long-term applicability and interoperability of the framework in domains. This flexibility reinforces its relevance as a generalizable tool for studying innovation dynamics beyond the CE context.

The paper is organized as follows. Section 2 discusses the existing literature on CE frameworks and identifies key methodologies for detecting CE principles in patents. Section 3 outlines the data and methods used to classify and identify CE patents. The methodology consists of a two-step approach: first, a binary classification of patents using GPT-3.5-turbo-16k and BERT for Patents, to identify CE-related patents; and second, the identification of CE subclasses using topic modeling techniques. Section 4 presents a comprehensive analysis of identified CE patents, providing insight into their distribution across various dimensions, temporal trends, geographic patterns, and sectoral contributions. In the last subsection of the results, the correlation between CE patents and the quality indicators identified by the OECD is investigated. Finally, the conclusions summarize the key findings and discuss the implications of the results for researchers and practitioners in the field of CE, offering recommendations for future research and potential policy applications.

2 Literature Review

2.1 Innovation, new technologies and the CE transition

Although the origins of the CE concept can be dated back to the second half of the 1900s, the debate around it gained momentum only a decade ago in policy circles. Environmental and industrial policies have, for a long time, substantially neglected the issue of resource depletion and waste production, leaving production and consumption activities to evolve along a trajectory marked by the *take-make-dispose* paradigm.

In this linear model, natural resources are extracted, transformed into products, and ultimately discarded, with minimal consideration for reuse or regeneration [Ellen MacArthur Foundation, 2013, Stahel, 2016]. The persistence of such linear economic models is largely explained by path dependency and technological lock-in [Arthur, 1989, Stack and Gartland, 2003, Boschma, 2007]. Path dependency describes how historical choices shape technological trajectories, often reinforcing inefficient or unsustainable practices over time Arthur [1989]. Similarly, technological lock-in occurs when dominant designs and established industrial ecosystems hinder the adoption of alternative, more sustainable technologies, making it challenging for circular innovations to emerge and scale [David, 1985, Unruh, 2002].

The growing emphasis on sustainability and circularity in policy has played a crucial role in breaking these deeply rooted patterns and promoting CE adoption. Governments and international organizations have introduced regulations, financial incentives, and strategic frameworks that encourage industries to transition toward more sustainable practices [Geissdoerfer et al., 2017, Kirchherr et al., 2017]. Examples include the European Union's Circular Economy Action Plan and national policies aiming at waste reduction, extended producer responsibility, and eco-design principles [European Commission, 2020b]. Multi-stakeholder participation is also key to fostering CE innovation, as collaboration between industries, policy makers, and consumers ensures that economic, social, and environmental considerations are integrated, reducing resistance to change and enhancing the effectiveness of circular strategies [Blomsma et al., 2019].

Innovation is essential to overcome lock-in effects and accelerate the CE transition. Firms can adopt new technologies and business models that improve resource efficiency, minimize waste, and enable circular material flows [Rennings, 2000]. Ecoinnovation, defined as innovation that reduces environmental impacts while enhancing economic performance, is closely related to CE as it promotes sustainable resource use, pollution reduction, and efficiency gains throughout the system [OECD, 2010, Kemp, 2010, de Jesus and Mendonça, 2018]. By embedding CE within ecoinnovation frameworks, companies can leverage synergies between environmental sustainability and economic growth, ensuring that CE-driven transformations are viable and scalable [Carrillo-

Hermosilla et al., 2010].

In summary, transitioning to CE requires a departure from established linear economic frameworks through innovation, policy support, and collaboration among multiple stakeholders. Despite the challenges posed by path dependency and technological lock-in, focused policies, advances in technology, and eco-innovation provide promising avenues to promote circularity. However, several barriers persist that hinder the widespread adoption of CE practices. These include institutional and regulatory uncertainties, high upfront investment costs, lack of consumer awareness, and insufficient market incentives [Rizos et al., 2016, Kirchherr et al., 2017, Guldmann and Huulgaard, 2020]. From a theoretical perspective, institutional theory emphasizes how rigid regulatory frameworks and established norms can hinder the adoption of innovative CE practices. In contrast, resource-based and capabilities-based approaches emphasize the importance of firm-specific capabilities and learning in overcoming these barriers [Teece et al., 1997, Daddi et al., 2020]. These theoretical perspectives highlight the multifaceted and systemic nature of CE transition challenges, underscoring the need for an integrated approach to foster adoption.

2.2 CE-enabling technologies and Industry 4.0

The successful implementation of CE practices increasingly depends on the adoption of enabling technologies, particularly those associated with Industry 4.0. These technologies, including the Internet of Things (IoT), artificial intelligence (AI), big data analytics, blockchain, additive manufacturing, and cyberphysical systems, play a critical role in enhancing resource efficiency, enabling closed-loop processes, and supporting real-time decision-making in circular business models. [de Sousa Jabbour et al., 2018, de Mattos Nascimento et al., 2024]. The IoT facilitates the tracking and monitoring of materials, products, and energy flows through supply chains, supporting extended product life cycles and reverse logistics [Tsai et al., 2021]. Big data analytics and AI contribute to predictive maintenance, process optimization, and demand forecasting, allowing firms to reduce waste and improve reuse and remanufacturing strategies [Ghobakhloo et al., 2021]. Blockchain technologies can improve transparency and traceability in circular value chains, increasing trust among stakeholders and enabling efficient product stewardship [Upadhyay et al., 2021]. Additive manufacturing, also known as 3D printing, enables the design and production of custom components using fewer materials, allowing for on-demand spare parts and supporting repair and refurbishment practices [Al Rashid and Koç, 2023, Tavares et al., 2023]. CE-enabling technologies not only offer new possibilities for operationalizing circularity, but also redefine the technological trajectory of industries transitioning from linear to circular paradigms. Integrating these technologies into CE research and policy frameworks is crucial to accelerate the transformation toward sustainable production and consumption models.

2.3 Technologies for CE: measurement challenges for a multi-dimensional concept

Building on the technological foundations discussed above, a key challenge remains in measuring and classifying the wide range of innovations contributing to CE. The multidimensional and cross-sectoral nature of CE makes its operationalization particularly complex. Scholars have provided several definitions and frameworks to capture CE principles and practices [Bocken et al., 2016, Geissdoerfer et al., 2017, Kirchherr et al., 2017, Ghisellini et al., 2018, Nobre and Tavares, 2021, Figge et al., 2023]. Kirchherr et al. [2017] emphasize that the main challenge in establishing a universally accepted definition of CE arises from its inherent complexity and multifaceted nature, which encompasses various dimensions, economic, social, and environmental. Bocken et al. [2016] and Geissdoerfer et al. [2017] highlight that the primary reason for this complexity lies in the multidisciplinary aspect of the CE concept, which can be viewed through lenses ranging from waste management to sustainable business practices, through efficiency and optimization methods, each providing a distinct focus that influences how the concept is understood and implemented. In addition to the diverse definitions of CE, scholars have also developed various operational frameworks to describe its principles. One of the most widely recognized is the 3R framework (Reduce, Reuse, and Recycle), which provides the foundational basis for understanding CE practices [King et al., 2006, Kirchherr et al., 2017].

This framework has evolved significantly over time, adapting to several variations [Sihvonen and Ritola, 2015, Kirchherr et al., 2017]: the Directive on the European Union Waste Framework introduced a fourth R (Recover) [European Commission, 2008], while other scholars have expanded this further, proposing 5R, 6R [Sihvonen and Ritola, 2015], 9R [Buren et al., 2016] or even 10R frameworks [Potting et al., 2017]. Other important models are the ReSOLVE framework, which categorizes the key interventions needed for the transition to a CE ("Regenerate, Share, Optimize, Loop, Virtualize, and Exchange") [Kouhizadeh et al., 2020], and the Resource Value Retention Options (RVRO) hierarchy [Reike et al., 2018]], which inform our approach to interpreting patent content across different circular strategies. . These frameworks are beneficial when applying CE principles to technological classifications and innovation metrics, as they align with the logic of value preservation central to circularity.

Considering the complexities inherent in the definition of CE, the development of a classification methodology capable of handling its heterogeneity thus appears to be a significant challenge. As highlighted, scholars have primarily employed two strategies to identify CE patents: the keyword approach on the one hand, and the use of CPC and IPC codes on the other. The first strategy, the keyword approach, relies on targeted keyword searches to identify CE-related documents based on specific terms associated with CE concepts. For example, Fontana et al. [2021] apply this methodology to identify academic papers related to CE, as well as de Jesus and Mendonça [2018], Okorie et al. [2018], Morales and Sossa [2020] and García-Valderrama et al. [2024]. de Freitas Juchneski and de Souza Antunes [2022] employ the keyword approach in patents, focusing on the intersection with electrical and electronic equipment. An enhanced variation of this methodology is employed by Spreafico et al. [2019], who perform syntactic analysis on sentences in documents retrieved through a search query involving terms such as "circular economy" along with related concepts, e.g. "recycle" paired with specific waste types. In a subsequent study, Spreafico and Spreafico [2021] propose a method to automatically extract information related to waste recycling and reuse from patents using syntactic analysis and word dependence patterns. Giordano et al. [2024] made a significant contribution to the identification of CE patents employing named entity recognition (NER) algorithms, as proposed by Giordano et al. [2021] and Bishop et al. [2022], to detect CE-related technologies. Although this approach represents an advance in automating the identification of CE innovations, the dataset on which the NER algorithm is applied was still selected using keyword retrieval methods, so it is subject to the limitations discussed here. Although the keyword retrieval approach is relatively straightforward and computationally efficient, it has two main limitations. The first is that, given the heterogeneity of the CE concept, it is difficult to capture it into a list of keywords. Relying on this strategy could easily lead to the inclusion of irrelevant patents or the exclusion of relevant ones that do not use standard CE terminology. Furthermore, patent abstracts focus on technical descriptions, often using highly specialized language, and for this reason, they might often lack explicit CE references, even when the invention aligns with circular strategies. [Terragno, 1979, Hambarde and Proença, 2023].

The second common approach involves the use of CPC/IPC codes. In their work on the relationship between local knowledge bases and recombinant dynamics in CE technologies, Fusillo et al. [2024] use the 4-digit CPC code Y02W, related to "Climate change mitigation technologies related to wastewater treatment or waste management", to identify relevant patents. Caldarola et al. [2024] use both the 3-digit CPC code Y02 (namely, "Technologies or applications for mitigation or adaptations against climate change") and the 4-digit CPC code Y04S ("Information or communication technologies having an impact on other technology area") to identify patents dealing with the environmental sustainability topic. The Eurostat indicator on patents related to waste management and recycling is based on the Y02W CPC code, which includes "Technologies for wastewater treatment", "Technologies for solid waste management", and "Enabling technologies or technologies with a potential or indirect contribution to greenhouse gas [GHG] emissions mitigation" [Eurostat, 2022]. Then, different scholars used this indicator to study CE dynamics in Europe, such as Ilić et al. [2022], Mazur-Wierzbicka [2021], Bianchi and Cordella [2023], and Platon et al. [2023]. Moreover, to identify Environmentally Sound Technologies (EST), Nikolova-Minkova [2023] refer to eight IPC codes. The main advantage of using these classifications is the fact that they are a structured and standardized way of categorizing patents that are widely recognized [Bonaccorsi et al., 2019]. However, they are not specifically designed for emerging fields like CE, which could easily lead to misclassification, reducing the visibility of CE innovations.

Given these limitations, this study proposes an alternative methodology that goes beyond the conventional use of keywords and CPC/IPC codes. By addressing the challenges posed by CE's inherent heterogeneity and the specialized language of patent documentation, this approach aims to enhance the precision and reliability of CE patent identification. The proposed method aims to capture a wider spectrum of CE-related innovations while minimizing misclassifications, offering a more comprehensive framework to track technological developments in the field.

3 Data and Methodology

3.1 Data

The 2023 Spring Edition of PATSTAT serves as the data source. A random sample of roughly 150,000 English-language patent abstracts was selected, limited to applications filed in the EU or the United States. One representative patent per family was retained to reduce redundancy and computational load. The developed LLM classified 21,310 of these as CE-related. A balanced control group of 21,310 non-CE patents was drawn to train the BERT for Patents model. The model was then applied to all English-language patents filed between 2000 and 2019 under European application authorities.
To improve the results of the LLM, a Retrieval-Augmented Generation (RAG) technique is implemented. As described in the methodological section, RAG is a machine learning technique that combines retrieval-based and generation-based models to enhance the precision and relevance of the output generated by an LLM [Melz, 2023, Gao et al., 2024, Zhao et al., 2024]. It is particularly effective in reducing LLM hallucinations and improving their performance and efficiency [Lewis et al., 2021, Izacard and Grave, 2021]. To effectively implement this technique, a set of 13 relevant documents is selected for retrieval as listed in Table A.1.
Regarding the OLS regression, four patent quality indicators proposed by the OECD Patent Quality Indicators database are used: generality, originality, radicalness, and a composite quality index [Squicciarini et al., 2013]. The control set is selected randomly among patents not classified as circular, with comparable application authority, earliest filing year, and technological sector.

3.2 Methodology

Recent advances in NLP, particularly in transformer-based and LLMs, have reshaped text analysis across disciplines. These tools enhance the semantic understanding of complex language and offer new opportunities for innovation studies [Just, 2024]. The methodology developed here uses these capabilities to identify and classify CE patents with greater accuracy and adaptability, while remaining transferable to other technological domains.
NLP comprises a set of algorithms and techniques for analyzing and extracting grammatical structure and meaning from textual data [Chowdhary, 2020, Khurana et al., 2023]. Among the most advanced tools within NLP, there are fine-tuned transformer models and LLMs [Naveed et al., 2023]. LLMs are a special class of pre-trained language models (PLMs) obtained by scaling model size, pre-training corpus, and computation [Naveed et al., 2023]. They demonstrate 'emerging abilities' that allow them to achieve remarkable performance without any task-specific training [Brown et al., 2020, Wei et al., 2022, Liu et al., 2024]. This capability has made LLMs particularly valuable in scenarios where labeled data is scarce [Gilardi et al., 2023, Alizadeh et al., 2023], and in particular when pre-trained language models such as BERT or GPT-2 cannot be

fine-tuned to downstream tasks [Devlin et al., 2019, Radford et al., 2019].

The methodology proposed in the following uses these tools to suggest a novel, adaptable classification strategy for CE patents. It is structured into two main steps:

1. **Binary classification of patents**. In this step, patents are classified as related to CE principles or not through a two-phase process. A sample of patent abstracts is classified as "CE-related" or "non-CE-related" using the GPT-3.5-turbo-16k model developed by OpenAI. The generated dataset serves as a training set for fine-tuning the BERT for Patents model [Srebrovic and Yonamine, 2022], which is then used to classify the selected set of English patent abstracts. Here, the pipeline is model-agnostic: the LLM step was implemented with GPT-3.5-turbo-16k at the time of study; the same procedure is compatible with current commercial (e.g., GPT-4-class) and open-weight models.

2. **Identification of CE subclasses**. This step utilizes topic-modeling algorithms to identify and organize specific subclasses within the CE domain. First, a zero-shot BERTopic algorithm is used to map patent abstracts to the most closely related 5R ('Reduce', 'Reuse', 'Repair', 'Refurbish', and 'Recycle')- In a second moment, clustering algorithms are used to classify patent abstracts into 10 CE topics.

The following sections provide a detailed analysis of these steps.

Binary classification of patents Patent classification using an LLM is based on three key steps: (1) building the RAG architecture, (2) designing an effective prompt, and (3) executing the classification process. A visual representation of this pipeline is shown in Figure 1.

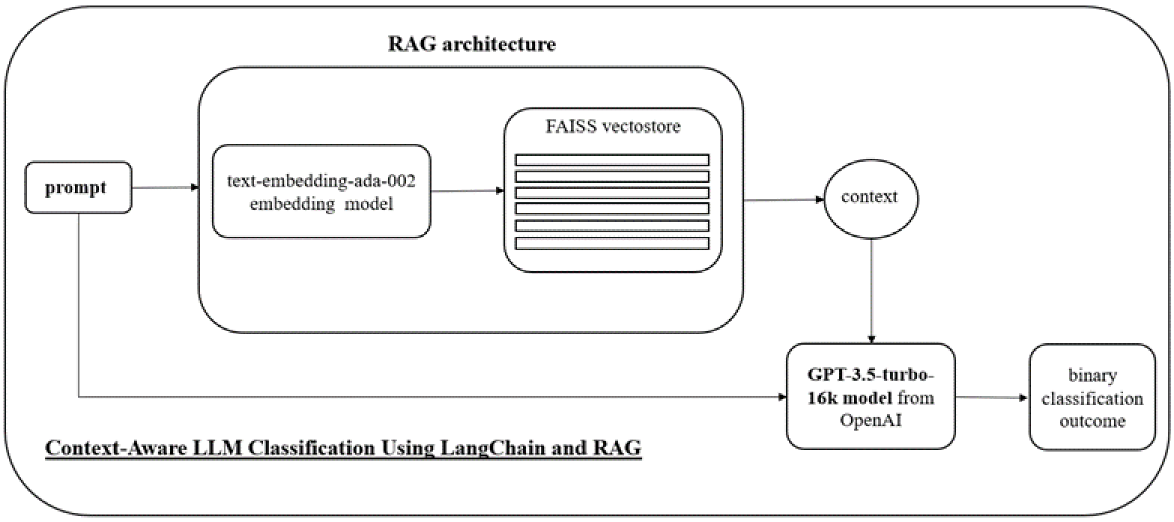

Figure 1: LLM classification pipeline

To improve the reliability of the LLM classification, a Retrieval-Augmented Generation (RAG) architecture was implemented. RAG combines retrieval- and generation-based processes to enhance contextual accuracy during inference. [Lewis et al., 2021].

Its inclusion was motivated by two main considerations. First, CE-related patents exhibit significant conceptual diversity, spanning distinct technological and sectoral contexts that are difficult to capture with static prompts [Kirchherr et al., 2017, Reike et al., 2018]. Second, with the RAG strategy, our objective was to ensure that the model's decisions were explicitly grounded in authoritative definitions of CE rather than relying solely on pre-trained associations. Although a few-shot prompt could, in principle, provide guidance, the limited context window of current LLM limits the number of examples and definitions that can be included at once, as has been proven by several studies [Li et al., 2025, Li, 2024, Guţu and Popescu, 2024]. RAG allows the model to retrieve and incorporate multiple excerpts from a curated corpus of CE literature, thus expanding its effective context and anchoring the classification in verified conceptual sources, supporting a more faithful and reproducible classification in a semantically heterogeneous corpus [Borgeaud et al., 2022, Mialon et al., 2023, Shinn et al., 2023]. Recent empirical studies have shown that retrieval-augmented prompting improves performance in tasks characterized by high conceptual variability and semantic ambiguity, particularly outperforming static prompt formulations [Schulhoff et al., 2025, Yoran et al., 2024, Izacard and Grave, 2021]. In our framework, RAG serves this purpose by reducing misclassification arising from missing contextual cues and by mitigating hallucination effects. In this study, no direct empirical comparison was made between the RAG configuration and a static prompt baseline. Our objective was primarily methodological: to adapt and document a reproducible pipeline for CE patent classification. A complete quantitative benchmark of RAG against static prompting is beyond the present scope but represents an important direction for future research.

The prompt was developed through an iterative process. Initially, a simple instruction that asked the model to classify each patent abstract as pertaining to the CE was used. Based on early results, the prompt was refined with more explicit instructions and illustrative examples. This level of specificity reduced interpretative ambiguity. A summary of the final prompt is included in the Appendix to support reproducibility (Table A.2). Once finalized, the prompt was integrated with the RAG architecture and executed via LangChain using GPT-3.5-turbo-16k. This model was selected since, at the time of the study, represented one of the most advanced and accessible LLMs for research purposes, and in particular for its extended context window and strong performance in domain-specific language understanding [Gilardi et al., 2023, Bai et al., 2024], which proved essential to capture the conceptual complexity of CE principles in various patent abstracts. This specific model version has since been superseded by newer releases, however, the methodological framework proposed here is model-agnostic and remains fully compatible with current architectures. The retrieval-augmented prompting approach and the fine-tuning procedure do not depend on proprietary features unique to GPT-3.5 but instead build on general principles of LLMs inference and retrieval integration. To assess the reliability of this initial LLM classification, the authors, experts in the CE innovation domain, conducted an iterative manual validation process in more than 1,500 patents. Each batch, approximately 400 abstracts, was independently reviewed against the CE definition proposed by [Kirchherr et al., 2017], which specifies when a technological innovation can be considered circular. In the final round, 84% of the sample was reviewed as correctly classified. This hybrid validation strategy cannot fully replace a human-annotated gold standard, but offers a reasonable compromise between feasibility and rigor. Establishing a larger, independently labeled dataset remains a necessary next step to more definitively benchmark the performance of the model.

To scale the classification across the entire corpus, a binary classifier was trained using BERT for Patents [Srebrovic and Yonamine, 2022], a transformer model based on BERTLARGE [Devlin et al., 2019], fine-tuned on more than 100 million patent texts. The pipeline for this step is shown in Figure 2. The training dataset consisted of 21,310 patents classified by the LLM as non-CE, sampled from an initial pool of around 150,000 abstracts. Stratified sampling by applicant geography was used to reflect the territorial heterogeneity of European innovation systems and to reduce regional bias in training. Although further stratification (e.g., by time or technology field) could enhance representativeness, geographic balance was prioritized due to its policy relevance. The dataset was split into training and validation sets, and hyperparameters were tuned using the Optuna library and were aligned with best practices for large transformer models. The final configuration employed the AdamW optimizer with a learning rate of 2×10^{-5} and default β_1 coefficients (0.9 and 0.999); a linear learning-rate scheduler without warm-up; a batch size of 32 for both training and validation; and mixed-precision training (automatic mixed precision). A fixed random seed of 42 ensured reproducible results. The model was fine-tuned for five epochs, the point at which validation F1 and accuracy plateaued, and no early stopping was required. This configuration yielded an evaluation accuracy of 0.823, precision of 0.824, recall of 0.823 and F1 score of 0.824 on the held-out validation set.

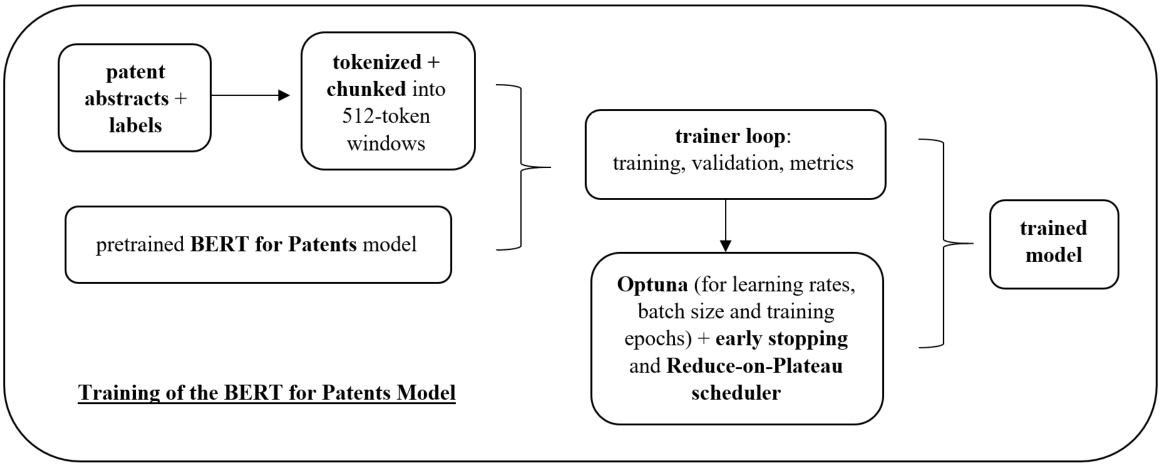

Figure 2: BERT for Patents classification pipeline

Identification of CE subclasses Beyond identifying CE patents, this study aims to explore their internal heterogeneity by classifying them into meaningful subclasses. To this end, both deductive and inductive strategies were adopted. The analysis is conceived as an exploratory step toward integrating LLMs into the empirical study of circular innovation. Its modular design allows each component of the pipeline to be replicated, extended, or adapted as improved models, labeled data, and validation techniques become available. In this sense, the study represents an initial but systematic attempt to operationalize LLM-based methods in this domain, providing both methodological insight and a basis for cumulative research.

To align with the dominant frameworks in the CE literature, such as the 5R hierarchy (Refuse, Rethink, Reduce, Reuse, Recycle) [Kirchherr et al., 2017, Geissdoerfer et al., 2017], a zero-shot classification approach was implemented using BERTopic. This method leverages pre-trained language models to map patent abstracts directly to 5R categories, eliminating the need for additional fine-tuning and thereby supporting scalability across various technology domains. The use of semantic similarity enables the model to reflect the conceptual breadth of each circular strategy while ensuring consistent application across a large corpus. It is essential to recognize that the 5R framework operates at a high level of abstraction and that the boundaries between categories are often fluid due to overlapping objectives and terminology. The intention is not to impose mutually exclusive classifications, but rather to apply a structured lens through which to interpret patterns of CE innovation. This mapping enhances interpretability and aligns with established CE principles, particularly in exploratory analyses.

To inductively classify CE subtopics, clustering algorithms were used to identify latent themes in the patent corpus. Document embeddings are generated using the all-MiniLM-L6-v2 model, followed by dimensionality reduction via UMAP, consistent with the BERTopic methodology proposed by Grootendorst [2022]. The selection of all-MiniLM-L6-v2 was guided by its strong performance on semantic similarity tasks and its computational efficiency, enabling scalable embedding across a large dataset. However, future work could benefit from a systematic comparison with domain-specific embedding models. After dimensionality reduction, the embeddings are clustered using HDBSCAN and refined through agglomerative clustering to generate 10 coherent CE topics. Outliers are subsequently assigned to their closest topic using cosine distance. Although this may introduce some thematic dilution in borderline cases, it ensures broader representativeness and supports a robust, systematic analysis of CE innovations across diverse domains.
Each topic is labeled according to the top 40 representative words identified using a class-based TF-IDF algorithm [Grootendorst, 2022], along with the most frequent CPC codes, NACE sectors, and technological fields associated with the cluster. To improve interpretability and validate topic coherence, a manual review of over 100 randomly selected patents was conducted on all topics. This validation assessed the alignment between the TF-IDF keywords, the classification codes, and the patent content.
The unsupervised topic-modeling phase was designed as an exploratory step to examine the internal heterogeneity of the CE patent corpus, rather than as a predictive or evaluative classifier, and, given the absence of a pre-classified dataset, a qualitative review was conducted to assess the interpretive validity of the resulting clusters. Although this approach provides confidence in the descriptive relevance of the clusters, developing a formal validation protocol, potentially involving human-labeled topic exemplars or statistical measures such as topic coherence, remains an important direction for future research.

4 Results

Using the methodology illustrated previously, 864,714 European patent families are identified as CE-related.

Comparison with keyword- and CPC-based approaches highlights how the proposed pipeline extends beyond the definitional limits of existing methods. Table 1 illustrates a patent that would not be recovered by keyword searches, since it contains no explicit CE-related terminology, but was correctly identified by the LLM-based classifier as circular. In contrast, Table 2 provides two examples of potential misclassification when relying solely on CPC/IPC codes: one CE-related patent overlooked by Y02W, and another Y02W patent unrelated to circular innovation. These examples illustrate both the inclusiveness and the precision gains achieved by using contextual text understanding rather than rigid taxonomic or lexical filters. Moreover, at an aggregate level, Figure 5 compares the annual trends of patents identified through our pipeline with those classified under the Y02W CPC code. The broader, faster-growing coverage observed in our dataset suggests that the proposed method captures a wider range of CE-related technologies, particularly those operating outside conventional waste management domains.

CE patent not mentioning keywords
Methods and systems are provided for **mapping the distribution of residue material in an environment in which one or more agricultural machines are operable**. A sensing arrangement comprising one or more sensors mounted or otherwise coupled to an agricultural machine operating within the environment is used to obtain sensor data indicative of residue material [...]

Table 1: Example of misclassification while using keywords

CE patent not Y02W	**Y02W patent not CE**
The invention discloses **kitchen garbage treatment equipment based on biodegradation**, the equipment comprises a filtering mechanism, a stirring mechanism, a crushing mechanism and a fermentation mechanism, the filtering mechanism is connected with the crushing mechanism and the stirring mechanism, and the fermentation mechanism is arranged in the crushing mechanism and the stirring mechanism; [...].	The present invention relates to a method and to the use of a composition, each for reducing the emission of the environmentally harmful climate gases methane and/or carbon dioxide from farm fertilizers while they are being stored.

Table 2: Example of potential misclassification while using CPC codes

When looking at the distribution of CE patents in the 5R, it is possible to observe a predominance of patents related to the categories "Reuse" and "Reduce", respectively, 29.7% and 26.2% of the total dataset (Figure 3). In third place there is the topic "Repair" (20.0%), followed by "Recycle" (15.91%), and "Refurbish" (8.2%). The prominence of "Reuse" and "Reduce" strategies in our data set mirrors the findings of Reike et al. [2018] on the dominance of lower-order strategies in practice, versus more transformative CE activities. Both "Reuse" and "Reduce" rely on established business models that are already economically viable and institutionally supported. In contrast, the lower shares of 'Reduce', 'Refurbish' and 'Repair' indicate the persistence of economic and organizational barriers to more radical circular strategies, such as design for minimal resource use or large-scale product redesign. The concentration of patents in these categories may also reflect the current state of technological maturity and path dependence, themes consistent with the institutional and technological lock-in discussed in Section 2.1.

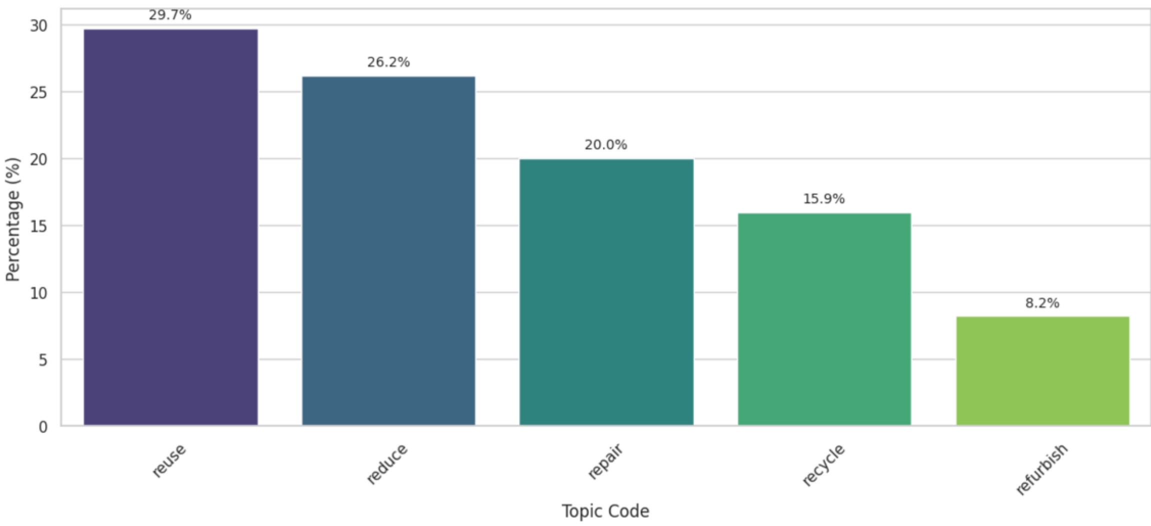

Figure 3: Distribution by 5R topics

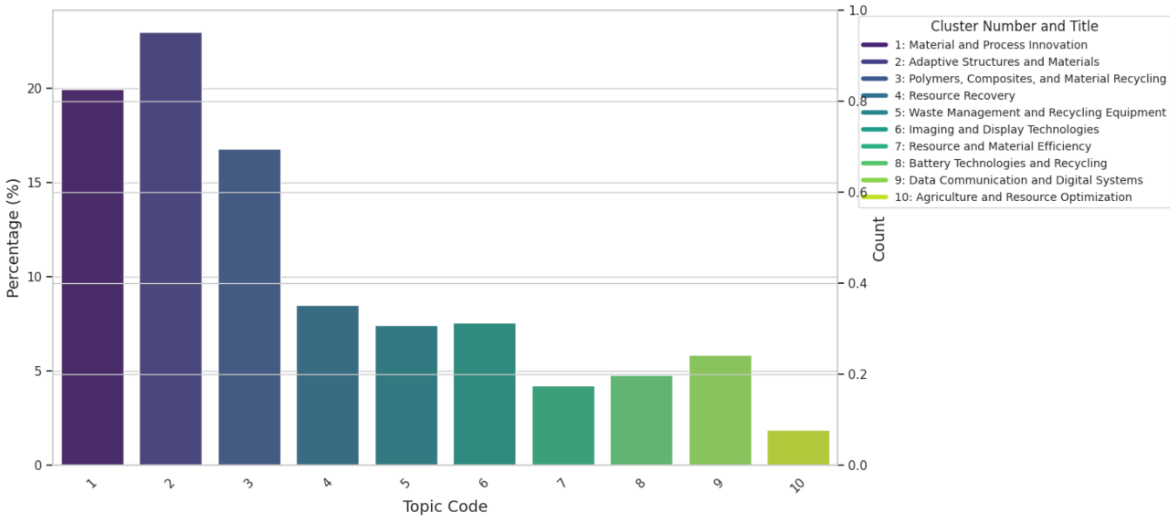

Figure 4: Distribution by 10 CE topics

Looking instead at the 10 CE topics, their distribution can be observed in Figure 4 (Table A.3). The topic of "Adaptive structures and materials" is the most common across patents, accounting for 23.07% of the dataset. This area corresponds to sectors where circularity is technologically embedded, such as advanced materials, polymer science, and process optimization, reflecting both incremental progress and enabling technologies that facilitate broader circular transitions, including modular design, smart manufacturing, and resource-efficient production systems. Almost 20% of the patents concern "Material and process innovation", while 16.8% concern "Polymers, composites, and material recycling". Moving on, there is a noticeable jump in terms of topic size, as the next one covers 8.5% of patents and it is related to "Resource efficiency and water treatment", 7.5% both to "Imaging and display technologies" and "Waste management and recycling equipment", and 5.8% to "Data communication and digital systems". Finally, 4.81% of the patents refer to "Battery technologies and recycling", 4.2% "Resource and material efficiency", and 1.9% "Agriculture and resource optimization". In general, the distribution of topics reveals a technological landscape with uneven maturity across CE domains. Mature, downstream practices, such as recycling, dominate patent activity, while upstream design and systemic strategies are comparatively underrepresented. This asymmetry provides an analytical basis for policy intervention, highlighting where innovation incentives may be needed to shift from incremental to transformative forms of circular innovation.

Table 5 provides examples for each of these topics. The following paragraphs provide a comprehensive mapping of the classified datasets. The analysis provides insight into the temporal patterns of CE innovation, its geographical distribution, and sectoral activity, incorporating data on CPC classes, NACE2 codes, and technology classifications. For each dimension, the analysis is conducted both at an aggregated level and by differentiating between the 5R principles and the 10 CE topics. This multifaceted approach ensures a thorough understanding of the dynamics that drive CE innovation.

4.1 Annual trend

Between 1990 and 2019, the trajectory of CE patents largely mirrors the overall growth trend, but exhibits a significantly steeper upward trend beginning in the early 2000s (Figure 5). As a benchmark, the NLP-classified CE patents was compared with those tagged under the Y02W CPC subclass. As previously stated, this class reflects a classification logic designed for climate-related technological domains, not specifically for CE principles, as noted by Favot et al. [2023].
Taking this into account, Figure A.1 highlights how, with respect to Y02W patents, CE patents demonstrate faster growth and a higher overall magnitude. Overall, CE patenting activity accelerates after the early 2000s, particularly in areas related to material efficiency and reuse. This rise coincides with the spread of Industry 4.0 technologies, which enable resource tracking, automation, and predictive maintenance. [de Sousa Jabbour et al., 2018]. Overall, CE patenting activity accelerates after the early 2000s, particularly in areas related to material efficiency and reuse. This rise coincides with the spread of Industry 4.0 technologies, which enable resource tracking, automation, and predictive maintenance. [Ghobakhloo et al., 2021]. This pattern holds across the 5R topics, with significant increases observed for "Reduce" and "Reuse" patents in the late 1990s. A distinct rise in "Repair" patents becomes evident starting in 2007, while growth in "Recycle" patents appears to plateau and converge from 2010

onward. Figure A.2 differentiates the trend in the ten CE topics previously described. Overall, the topic "Material and process innovation" and "Adaptive structures and materials" consistently shows the highest counts throughout the period, peaking around 2010 and exhibiting slight fluctuations thereafter. Other topics like "Polymers, composites, and material recycling" show a steady upward trend, stabilizing in the later years, while "Resource recovery", "Battery technologies and recycling", and "Resource and material efficiency" exhibit moderate but consistent growth.

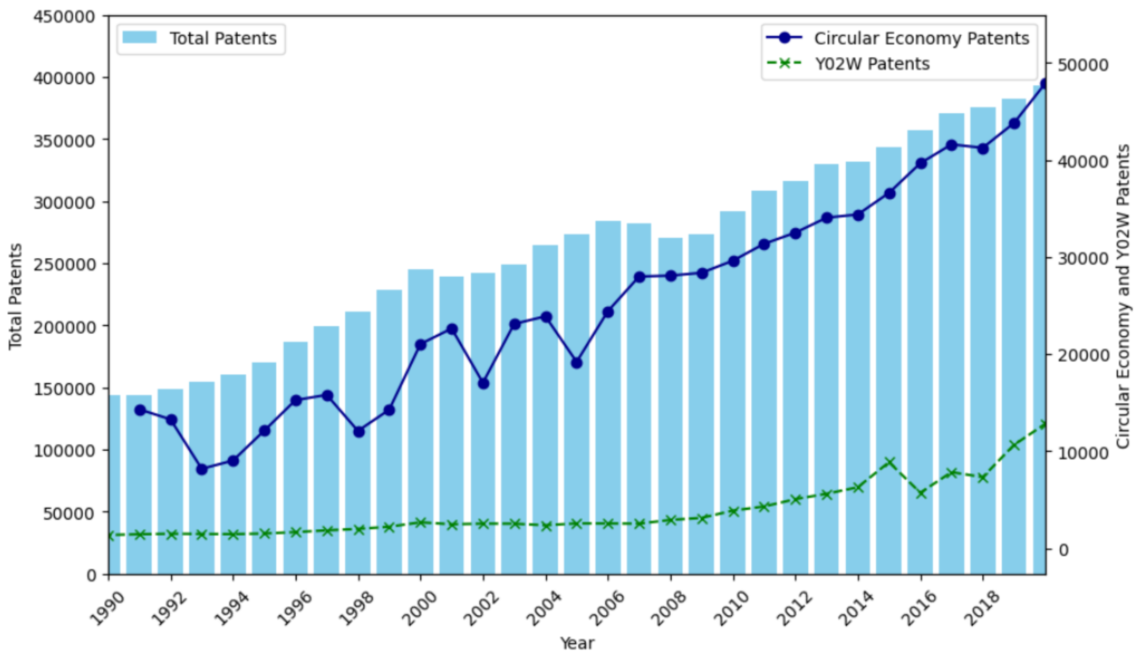

Figure 5: Annual trend of CE patents

4.2 Geographical mapping

At a spatial level, CE patent activity shows a marked concentration in key innovation hubs throughout Europe, as shown in Figure 6 (the top 10 Nuts 3 areas are listed in Table A.5). Main-Kinzig-Kreis, in Germany (5,382 patents, 2.08%), Paris, in France (4,060 patents, 1.57%), and Helsinki, in Finland (3,179 patents, 1.23%) lead the rankings. Other industrial centers, such as Hauts-de-Seine, Zurich, and Milan, also show significant activity. When analyzed according to 5R topics, the distribution of CE patents reveals nuanced regional strengths (Table A.6). Regions such as Main-Kinzig-Kreis, in Germany, excel in "Reduce" (1.90%) and "Repair" (1.61%) innovations, while Paris leads in both "Reuse" (1.67%) and "Refurbish" (1.53%). Milan, Zurich, and Copenhagen show strong, balanced contributions across multiple Rs, reflecting their diverse industrial and technological bases. Further analysis of the 10 CE topics further enriches this geographical mapping in Table A.7. Main-Kinzig-Kreis stands out across multiple CE topics, with a notable focus on "Data Communication and Digital Systems" (4.31%), "Material and Process Innovation" (2.11%), and "Adaptive Structures and Materials" (2.32%). Paris, in contrast, shows a more diversified profile, leading in categories such as "Resource and Material Efficiency" (1.92%) and "Resource Recovery" (1.86%), reflecting its advanced infrastructure and role in digital transformation. Copenhagen performs well in "Polymers, composites, and material recycling" (2.55%), while Freiburg is recognized for its strengths in "Recycling equipment and waste management" (2.08%). The geographic concentration of CE patenting in Europe is consistent with previous studies that highlight the role of institutional frameworks in shaping innovation pathways [Kirchherr et al., 2017]. Meanwhile, the variety of organizational actors, including large corporations and specialized firms, reflects a capability-based view of innovation, where absorptive capacity and firm-level learning play a central role [Teece et al., 1997].

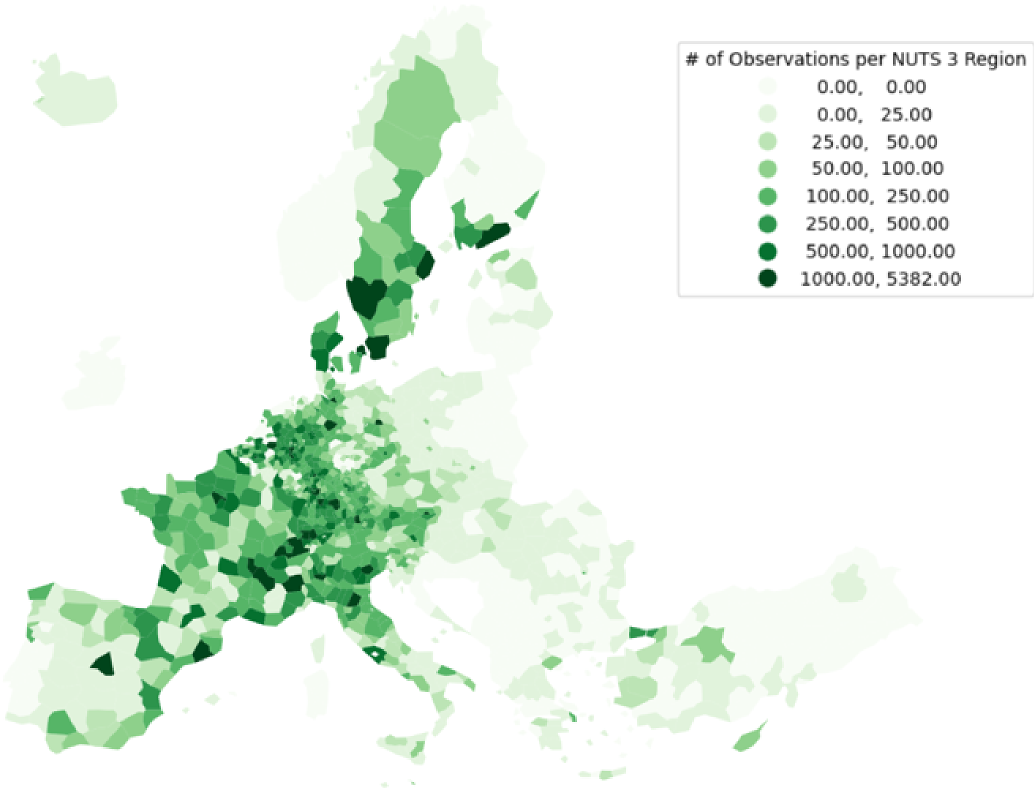

Figure 6: Distribution of CE patents at Nuts3 level

4.3 Distribution per CPC codes

At the aggregate level, the technological classifications reveal a strong focus on class B32B for layered products (38.68%), H01M focuses on processes or means for the direct conversion of chemical energy into electrical energy, for example batteries (35.64%), B29C on the shaping or joining of plastics (23.36%), as can be observed in Table 3. In terms of technological focus according to 5R principles (Table A.8), "Reduce" emphasizes energy and material efficiency, with processes such as H01M (processes or means, for example batteries, 5.80%) and B01D (separation, 4.27%) leading. "Reuse" is dominated by layered products (B32B, 5.59%) and plastic shaping technologies (B29C, 4.94%). "Recycle" highlights innovations in plastic reprocessing (B29C, 7.37%) and waste management (Y02W, 3.59%). "Repair" technologies are prominent in batteries and water treatment, while "Refurbish" emphasizes layered materials and structural enhancements in building and manufacturing.

Code	Title	n. patents	% patents
B32B	Layered products	106,388	38.68%
H01M	Processes or means	104,980	38.17%
B29C	Shaping or joining of plastics	96,691	35.16%
C02F	Treatment of water, waste water, sewage, or sludge	75,929	27.61%
H01L	Semiconductor devices not covered by class H10	63,859	23.22%
Y10T	Technical subjects covered by former US classification	59,281	21.56%
B01D	Separation	57,754	21.00%
B65D	Containers for storage or transport of articles or materials	57,551	20.93%
C04B	Lime, magnesia; slag; cements; compositions thereof	47,150	17.14%
Y02E	Reduction of greenhouse gas (GHG) emissions, related to energy generation, transmission or distribution	39,573	14.39%

Table 3: Distribution of CE patents across CPC codes

The 10 CE topics illustrate a nuanced distribution of patents in various technological domains (Table A.9). "Material and process innovation" is a significant factor in container technology (B65D, 5.66%) and semiconductor devices (H01L, 5.21%). Similarly, "Adaptive structures and materials" is characterized by a strong presence of plastic shaping technologies (B29C, 6.29%) and layered products (B32B 5.61%). In "Polymers, composites and material recycling," layered products and plastic technologies (B32B, 10.29%; B29B, 7.29%) are dominant, illustrating a focus on high-tech materials essential for recycling and reuse. For "Resource recovery", treatment of water (C02F, 10.32%) and separation (B01D, 9.46%) lead, highlighting the integration of advanced materials in the management of environmental resources. Moreover, the emergence of topics related to blockchain, digital twins, and additive manufacturing confirms their theorized role as critical CE enablers, particularly in supporting transparency and predictive optimization [Upadhyay et al., 2021, Al Rashid and Koç, 2023, Tavares et al., 2023].

4.4 Sectorial level

The industries identified through the NACE classification illustrate a broad commitment to CE (Table 4). The manufacture of basic chemicals dominates (16.79%), while other sectors such as special purpose machinery (10.28%) and rubber and plastic products (6.94%) also show significant contributions, underscoring the diverse applicability of CE approaches in industrial domains. Sectoral diversification expands further when the focus shifts to the differences between the 5R categories (Table A.10). For "Re-

duce," the chemical and pharmaceutical industries dominate, while "Reuse" shows strong engagement from rubber and plastic manufacturing (5.22%), and "Recycle" is led by machinery and motor vehicle manufacturing. .
The 10 CE topics insights presented in Table A.11 further delineate the sectoral contributions. For "Material and process innovation", the manufacture of other special-purpose technologies (8.78%) plays a significant role, while "Data Communication and Digital Systems" sees a robust presence of computer manufacturing (15.54%). "Agriculture and Resource Optimization" stands out for the dominance of basic chemicals (20.90%), pharmaceuticals (16.54%), and food preparations (9.44%). Across all topics, the assigned NACE codes appear to align well with the corresponding CE dimensions, reflecting the sectoral relevance to each area of CE innovation.

	Code	Name	n. patents	% patents (%)
1	20.10	Manufacture of basic chemicals	46,185	16.79%
2	28.90	Manufacture of other special-purpose machinery	28,296	10.28%
3	22.00	Manufacture of rubber and plastic products	19,109	6.94%
4	26.10	Manufacture of electronic components and boards	17,489	6.35%
5	21.00	Manufacture of basic pharmaceutical products	15,840	5.75%
6	28.29	Manufacture of other general-purpose machinery n.e.c.	15,623	5.68%
7	26.30	Manufacture of communication equipment	13,914	5.05%
8	27.20	Manufacture of batteries and accumulators	13,242	4.81%
9	26.20	Manufacture of computers and peripheral equipment	12,795	4.65%
10	28.10	Manufacture of general-purpose machinery	12,639	4.59%

Table 4: Distribution of CE patents across NACE codes

4.5 Technical Fields

At the aggregate level, the largest share is held by "Other special machines", accounting for 13.3% of total patents. This category encompasses a wide variety of specialized machinery, reflecting the broad scope of innovation in manufacturing and industrial technologies. The following are "Electrical machinery, apparatus, and energy" (10.3%), and "Chemical engineering" (8.8%). The fields of "Electronic components and boards manufacturing" (8.6%) and "Handling" (8.2%) also contribute significantly, demonstrating the importance of advanced manufacturing, logistics, and automation technologies in the wider technological landscape.

When examining the distribution of patents across the 5R topics, the "Reduce" one is dominated by "Electrical machinery, apparatus, energy" (7.93%), followed by "Chemical engineering" (7.16%) and "Other special machines" (6.56%). The "Reuse" category exhibits a clear dominance of "Other special machines" (10.14%) and "Manufacture of electronic components and boards" (5.62%). In contrast, patents under the "Recycle" category are heavily concentrated in "Other special machines" (8.86%), followed by "Transport" (7.54%) and "Mechanical elements" (6.48%), while "Handling" stands out as the most patent-intensive field in the "Repair" category, with 17.65% patents.

Tech. Field	Name	n. patents	% patents (%)

29	Other special machines	36,586	13.30%
1	Electrical machinery, apparatus, energy	28,388	10.32%
23	Chemical engineering	24,210	8.80%
25	Manufacture of electronic components and boards	23,590	8.57%
24	Handling	22,669	8.24%
35	Civil engineering	18,165	6.60%
20	Materials, metallurgy	17,978	6.53%
19	Basic materials chemistry	17,550	6.38%
28	Textile and paper machines	17,210	6.25%
32	Transport	17,126	6.22%

Table 5: Distribution of CE patents across CPC technological fields

At a more granular level, when examining the 10 CE topic distribution of patents across specific categories, in the category "Material and Process Innovation", "Handling" (10.70%) leads the charge. "Other special machines" (7.44%) and "Chemical engineering" (7.10%) also play an essential role. Patents in the "Imaging and Display Technologies" category show a focus on "Optics" (17.82%), while the "Resource recovery" category sees strong contributions from "Environmental technologies" (15.21%).

4.6 Main Actors

At the company level, Table A.14 presents the top ten patent applicants in the CE sector. The leader of the list is Procter & Gamble, known for its consumer goods, including household and personal care products, with 3,631 patents, accounting for 1.32% of the total. Samsung Electronics Co. Ltd., a leader in consumer electronics, follows with 3,506 patents (1.27%). Siemens AG, a multinational company focused on industrial automation, energy, healthcare, and digital transformation, ranks third with 3,305 patents (1.20%), just ahead of Robert Bosch GmbH, which holds 3,200 patents (1.16%) and specializes in engineering and electronics. Novozymes A/S, a biotechnology company, follows closely with 3,151 patents (1.15%). Other notable contributors include Hewlett-Packard Development Co. LP and Matsushita Electric Industrial Co. Ltd.

The leading actors are especially focused on the 5R principles, as illustrated in Table A.15. Procter & Gamble's dominance is particularly evident in "Reduce" and "Refurbish", as their innovations aim to reduce resource consumption in consumer goods and enhance product longevity. Samsung Electronics and Siemens AG are pivotal in "Repair," leveraging advancements in electronic components and modular systems. Robert Bosch GmbH demonstrates strong engagement with "Recycle" through its contributions to material recovery technologies. Meanwhile, Novozymes A/S drives innovation in "reuse," with biobased solutions enabling the reintegration of biological materials into production cycles.

Looking at the leading actors per CE topic, the data reveal a diverse range of company specializations across CE topics within the CE. In "Material and process innovation", Hewlett-Packard Development Co. LP and LG Electronics prevail (0.67%), while in "Adaptive structures and materials, Novozymes A/S stands out with 728 patents (0.948%). or "Imaging and Display Technologies", Samsung Electronics Co. Ltd. excels with 510 patents (1.483%). "Adaptive Structures and Materials" is once again notably influenced by the activities of Hewlett-Packard. At the same time, in "Agriculture and Resource Optimization", E.I. du Pont de Nemours & Co prevails among others. Table A.16 provides a complete mapping of the principal applicant.

4.7 Addressing the CE patents quality

To investigate the correlation between CE patents and several key quality measures, the OECD Patent Quality Indicator database was analyzed. In particular, four indices were selected: generality, originality, radicalness, and a composite quality index. The paper by Squicciarini, Dernis, and Criscuolo illustrates how these measures were constructed [Squicciarini et al., 2013]. The generality index is higher when a patent is cited by patents belonging to a wide range of fields. In contrast, the originality index refers to the breadth of the technology fields on which a patent relies: inventions relying on a large number of diverse knowledge sources are supposed to lead to original results. Radicalness is related to the fact that the more patent citations belong to classes other than the one in which it is, the more the invention should be considered radical. Finally, the 4-4 quality index components consist of the number of forward citations (up to 5 years after publication), the size of the patent family, the number of claims, and the patent generality index.

Three OLS regressions are performed to explore the correlation between quality indicators and circularity, assessing the strength of these relationships. As shown in Table 6, the first regression analyzes circular patents in general, while the second distinguishes between the five 5R categories ("Recycle", "Reduce", "Refurbish", "Repair", and "Reuse"). Finally, the third incorporates the 10 CE topics to gain a more nuanced view. The following discussion delves into the results of these three regressions, highlighting key insights and patterns.

In the first regression, CE patents exhibit a positive and statistically significant relationship with all four quality measures. CE patents are generally more cited across a broad range of technologies, are more original, more radical in their approach, and have higher overall quality, as captured by the composite index. This is relevant because it suggests that CE patents tend to span multiple areas of technology and introduce novel solutions.

Regr.	**Independent Variables**	**Generality**	**Originality**	**Radicalness**	**Quality Index**
1.	Circular	0.0155*** (0.0015)	0.0241*** (0.0012)	0.0224*** (0.0013)	0.0256*** (0.0007)
	Sector controls	Yes	Yes	Yes	Yes

Regr.	Independent Variables	Generality	Originality	Radicalness	Quality Index
	Country controls	Yes	Yes	Yes	Yes
2.	Recycle	0.0184*** (0.0032)	0.0205*** (0.0026)	0.0184*** (0.0028)	0.0203*** (0.0015)
	Reduce	0.0065* (0.0025)	0.0116*** (0.0020)	0.0096*** (0.0022)	0.0232*** (0.0012)
	Refurbish	0.0445*** (0.0055)	0.0422*** (0.0043)	0.0024*** (0.0048)	0.0358*** (0.0027)
	Repair	−0.0195*** (0.0059)	0.0026 (0.0045)	0.0024 (0.0051)	0.0141*** (0.0027)
	Reuse	0.0236*** (0.0026)	0.0399*** (0.0019)	0.0366*** (0.0023)	0.0316*** (0.0012)
	Sector controls	Yes	Yes	Yes	Yes
	Country controls	Yes	Yes	Yes	Yes
3.	Material and process innovation	0.0013 (0.0032)	0.0051 (0.0026)	0.0119*** (0.0028)	0.0250*** (0.0015)
	Adaptive structures and materials	0.0235*** (0.0029)	0.0213*** (0.0024)	0.0177*** (0.0026)	0.0236*** (0.0013)
	Polymers, composites, and material recycling	0.0424*** (0.0034)	0.0585*** (0.0023)	0.0595*** (0.0031)	0.0334*** (0.0016)
	Resource recovery	−0.0135 (0.0060)	−0.0078 (0.0047)	0.0042 (0.0051)	0.0044*** (0.0026)
	Recycling equipment and waste management	−0.0217*** (0.0054)	−0.0053 (0.0045)	−0.0076 (0.0046)	0.0025*** (0.0024)
	Imaging and display technologies	0.0480*** (0.0053)	0.0457*** (0.0038)	0.0449*** (0.0046)	0.0457*** (0.0026)
	Resource and material efficiency	−0.0218** (0.0079)	0.0474*** (0.0054)	0.0262*** (0.0067)	0.0106*** (0.0034)
	Battery technologies and recycling	−0.0498*** (0.0062)	0.0030 (0.0042)	−0.0456*** (0.0053)	0.0187*** (0.0029)
	Data communication and digital system	0.0548*** (0.0065)	0.0419*** (0.0048)	0.0466*** (0.0059)	0.0499*** (0.0032)
	Agriculture and resource optimization	0.0599*** (0.0109)	0.0322*** (0.0078)	0.0481*** (0.0110)	0.0386*** (0.0055)
	Sector controls	Yes	Yes	Yes	Yes
	Country controls	Yes	Yes	Yes	Yes

Table 6: OLS regressions over Patent Quality Indexes

The second regression analysis differentiates the 5R categories, revealing different patterns in patent characteristics. The "Recycle" category exhibits strong positive correlations with all quality measures, while "Reduce" has a modest effect on the generality index, indicating that patents in this category tend to be more specific and less broad in their applications. "Refurbish" patents exhibit a powerful positive impact on both the generality and originality indexes. In contrast, patents in the "Repair" category show a negative generality index, albeit still making a positive and significant contribution to overall patent quality. Finally, "Reuse" patents demonstrate consistent and significant positive relationships across all quality measures, being not only innovative and high-quality but also making significant contributions to technological progress.

The third regression focuses on the 10 CE topics as previously defined. Topics regarding "Polymers, composites, and material recycling", "Imaging and display technologies", and "Data communication and digital systems" exhibit positive correlations with all quality measures. The topics "Resource recovery", "Recycling equipment and waste management", and "Battery technologies and recycling" show instead a more mixed pattern, with negative correlations in some measures (e.g., generality and originality) but still a positive relationship with the quality index.

5 Conclusions

This study proposes a novel framework for identifying and classifying CE patents through advanced natural language processing techniques. By combining LLMs, a fine-tuned transformer classifier, and topic modeling, the paper addresses a long-standing gap in existing CE patent classification systems, which have largely relied on keyword searches or CPC codes.

From a theoretical perspective, the study contributes to the literature by operationalizing CE in a data-driven, scalable, and interpretable way that remains consistent with established conceptual frameworks. It enriches innovation studies by providing a replicable method for detecting and monitoring technological contributions to circularity, grounded in recent advances in NLP. Although current evaluations of classification accuracy and topic coherence are heuristic and expert-based—reflecting the absence of a validated gold standard for CE patents—the pipeline's modular and transparent design ensures that results can be reproduced and extended in future work. The managerial and policy implications are also significant. Policymakers and practitioners can apply this classification system to track sectoral and regional patterns of CE innovation with greater precision, target funding, and design interventions that accelerate the transition toward circularity. The integration of deductive (5R) and inductive (topic-based) sub-classifications provides actionable insights into the technological domains driving this transition. Mapping patent abstracts to 5R principles helps bridge the gap between qualitative conceptualizations of circularity and quantitative indicators of technological change, offering a more nuanced understanding of how firms embed CE strategies in research and development. Empirical results highlight the predominance of "Reuse" and "Recycle," indicating that current innovation activity focuses on resource recovery and waste reduction—key levers of circular practice. Among the ten inductively derived CE topics, "Adaptive Structures and Materials" and "Material and Process Innovation" emerge as leading domains, reflecting ongoing efforts to develop flexible and sustainable production systems. The geographical distribution of CE patents reveals strong innovation hubs in Europe, while sectoral and technological classifications show broad integration of CE principles across materials science, machinery, polymers, and battery technologies. Circular patents also display higher quality scores, measured by generality, originality, and radicalness, suggesting that CE-related innovation is both cross-cutting and potentially transformative.

Despite these contributions, several limitations remain. First, while LLMs reduce dependence on narrow keyword definitions, they also introduce interpretability challenges. Their decision logic is difficult to trace, and performance depends on the relevance of the data used during pretraining. Second, the analysis focuses on English-language patents and European authorities, which may omit relevant CE innovations from other linguistic or regional contexts. Third, the framework proposed here is descriptive rather than predictive; it does not assess how CE-related innovation translates into environmental or economic outcomes. These limitations open meaningful avenues for future research. As computational and annotation resources expand, integrated multi-label architectures or direct LLM-based inference could be tested to capture overlapping dimensions of circularity. Regarding the RAG component, future studies should compare retrieval-augmented prompting with static or few-shot strategies under controlled conditions to assess relative accuracy and efficiency. Expanding such benchmarks would clarify whether retrieval augmentation consistently improves performance in large, semantically heterogeneous corpora such as patent databases. Further work should also develop human-labeled CE patent datasets to validate model outputs against independent benchmarks. Combining expert annotation with semi-automated approaches—such as annotation platforms or "LLM-as-a-judge" frameworks—could enhance reliability and inter-rater agreement. Similarly, the exploratory topic modeling step should be complemented by formal evaluation procedures, including topic coherence measures or human-labeled exemplars, to strengthen the methodological rigor of clustering-based analyses and enable direct comparison with legacy classification systems. Finally, future research should extend this framework to non-European and multilingual patent corpora and link CE innovation patterns to environmental and firm-level performance indicators. Comparative testing of alternative NLP architectures and embedding models across CE domains would further refine the robustness and applicability of this approach.

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Appendix

Title and Reference	n. pages
Circular chemistry to enable a circular economy [Keijer et al., 2019]	1-4
Towards a Circular Economy - Waste management in the EU [Lee et al., 2017]	63-88
Artificial Intelligence and the Circular Economy [Ellen MacArthur Foundation, 2019]	6-34
Logistics in the Circular Economy: Challenges and Opportunities [Beames et al., 2021]	5-12
Circular Business Models for the Circular Economy [OECD, 2019]	23-60
Circular Economy Action Agenda: Food [Platform for Accelerating the Circular Economy, 2021]	16-23, 28-44
Jobs & Skills in the Circular Economy [Ellen MacArthur Foundation, 2021]	6-7
Digitalisation for the transition to a resource efficient and circular economy [Eva Börkey, 2022]	16-30
Redefining Value: The Manufacturing Revolution [UNESCO, 2018]	39-58
Circular Economy Gap Report 2023 [Circle Economy, 2023]	13-59
Circular Economy Action Plan [European Commission, 2020a]	6-22
Towards the Circular Economy [Ellen MacArthur Foundation, 2013]	full report
Designing innovations for the circular economy [World Economy Forum, 2023]	full page

Table A.1: Key Documents and Page Ranges Related to Circular Economy

Final Prompt
The implemented LangChain pipeline uses a single prompt instructing the model to act as a circular-economy expert. For each patent abstract, the model is asked to (i) extract the main processes, technologies, or methods described in the abstract; (ii) decide whether the extracted elements align with circular-economy principles; and (iii) answer YES if they do or NO if they do not. A patent is considered circular when it concerns practices such as recycling, reuse, recovery or refurbishment; the use of renewable, reusable or non-toxic resources and energy; environmental regeneration and restoration; maximising product life and efficiency; maintenance, repair or upgrade of resources; the use of waste streams as secondary resources; waste recovery for reuse or recycling; improving resource efficiency (e.g. reducing material or energy consumption while maintaining functionality); designing products for extended lifetime and future reuse; digital platforms for tracing and optimising resource use; biological cycles such as composting or anaerobic digestion; and other strategies that enable resource recycling and efficient use. The model responds only with "YES" for circular-economy patents or "NO" otherwise.

Table A.2: Summary of the final prompt

Topic	Title	Description	n. patents	% patents
2	Adaptive Structures and Materials	This topic focuses on the design, manufacture, and application of collapsible, foldable, or layered structures integrated with advanced materials. These structures are developed using shaping, joining, and compounding processes, enabling flexible, multifunctional, and lightweight solutions	63,242	22.99%
1	Material and Process Innovation	This topic focuses on innovative approaches to materials and processes, emphasizing the development of new technologies to improve functionality, sustainability, and efficiency across various sectors	54,833	19.93%
3	Polymers, Composites, and Material Recycling	This topic focuses on advancements in polymer and composite materials, their synthesis, applications, and recycling processes, emphasizing sustainable material use and circular economy principles	46,164	16.78%
4	Resource Recovery	This topic addresses processes and technologies for water purification, wastewater treatment, and the recovery of resources such as energy, nutrients, and biogas from organic and industrial waste streams	23,419	8.51%
6	Imaging and Display Technologies	This topic explores innovations in imaging, display, and sensor technologies, with applications in electronics, visual systems, and devices for communication and interaction	20,757	7.54%
5	Recycling Equipment and Waste Management	This topic addresses equipment and processes for waste sorting, recycling, and disposal, including pyrolysis, crushing, separation mechanisms, and machinery for handling plastics, metals, and other materials	20,496	7.45%
9	Data Communication and Digital Systems	This topic encompasses the development and application of digital systems used for communication, data transmission, and secure transactions. It includes technologies like cloud computing, blockchain, cryptography, and telecommunications, with a focus on improving energy efficiency, reducing emissions, and optimizing resource use	16,067	5.84%
8	Battery Technologies and Recycling	This topic covers advancements in batteries and energy storage, emphasizing recycling, electrochemical processes, and materials for efficient and sustainable energy systems	13,204	4.80%
7	Resource and Material Efficiency	This topic emphasizes the efficient use of resources and materials across industries, focusing on reducing waste, optimizing supply chains, and enhancing resource recovery through advanced processes and technologies	11,663	4.24%
10	Agriculture and Resource Optimization	This topic focuses on sustainable agricultural practices, optimizing soil management, nutrient cycles, and resource use for efficient cultivation and farming systems	5,168	1.87%

Table A.3: Distribution of patents per CE topics

Topic	Example a	Example b	Example c
Material and Process Innovation	The invention relates to an installation for purifying a fibrous suspension, having multiple hydrocyclones (1) arranged adjacent to one another in a row, which hydrocyclones each have at least one feed connection (2), one accepted stock connection (3) and one reject material connection (4), and having at least one supply collecting line (5) which is connected to multiple feed connections (2) and which serves for the feed of the fibrous suspension, and/or having at least one accepted stock collecting line (6) which is connected to multiple accepted stock connections (3) and which serves for the drainage of the accepted stock [...].	A recyclable, laminated polyolefin-based film structure comprises two or more film plies laminated to each other. Each of the laminated film plies comprises one or more polyolefin-based films. The film structure has an energy-cured coating layer disposed on the outermost outward facing surface of the film structure and a printed ink layer on an interior surface of one of the polyolefin-based polyolefin layers.	According to one embodiment, a method for generating a dynamic watering plan that reduces water consumption requirements for vegetation is disclosed. An example method includes estimating root depth of vegetation watered by a watering system; determining an allowed water depletion threshold of the vegetation based on the root depth; determining a training watering plan to increase the root depth of the vegetation over time based on the root depth and the allowed water depletion threshold; and transmitting the training watering plan to a flow controller for execution by the watering system.
Adaptive Structures and Materials	Devices and methods for cleaning an array of solar panels in side-by-side relation employ one or more elongated flexible elements, preferably implemented as translucent strips (14a, 14b, 14c, 14d), anchored at their ends relative to the array of solar panels (12). Each strip spans two or more solar panels, and is wind-displaceable so as to contribute to cleaning of at least two of the solar panels (12).	A watchband, the watchband comprising: a substantially non-flexible main member (100A, 100B); a flexible auxiliary member (102) coupled to the substantially non-flexible main member (100A, 100B); and a tensioning member (104) coupled to the flexible auxiliary member (102). In use, the tensioner (104) is configured to maintain a selected degree of tension, and the flexible auxiliary member (102) is configured to be resilient.	Collapsible reusable carrying cases are provided in sizes varying from small food containers to large push cart bins on casters. The cases are assembled or disassembled from a joined flat space-saving configuration to a functioning case and vice-versa. All parts that make up a carrying case do not separate from the carrying case and no parts can be removed. The cases are formed from rigid plastic panels, and are assembled or disassembled without tools. [...] The carrying cases are resistant to water, dirt, bacteria, molds, allergens, and inclement weather.

Topic	Example a	Example b	Example c
Polymers, Composites, and Material Recycling	Provided are a method and an apparatus for manufacturing a fiber-reinforced resin molding material by which, when the fiber-reinforced resin molding material is manufactured, separated fiber bundles can be supplied to a cutting machine in stable condition while avoiding the influence of meandering of the fiber bundles or slanting or meandering of filaments occurring in the fiber bundles. A method for manufacturing a sheet-shaped fiber-reinforced resin molding material in which spaces between filaments of cut-out fiber bundles (CF) are impregnated with resin includes [...].	A method of upcycling polymers to useful hydrocarbon materials. A catalyst with nanoparticles on a substrate selectively docks and cleaves longer hydrocarbon chains over shorter hydrocarbon chains. The nanoparticles exhibit an edge to facet ratio to provide for more interactions with the facets.	A resealable beverage can lid has a lid having a top side having a score line forming a panel, a first rivet formed in the lid and extending outwardly from the top side of the lid, a second rivet formed in the panel and extending outwardly from the top side of the lid, and a tab portion connected to the first rivet and the second rivet.
Resource Recovery	The disclosed technology includes blister package assemblies that include a reusable blister pouch. The blister package assembly can have an enclosure housing having a first card and a second card. The second card can be opposed to a separably joinable to the first card. The blister package assembly can have a reusable blister pouch that can enclose an object and have a fastener that transition the reusable blister pouch between an open configuration and a closed configuration.	Hydro excavation vacuum apparatus that process spoil material onboard the apparatus by separating water from the cut earthen material are disclosed. C)0 (N	A semiconductor apparatus may include a repair circuit configured to activate a redundant line of a cell array region by comparing repair information and address information. The semiconductor apparatus may include a main decoder configured to perform a normal access to the cell array region by decoding the address information. The address information may include both column information and row information.

Topic	Example a	Example b	Example c
Waste Management and Recycling Equipment	A knife is provided that includes a replaceable blade element. The knife employs a blade carrier that is fixedly interconnected to or foldable with respect to a handle. The blade carrier selectively receives the replaceable blade element that is locked into the blade carrier by way of a hook and movable pin combination. The replaceable blade element is designed to be inserted within the blade carrier quickly, easily, and safely.	Systems and methods for detecting a waste receptacle, the system including a camera for capturing an image, a convolutional neural network, and processor. The convolutional neural network can be trained for identifying target waste receptacles. The processor can be mounted on the waste-collection vehicle and in communication with the camera and the convolutional neural network configured for using the convolutional neural network. The processor can be configured for using the convolutional neural network to generate an object candidate based on the image [...]	Systems and methods for classifying and sorting of plastic materials utilizing a vision system and one or more sensor systems, which may implement a machine learning system in order to identify or classify each of the materials, which may then be sorted into separate groups based on such an identification or classification.

Topic	Example a	Example b	Example c
Imaging and Display Technologies	A material sorting system sorts materials utilizing a vision system that implements a machine learning system in order to identify or classify each of the materials, which are then sorted into separate groups based on such an identification or classification. The material sorting system may include an x-ray fluorescence system to perform a classification of the materials in combination with the vision system, whereby the classification efforts of the vision system and x-ray fluorescence system are combined in order to classify and sort the materials.	A bifacial solar module with enhanced power output including first and second transparent support layers, a plurality of electrically interconnected bifacial solar cells arranged between the transparent support layers with gaps between one or more of the interconnected solar cells and edges of the first and second transparent support layers, the bifacial solar cells having a first side directly exposed to solar radiation and a second side opposite the first. The bifacial solar module further includes one or more micro-structured reflective tapes positioned coincidentally with the gaps and attached to a surface of the second support layer such that light passing through the second support layer is reflected back into the second support layer at angles such that light reflecting from the tape is absorbed by either the first or second side of the bifacial solar cells.	A device and/or apparatus that comprises a dynamic optical lens is provided. A first apparatus includes a first lens component having a first surface and a second surface. The first apparatus further includes a second lens component that comprises a flexible element. [...] The flexible element of the second lens component is such that it conforms to the first surface of the first lens component when an amount of fluid between the first surface of the first lens component and the second lens component is sufficiently low. The flexible element of the second lens component is also such that it does not conform to the first surface of the first lens component when an amount of fluid between the first surface of the first lens component and the second lens component is sufficiently great.

Topic	Example a	Example b	Example c
Resource and Material Efficiency	The invention relates to the supplemental generation of energy from operation of a train, and specifically to the generation of energy in connection to the rotation of disc brake rotors in combination with generators. Rotation of the disc brake rotors creates rotational energy that is transmitted to the generators, which then transmits the energy to a series of batteries for storage. The batteries may be stored in the platform for the train and/or within the train car itself. Energy from the batteries may be utilized by removal of the batteries from the train or through a number of outlets, sockets or connectors associated with the train car or platform.	[Problem] To provide a building material having excellent durability. [Solution] A building material having a convex part formed on a surface thereof, the convex part having a first lateral surface part and a second lateral surface part corresponding to the first lateral surface part. The building material is made of a mixture containing a hydraulic material, an admixture, and a plant-based reinforcing material. The plant-based reinforcing material, at least in the convex part, is distributed in the mixture with the hydraulic material and the admixture attached thereto. The distribution of the plant-based reinforcing material in the first lateral surface part and the distribution of the plant-based reinforcing material in the second lateral surface part are substantially the same. [...]	Described herein are compositions and methods for waste-to-energy ash in engineered aggregate in road construction.
Battery Technologies and Recycling	The invention relates to a system for wirelessly charging an electrically chargeable device, in particular a mobile inspection robot, in a potentially explosive environment. The invention also relates to a charging station for use in such a system according to the invention. The invention further relates to an electrically chargeable device, in particular an inspection robot, for use in such a system according to the invention. [...]	The present invention provides a secondary battery which comprises an electrode assembly and an outer package that houses the electrode assembly. With respect to this secondary battery, the outer package is provided with a metal plate that is bonded thereto with an insulating material being interposed therebetween; the outer package has an opening; and either the peripheral edge of the opening or the outer edge of the metal plate is bent so as to be away from the insulating material.	A process for removal of aluminium and iron in the recycling of rechargeable batteries comprising providing a leachate from black mass, adding phosphoric acid (H3PO4) to said leachate and adjusting the pH to form iron phosphate (FePO4) and aluminium phosphate (AlPO4), precipitating and removing the formed FePO4 and AlPO4, and forming a filtrate for further recovery of cathode metals, mainly NMC-metals and lithium.

Topic	Example a	Example b	Example c
Data Communication and Digital Systems	A computer-based system collects data associated with a user activity. The data is transmitted from an app running on a computing device with a user account authenticated by the computer-based system. A carbon footprint of the user activity is calculated based on the data associated with the user activity. The system calculates a proof of environmental impact in response to a function of the carbon footprint and a baseline value. An amount of cryptocurrency is generated based on the proof of environmental impact by writing a transaction for the amount of cryptocurrency to a blockchain in response to proof of environmental impact. The amount of cryptocurrency is assigned to the user account authenticated with the computer-based system.	A method for providing economic information based on geographic parameters that includes providing a map for display on a device, receiving a user-defined area on the map, and providing data relating to the user-defined area. Obtaining the relevant information or data about a particular geographic region frequently involves consulting a plurality of sources. The current method is much more efficient and cost effective to retrieve from fewer sources and provide the information in a quick and easy to comprehend format.	A computer-implemented system and method for inferring operational specifications of a photovoltaic power generation system using net load is provided. Photovoltaic plant configuration specifications can be accurately inferred with net load data and measured solar resource data. A time series of net load data is evaluated to identify, if possible, a time period with preferably minimum and consistent power consumption. Power generation data is simulated for a range of hypothetical photovoltaic system configurations based on a normalized solar power simulation model. Net load data is estimated based on a base load and, if applicable, any binary loads and any variable loads.

Topic	Example a	Example b	Example c
Agriculture and Resource Optimization	Techniques for providing improvements in agricultural science by optimizing irrigation treatment placements for testing are provided, including analyzing a plurality of digital images of a field to determine vegetation density changes in a sector of the field. The techniques proceed by comparing a distribution of pixel characteristics in the digital images for each field sector to determine sectors in which minimal density deviations are present. Instructions for irrigation placements and testing may be displayed or modified based on the results of the sector determinations.	Implementations are described herein for edge-based real time crop yield predictions made using sampled subsets of robotically-acquired vision data. In various implementations, one or more robots may be deployed amongst a plurality of plants in an area such as a field. [...] A subset of multiple high resolution images may then be sampled from the superset of high resolution images. Data indicative of the subset of high resolution images may be applied as input across a machine learning model, with or without additional data, to generate output indicative of a real time crop yield prediction.	System and method for treating harvested plant material, such as cannabis, with ozone. Embodiments include tumbling the plant material in a rotating vessel, such as a drum, while exposing the plant material to ozone.

Table A.4: Examples CE topics

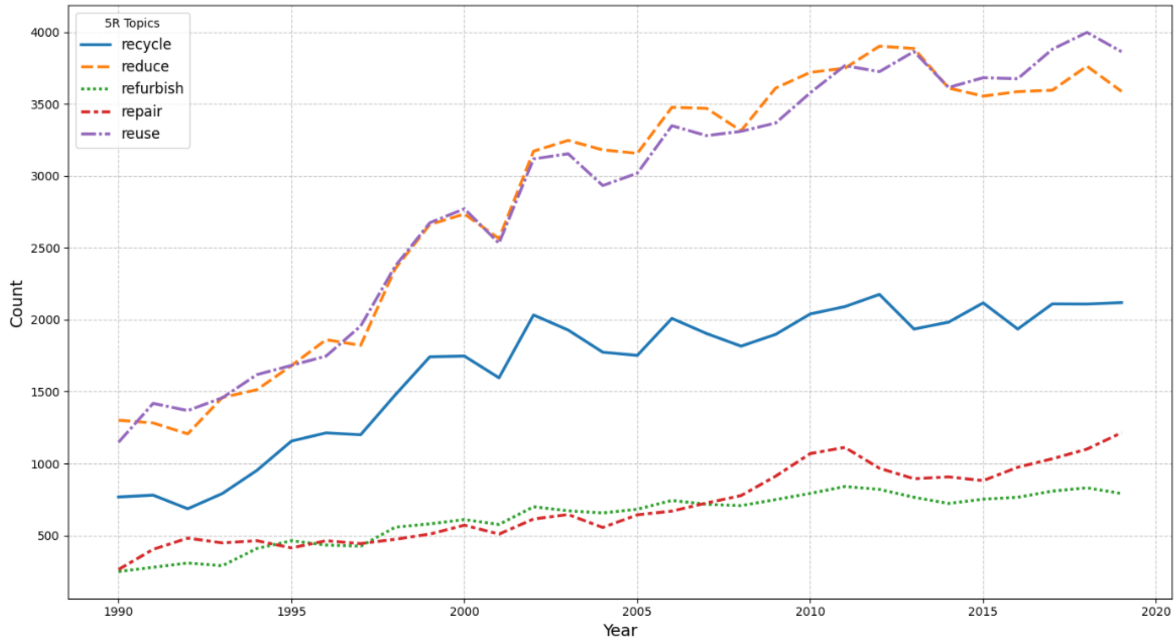

Figure A.1: Annual trend of CE patents by 5R topics

	NUTS Code	Region Name	n. patents	% patents
1	DE212	Main-Kinzig-Kreis, Germany	5,382	2.08%
2	FR101	Paris, France	4,060	1.57%
3	FI1B1	Helsinki-Uusimaa, Finland	3,179	1.23%
4	FR105	Hauts-de-Seine, France	3,101	1.20%
5	CH040	Zurich, Switzerland	2,817	1.09%
6	NL414	Flevoland, Netherlands	2,595	1.00%
7	ITC4C	Milan, Italy	2,542	0.98%
8	DK012	Copenhagen City, Denmark	2,359	0.91%
9	DE111	Region Hannover, Germany	2,257	0.87%
10	SE224	Västra Götaland, Sweden	2,191	0.84%

Table A.5: Distribution of CE patents at Nuts3 level

Topic	NUTS3 Code	Region Name	n. patents	% patents
Reduce	DE212	Main-Kinzig-Kreis, Germany	1,446	1.90%
	FR101	Paris, France	1,230	1.62%
	NL414	Flevoland, Netherlands	1,114	1.47%
	FI1B1	Helsinki-Uusimaa, Finland	1,020	1.34%
	FR105	Hauts-de-Seine, France	908	1.20%
	ITC4C	Milan, Italy	847	1.12%
	CH040	Zurich, Switzerland	816	1.07%
	CH011	Lausanne, Switzerland	739	0.97%

Topic	NUTS3 Code	Region Name	n. patents	% patents
	DK012	Copenhagen City, Denmark	722	0.95%
	SE110	Stockholm, Sweden	708	0.93%
Reuse	DE212	Main-Kinzig-Kreis, Germany	1,638	1.85%
	FR101	Paris, France	1,476	1.67%
	DK012	Copenhagen City, Denmark	1,263	1.43%
	FI1B1	Helsinki-Uusimaa, Finland	1,221	1.38%
	DEA11	Düsseldorf, Germany	1,099	1.24%
	FR105	Hauts-de-Seine, France	1,014	1.14%
	CH040	Zurich, Switzerland	915	1.03%
	NL414	Flevoland, Netherlands	901	1.02%
	ITC4C	Milan, Italy	851	0.96%
	DEB34	Region Hannover, Germany	782	0.88%
Recycle	DE212	Main-Kinzig-Kreis, Germany	1,643	2.88%
	FR101	Paris, France	783	1.37%
	DE111	Region Hannover, Germany	686	1.20%
	FR105	Hauts-de-Seine, France	675	1.18%
	CH040	Zurich, Switzerland	668	1.17%
	FI1B1	Helsinki-Uusimaa, Finland	531	0.93%
	DE115	Karlsruhe, Germany	519	0.91%
	DE929	Gießen, Germany	506	0.89%
	ITC4C	Milan, Italy	497	0.87%
	DE600	Hamburg, Germany	453	0.79%
Repair	DE212	Main-Kinzig-Kreis, Germany	279	1.61%
	FR101	Paris, France	262	1.51%
	FI1B1	Helsinki-Uusimaa, Finland	231	1.33%
	DE111	Region Hannover, Germany	207	1.19%
	FR105	Hauts-de-Seine, France	206	1.19%
	CH040	Zurich, Switzerland	199	1.14%
	DE300	Berlin, Germany	193	1.11%
	SE110	Stockholm, Sweden	184	1.06%
	ITC4C	Milan, Italy	176	1.01%
	DE600	Hamburg, Germany	152	0.87%
Refurbish	DE212	Main-Kinzig-Kreis, Germany	376	1.86%
	SE224	Västra Götaland, Sweden	324	1.60%
	FR101	Paris, France	309	1.53%
	FR105	Hauts-de-Seine, France	298	1.47%
	CH040	Zurich, Switzerland	212	1.05%
	DE600	Hamburg, Germany	203	1.00%
	FI1B1	Helsinki-Uusimaa, Finland	176	0.87%
	FR714	Haute-Garonne, France	173	0.86%
	ITC4C	Milan, Italy	171	0.85%
	DE111	Region Hannover, Germany	139	0.69%

Table A.6: Distribution of patents per 5R topics across at Nuts3 level

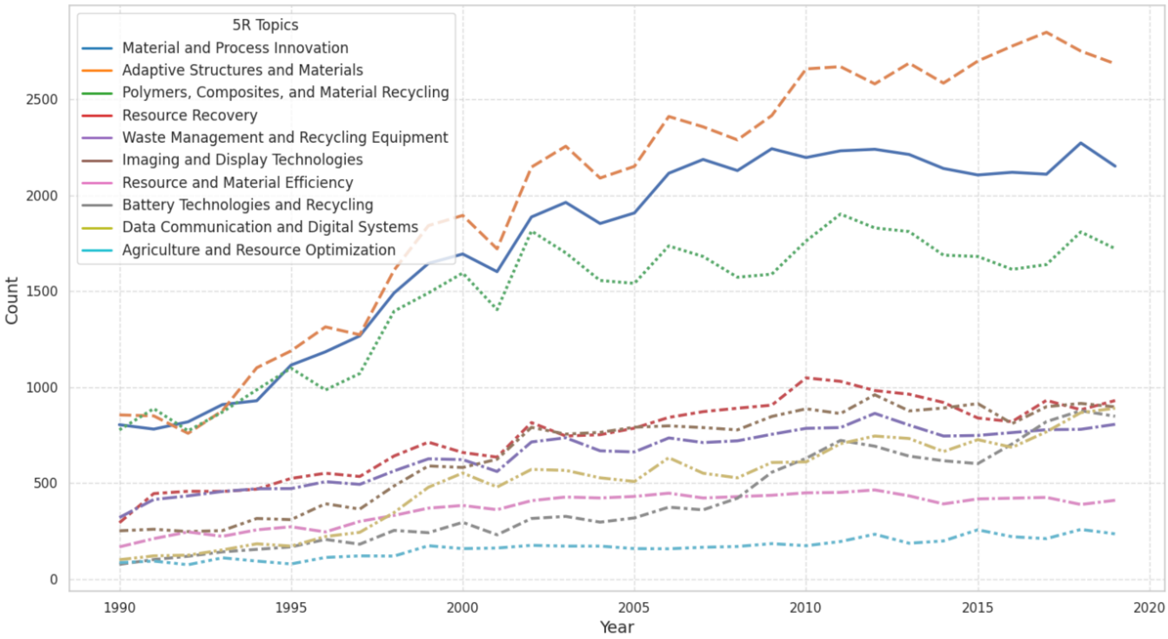

Figure A.2: Annual trend of CE patents by 10 CE topics

Topic	NUTS Code	Region Name	n. patents	% patents
Material and Process Innovation	DE212	Main-Kinzig-Kreis, Germany	1,048	2.11%
	FR101	Paris, France	802	1.62%
	CH040	Zurich, Switzerland	566	1.14%
	FR105	Hauts-de-Seine, France	566	1.14%
	DE11C	Düsseldorf, Germany	495	1.00%
	ITC4C	Lombardy, Italy	477	0.96%
	DE111	Stuttgart, Germany	452	0.91%
	FI1B1	Uusimaa, Finland	431	0.87%
	CH011	Lausanne, Switzerland	429	0.87%
	ITH55	Tuscany, Italy	417	0.84%
Polymers, Composites, and Material Recycling	DK012	Copenhagen, Denmark	1,443	2.55%
	DE212	Main-Kinzig-Kreis, Germany	952	1.68%
	FI1B1	Uusimaa, Finland	945	1.67%
	FR101	Paris, France	863	1.53%
	DEA11	Düsseldorf, Germany	821	1.45%
	DEB34	Karlsruhe, Germany	751	1.33%
	DK013	Zealand, Denmark	688	1.22%
	CH011	Lausanne, Switzerland	659	1.17%
	FR105	Hauts-de-Seine, France	563	0.99%
	CH040	Zurich, Switzerland	541	0.96%
Imaging and Display Technologies	NL414	North Brabant, Netherlands	426	2.71%
	DE212	Main-Kinzig-Kreis, Germany	417	2.66%

Topic	**NUTS3 Code**	**Region Name**	**n. patents**	**% patents**
	FR101	Paris, France	361	2.30%
	FR105	Hauts-de-Seine, France	246	1.57%
	DE11D	Upper Bavaria, Germany	222	1.41%
	ITC4C	Lombardy, Italy	219	1.39%
	FR107	Rhône, France	200	1.27%
	FR714	Provence-Alpes-Côte d'Azur, France	193	1.23%
	SE110	Stockholm, Sweden	185	1.18%
	CH040	Zurich, Switzerland	177	1.13%
Adaptive Structures and Materials	DE212	Main-Kinzig-Kreis, Germany	1,402	2.32%
	FI1B1	Uusimaa, Finland	741	1.23%
	NL414	North Brabant, Netherlands	717	1.19%
	SE224	Västra Götaland, Sweden	681	1.13%
	FR101	Paris, France	675	1.12%
	ITH34	Emilia-Romagna, Italy	662	1.10%
	ITC4C	Lombardy, Italy	646	1.07%
	DE929	Bavaria, Germany	601	0.99%
	FR105	Hauts-de-Seine, France	596	0.99%
	DE111	Stuttgart, Germany	588	0.97%
Agriculture and Resource Optimization	DK012	Copenhagen, Denmark	114	2.21%
	DE300	Berlin, Germany	94	1.82%
	FR101	Paris, France	84	1.63%
	ITC4C	Lombardy, Italy	72	1.39%
	NL221	Groningen, Netherlands	71	1.37%
	FI1B1	Uusimaa, Finland	61	1.18%
	DEB3I	Freiburg, Germany	59	1.14%
	DEA1C	Lower Saxony, Germany	59	1.14%
	DK013	Zealand, Denmark	59	1.14%
	DEA11	Düsseldorf, Germany	59	1.14%
Data Communication and Digital Systems	DE212	Main-Kinzig-Kreis, Germany	408	4.31%
	SE110	Stockholm, Sweden	225	2.38%
	FR105	Hauts-de-Seine, France	208	2.20%
	FR101	Paris, France	208	2.20%
	SE224	Västra Götaland, Sweden	167	1.77%
	FI1B1	Uusimaa, Finland	165	1.74%
	NL414	North Brabant, Netherlands	154	1.63%
	CH040	Zurich, Switzerland	147	1.55%
	DE111	Stuttgart, Germany	130	1.37%
	UKH12	East of England, UK	94	0.99%
Resource and Material Efficiency	FR101	Paris, France	234	1.92%
	CH040	Zurich, Switzerland	230	1.89%

Topic	NUTS3 Code	Region Name	n. patents	% patents
	FR105	Hauts-de-Seine, France	222	1.82%
	DE212	Main-Kinzig-Kreis, Germany	169	1.39%
	DE128	Bremen, Germany	140	1.15%
	CH033	Espace Mittelland, Switzerland	139	1.14%
	DEA11	Düsseldorf, Germany	136	1.12%
	FR714	Provence-Alpes-Côte d'Azur, France	131	1.07%
	DE125	Baden-Württemberg, Germany	119	0.98%
	DK013	Zealand, Denmark	119	0.98%
Resource Recovery	FR101	Paris, France	369	1.86%
	FR105	Hauts-de-Seine, France	355	1.79%
	DE212	Main-Kinzig-Kreis, Germany	345	1.74%
	FR103	Île-de-France, France	253	1.28%
	FI1B1	Uusimaa, Finland	233	1.17%
	SE224	Västra Götaland, Sweden	215	1.08%
	CH040	Zurich, Switzerland	211	1.06%
	DE111	Stuttgart, Germany	209	1.05%
	ITC4C	Lombardy, Italy	205	1.03%
	SE110	Stockholm, Sweden	175	0.88%
Battery Technologies and Recycling	FR101	Paris, France	247	3.03%
	DE212	Main-Kinzig-Kreis, Germany	236	2.90%
	DE111	Stuttgart, Germany	235	2.88%
	FR714	Provence-Alpes-Côte d'Azur, France	181	2.22%
	CH011	Lausanne, Switzerland	136	1.67%
	NL414	North Brabant, Netherlands	128	1.57%
	FR105	Hauts-de-Seine, France	123	1.51%
	DEB34	Karlsruhe, Germany	117	1.44%
	CH040	Zurich, Switzerland	116	1.42%
	DE300	Berlin, Germany	102	1.25%
Recycling Equipment and Waste Management	DE115	Freiburg, Germany	461	2.08%
	DE212	Main-Kinzig-Kreis, Germany	358	1.61%
	FI1B1	Uusimaa, Finland	279	1.26%
	BE251	Flanders, Belgium	269	1.21%
	AT312	Upper Austria, Austria	254	1.15%
	CH040	Zurich, Switzerland	235	1.06%
	DE111	Stuttgart, Germany	224	1.01%
	FR101	Paris, France	217	0.98%
	DEA11	Düsseldorf, Germany	211	0.95%
	NL414	North Brabant, Netherlands	196	0.88%

Topic	NUTS3 Code	Region Name	n. patents	% patents

Table A.7: Distribution of patents per CE topics across at Nuts3 level

Topic	CPC Code	CPC Title	n. patents	% patents
Reduce	H01M	Processes or means, e.g., batteries	40,806	5.80%
	B01D	Separation	30,033	4.27%
	C02F	Treatment of water, waste water, sewage, or sludge	29,145	4.14%
	H01L	Semiconductor devices not covered by class H10	19,264	2.74%
	B29C	Shaping or joining of plastics	18,800	2.67%
	B32B	Layered products, i.e., products built-up of strata of flat or non-flat	16,934	2.41%
	B65D	Containers for storage or transport of articles or materials	16,343	2.32%
	Y10T	Technical subjects covered by former US classification	15,359	2.18%
	Y02E	Reduction of greenhouse gas [GHG] emissions, related to energy generation, transmission or distribution	13,918	1.98%
	G06F	Electric digital data processing	13,633	1.94%
Reuse	B32B	Layered products, i.e., products built-up of strata of flat or non-flat	42,328	5.59%
	B29C	Shaping or joining of plastics	37,393	4.94%
	H01M	Processes or means	32,781	4.33%
	C04B	Lime, magnesia; slag; cements; compositions thereof	23,621	3.12%
	B65D	Containers for storage or transport of articles or materials	22,759	3.01%
	H01L	Semiconductor devices not covered by class H10	22,627	2.99%
	Y10T	Technical subjects covered by former US classification	21,149	2.80%
	C12N	Microorganisms or enzymes	13,861	1.83%
	C02F	Treatment of water, waste water, sewage, or sludge	13,384	1.77%
	Y02W	Climate change mitigation technologies related to wastewater treatment or waste management	13,166	1.74%
Recycle	B29C	Shaping or joining of plastics	28,654	7.37%
	B32B	Layered products, i.e., products built-up of strata of flat or non-flat	18,900	4.86%
	Y10T	Technical subjects covered by former US classification	13,954	3.59%
	B65D	Containers for storage or transport of articles or materials	10,498	2.70%

Topic	CPC Code	CPC Title	n. patents	% patents
	H01L	Semiconductor devices not covered by class H10	9,703	2.50%
	C02F	Treatment of water, waste water, sewage, or sludge	8,617	2.22%
	H01M	Processes or means, e.g., batteries, for the direct conversion of chemical energy into electrical energy	6,511	1.68%
	G06F	Electric digital data processing	6,340	1.63%
	F16C	Shafts; flexible shafts; elements or crankshaft mechanisms; rotary bodies other than gearing elements	5,883	1.51%
	C04B	Lime, magnesia; slag; cements; compositions thereof	5,486	1.41%
Repair	H01M	Processes or means, e.g., batteries	23,494	11.90%
	C02F	Treatment of water, waste water, sewage, or sludge	21,302	10.79%
	Y02W	Climate change mitigation technologies related to wastewater treatment or waste management	9,677	4.90%
	B01D	Separation	9,202	4.66%
	Y02E	Reduction of greenhouse gas [GHG] emissions, related to energy generation, transmission or distribution	7,326	3.71%
	H01L	Semiconductor devices not covered by class H10	5,480	2.78%
	A47L	Domestic washing or cleaning	5,003	2.53%
	B65D	Containers for storage or transport of articles or materials	4,355	2.21%
	B32B	Layered products, i.e., products built-up of strata of flat or non-flat, e.g., cellular or honeycomb, form	4,352	2.20%
	Y02P	Climate change mitigation technologies in the production or processing of goods	3,941	2.00%
Refurbish	B32B	Layered products, i.e., products built-up of strata of flat or non-flat	23,874	14.27%
	B29C	Shaping or joining of plastics	9,225	5.51%
	Y10T	Technical subjects covered by former US classification	6,927	4.14%
	H01L	Semiconductor devices not covered by class H10	6,785	4.05%
	C04B	Lime, magnesia; slag; cements; compositions thereof; artificial stone; ceramics; refractories; treatment of natural stone	5,673	3.38%
	B65D	Containers for storage or transport of articles or materials	3,596	2.14%
	C02F	Treatment of water, waste water, sewage, or sludge	3,481	2.08%
	E04F	Finishing work on buildings	3,203	1.91%
	B01D	Separation	2,807	1.67%

Topic	CPC Code	CPC Title	n. patents	% patents
	E04B	General building constructions	2,767	1.65%

Table A.8: Distribution of patents per 5R topic across CPC codes

Topic	CPC Code	CPC Title	n. patents	% patents
Material and Process Innovation	B65D	Containers for storage or transport of articles or materials	23,690	5.66%
	H01L	Semiconductor devices not covered by class H10	21,797	5.21%
	B29C	Shaping or joining of plastics	21,100	5.04%
	B32B	Layered products	14,689	3.51%
	H01M	Processes or means, e.g., batteries, for the direct conversion of chemical energy into electrical energy	14,010	3.35%
	B01D	Separation	12,550	3.00%
	Y10T	Technical subjects covered by former US classification	11,098	2.65%
	C02F	Treatment of water, waste water, sewage, or sludge	9,953	2.38%
	B01L	Chemical or physical laboratory apparatus for general use	9,156	2.19%
	B41J	Typewriters; selective printing mechanisms	8,261	1.97%
Polymers, Composites, and Material Recycling	B32B	Layered products	40,999	10.29%
	B29C	Shaping or joining of plastics	29,022	7.29%
	C12N	Microorganisms or enzymes; compositions thereof; genetic engineering	16,034	4.03%
	Y10T	Technical subjects covered by former US classification	15,657	3.93%
	C08J	Working-up; general processes of compounding	13,199	3.31%
	C08L	Compositions of macromolecular compounds	10,000	2.51%
	B29K	Indexing scheme associated with moulding materials or materials for moulds	9,764	2.45%
	B65D	Containers for storage or transport of articles or materials	9,102	2.28%
	B01J	Chemical or physical processes, e.g., catalysis	9,062	2.27%
	C04B	Lime, magnesia; slag; cements	8,180	2.05%
Imaging and Display Technologies	G02B	Optical elements, systems or apparatus	15,572	9.30%
	H01L	Semiconductor devices not covered by class H10	14,455	8.63%
	B32B	Layered products	8,362	5.00%
	H04N	Pictorial communication, e.g., television	7,310	4.36%
	G06F	Electric digital data processing	5,223	3.12%
	G02F	Optical devices or arrangements for the control of light	4,390	2.62%
	Y10T	Technical subjects covered by former US classification	3,877	2.31%
	C08L	Compositions of macromolecular compounds	3,837	2.29%

Topic	CPC Code	CPC Title	n. patents	% patents
	G06T	Image data processing or generation	3,779	2.26%
	B29C	Shaping or joining of plastics	3,598	2.15%
Adaptive Structures and Materials	B29C	Shaping or joining of plastics; shaping of materials or articles made of plastics	29,572	6.29%
	B32B	Layered products, i.e., products built-up of strata of flat or non-flat materials	26,361	5.61%
	Y10T	Technical subjects covered by former US classification	17,634	3.75%
	A43B	Characteristic features of footwear	16,088	3.42%
	B65D	Containers for storage or transport of articles or materials	12,836	2.73%
	H01L	Semiconductor devices not covered by class H10	12,520	2.66%
	H01M	Processes or means, e.g., batteries, for the direct conversion of chemical energy into electrical energy	9,324	1.98%
	B33Y	Additive manufacturing, e.g., 3D printing	8,218	1.75%
	B22F	Working metallic powder; manufacture of articles from metallic powder	8,113	1.73%
	G06F	Electric digital data processing	6,665	1.42%
Agriculture and Resource Optimization	C12N	Microorganisms or enzymes; compositions thereof; genetic engineering; culture media	2613	7.41%
	C02F	Treatment of water, waste water, sewage, or sludge	1906	5.4%
	C05F	Organic fertilisers not covered by subclasses C05B, C05C, e.g. fertilisers from waste or refuse	1469	4.16%
	C12P	Fermentation or enzyme-using processes to synthesise a desired chemical compound or composition	1249	3.54%
	A23L	Foods, foodstuffs, or non-alcoholic beverages	1242	3.52%
	H01M	Processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy	1178	3.34%
	Y02W	Climate change mitigation technologies related to wastewater treatment or waste management	1142	3.24%
	A01N	Preservation of bodies of humans or animals or plants or parts thereof	1085	3.07%
	A01G	Horticulture; cultivation of vegetables	968	2.74%
	Y02P	Climate change mitigation technologies in the production or processing of goods	852	2.41%
Data Communication and Digital Systems	G06F	Electric digital data processing	12096	9.02%
	H04L	Transmission of digital information	9076	6.77%
	G06Q	Information and communication technology	8709	6.50%
	H04N	Pictorial communication	6817	5.08%
	H02J	Circuit arrangements or systems for supplying or distributing electric power	5501	4.10%
	H01M	Processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy	5397	4.02%
	B60L	Propulsion of electrically-propelled vehicles	4239	3.16%
	H04M	Telephonic communication	3597	2.68%

Topic	CPC Code	CPC Title	n. patents	% patents
	H04W	Wireless communication networks	2861	2.13%
	B29C	Shaping or joining of plastics	2601	1.94%
Resource and Material Efficiency	C04B	Lime, magnesia; slag; cements; compositions thereof	22239	11.19%
	B32B	Layered products	4920	5.11%
	Y02W	Climate change mitigation technologies related to wastewater treatment or waste management	4504	4.68%
	H01M	Processes or means	3941	4.10%
	B01J	Chemical or physical processes, e.g. catalysis or colloid chemistry	2170	2.25%
	Y10T	Technical subjects covered by former US classification	2147	2.23%
	G11B	Information storage based on relative movement between record carrier and transducer	2138	2.22%
	C02F	Treatment of water, waste water, sewage, or sludge	1663	1.73%
	H04R	Loudspeakers, microphones, gramophone pick-ups or like acoustic electromechanical transducers	1626	1.69%
	B29C	Shaping or joining of plastics	1616	1.68%
Resource Recovery	C02F	Treatment of water, waste water, sewage, or sludge	46014	10.32%
	B01D	Separation	18782	9.46%
	Y02W	Climate change mitigation technologies related to wastewater treatment or waste management	8714	4.38%
	H01M	Processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy	6061	3.05%
	Y02E	Reduction of greenhouse gas [GHG] emissions, related to energy generation, transmission or distribution	4841	2.43%
	B01J	Chemical or physical processes, e.g. catalysis or colloid chemistry	4616	2.32%
	C12M	Apparatus for enzymology or microbiology; bioreactors or fermenters	3585	1.80%
	B32B	Layered products	3543	1.78%
	H01L	Semiconductor devices not covered by class H10	3236	1.63%
	F24S	Solar heat collectors; solar heat systems	3062	1.54%
Battery Technologies and Recycling	H01M	Processes or means, e.g. batteries	57519	7.84%
	Y02E	Reduction of greenhouse gas [GHG] emissions, related to energy generation, transmission or distribution	8719	6.29%
	H02J	Circuit arrangements or systems for supplying or distributing electric power	5388	3.88%
	B60L	Propulsion of electrically-propelled vehicles	4643	3.34%
	C01P	Indexing scheme relating to structural and physical aspects of solid inorganic compounds	3184	2.29%
	Y02T	Climate change mitigation technologies related to transportation	3159	2.27%
	Y02P	Climate change mitigation technologies in the production or processing of goods	2805	2.02%

Topic	CPC Code	CPC Title	n. patents	% patents
	H01L	Semiconductor devices not covered by class H10	2706	1.95%
	H01G	Capacitors	2001	1.44%
	B65D	Containers for storage or transport of articles or materials	1978	1.42%
Recycling Equipment and Waste Management	B65D	Containers for storage or transport of articles or materials	1978	5.01%
	B01D	Separation	13002	4.95
	B29C	Shaping or joining of plastics	6128	3.90%
	Y02W	Climate change mitigation technologies related to wastewater treatment or waste management	5380	3.42%
	B29B	Preparation or pretreatment of the material to be shaped	4498	2.86%
	B32B	Layered products, i.e. products built-up of strata of flat or non-flat form	4346	2.76%
	H01M	Processes or means	4173	2.65%
	F16C	Shafts; flexible shafts; elements or crankshaft mechanisms	4046	2.57%
	B65D	Containers for storage or transport of articles or materials	3915	2.49%
	C02F	Treatment of water, waste water, sewage, or sludge	3701	2.35%
	Y10T	Technical subjects covered by former US classification	3583	2.28%

Table A.9: Distribution of patents per CE topics across CPC codes

Topic	NACE Code	NACE Title	n. patents	% patents
Reduce	20.10	Manufacture of basic chemicals	14,197	10.13%
	28.90	Manufacture of other special-purpose machinery	9,082	6.48%
	28.29	Manufacture of other general-purpose machinery	7,290	5.20%
	26.30	Manufacture of communication equipment	6,061	4.32%
	26.10	Manufacture of electronic components and boards	5,641	4.02%
	21.00	Manufacture of basic pharmaceutical products and preparations	5,501	3.92%
	26.20	Manufacture of computers and peripheral equipment	5,437	3.88%
	27.20	Manufacture of batteries and accumulators	5,191	3.70%
	29.10	Manufacture of motor vehicles	4,177	2.98%
	28.10	Manufacture of general-purpose machinery	4,172	2.98%
Reuse	20.10	Manufacture of basic chemicals	16,522	11.38%
	28.90	Manufacture of other special-purpose machinery	9,684	6.67%
	21.00	Manufacture of basic pharmaceutical products and preparations	7,782	5.36%
	22.00	Manufacture of rubber and plastic products	7,580	5.22%
	26.10	Manufacture of electronic components and boards	5,601	3.86%
	26.20	Manufacture of computers and peripheral equipment	4,333	2.99%

Topic	NACE Code	NACE Title	n. patents	% patents
	32.90	Manufacturing	4,197	2.89%
	28.23	Manufacture of office machinery and equipment	4,161	2.87%
	26.30	Manufacture of communication equipment	4,047	2.79%
	23.50	Manufacture of cement, lime and plaster	3,999	2.76%
Recycle	28.10	Manufacture of general-purpose machinery	5,499	6.91%
	22.00	Manufacture of rubber and plastic products	5,070	6.37%
	20.10	Manufacture of chemicals and chemical products	5,023	6.31%
	29.10	Manufacture of motor vehicles	4,586	5.76%
	28.90	Manufacture of other special-purpose machinery	4,488	5.64%
	26.30	Manufacture of communication equipment	3,078	3.87%
	28.40	Manufacture of metal forming machinery and machine tools	3,060	3.85%
	26.10	Manufacture of electronic components and boards	2,725	3.43%
	26.50	Manufacture of instruments for measuring, testing and navigation	2,404	3.02%
	26.20	Manufacture of computers and peripheral equipment	2,246	2.82%
Repair	20.10	Manufacture of basic chemicals	7,726	21.56%
	28.90	Manufacture of other special-purpose machinery	3,006	8.39%
	27.20	Manufacture of batteries and accumulators	2,916	8.14%
	28.29	Manufacture of other general-purpose machinery	2,198	6.13%
	26.10	Manufacture of electronic components and boards	1,827	5.10%
	27.50	Manufacture of electric lighting equipment	1,195	3.33%
	28.99	Manufacture of other special-purpose machinery	1,078	3.01%
	22.20	Manufacture of plastics products	1,059	2.95%
	24.00	Manufacture of basic metals	728	2.03%
	29.10	Manufacture of motor vehicles	698	1.95%
Refurbish	20.10	Manufacture of basic chemicals	2,717	8.59%
	43.00	Specialised construction activities	2,429	7.68%
	28.90	Manufacture of other special-purpose machinery	2,036	6.44%
	22.00	Manufacture of rubber and plastic products	1,896	6.00%
	23.00	Manufacture of other non-metallic mineral products	1,841	5.82%
	26.10	Manufacture of electronic components and boards	1,695	5.36%
	29.10	Manufacture of motor vehicles	1,467	4.64%
	23.50	Manufacture of cement, lime and plaster	979	3.10%
	31.00	Manufacture of furniture	873	2.76%
	28.29	Manufacture of other general-purpose machinery	838	2.65%

Table A.10: Distribution of patents per 5R topics across NACE codes

Topic	NACE Code	NACE Title	n. patents	% patents
Material and Process Innovation	28.90	Manufacture of other special-purpose machinery	7,322	8.78%
	20.10	Manufacture of basic chemicals	6,525	7.83%
	26.10	Manufacture of electronic components and boards	4,807	5.77%

Topic	NACE Code	NACE Title	n. patents	% patents
	32.90	Manufacturing	4,205	5.04%
	28.29	Manufacture of other general-purpose machinery	3,967	4.76%
	22.00	Manufacture of rubber and plastic products	3,530	4.23%
	27.50	Manufacture of domestic applianceManufacture of general-purpose machinery	3,316	3.98%
	28.10	Manufacture of general-purpose machinery	3,114	3.73%
	28.23	Manufacture of office machinery and equipment	3,023	3.63%
	26.50	Manufacture of instruments and appliances for measuring, testing and navigation	2,564	3.08%
Polymers, Composites, and Material Recycling	20.10	Manufacture of basic chemicals	12,601	16.41%
	21.00	Manufacture of basic pharmaceutical products and preparations	8,750	11.39%
	22.00	Manufacture of rubber and plastic products	5,277	6.87%
	28.90	Manufacture of other special-purpose machinery	4,062	5.29%
	10.00	Manufacture of food products	3,844	5.01%
	23.00	Manufacture of other non-metallic mineral products	3,660	4.77%
	22.20	Manufacture of plastics products	1,715	2.23%
	26.50	Manufacture of instruments and appliances for measuring, testing and navigation	1,652	2.15%
	28.29	Manufacture of other general-purpose machinery	1,637	2.13%
	13.00	Manufacture of textiles	1,626	2.12%
Imaging and Display Technologies	26.70	Manufacture of other electrical equipment	4,699	13.67%
	26.10	Manufacture of electronic components and boards	3,501	10.18%
	26.20	Manufacture of computers and peripheral equipment	2,879	8.37%
	26.30	Manufacture of communication equipment	2,742	7.98%
	20.10	Manufacture of basic chemicals	2,357	6.86%
	28.23	Manufacture of office machinery and equipment	1,857	5.40%
	26.50	Manufacture of instruments and appliances for measuring, testing and navigation	1,506	4.38%
	28.90	Manufacture of other special-purpose machinery	1,090	3.17%
	32.90	Manufacturing	1,036	3.01%
	27.40	Manufacture of electric lighting equipment	902	2.62%
Adaptive Structures and Materials	28.90	Manufacture of other special-purpose machinery	7,548	7.91%
	22.00	Manufacture of rubber and plastic products	6,734	7.05%
	28.10	Manufacture of general-purpose machinery	5,381	5.64%
	29.10	Manufacture of motor vehicles	4,911	5.14%
	43.00	Specialised construction activities	4,569	4.79%
	20.10	Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms	3,970	4.16%

Topic	NACE Code	NACE Title	n. patents	% patents
	28.40	Manufacture of metal forming machinery and machine tools	3,904	4.09%
	26.10	Manufacture of electronic components and boards	3,555	3.72%
	32.00	Other manufacturing	3,510	3.68%
	15.00	Manufacture of leather and related products	3,302	3.46%
Agriculture and Resource Optimization	20.10	Manufacture of basic chemicals	1,666	20.90%
	21.00	Manufacture of basic pharmaceutical products and preparations	1,319	16.54%
	10.00	Manufacture of food products	753	9.44%
	28.30	Manufacture of other machinery	656	8.23%
	20.20	Manufacture of pesticides	441	5.53%
	20.20	Manufacture of pesticides and other agrochemical products	441	5.53%
	28.90	Manufacture of other special-purpose machinery	270	3.39%
	26.50	Manufacture of instruments and appliances for measuring, testing and navigation	192	2.41%
	28.29	Manufacture of other general-purpose machinery	165	2.07%
	32.90	Manufacturing	165	2.07%
	22.00	Manufacture of rubber and plastic products	162	2.03%
Data Communication and Digital Systems	26.20	Manufacture of computers and peripheral equipment	3,958	15.54%
	26.30	Manufacture of communication equipment	3,896	15.29%
	62.00	Computer programming	2,089	8.20%
	28.23	Manufacture of office machinery	2,062	8.09%
	26.50	Manufacture of measuring instruments	1,345	5.28%
	26.50	Manufacture of instruments and appliances for measuring, testing and navigation	1,345	5.28%
	27.12	Manufacture of electricity distribution and control apparatus	1,188	4.66%
	29.10	Manufacture of motor vehicles	1,086	4.26%
	27.20	Manufacture of batteries and accumulators	754	2.96%
	28.90	Manufacture of other special-purpose machinery	601	2.36%
	26.10	Manufacture of electronic components and boards	590	2.32%
Resource and Material Efficiency	23.50	Manufacture of cement, lime and plaster	4,129	21.95%
	20.10	Manufacture of basic chemicals	2,642	14.04%
	28.90	Manufacture of other special-purpose machinery	1,211	6.44%
	43.00	Specialised construction activities	1,106	5.88%
	24.00	Manufacture of basic metals	570	3.03%
	24.00	Manufacture of basic metals	570	3.03%
	23.30	Manufacture of clay building materials	564	2.99%
	27.20	Manufacture of batteries and accumulators	542	2.88%
	26.30	Manufacture of communication equipment	529	2.81%

Topic	NACE Code	NACE Title	n. patents	% patents
	23.00	Manufacture of other non-metallic mineral products	461	2.45%
	22.00	Manufacture of rubber and plastic products	393	2.09%
Resource Recovery	20.10	Manufacture of basic chemicals	10,361	28.04%
	28.29	Manufacture of other general-purpose machinery	4,083	11.05%
	28.90	Manufacture of other special-purpose machinery	1,486	4.02%
	21.00	Manufacture of basic pharmaceutical products and preparations	1,263	3.42%
	32.50	Manufacture of electronic equipment	1,146	3.10%
	28.30	Manufacture of agricultural and forestry machinery	1,048	2.84%
	27.50	Manufacture of domestic appliances	977	2.64%
	26.10	Manufacture of electronic components and boards	946	2.56%
	28.99	Manufacture of other special-purpose machinery	939	2.54%
	27.20	Manufacture of batteries and accumulators	902	2.44%
Battery Technologies and Recycling	27.20	Manufacture of batteries and accumulators	6,816	33.80%
	20.10	Manufacture of basic chemicals	2,109	10.46%
	26.10	Manufacture of electronic components and boards	1,423	7.06%
	27.12	Manufacture of electric batteries	1,251	6.20%
	29.10	Manufacture of motor vehicles	838	4.16%
	28.90	Manufacture of other special-purpose machinery	571	2.83%
	27.90	Manufacture of other electrical equipment	496	2.46%
	24.00	Manufacture of basic metals	495	2.45%
	30.00	Manufacture of other transport equipment	382	1.89%
	28.23	Manufacture of office machinery and equipment	365	1.81%
Recycling Equipment and Waste Management	28.90	Manufacture of other special-purpose machinery	4,135	12.56%
	20.10	Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms	3,411	10.36%
	28.29	Manufacture of other general-purpose machinery	2,622	7.97%
	28.40	Manufacture of metal forming machinery and machine tools	1,883	5.72%
	22.20	Manufacture of rubber and plastic products	1,284	3.90%
	28.10	Manufacture of general-purpose machinery	1,225	3.72%
	28.99	Manufacture of other special-purpose machinery	1,133	3.44%
	22.00	Manufacture of rubber and plastic products	1,112	3.38%
	28.30	Manufacture of agricultural and forestry machinery	1,065	3.24%
	27.50	Manufacture of domestic appliances	1,012	3.07%

Table A.11: Distribution of patents per CE topics across NACE codes

Topic	Tech. Field	Name	n. patents	% patents
Reduce	1	Electrical machinery, apparatus, energy	11,027	7.93%
	23	Chemical engineering	9,964	7.16%
	29	Other special machines	9,124	6.56%
	24	Handling	8,375	6.02%
	25	Manufacture of electronic components and boards	7,655	5.50%
	32	Transport	5,685	4.09%
	15	Biotechnology	5,538	3.98%
	6	Computer technology	5,427	3.90%
	9	Optics	5,095	3.66%
	28	Textile and paper machines	4,978	3.58%
Reuse	29	Other special machines	14,714	10.14%
	25	Manufacture of electronic components and boards	8,150	5.62%
	19	Basic materials chemistry	8,081	5.57%
	20	Materials, metallurgy	8,081	5.57%
	15	Biotechnology	7,798	5.38%
	28	Textile and paper machines	7,563	5.21%
	23	Chemical engineering	7,226	4.98%
	1	Electrical machinery, apparatus, energy	7,193	4.96%
	21	Surface technology, coating	5,895	4.06%
	17	Macromolecular chemistry, polymers	5,515	3.80%
Recycle	29	Other special machines	6,962	8.86%
	32	Transport	5,922	7.54%
	31	Mechanical elements	5,092	6.48%
	1	Electrical machinery, apparatus, energy	5,029	6.40%
	25	Manufacture of electronic components and boards	4,592	5.85%
	35	Civil engineering	4,350	5.54%
	34	Other consumer goods	3,144	4.00%
	26	Machine tools	3,000	3.82%
	28	Textile and paper machines	2,683	3.42%
	33	Furniture, games	2,669	3.40%
Repair	24	Handling	6,303	17.65%
	1	Electrical machinery, apparatus, energy	4,222	11.83%
	23	Chemical engineering	3,755	10.52%
	29	Other special machines	2,575	7.21%
	19	Basic materials chemistry	2,010	5.63%
	20	Materials, metallurgy	1,812	5.08%
	25	Handling	1,749	4.90%
	8	Semiconductors	1,472	4.12%
	33	Furniture, games	1,292	3.62%
	35	Civil engineering	1,248	3.50%
Refurbish	35	Civil engineering	3,223	10.40%
	29	Other special machines	3,211	10.36%
	21	Surface technology, coating	2,406	7.76%
	32	Transport	1,898	6.12%
	20	Materials, metallurgy	1,738	5.61%

Topic	Tech. Field	Name	n. patents	% patents
	33	Furniture, games	1,525	4.92%
	25	Manufacture of electronic components and boards	1,444	4.66%
	8	Semiconductors	1,334	4.30%
	34	Other consumer goods	1,246	4.02%
	28	Textile and paper machines	1,123	3.62%

Table A.12: Distribution of patents per 5R topics across IPC technological fields

Topic	Tech. Field	Name	n. patents	% patents
Material and Process Innovation	25	Handling	8,984	10.70%
	29	Other special machines	6,249	7.44%
	23	Chemical engineering	5,961	7.10%
	28	Textile and paper machines	4,767	5.68%
	33	Furniture, games	4,110	4.89%
	1	Electrical machinery, apparatus, energy	3,982	4.74%
	24	Environmental technology	3,684	4.39%
	8	Semiconductors	3,638	4.33%
	35	Civil engineering	3,119	3.71%
	32.0	Transport	3,032	3.61%
Polymers, Composites, and Material Recycling	29.0	Other special machines	10,365	13.26%
	15.0	Biotechnology	8,308	10.63%
	17.0	Macromolecular chemistry, polymers	5,940	7.60%
	19.0	Basic materials chemistry	5,792	7.41%
	28.0	Textile and paper machines	5,318	6.80%
	21.0	Surface technology, coating	4,498	5.75%
	18.0	Civil engineering	4,029	5.15%
	23.0	Chemical engineering	3,938	5.04%
	25.0	Handling	3,900	4.99%
	20.0	Basic communication processes	2,617	3.35%
Imaging and Display Technologies	9	Optics	6,053	17.82%
	8	Semiconductors	3,070	9.04%
	2	Audio-visual technology	2,770	8.15%
	6	Computer technology	2,211	6.51%
	1	Electrical machinery, apparatus, energy	2,108	6.21%
	29	Other special machines	1,655	4.87%
	10	Measurement	1,492	4.39%
	17	Macromolecular chemistry, polymers	1,348	3.97%
	21	Surface technology, coating	1,222	3.60%
	3	Telecommunications	1,025	3.02%
Adaptive Structures and Materials	29	Other special machines	9,228	10.01%

Topic	**Tech. Field**	**Name**	**n. patents**	**% patents**
	32	Transport	7,325	7.95%
	35	Civil engineering	7,287	7.91%
	34	Other consumer goods	6,864	7.45%
	1	Electrical machinery, apparatus, energy	6,164	6.69%
	25	Handling	5,469	5.93%
	33	Furniture, games	5,042	5.47%
	31	Mechanical elements	4,655	5.05%
	26.0	Machine tools	4,329	4.70%
	28	Textile and paper machines	3,487	3.78%
Agriculture and Resource Optimization	19	Basic materials chemistry	1,493	18.53%
	15	Biotechnology	1,343	16.67%
	29	Other special machines	910	11.29%
	18	Civil engineering	781	9.69%
	24	Environmental technology	592	7.35%
	25	Handling	5,469	5.93%
	33	Furniture, games	5,042	5.47%
	31	Mechanical elements	4,655	5.05%
	26	Machine tools	4,329	4.70%
	28	Textile and paper machines	3,487	3.78%
Data Communication and Digital Systems	6	Computer technology	4,677	18.21%
	1	Electrical machinery, apparatus, energy	2,195	8.54%
	7	IT methods for management	2,089	8.13%
	4	Digital communication	2,073	8.07%
	3	Telecommunications	1,818	7.08%
	12	Control	1,418	5.52%
	10	Measurement	1,311	5.10%
	2	Audio-visual technology	1,230	4.79%
	32	Transport	1,225	4.77%
	29	Other special machines	883	3.44%
Resource and Material Efficiency	20	Materials, metallurgy	5,073	17.31%
	35	Civil engineering	1,742	9.38%
	29	Other special machines	1,481	7.97%
	19	Basic materials chemistry	1,241	6.68%
	1	Electrical machinery, apparatus, energy	932	5.02%
	24	Materials, metallurgy	870	4.68%
	2	Audio-visual technology	802	4.32%
	23	Chemical engineering	766	4.12%
	21	Surface technology, coating	743	4.00%
	17	Macromolecular chemistry, polymers	657	3.54%
Resource Recovery	24	Environmental technology	9,435	15.21%
	23	Chemical engineering	4,901	13.10%
	19	Basic materials chemistry	1,933	5.17%

Topic	Tech. Field	Name	n. patents	% patents
	15	Biotechnology	1,781	4.76%
	29	Other special machines	1,738	4.64%
	35	Civil engineering	1,628	4.35%
	25	Handling	1,477	3.95%
	1	Electrical machinery, apparatus, energy	1,350	3.61%
	30	Thermal processes and apparatus	1,308	3.50%
	33	Furniture, games	1,062	2.84%
Battery Technologies and Recycling	1	Electrical machinery, apparatus, energy	8,525	14.71%
	20	Materials, metallurgy	1,694	8.88%
	32	Transport	1,198	6.28%
	8	Semiconductors	848	4.45%
	21	Surface technology, coating	837	4.39%
	23	Chemical engineering	620	3.25%
	25	Handling	468	2.45%
	29	Other special machines	434	2.28%
	28	Textile and paper machines	417	2.19%
	24	Environmental technology	404	2.12%
Recycling Equipment and Waste Management	23	Chemical engineering	4,542	14.06%
	29	Other special machines	3,643	11.28%
	24	Environmental technology	3,314	10.26%
	26	Machine tools	2,068	6.40%
	25	Handling	1,634	5.06%
	20	Materials, metallurgy	1,532	4.74%
	19	Basic materials chemistry	1,364	4.22%
	35	Civil engineering	1,300	4.02%
	1	Electrical machinery, apparatus, energy	1,224	3.79%
	31	Mechanical elements	1,119	3.46%

Table A.13: Distribution of patents per CE topics across IPC technological fields

Name	n. patents	% patents	
1	Procter & Gamble	3,631	1.32%
2	Samsung Electronics Co., Ltd.	3,506	1.27%
3	Siemens AG	3,305	1.20%
4	Robert Bosch GmbH	3,200	1.16%
5	Novozymes A/S	3,151	1.15%
6	Hewlett Packard Development Company, L.P.	2,723	0.99%
7	Matsushita Electric Industrial Co., Ltd.	2,644	0.96%
8	BASF SE	2,627	0.96%
9	E.I. du Pont de Nemours and Company & CO	2,488	0.90%
10	LG Electronics	2,481	0.90%

Name	n. patents	% patents	

Table A.14: Top applicants CE patents

Topic	Company Name	n. patents	% patents
Reduce	Samsung Electronics Co., Ltd.	1,217	0.87%
	Matsushita Electric Industrial Co., Ltd.	839	0.60%
	LG Electronics	642	0.46%
	Hewlett Packard Development Company	607	0.43%
	Robert Bosch GmbH	542	0.39%
	General Electric Co.	536	0.38%
	E.I. du Pont de Nemours and Company	492	0.35%
	Siemens AG	474	0.34%
	Toyota Jidosha CO. Ltd.	462	0.33%
	Procter & Gamble	459	0.33%
Reuse	Hewlett Packard Development Company, L.P.	1,172	0.81%
	Procter & Gamble	1,066	0.73%
	LG Chem Ltd.	645	0.44%
	E.I. du Pont de Nemours and Company	624	0.43%
	Novozymes A/S	594	0.41%
	Samsung Electronics Co., Ltd.	584	0.40%
	3M Innovative Properties Co.	540	0.37%
	BASF SE	534	0.37%
	Matsushita Electric Industrial Co., Ltd.	476	0.33%
	General Electric Co.	446	0.31%
Recycle	Siemens AG	572	0.72%
	General Electric Co.	470	0.59%
	Samsung Electronics Co., Ltd.	433	0.54%
	Robert Bosch GmbH	415	0.52%
	The Boeing Co.	394	0.50%
	LG Electronics	377	0.47%
	Bayerische Motoren Werke AG	367	0.46%
	E.I. du Pont de Nemours and Company	288	0.36%
	Hewlett Packard Development Company, L.P.	260	0.33%
	Halliburton Energy Services Inc.	254	0.32%
Repair	Samsung Electronics Co., Ltd.	299	0.83%
	LG Chem Ltd.	208	0.58%
	Robert Bosch GmbH	186	0.52%
	LG Electronics	167	0.47%
	Matsushita Electric Industrial Co., Ltd.	157	0.44%
	Voith Patent GmbH	125	0.35%
	Procter & Gamble	123	0.34%
	SANYO Electric Co., Ltd.	120	0.33%
	Siemens AG	117	0.33%

Topic	Company Name	n. patents	% patents
	BASF SE	91	0.25%
Refurbish	The Boeing Co.	225	0.71%
	General Electric Co.	177	0.56%
	3M Innovative Properties Co.	142	0.45%
	E.I. du Pont de Nemours and Company	136	0.43%
	Procter & Gamble	125	0.40%
	Siemens AG	112	0.35%
	Airbus Operations GmbH	97	0.31%
	Hewlett Packard Development Company, L.P.	92	0.29%
	Hoechst AG	85	0.27%
	SCHOTT AG	82	0.26%

Table A.15: Top applicants per 5R topics

Topic	Company Name	n. patents	% patents
Material and Process Innovation	Hewlett Packard Dev Co LP	562	0.67%
	LG Electronics Inc	557	0.67%
	The Procter & Gamble Co	459	0.55%
	Samsung Electronics Co Ltd	412	0.49%
	Matsushita Electric Ind Co Ltd	395	0.47%
	Voith Patent Gmbh	292	0.35%
	The Boeing Co	279	0.33%
	Siemens Ag	278	0.33%
	Robert Bosch Gmbh	273	0.33%
	E I Du Pont De Nemours & Co	255	0.31%
Polymers, Composites, and Material Recycling	Novozymes As	728	0.95%
	The Procter & Gamble Co	649	0.85%
	E I Du Pont De Nemours & Co	641	0.83%
	Basf Se	464	0.60%
	Basf Ag	404	0.53%
	Voith Patent Gmbh	377	0.49%
	Dsm Ip Assets Bv	314	0.41%
	The Regents Of The University Of California	300	0.39%
	Henkel Ag&Co Kgaa	291	0.38%
	Bayer Ag	268	0.35%
Imaging and Display Technologies	Samsung Electronics Co Ltd	510	1.48%
	Matsushita Electric Ind Co Ltd	280	0.81%
	3M Innovative Properties Co	265	0.77%
	Fujifilm Corp	249	0.72%
	Eastman Kodak Co	242	0.70%
	Canon Co Ltd	231	0.67%

Topic	Company Name	n. patents	% patents
	Apple Inc	193	0.56%
	LG Electronics Inc	179	0.52%
	Kon Philips Elect Nv	171	0.50%
	Halliburton Energy Services Inc	160	0.47%
Adaptive Structures and Materials	Hewlett Packard Dev Co LP	896	0.94%
	Samsung Electronics Co Ltd	681	0.71%
	General Elect Co	638	0.67%
	Nike Inc	523	0.55%
	Siemens Ag	483	0.51%
	The Boeing Co	427	0.45%
	Robert Bosch Gmbh	410	0.43%
	LG Electronics Inc	392	0.41%
	The Procter & Gamble Co	360	0.38%
	United Tech Corp	298	0.31%
Agriculture and Resource Optimization	E I Du Pont De Nemours & Co	75	0.94%
	Novozymes As	58	0.73%
	Basf Ag	56	0.70%
	Varco I P Inc	56	0.70%
	Dsm Ip Assets Bv	49	0.61%
	Fujifilm Corp	40	0.50%
	The Regents Of The University Of California	30	0.38%
	Michelin Recherche Et Technique Sa	27	0.34%
	Farmer, Sean	26	0.33%
	Murata Manufacturing Co Ltd	26	0.33%
Data Communication and Digital Systems	Samsung Electronics Co Ltd	291	1.14%
	Hewlett Packard Dev Co LP	255	1.00%
	Apple Inc	213	0.84%
	Siemens Ag	185	0.73%
	General Elect Co	181	0.71%
	Sony Corp	158	0.62%
	Robert Bosch Gmbh	140	0.55%
	Matsushita Electric Ind Co Ltd	133	0.52%
	Toyota Jidosha Co Ltd	123	0.48%
	Silverbrook Research Pty Ltd	122	0.48%
Resource and Material Efficiency	Halliburton Energy Services Inc	177	0.94%
	Ajinomoto Co Inc	102	0.54%
	Sika Tech Ag	88	0.47%
	United States Gypsum Co	81	0.43%
	Basf Se	78	0.41%
	Construction Research & Tech Gmbh	75	0.40%
	3M Innovative Properties Co	70	0.37%

Topic	Company Name	n. patents	% patents
	Siemens Ag	61	0.32%
	Matsushita Electric Ind Co Ltd	57	0.30%
	Degussa Ag	54	0.29%
Resource Recovery	Samsung Electronics Co Ltd	139	0.38%
	Robert Bosch Gmbh	135	0.37%
	LG Chem Ltd	122	0.33%
	Siemens Ag	112	0.30%
	The Procter & Gamble Co	110	0.30%
	General Elect Co	99	0.27%
	LG Electronics Inc	94	0.25%
	The Regents Of The University Of California	92	0.25%
	Matsushita Electric Ind Co Ltd	88	0.24%
	Degremont	85	0.23%
Battery Technologies and Recycling	LG Chem Ltd	517	2.56%
	Matsushita Electric Ind Co Ltd	306	1.52%
	Samsung Electronics Co Ltd	271	1.34%
	Robert Bosch Gmbh	261	1.29%
	Toyota Jidosha Co Ltd	241	1.20%
	Contemporary Amperex Tech Co Ltd	131	0.65%
	Murata Manufacturing Co Ltd	122	0.61%
	Siemens Ag	114	0.57%
	Sanyo Elect Co Ltd	113	0.56%
	Basf Se	107	0.53%
Recycling Equipment and Waste Management	Mann Hummel Gmbh	272	0.83%
	The Procter & Gamble Co	167	0.51%
	Siemens Ag	148	0.45%
	Deere & Co	133	0.40%
	Robert Bosch Gmbh	128	0.39%
	Ntn Corp	118	0.36%
	Cnh Industrial Belgium Nv	108	0.33%
	Matsushita Electric Ind Co Ltd	107	0.33%
	Samsung Electronics Co Ltd	101	0.31%
	Ab Skf	88	0.27%

Table A.16: Top applicants per CE topics

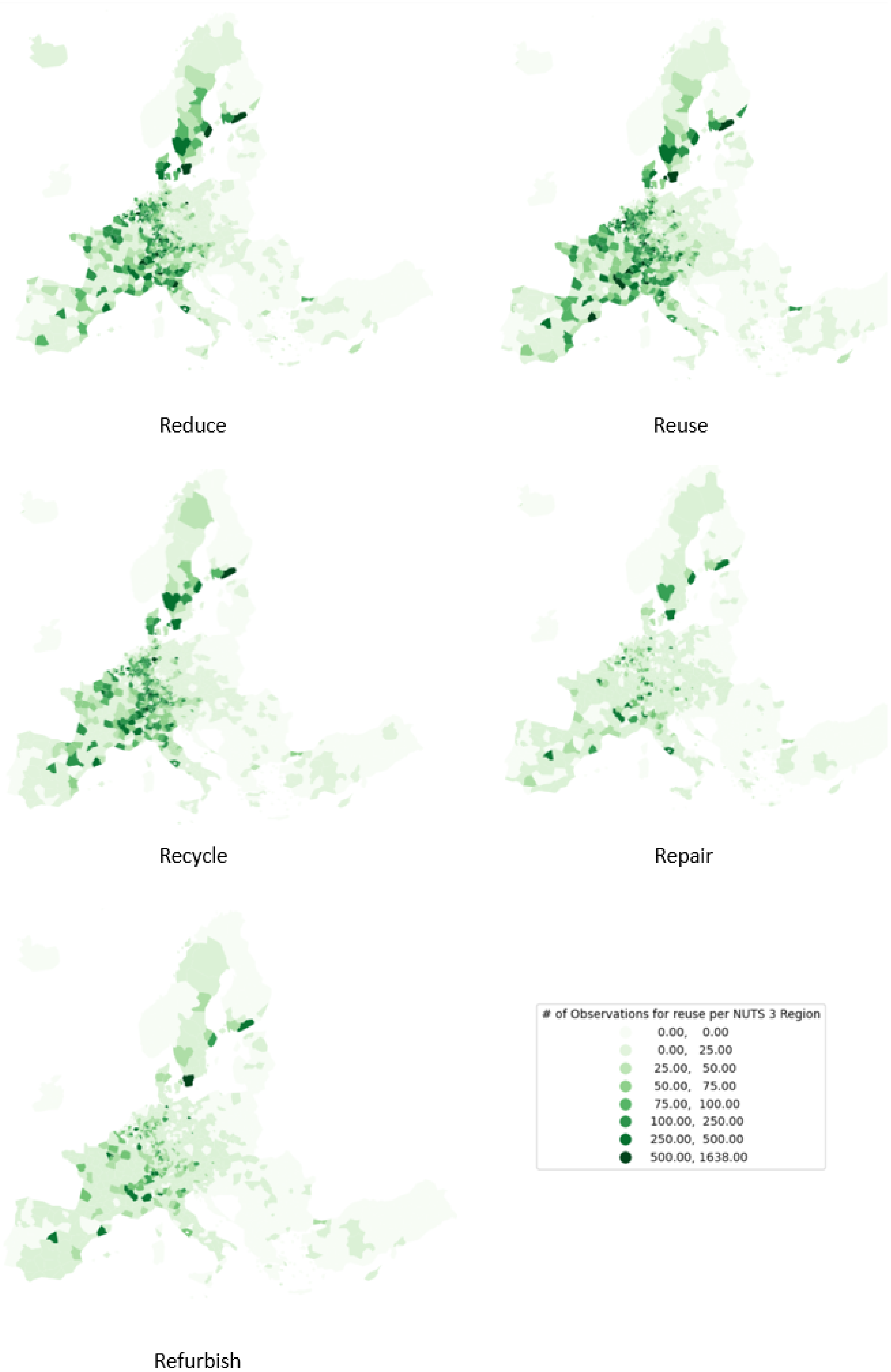

Figure A.3: Distribution of CE patents per 5R topics at Nuts3 level