The Functional Role of Critical Raw Materials in Technological Innovation

Francesco de Cunzo, Aurelio Patelli, Angelica Sbardella and Andrea Tacchella

Papers in Evolutionary Economic Geography

25.16

Utrecht University Human Geography and Planning

The Functional Role of Critical Raw Materials in Technological Innovation

Francesco de Cunzo[1], Aurelio Patelli[1], Angelica Sbardella[1,2], and Andrea Tacchella[1]

[1]Enrico Fermi Research Center, Rome, Italy
[2]School of Finance and Management, SOAS University of London, London, UK

Abstract

This paper presents new evidence on how countries are innovating in response to the growing strategic importance of critical raw materials (CRMs). Using millions of patent abstracts from the PATSTAT database, we apply a large language model (LLM) to classify CRM-related inventions into four functional roles: use, refine, recycle, and remove. A fifth category, wrong, flags false positives and improves classification accuracy. This approach moves beyond simple patent counts by identifying the specific roles CRMs play in technological development, enabling a more nuanced view of innovation strategies. Our classification reveals a significant increase in CRM-related innovation over the past two decades, with notable variation across materials, functions, and countries. While use-related patents remain dominant, recent growth in recycle and remove functions points to a shifting emphasis on circularity. Geographically, China leads across all functions, while an upward trend in recycling activity is observed across several advanced economies. A panel data analysis reveals that innovation in refining, recycling, and removing CRMs is positively associated with innovation in their use, suggesting functional complementarities that can enable both technological progress and more sustainable material strategies. These findings have important implications for policy, highlighting the value of supporting functionally diverse CRM innovation, fostering international coordination, and adopting tools for real-time innovation monitoring. By combining text mining with AI-driven functional classification of patented inventions, this study offers a scalable method for tracking material-related innovation and informing policies aimed at sustainability and technological resilience.

Keywords — Critical Raw Materials, Green and Digital Technologies, Large Language Models, Text Mining

1 Introduction

The digital and energy transitions are increasingly recognised as material transitions, entailing not only systemic technological change, but also fundamental shifts in the material foundations that sustain these processes (European Commission, 2023*c*). This marks a broader shift "from emissions to resources" (Mertens et al., 2024, p.671): while global attention remains focused on reducing greenhouse gas emissions, the pursuit of carbon neutrality simultaneously amplifies concerns over the availability and governance of critical raw materials (CRMs). CRMs comprise a group of minerals and metals, including lithium, cobalt, and rare earths, that are essential to strategic technologies and industries, yet face high supply risks due to scarcity, geographic concentration, and limited substitutability. From batteries to microchips, they are essential enablers of a wide array of digital and low-carbon technologies, supporting key sectors such as renewable energy, electric mobility, digital infrastructure, defence, and aerospace (European Commission, 2023*c*; International Energy Agency, 2021, 2024). These materials are often irreplaceable and are also used far more intensively than in fossil fuel systems—placing them at the core of industrial, innovation, and geopolitical agendas (Graedel et al., 2013; Herrington, 2021; International Energy Agency, 2024; Leader et al., 2019; Sovacool et al., 2020). For instance, producing a standard electric vehicle (EV) requires roughly six times more raw materials than a conventional internal combustion engine vehicle; while building an onshore wind farm involves approximately nine times the mineral input of a gas-powered plant (Gielen, 2021; International Energy Agency, 2021). Rare earth elements (REEs), such as neodymium, dysprosium, praseodymium, and terbium, are indispensable for permanent magnets used in wind turbines, EV motors, robotics, and high-tech consumer products, such as smartphones and computer hard drives, but also for defence applications including lasers, radars, sonar and guidance systems. Lithium is critical for lithium-ion batteries powering EVs, energy storage systems, portable electronics, and aerospace technologies such as satellites and drones. Cobalt, nickel, graphite, and manganese are also vital for battery chemistries and energy storage infrastructure; copper enables the expansion of electricity grids; and platinum supports fuel cells and green hydrogen electrolysers (Hund et al., 2020; European Commission, 2023*c*). As a consequence, global demand for raw materials is projected to rise sharply in the coming decades (IRP, 2019; OECD, 2019), with demand for energy transition materials alone potentially quadrupling by 2040 if the Paris Agreement targets are met (International Energy Agency, 2021). EU forecasts further predict that by 2050 demand for lithium, graphite, nickel, neodymium and dysprosium could increase between two- and twenty-fold (European Commission, 2023*c*).

While it remains debated whether Earth's crust contains sufficient accessible resources to meet this demand surge (Grandell et al., 2016; Mertens et al., 2024; Pommeret et al., 2022), the required scale of extraction is already driving an expansion of the mining sector with far-reaching environmental and socio-economic harms. The mining and early processing of critical raw materials in source countries has been in fact linked to ecosystem destruction and biodiversity loss due to deforestation, toxic pollution and waste, emissions, and water contamination, as well as extremely exploitative labour conditions, human rights violations, and the displacement of local communities (Arendt et al., 2022; Conde, 2017; Marín and Goya, 2021; Que et al., 2018; Wang and Yang, 2024). These negative externalities are largely unaccounted for in global markets and fall disproportionately on countries in the Global South (Arendt et al., 2022; Berman et al., 2017; Church and Crawford, 2018; Dowling and Otero, 2025; Norgate and Haque, 2010; Sovacool et al., 2020). A growing body of literature emphasises how the resource-intensive nature of the energy and digital transitions risks reproducing historical patterns of ecological degradation and global inequality—echoing the dynamics of the "resource curse" and raising questions about whether resource-rich nations may be drawn into a new phase of extractive dependency (Bonds and Downey, 2012; Davis and Tilton, 2005; Dowling and Otero, 2025). Although the socio-environmental risks associated with CRM extraction have been widely documented, policy attention, especially in the Global North, has largely prioritised the stability and the security of access to these critical resources.

The strategic importance of CRMs is now widely recognised by international institutions, including the European Commission (European Commission, 2024), the G7 (G7 Ministers' Meeting on Climate, Energy and Environment, 2023), the World Bank (Hund et al., 2020), the International Energy Agency (International Energy Agency, 2021, 2023*a*), and the OECD (Kowalski and Legendre, 2023). The emphasis towards the high degree of geographical concentration and potential supply bottlenecks or disruptions was further intensified by recent global shocks such as the COVID-19 pandemic, the war in Ukraine, and escalating geopolitical tensions, which revealed the exposure of CRM supply chains to volatility within broader global value chains (International Renewable Energy Agency, 2023; G7 Leaders, 2023). Among the most pressing concerns is the effort to *de-risk* China's dominant position across both upstream and midstream stages of key CRM supply chains. In fact, with approximately 90% of global rare earth refining, over 60% of cobalt refining, and more than half of global lithium processing under its control, China has emerged as the main global CRM actor, intensifying debates over strategic dependency and the weaponisation of export restrictions, particularly in high-tech sectors such as semiconductors and batteries (G7 Leaders, 2023; Zhou et al., 2023). The European Union has positioned itself as a global leader in the push for electrification and in its commitment to achieving climate neutrality by 2050, despite having limited domestic CRM reserves and relying heavily on imports from a small number of suppliers across multiple stages of the value chain—from raw and processed materials to finished components of strategic technologies. To address this vulnerability, the EU introduced the Critical Raw Materials Act (European Commission, 2023*b*; European Commission, 2024), aimed at boosting domestic CRM mining and recycling while securing diversified international partnerships to strengthen the resilience and sustainability of its supply chains. In parallel, the G7 Five-Point Plan for Critical Minerals Security (G7 Ministers' Meeting on Climate, Energy and Environment, 2023), launched in 2023, seeks to safeguard global decarbonisation efforts, energy security, as well as to mitigate geopolitical risk by investing in circular economy solutions, while supporting international cooperation to reduce dependency and ensure responsible CRM sourcing.

Although recent international initiatives have focused on reducing external dependencies by increasing domestic extraction and diversifying imports, these efforts also reflect a growing recognition of the limitations and risks associated with primary sourcing alone. As a result, increasing policy and scholarly attention is being directed towards complementary strategies to ensure a more secure, sustainable, and just supply of critical raw materials for emerging technologies (Gong and Andersen, 2024; International Energy Agency, 2023*b*; Jowitt et al., 2018; Pommeret et al., 2022; Vikström et al., 2013; Wang et al., 2014), with a special focus on circularity, material substitution, and improved resource efficiency through technological innovation. In fact, unlike fossil fuels, which are consumed upon use, CRMs generally remain embedded in devices and infrastructure at the end of their lifecycle, offering the potential for recovery, reuse, and recycling (International Renewable Energy Agency, 2023; International Energy Agency, 2023*a*,*b*), but the practical implementation of these strategies faces significant barriers. Recycling rates for most CRMs are low due to technical complexity, high costs, and limited end-of-life volumes (International Energy Agency, 2021), while substitution efforts are constrained by the unique functional properties of certain materials (International Energy Agency, 2024). One such example is neodymium–iron–boron magnets, for which there are currently no high-performance alternatives (Junne et al., 2020).

Despite the large body of literature on CRM supply chain and the foundational role they play in enabling frontier technologies, the innovation literature has long remained silent on the nexus between critical raw materials and technological change and only recently has begun to explore it through patent analysis. Most existing studies rely on keyword searches in patent texts to identify CRM-related inventions, offering useful indicators of CRM presence in patents and CRM exposure via countries patenting activity. Li et al. (2024) provide the first large-scale mapping of rare metal dependence, demonstrating an increasing material intensity in frontier technologies and showing that the supply of rare metals influences the generation of new frontier technologies based on these materials. Diemer et al. (2022) examine the technological and geographic associations between ICTs and critical materials, revealing asymmetries between source countries and value creation. de Cunzo et al. (2023) examine the CRM dependence of green technologies by mapping country-level exposure and global demand–supply mismatches, highlighting the spatial disconnect between CRM production and the deployment of CRM-intensive green innovations. More recently, Fusillo et al. (2025) and Manera et al. (2025) advance CRM detection in patent texts by introducing a large language model-based indicator to identify indirect references to CRM in inventions—for instance, through mentions of CRM-intensive components—examining the extent to which these inventions reflect potential substitution strategies and revealing sectoral and regional exposure.

Against this backdrop, understanding the full structure of CRM supply chains—from extraction to refining, use, and end-of-life—is essential. However, it is not only the structure, but also the direction of technological change across these stages that demands closer scrutiny. Building on Li et al. (2024)'s hypothesis of an interdependence between material supply and technological progress, analysing how innovation evolves in relation to CRMs can reveal where pressures, bottlenecks, or breakthroughs are emerging, and which functions these materials fulfil within technological systems. Although recent studies have begun to map CRM occurrences in patents, they typically focus on simple mentions without systematically investigating the functional roles that CRMs play within inventions, a gap this paper seeks to address. Adopting a function-sensitive perspective enables a more granular examination of how innovation systems respond to critical raw material constraints, highlighting whether firms and countries are reinforcing CRM dependency or pursuing strategies of efficiency, substitution, and circularity. Understanding these dynamics is crucial to analyse shifts in patenting strategies driven by supply chain pressures and environmental priorities, and for informing the design of industrial, innovation, and sustainability policies. Until recently, the ability to extract this level of information from large-scale patent data was limited. However, the emergence of large language models now offers powerful tools to uncover the nuanced ways in which CRMs are embedded within inventions, providing a new lens to trace how material-critical innovation is unfolding.

To this aim, we develop a novel multi-step methodology that combines traditional keyword filtering with state-of-the-art large language model classification to map CRM-related invention activity into five functional categories: *use*, *refine*, *recycle*, *remove*, and *wrong*. The first four capture the distinct roles that critical raw materials play across the supply chain and within technological systems. The *wrong* category, by contrast, is designed to flag cases where a CRM is not functionally related to the invention—its mention being incidental or spurious, often arising from textual ambiguities. Including this category enhances the precision of our classification and reduces noise introduced by keyword-based detection, offering a robust, scalable, and replicable framework for understanding and monitoring the material foundations of new technological trajectories. In particular, we address three main research questions aimed at understanding the structure, geography, and interdependencies of CRM-related innovation:

1. How is innovation in critical raw materials distributed across functions, materials, and technologies?
2. Which countries are leading CRM-related innovation across functions?
3. How is technological innovation in CRM refining, recycling and removing linked to that in CRM use?

Operationally, we first identify CRM-related patents within the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT) using a keyword search strategy based on the 2023 European Commission's CRM list (European Commission, 2023*a*) geolocalised throuhg an ad hoc strategy described in Section 4. Second, we construct a human-validated training set, labelling patents according to the functional role that CRMs fulfil in the invention. Third, we implement a two step fine-tuning procedure of the domain-adapted transformer model BERT for Chemical Industry to classify the corpus of CRM-related patents into the five functional categories. This allows us to address the first two research questions. Finally, to address the third research question, we conduct a panel data analysis examining how country patenting in CRM *refining*, *recycling*, and *removing* are associated with the development of CRM *use*-related patents. Our findings reveal a sharp increase in CRM-related innovation between 1999 and 2018, with significant variation across materials, functions, technologies, and countries. Use-related inventions dominate, but innovation in the recycling, refining, and removal functions accelerated in recent years, highlighting a gradual shift toward circularity strategies. Lithium, graphite, and copper drive much of this growth, reflecting the technological momentum behind electrification and energy storage. China leads CRM innovation in all functional categories, underscoring its growing technological influence, while advanced economies like the US and South Korea show increasing, albeit limited, specialisation in recycling patents. Moreover, our analysis suggests that functional trajectories are not inherently in competition. In contrast, innovation in refining, recycling, and removing CRMs is positively associated with use-related innovation, indicating that circular and upstream strategies can go hand in hand with, and even reinforce, CRM-based technological advancement.

The remainder of the paper is structured as follows. Section 2 delves deeper into the different stages of the CRM supply chain and their correspondence with the functional categories we identify in patents mentioning CRMs. Section 3 and Section 4 detail the data and the LLM-based empirical strategy we employ. Section 5 presents our empirical findings. Section 6 concludes.

2 The supply chain of critical raw materials

Critical raw materials underpin a wide range of low-carbon and digital technologies and are increasingly understood as both essential enablers and potential sources of strategic vulnerability in the transition toward more sustainable industrial systems. These vulnerabilities stem mainly from the structure of their supply chains, which are geographically concentrated and institutionally fragmented. On the one hand, this creates heightened exposure to supply disruptions and geopolitical tensions; on the other, the mining and extraction of critical materials often generate substantial socio-environmental harms in resource-rich regions, including ecosystem degradation, local conflict, and human rights violations.

Understanding the real-world dynamics of CRM supply chains is essential for interpreting the roles that critical raw materials play in patented inventions. To this aim, in what follows, we connect four key stages of these supply chains, extraction, processing, manufacturing, and end-of-life recovery, [1]with the four[2] CRM functional categories *use*, *refine*, *remove*, and *recycle* we identify in patents. As schematically illustrated in Figure 1, each function reflects an innovation strategy oriented toward specific stages of the CRM supply chain.

2.1 Extraction: Supply Concentration and Sustainability Risks

The supply chain begins with the extraction stage, where CRM ores are mined. This phase is heavily concentrated in a small group of resource-rich countries. For instance, over 65% of global cobalt originates from the Democratic Republic of Congo (DRC), where it is primarily extracted as a by-product of copper and nickel (U.S. Geological Survey, 2022). Similarly, 77% of the world's lithium supply comes from Australia and Chile—Australia being the leading producer through hard-rock mining, while Chile relies on lithium-rich brine evaporation—and China dominates the extraction of rare earth elements, along with other key materials such as phosphorus, gallium, and indium (European Raw Materials Alliance, 2021; International Energy Agency, 2021). Beyond geographic concentration, extraction is also marked by concentrated ownership, with a small number of multinational firms exerting disproportionate control over production volumes, pricing, and access to strategic deposits (Arendt et al., 2022; Dou et al., 2023). A key example is China's strategic involvement in extraction beyond its borders, with Chinese firms holding significant stakes in cobalt mining operations in the DRC (Van den Brink et al., 2020).

Alongside concerns over supply security, the extraction stage also entails serious environmental and social risks. For example, in the DRC, cobalt extraction is often linked to informal mining, human rights violations and child labour, as well as to severe ecological degradation—ranging from ecosystem disruption to water contamination (Beales et al., 2021; Mancini et al., 2021; Marin and Palazzo, 2025; Sovacool et al., 2020).[3] In South America's lithium triangle—covering parts of Chile, Argentina, and

[1]See (European Commission, 2020*b*) for reference.

[2]The *wrong* function, included to flag for false positives in the keyword search, is not related to CRMs. Thus, we exclude it from the discussion of the CRM supply chain.

[3]On the human and toxic pollution costs of cobalt mining in the Democratic Republic of the Congo, see also: https://raid-uk.org/report-environmental-pollution-human-costs-drc-cobalt-demand-industrial-mines-green-energy-evs-2024.

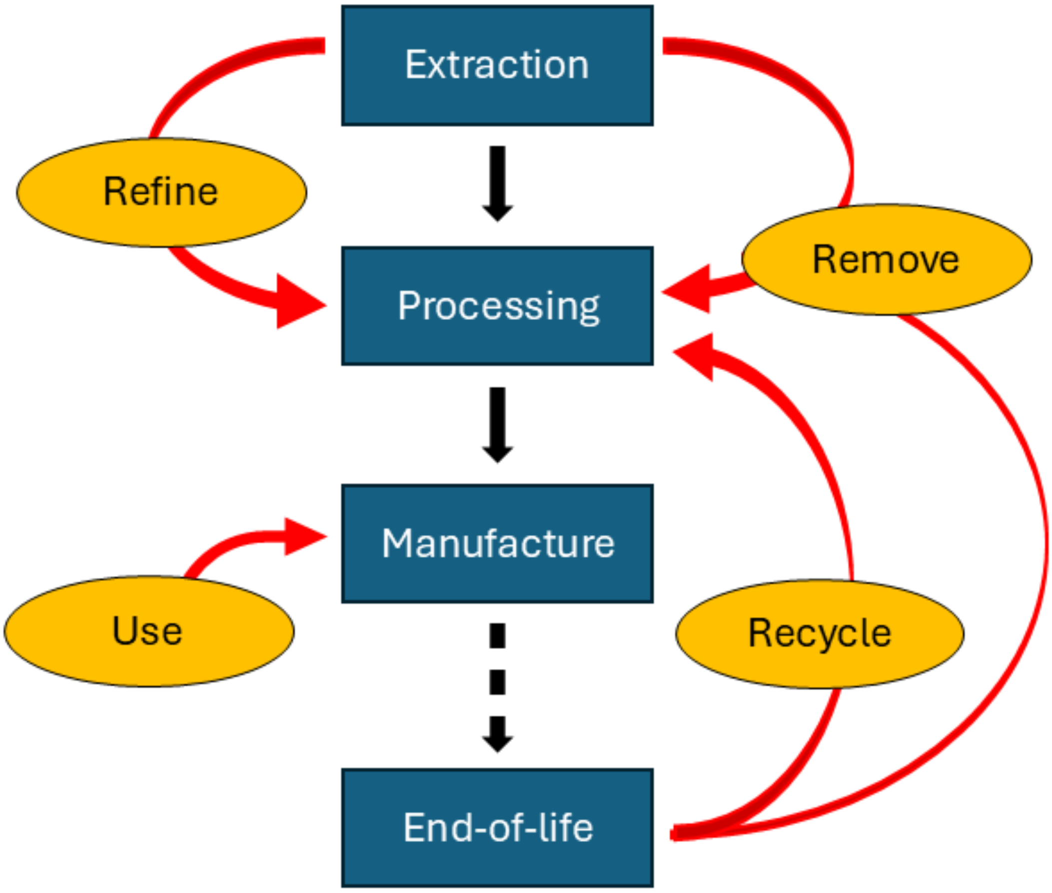

Figure 1: Schematic representation of the CRM supply chain and corresponding CRM functional categories in patented inventions. The figure maps the core stages of the critical raw material supply chain—extraction, processing, manufacture, and end-of-life recovery—onto the four CRM innovation functions identified in patent data: *use*, *refine*, *remove*, and *recycle*. Red arrows indicate where each function intervenes along the supply chain. *Refining* technologies support the transition from raw extraction to usable materials; *remove* operates both during processing (e.g., impurity separation) and at end-of-life (e.g., targeted disassembly or hazardous material extraction); *use* is linked to the integration of CRMs into manufactured products; and *recycling* captures the reintegration of recovered materials into earlier supply stages. The dotted arrow between manufacture and end-of-life recovery indicates that CRM-containing technologies and products do not enter the waste stream immediately, but only after potentially long operational lifespans.

Bolivia—extraction via brine evaporation has resulted in acute water depletion, jeopardizing fragile desert ecosystems, displacing Indigenous communities and undermining their water access for agriculture and grazing (Giglio, 2021; Jerez et al., 2021; Marin and Palazzo, 2025).

2.2 Processing and Refining: Strategic Control and Enabling Technologies

Once extracted, CRMs enter the processing stage, where they are refined in high-purity materials suitable for advanced manufacturing. This stage plays a pivotal role in the supply chain and aligns closely with our *refine* function. In particular, *refine*-related innovations typically focus on improving the quality, purity, or performance of CRMs, enabling their integration into downstream applications and reducing losses or inefficiencies during transformation. In addition, the *remove* function is also relevant at this stage, capturing innovations aimed at separating materials, impurities, or by-products that arise during the processing phase. Similarly to extraction, processing is also highly geographically concentrated. China holds a dominant position, refining more than half of the world's lithium and cobalt, and up to 90% of rare earth elements (European Commission, 2023*c*; Jowitt, 2022). China's control of global refining capacity raises geopolitical concerns, as it introduces systemic dependencies and potential bottlenecks in downstream supply chains. Other relevant hubs include Chile, which accounts for approximately one-third of global lithium refining, and South Africa, which processes more than 90% of the world's iridium (Jowitt, 2022).

CRM processing is highly energy-intensive and generates toxic and even radioactive waste, as documented in rare earth operations in China (Hofmann et al., 2018; Lee and Wen, 2017).[4] These risks highlight the importance of technological advances in both refining processes and material removal. For instance, innovations in the *remove* function—such as those enabling cleaner separation, selective purification, or the elimination of hazardous by-products—are increasingly relevant not only for improving processing efficiency, but also for advancing environmental sustainability and supporting circularity objectives within CRM supply chains.

2.3 Manufacturing and use: Technology integration and innovation intensity

Following processing, CRMs enter as material inputs to the manufacturing stage, where refined materials are incorporated into intermediate components and final technologies—such as batteries, magnets, motors, and semiconductors. This phase is linked to the *use* function in our framework, which not only accounts for the dominant share of CRM-related patenting activity, but is also directly associated with the increasing demand for CRMs, as it involves the direct material integration into high-performance technologies. At this stage, industrial leadership is heavily concentrated in Asia. China accounts for over 90% of global solar wafer production, 70% of solar PV system assembly, and it is currently the only country with a fully integrated supply chain for permanent magnets (European Commission, 2023*c*). Japan is also an important actor in magnet manufacturing, supported by longstanding intellectual property protections from firms such as Hitachi, which have historically limited international competition (Smith et al., 2022). In contrast, Western countries have struggled to scale up their manufacturing capacity for CRM-intensive components. In particular, despite targeted

[4] On the toxic waste effect of rare earth mining, see also Michael Standaert's article on *Yale Environment 360*: https://e360.yale.edu/features/china-wrestles-with-the-toxic-aftermath-of-rare-earth-mining.

policy initiatives, the EU produces just 2% of global solar PV systems and remains largely dependent on foreign supply chains for batteries, permanent magnets, and other advanced technologies (European Commission, 2023*b*).

2.4 End-of-life recovery: Removal and recycling challenges

As products reach the end of their life cycle, critical raw materials can be recovered through disassembly, separation, and reintegration into production processes. In our framework, innovation efforts targeting this stage are captured by both the *remove* and *recycle* functions. *Remove*-related innovations typically appear in patents addressing the early steps of recovery—for instance, through disassembly techniques or the removal of impurities prior to recycling. The *recycle* function instead captures innovation focused on the reintegration of recovered materials into production. While material recycling is one of the most crucial strategies for reducing dependence on primary extraction and advancing circularity, it currently represents the weakest link in the CRM supply chain. Recycling rates are constrained by inefficient collection systems, high costs, economic disincentives, and technical barriers that limit efficient material separation in complex and non-standardised devices. As a result, they remain below 1% for lithium and rare earth elements, and below 10% for most critical materials (International Energy Agency, 2021; Swain, 2017).

To explore these dynamics more concretely, we focus on three illustrative cases differing in their material properties, levels of technological maturity, and supply chain integration: lithium, rare earth elements, and cobalt. For lithium, the growing volume of spent lithium-ion batteries has spurred investment in recycling technologies (Ambrose and Kendall, 2020; Harper et al., 2019; International Energy Agency, 2021; Swain, 2017). Advances in separation and leaching processes show promise (Baum et al., 2022; Jin et al., 2022), but recovery rates remain low, constrained by the heterogeneity of battery chemistries and formats that complicate economies of scale (Bae and Kim, 2021; Huang et al., 2018). Recycling of rare earth elements and cobalt is also expanding but remains limited. Rare earth recovery focuses mainly on Neodymium–Iron–Boron magnets, nickel–metal hydride batteries, and LEDs, with industrial-scale progress concentrated in Japan, the United States, and Germany (De Oliveira et al., 2021; Mertens et al., 2024; Mudali et al., 2021; München et al., 2021). In the case of cobalt, secondary sources accounted for just 5% of global supply in 2022, though projections suggest significant growth in the coming decades (Cobalt Institute, 2023). China and the United States show the highest recycling rates to date, but industrial-scale cobalt recovery remains at an early stage, with research efforts focused on batteries, catalysts, and metallurgical waste streams (Chandra et al., 2022; International Energy Agency, 2021; U.S. Geological Survey, 2022; Zeng et al., 2018, 2022).

Taken together, these cases illustrate the uneven maturity of CRM recycling across materials and countries: despite growing research and policy attention, recovery technologies remain fragmented, with progress concentrated in a few regions and applications. As boosting secondary production becomes a strategic priority, innovation in both *recycle* and *remove* functions will play a key role in reshaping CRM supply chains.

In sum, linking the extraction, processing, manufacturing, and end-of-life recovery stages of the CRM supply chain to the functional categories identified in CRM-related patents enables us to interpret patented inventions as technological responses to systemic vulnerabilities. *Use* innovations are linked to the manufacturing stage, reflecting how CRMs are directly integrated into frontier technologies, serving as key drivers of technological advancement but also as primary channels through which countries deepen their material dependence. *Refine* innovations enable more efficient supply inputs. Finally, although still underdeveloped, *recycle* and *remove* innovations reflect emerging circular strategies that are beginning to show signs of acceleration. Embedding these patent functions within the CRM supply chain structure helps clarify where innovation is concentrated, and where strategic and technical gaps persist. This framework provides the basis for the empirical analysis that follows, which examines the global dynamics of CRM innovation and its alignment with long-term goals of sustainability and mineral security.

3 Data

3.1 Patent data

We retrieve patent data from the PATSTAT database (European Patent Office, 2021), which contains over 100 million patent documents from patent offices around the world. Patents are a widely used proxy for inventive activity. Although they capture invention rather than the full innovation process, and the propensity to patent varies by sector, patent data remain one of the most comprehensive, harmonised, and accessible sources for tracking technological development (Arts et al., 2013; Dechezleprêtre et al., 2011; Griliches, 1998; Lanjouw et al., 1998). They provide rich, structured information on inventors, applicants, and technological fields, classified under standardised systems and spanning long time series. In this study, we organise patent documents into INPADOC patent families to avoid double counting of the same invention. Each family groups technically related applications—such as those filed in different jurisdictions or extensions over time—and is identified by a shared family ID.

In the context of CRM-related innovation, patents are particularly valuable because they allow for the systematic analysis and interpretation of technical mentions of materials within inventions. While patents cannot track technology adoption or diffusion directly, CRM-related innovation often occurs in extraction, chemical, and industrial processes, i.e. sectors where patenting is common, especially in green and digital technologies. For this reason, patent data provide a reliable lens to trace the evolving technical frontier of material-intensive innovation.

For our study, we select patents with abstracts–i.e. short technical descriptions of the inventions–written in English, and extract information on the year of first filing, the Cooperative Patent Classification (CPC) codes assigned, and the country of origin of inventors and applicants. In particular, CPC codes provide a structured representation of the technological content of each invention, and are used in this study to enrich the language model classification and interpret patterns of technological specialization. The CPC system[5] was launched in 2013 by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO) to harmonise classification schemes. CPC is highly granular, comprising around 250,000 entries, and is organised into nine main sections labelled with single letters *A*–*H* and *Y* (see Table 1). Section

[5] See https://www.cooperativepatentclassification.org/home.

Y is especially relevant, as it includes the Y02 subclass, which identifies technologies related to climate change mitigation or adaptation-areas that tend to be more CRM-intensive than others (de Cunzo et al., 2023).

Label	Description
A	Human necessities
B	Performing operations; Transporting
C	Chemistry; Metallurgy
D	Textiles; Paper
E	Fixed constructions
F	Mechanical engineering; Lighting; Heating; Weapons; Blasting
G	Physics
H	Electricity
Y	General tagging of new technological developments

Table 1: CPC technology sections. The first column lists the letters with which each section is labelled, while the second column lists the corresponding descriptions.

4 Methods

4.1 Keyword search of CRMs in patent abstracts

As a first step in our text analysis, we target the materials included in the 2023 Critical Raw Materials list published by the European Commission (European Commission, 2023*a*), which are reported in Table 2. These 31 materials are considered critical based on their economic importance and supply risks[6]. To identify CRM-related patents, we run a keyword search for mentions of these materials across all English-language patent abstracts filed in PATSTAT between 1999 and 2018.

To carry out the keyword search, we follow a set of specific criteria and methodological adjustments aimed at improving the precision and reliability of CRM identification. First, for many CRMs, we search for both the full material name and its chemical element symbol. However, we exclude element symbols consisting of a single letter—such as "B" for boron or "W" for tungsten—as these can easily be confused with unrelated abbreviations in patent abstracts. Similarly, we exclude specific two-letter symbols, such as "As" for arsenic, which are identical to common English words and cannot be reliably distinguished in text searches. The investigated element symbols are listed alongside the corresponding CRMs in Table 2. Second, for platinum group metals and rare earth elements, we search for both generic terms (e.g., "rare earth," "REE") and individual material names within each category. Third, given the difficulty of distinguishing "silicon metal" and "titanium metal" from generic mentions of silicon and titanium, we search for both the specific metal terms and the corresponding element names in the abstracts.

[6]Originally, the 2023 EU CRM list comprises 34 materials. In our analysis, however, we group scandium, light, and heavy rare earths into a single rare earth category, and we merge phosphorus with phosphate rock.

Critical Raw Material keywords list			
aluminium/bauxite (Al)	antimony (Sb)	arsenic	baryte
beryllium (Be)	bismuth (Bi)	boron/borate	cobalt (Co)
coking coal	copper (Cu)	feldspar	fluorspar
gallium (Ga)	germanium (Ge)	hafnium (Hf)	graphite
helium (He)	lithium (Li)	magnesium (Mg)	manganese (Mn)
nickel (Ni)	niobium (Nb)	PGM[I]	phosphorus
REE[II]	silicon metal[III]	strontium (Sr)	tantalum (Ta)
titanium metal[III]	tungsten	vanadium	

[I] Under PGM we group the detections associated with the following list of keywords: iridium (Ir), osmium (Os), palladium (Pd), platinum (Pt), rhodium (Rh), and ruthenium (Ru).
[II] Under REE we group the detections associated to the following list of keywords: ree, rare earth, cerium (Ce), dysprosium (Dy), erbium (Er), europium (Eu), gadolinium (Gd), holmium (Ho), lanthanum (La), lutetium (Lu), neodymium (Nd), praseodymium (Pr), samarium (Sm), scandium (Sc), terbium (Tb), thulium (Tm), yetterbium (Yb), and yttrium
[III] For silicon and titanium metals, we also investigate silicon (Si) and titanium (Ti) alone.

Table 2: CRM keyword list (and corresponding material elements) investigated in patent abstracts. The list refers to the fifth list of CRMs published in 2023 (European Commission, 2023*a*; European Commission, 2023*b*).

4.2 CRM function categories

The core novelty of our methodology is the use of large language models to classify CRM–abstract pairs—obtained through the keyword search—into five distinct functional categories. This classification allows us to distinguish the role that each critical material plays within the context of the patented invention. While the technical details of the LLM-based classification process are discussed in the next sections, here we define the five functional categories based on the specific relationship between the CRM and the invention.

A *Use*: the CRM is integral to the invention, either as a material directly used in the manufacturing process or as a key input enabling the invention's intended purpose.

B *Recycle*: the invention focuses on recovering and reusing the CRM from waste streams, discarded products, or secondary sources, with the goal of extending its lifecycle and reducing reliance on primary extraction.

C *Refine*: the invention involves refining, purifying, or otherwise processing the CRM from existing sources into a usable form, typically to improve its quality or performance.

D *Remove*: the CRM is targeted for separation, elimination, or reduction from a material, process, or environment, either to reduce harmful effects, enable purification, or facilitate subsequent recovery.

E *Wrong*: the CRM is not functionally related to the invention. Its mention is incidental or spurious, often due to textual ambiguities.[7]

4.3 Classifying CRM functions with Large Language Models

After matching CRM keywords within patent abstracts, we obtain 3,866,770 associations between a CRM and a patent filed in PATSTAT between 1999 and 2018. Each patent can, in principle, be linked to more than one CRM. The goal of the pipeline described in this section is to determine, for each CRM–patent pair, the most likely functional role of the material among the five categories defined previously. Our classification approach builds on the BERT for the Chemical Industry model (Chemical-BERT-uncased[8]), a large language model pre-trained on over 40,000 technical documents from the chemical industry and 13,000 chemistry-related Wikipedia entries. To adapt the model to our specific task, we implement the following two-step fine-tuning procedure.

1. *Patent Domain Adaptation.* We fine-tune the language model on the patent domain using a technique developed by Aroyehun et al. (2025), which augments each patent abstract with auxiliary special tokens representing its associated CPC technological codes. This step allows the model to better capture the structured relationship between patent text and technological classifications.

2. *Function Classification Fine-Tuning.* We further fine-tune the domain-adapted model for a supervised classification task, training it to assign each CRM–patent pair to one of the five functional categories defined earlier. The model is trained on a manually validated dataset of CRM–abstract pairs, each labelled with one of the five functions according to the role the material fulfils in the invention (see Appendix A).

Each of these steps is discussed in more detail in the following subsections.

4.3.1 Patent Domain Fine-Tuning

In the first step, we adopt the methodology introduced by Aroyehun et al. (2025), fine-tuning the language model to better capture the specific linguistic patterns of the patent domain. To further enhance the model's contextual understanding, we expand its vocabulary by adding auxiliary tokens corresponding to CPC technological codes. Specifically, we introduce one token for each 4-digit CPC A–H code, and one additional token for each code at the most granular level of aggregation within the Y section. This token augmentation strategy balances the total number of new tokens added with the

[7]E.g., the CRM symbol "Ti" for titanium being misidentified when used to denote temperature in patent abstracts.

[8]Chemical-BERT-uncased is a BERT-based language model further pre-trained from the checkpoint of SciBERT(Beltagy et al., 2019). It was adapted using a specialised corpus of over 40,000 technical documents from the chemical industry and 13,000 chemistry-related Wikipedia articles, including Safety Data Sheets and Product Information Documents. The pre-training involved over 250,000 chemical domain-specific tokens and more than 9.2 million paragraphs, using a masked language modelling objective, to better capture the technical terminology and linguistic structure of chemical and materials science texts. Chemical-BERT-uncased is available at: `https://huggingface.co/recobo/chemical-bert-uncased`.

need for a more detailed representation of the environmental dimensions of patented inventions, as captured by the Y02 codes.

We collect approximately 8 million patents from the PATSTAT database (de Rassenfosse et al., 2019), spanning from 1980 to 2014, each containing an English abstract and the associated CPC codes. For each patent document, we create a structured input sample in the format shown in Table 3, where an additional separator token distinguishes the list of CPC tokens from the abstract text. Finally, we fine-tune the base language model with a standard Masked Language Modelling task. As discussed in Aroyehun et al. (2025), this approach enables the language model to learn a more structured representation of the patent domain by incorporating explicit attention mechanisms that link textual content with technological classifications, such as CPC codes we employ.

CPC Codes	Abstract Text	Formatted Sample
A01B, C01F, Y02P 10/134	The present invention...	`<A01B_token>` `<C01F_token>` `<Y02P10/134_token>` `<tech_separator_token>` `The present invention...`

Table 3: Example of a patent sample showing CPC codes, abstract text, and the corresponding formatted input used for the domain adaptation fine-tuning.

4.3.2 Function Classification Fine-Tuning

In the second step of fine-tuning, we leverage the labelled dataset described in Appendix A, which contains approximately 11,000 human-validated associations between patent-CRM pairs and their corresponding functional categories. This sample is further augmented with data-augmentation techniques–we refer to Appendix A for more details on the labelling. To perform this task, we format the inputs as detailed in Table 4. We attach a classification head to the domain-adapted language model, and we perform a full fine-tuning of both the language model's weights and the classification head with a cross-entropy loss of the 5 possible predicted classes against the labelled class. Thus, the model receives a formatted sample as an input and outputs a 5-dimensional probability vector, containing the estimated probability of each of the 5 functions.

4.3.3 Validation

In this section we discuss the overall quality of the classification that we obtain with the described pipeline. First, we split our labelled dataset in a training, validation, and test set. Specifically, we keep 70% of the manually labelled data in the training set, use 15% for validation during training, and 15% for testing. The examples obtained via data augmentation, as described in Appendix A, are added to the training set only, resulting in approximately 15,000 examples in the training set and approximately 1,700 examples in the validation and test set.

In Table 5, we report standard classification metrics—specifically precision, recall and F1 score—computed on the test set to evaluate the performance of the fine-tuned

Material	**CPC Codes**	**Abstract Text**	**Formatted Sample**
Manganese	A01B, C01F, Y02P 10/134	The present invention...	<A01B_token> <C01F_token> <Y02P10/134_token> <tech_separator_token> Manganese <material_separator_token> The present invention...

Table 4: Example of a patent sample showing a material matched through keyword search in the patent abstract, CPC codes, abstract text, and the corresponding formatted input used for the classification fine-tuning.

language model in assigning CRM–patent pairs to their correct functional categories (*use*, *refine*, *recycle*, *remove*, or *wrong*). The table also includes the confusion matrix, illustrating the distribution of true versus predicted functional categories in the test set. Precision measures the proportion of correct positive predictions among all predicted positives, while recall measures the proportion of correct positives among all actual positives. The F1 score is the harmonic mean of precision and recall, balancing the two metrics. The confusion matrix summarises the number of correct and incorrect classifications across all categories. The per-function precision and recall scores are consistently high, with the lowest values—0.73 and 0.74, respectively—observed for the *recycle* function, resulting in an F1 score of 0.73. For all other functional categories, the scores are higher, with near-perfect classification performance for the *use* and *remove* functions. Approximately 6% of the examples—100 out of 1,691—are misclassified in the test set, resulting in an overall precision of 94%.

	Classification Metrics			Confusion Matrix				
	Precision	Recall	F1	Wrong	Recycle	Remove	Use	Refine
Wrong	0.74	0.76	0.75	35	0	0	10	1
Recycle	0.73	0.74	0.73	0	37	0	12	1
Remove	0.90	0.98	0.94	0	0	53	1	0
Use	0.97	0.96	0.97	12	14	6	1385	20
Refine	0.79	0.78	0.78	0	0	0	23	81

Table 5: The left part of the table shows per-class Precision, Recall and F1 score on the test set. The right part of the table is the confusion matrix: element in row i and column j is the count of how many examples with true label i have been labelled j by the model.

We assess the performance of the classifier as satisfactory, particularly in view of the complexity of the classification task. In Table 6, we provide two examples that highlight the nuances involved in assigning functional categories to CRMs within patent abstracts. In both cases, two different CRM mentions are identified within the same patent, and the model correctly assigns distinct functional categories to each material within the specific context of the invention.

The first example concerns a process for surface treatment of aluminium, where an oxidised layer is first removed and the surface is subsequently sealed with titanium. The model correctly classifies aluminium as undergoing *refinement* and titanium as being *used* as an input. Notably, although the word “removed” appears in close proximity to “aluminium” (“...an oxide layer on the aluminium surface is removed...”), the model is not misled into classifying aluminium under the *remove* function. The second example involves an invention where cobalt is used in the formation of anodes employed in the refinement of copper ores through electrowinning—an electrolytic process used to extract metals from solution. Here, the model accurately distinguishes between the *use* of cobalt and the *refine* of copper, demonstrating strong domain understanding by correctly inferring the function of electrowinning, even though it is not explicitly described as a copper refinement process in the abstract.

These examples very clearly illustrate the significant advantage of using a properly fine-tuned language model over classification methods based purely on keywords and/or CPC codes, which would be unlikely to capture such functional distinctions in complex and context-dependent cases.

Abstract	**Material**	**Predicted Function**
A process for the surface treatment of aluminium for producing an electric contact and a corresponding component, in which, in a first step, an oxide layer on the aluminium surface is removed, for example by pickling, and, in a second step, the surface is sealed by wet-chemical means with a conversion layer, comprising metal ions of zirconium or titanium before renewed formation of an oxide layer occurs, is proposed.	Aluminium	Refine
	Titanium	Use
A lead calcium tin alloy to which cobalt has been added is described. The alloy is useful in the formation of anodes to be used in electrowinning cells. Electrowinning cells containing the cobalt alloys are particularly suited for electrowinning metals, such as copper, from sulfuric acid electrolytes. The cobalt-containing anodes improve the efficiency of oxygen evolution at the anode during electrowinning and reduce corrosion of the anode.	Cobalt	Use
	Copper	Refine

Table 6: Examples of predicted functions for multiple materials mentioned in two patent abstracts.

5 Results

In this three-part section presenting our empirical findings, we begin by addressing our RQ1 in Section 5.1, providing a descriptive analysis of CRM-related innovations across functional categories, and documenting the emergence of new technological strategies related to circularity and sustainability. We then turn to the RQ2 in Section 5.2, examining the geographic distribution of CRM-related patents, identifying national patterns of specialisation and change over time, and highlighting which countries are emerging as leaders in specific CRM innovation functions. Finally, to answer the RQ3, in Section 5.3 we explore functional interdependencies through a panel data analysis, assessing how upstream (*refine*) and circular (*recycle*, *remove*) patenting is related to downstream CRM use.

5.1 Mapping CRM Innovation Across Functions, Materials, and Technologies

To explore how technological innovation in critical raw materials is distributed across functions and materials, we present a descriptive overview of the distribution of CRM patent activity across the four functional categories—*use*, *recycle*, *refine*, and *remove*. By following the pipeline discussed in Section 4, we begin by identifying CRM mentions in all PATSTAT patent abstracts between 1999 and 2018, using a targeted keyword search. This yields 3,866,770 CRM–abstract associations, corresponding to 1,873,724 distinct CRM-related patent families. Before introducing the functional classification, we first examine which CRMs are most frequently mentioned over time and interpret the resulting patterns in light of the technological domains where they are known to play a critical role. Figure 2 displays the 1999–2018 evolution of CRM mentions in patent abstracts for the top 10 CRMs, based on total patent family counts and indexed to 1999 (1999 = 1).

From the Figure it is possible to appreciate that, across all materials, CRM-related patenting shows a pronounced upward trend, particularly from 2008 onward—a period that also witnessed a broader surge in global patenting activity. While this growth partly reflects general increases in innovation intensity, the rising prominence of CRMs in patents from around 2010 onwards across most materials is consistent with recent literature on CRM innovation (de Cunzo et al., 2023; Diemer et al., 2022; Li et al., 2024) and with rising global interest in clean energy technologies and digital innovation. Within this broader pattern, the figure reveals heterogeneous trajectories across materials. Lithium emerges as the most dynamic CRM, with patent mentions increasing more than tenfold over the period, reflecting its critical role in lithium-ion batteries and the broader electrification of transport and energy systems. Graphite follows closely, with an eightfold increase, driven by its essential function as an anode material in lithium-ion batteries and its use in other high-performance energy storage applications. Copper, which shows a sixfold growth, remains indispensable for power transmission, electric vehicle manufacturing, and the development of smart grids, owing to its superior electrical conductivity. Aluminium, also displaying a sixfold increase, is fundamental to lightweighting strategies in electric mobility and renewable energy infrastructure, particularly in solar and wind energy generation (European Commission, 2023*c*; International Energy Agency, 2021; Scrosati and Garche, 2010). Titanium, and

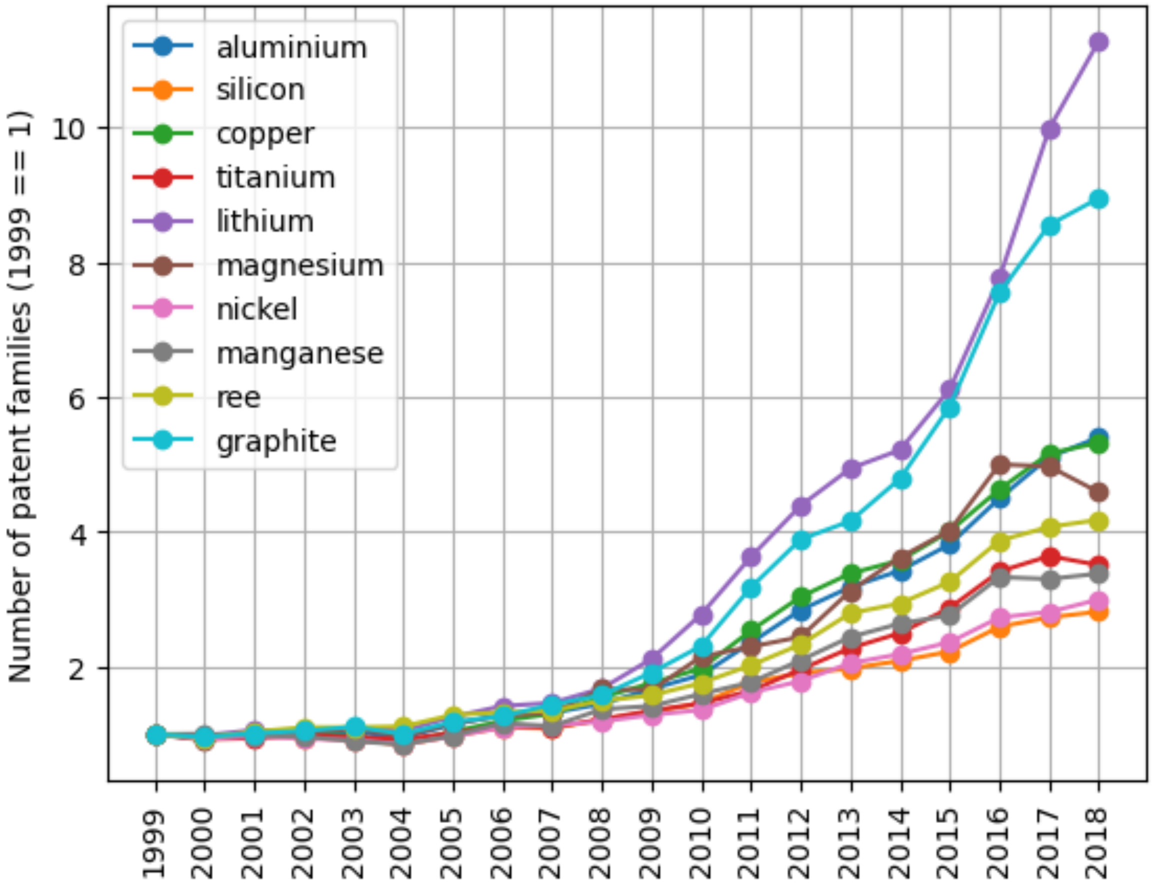

Figure 2: Evolution of CRM patent families (1999=1). Evolution of CRM mentions in patent abstracts over the period 1999-2018, normalised to their 1999 level. Highlighted are the top 10 CRMs based on the total number of patent families with at least one detection over the period under analysis.

manganese show more moderate but steady growth, while nickel, magnesium, silicon, and rare earth elements follow similar but slightly flatter trajectories.

We proceed to the functional classification of CRM innovation, which constitutes the core contribution of this paper. Following the methodology outlined in Section 4.3, the 3.87 million CRM–abstract pairs are classified into one of five functional categories. As reported in Table 7, among the resulting 1,873,724 CRM-related patent families, the 95.5% is classified as *use*, the 2.1% as *refine*, the 0.5% as *recycle*, and the 1.6% as *remove*. An additional 1.6% is identified as false positives (*wrong*) and excluded from further analysis.[9] These absolute counts underscore the clear dominance of CRM-*use* patents, where materials are directly used as material inputs for the invention.

At first glance, the overwhelming predominance of the *use* function might suggest limited relevance for other CRM roles. However, the trends shown in Figure 3 reveal a more nuanced picture. Although *recycle*, *refine*, and *remove* account for a

[9]Please note that the sum of function-tagged families exceeds the total number of unique CRM-related families, as a single patent can reference multiple CRMs with distinct functional roles.

Function	Number of Patent Families	Share (%)
Use	1,789,081	95.5
Refine	38,602	2.1
Recycle	10,235	0.5
Remove	30,710	1.6
Wrong (False Positive)	29,515	1.6

Table 7: Classification of CRM-related patent families by functional category

smaller share of total patenting activity, their trajectories over time indicate important shifts in innovation dynamics—especially in the period after 2010. In fact, while *use* innovations remain dominant over 1999–2018, all four functional categories exhibit substantial growth. *Recycle* and *remove* functions display the steepest relative increases—approximately tenfold and sixfold, respectively—compared to a fourfold rise in *use* and *refine*. Although some of this expansion reflects broader trends in global patenting, the disproportionately rapid growth of *recycle* and *remove* innovations suggests a strategic shift toward circularity, recovery, and material efficiency. In particular, this evolving pattern aligns with growing policy attention to CRM reuse, supply resilience, and environmental sustainability—especially for materials with complex processing requirements or geopolitical sensitivity.

To explore the relationship between functional categories and specific materials, Figure 4 presents a cross-sectional decomposition of function shares for the top 10 CRMs, as identified from the CRM-specific trends of Figure 2. As expected, *use* dominates across all top materials, consistently accounting for more than 95% of functional classifications. However, notable heterogeneity emerges within the residual shares associated with *recycle*, *refine*, and *remove* functions. Lithium, manganese, and nickel display relatively higher shares of recycling-related patents, reflecting increasing innovation efforts aimed at recovering end-of-life batteries and associated materials (Harper et al., 2019). In contrast, rare earth elements exhibit a stronger emphasis on refining, consistent with the complex technical requirements and geopolitical sensitivities surrounding the processing of these materials. Copper and nickel also show a relatively greater proportion of patents associated with both refining and removal functions, suggesting heightened attention to process improvements and circularity in their value chains.

These functional patterns are corroborated by the technological classification analysis extensively detailed in Appendix B. Refining patents across CRMs are primarily concentrated in metallurgical processing subclasses—especially C22B and Y02P 10/20—while lithium and graphite recycling is strongly associated with electrochemical cell technologies (H01M and Y02W 30/84). Removal-related innovations are often linked to water treatment and metal recovery codes (C02F and Y02P 10/20), reflecting environmental remediation and purification goals. Use-related patents, by contrast, span a broader range of application-driven subclasses—most notably Y02E 60/10, H01M, C22C, and H01L—highlighting how CRMs are increasingly embedded in energy storage, alloy design, and semiconductor devices.

Taken together, these patterns illustrate a complex and evolving CRM innovation landscape. While *use* continues to dominate in absolute terms, the growing shares of *recycle*, *refine*, and *remove* functions highlight an expansion of innovation strategies for CRM recovery, substitution, and process optimisation. Finally, by linking functional

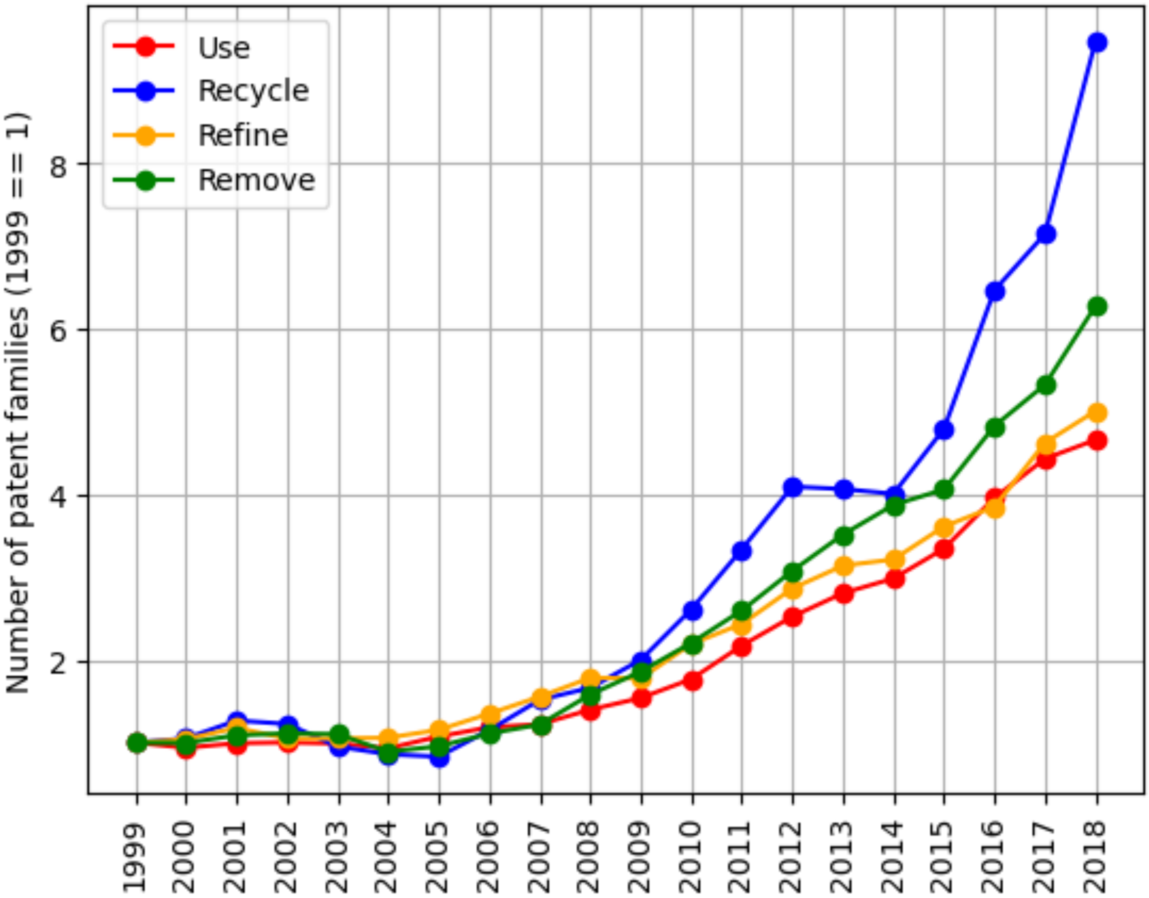

Figure 3: Evolution of CRM patent families per function category relative to 1999. Evolution of the number of patent families over the period 1999-2018 across the 4 functions use, remove, recycle, refine. The plot is relative to 1999 levels.

roles to CPC classifications our analysis reveals not only the scale but also the technological structure of CRM innovation, shedding light on how specific materials are embedded in different domains of technological development.

5.2 Geographic patterns in CRM innovation

In this section, we investigate the geographic dimension of CRM-related innovation, analysing how countries specialise across different functional categories. Linking patent data to the country of origin of inventors and applicants allows us to identify the leading actors in CRM innovation and uncover distinct national patterns of technological specialisation across functional categories, shedding light on how different economies are positioning themselves in the evolving landscape of material-critical technologies. To geolocalise patent families, we adapt the methodology proposed by de Rassenfosse et al. (2013), tailoring it to our family-level analysis. First, when inventor country information is available, we assign the family to all countries of the listed inventors. Second, when the inventor information is missing, we use the applicant's country. Third, if neither inventor and applicant countries are available, we geolocalise the family based

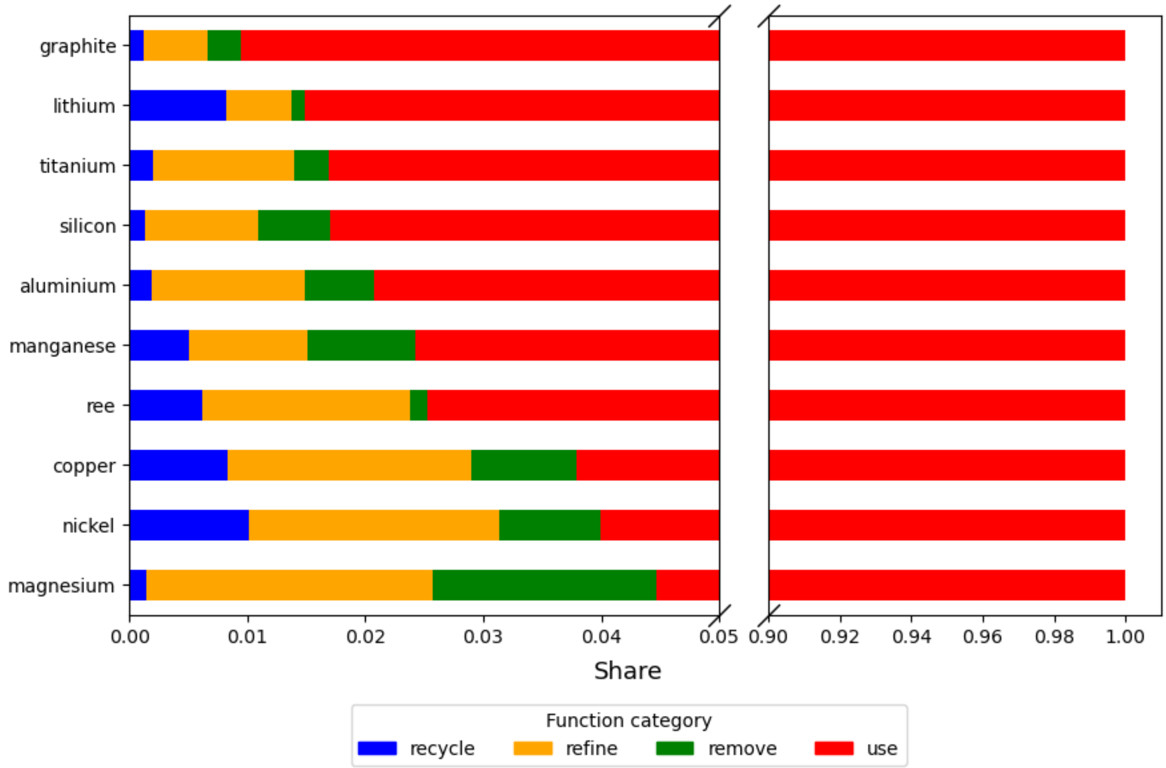

Figure 4: Material composition by function category. Histogram plotting the distribution of patent families across functions for the top 10 CRMs of Figure 2.

on the country of the patent office associated with the earliest filed application within the family.

Table 8 presents the distribution of CRM-related patent families across functional categories in the top innovating countries. The table includes nine individual countries and the European Union, considered as a single entity by aggregating patents from its 27 member states (EU27 hereafter). This approach allows us to assess European innovation efforts in light of the EU's strategic policy agenda on critical raw materials (European Commission, 2024). Collectively, these countries plus the EU27 account for 99.2% of all CRM-related patent families filed between 1999 and 2018, thus capturing nearly the entire global CRM patenting.

Looking at Table 8, China clearly emerges as the dominant force, accounting for more than 60% of all CRM-related patent families. This reflects China's leading position across multiple stages of the CRM supply chain—from extraction to processing and downstream applications (European Commission, 2023*c*). This large dominance also signals a broader caveat: global aggregate patent trends may disproportionately reflect China's trajectory, underscoring the importance of decomposing analyses geographically. Beyond China, distinct country-specific patterns emerge. Resource-rich countries such as Russia (Safirova, 2024) and Ukraine (Safirova, 2025)[10] stand out for their relatively high shares of refining-related patents (6.04% and 13.58%, respectively),

[10]For an overview of Ukraines's mineral industry see also the US Geological Survey table: https://www.usgs.gov/media/files/mineral-industry-ukraine-2017-18-xlsx-tables-only-release.

Country	Use	Refine	Recycle	Remove
China	1,130,210 (95.49%)	24,988 (2.11%)	6,850 (0.58%)	21,594 (1.82%)
Japan	332,292 (97.36%)	3,765 (1.1%)	1,435 (0.42%)	3,802 (1.11%)
South Korea	108,035 (96.87%)	909 (0.82%)	556 (0.5%)	2,023 (1.81%)
European Union	75,313 (95.42%)	2,274 (2.88%)	416 (0.53%)	929 (1.18%)
United States	75,579 (96.19%)	1,401 (1.78%)	268 (0.34%)	1,323 (1.68%)
Russia	39,866 (92.17%)	2,612 (6.04%)	235 (0.54%)	539 (1.25%)
Taiwan	22,494 (95.93%)	465 (1.98%)	194 (0.83%)	296 (1.26%)
United Kingdom	10,149 (96.76%)	179 (1.71%)	33 (0.31%)	128 (1.22%)
Ukraine	8,509 (84.26%)	1371 (13.58%)	75 (0.74%)	144 (1.43%)
Canada	4,987 (90.8%)	291 (5.3%)	87 (1.58%)	127 (2.31%)

Table 8: Distribution of CRM-related patent families across functional categories by country. For each country, the table reports the number of patent families in each function, with corresponding percentage shares shown in parentheses.

suggesting the presence of industrial processing capabilities developed alongside their extraction sectors (Blum et al., 2023; Liventseva, 2022). Japan, while ranking among the top CRM innovators, concentrates overwhelmingly on *use* patents (97.36%), consistent with its industrial focus on high-tech manufacturing and advanced electronics. South Korea shows a similar profile, although with a slightly higher engagement in recycling and removal functions. Finally, western countries—including the United States, United Kingdom, and the EU27—show more balanced engagement across non-use functions, particularly in refining and removing. However, their absolute volumes are modest compared to global leaders, suggesting that their innovation strategies may be less CRM-intensive or more reliant on global supply chains–e.g. via the import of CRM intensive technologies.

To enrich this cross-sectional picture, we examine the dynamic evolution of country-level CRM innovation over time in Figure 5, presenting the evolution of CRM-related patent families across the four functions for the top 10 countries, broken down into four five-year intervals. The patent counts are indexed to each country's level in the initial period (1999–2003), allowing us to more clearly track growth trends across functions. The dynamic analysis reinforces China's dominance in CRM innovation, with steep increases observed across all functions. CRM-related recycling patents go from just 70 families in 1999–2003 to 4,664 in 2014–2018—a 66-fold increase. Refining patents display a 21-fold increase, and remove-related innovations a 37-fold increase over the same period. Use-related patents also experienced a large increase, growing by a factor of 27—from 25,925 to 717,853 families. No other country exhibits a comparable trajectory across functional categories. In contrast, Japan's position in CRM-related innovation appears to be rooted in earlier periods, with a noticeable decline in patent activity after 2008. Unlike China, whose leadership has intensified over time, Japan's role has progressively declined—potentially reflecting an industrial restructuring or a shift in its position within CRM supply chains. The contrast is particularly striking in the use function: in 1999–2003, Japan filed over four times the number of families compared to China (108,338 vs. 25,925), while by 2014–2018, Japan's output had dropped to under 10% of China's (58,081 vs. 717,853). South Korea shows more modest but positive growth, particularly in recycling, where patent volumes more than tripled. As

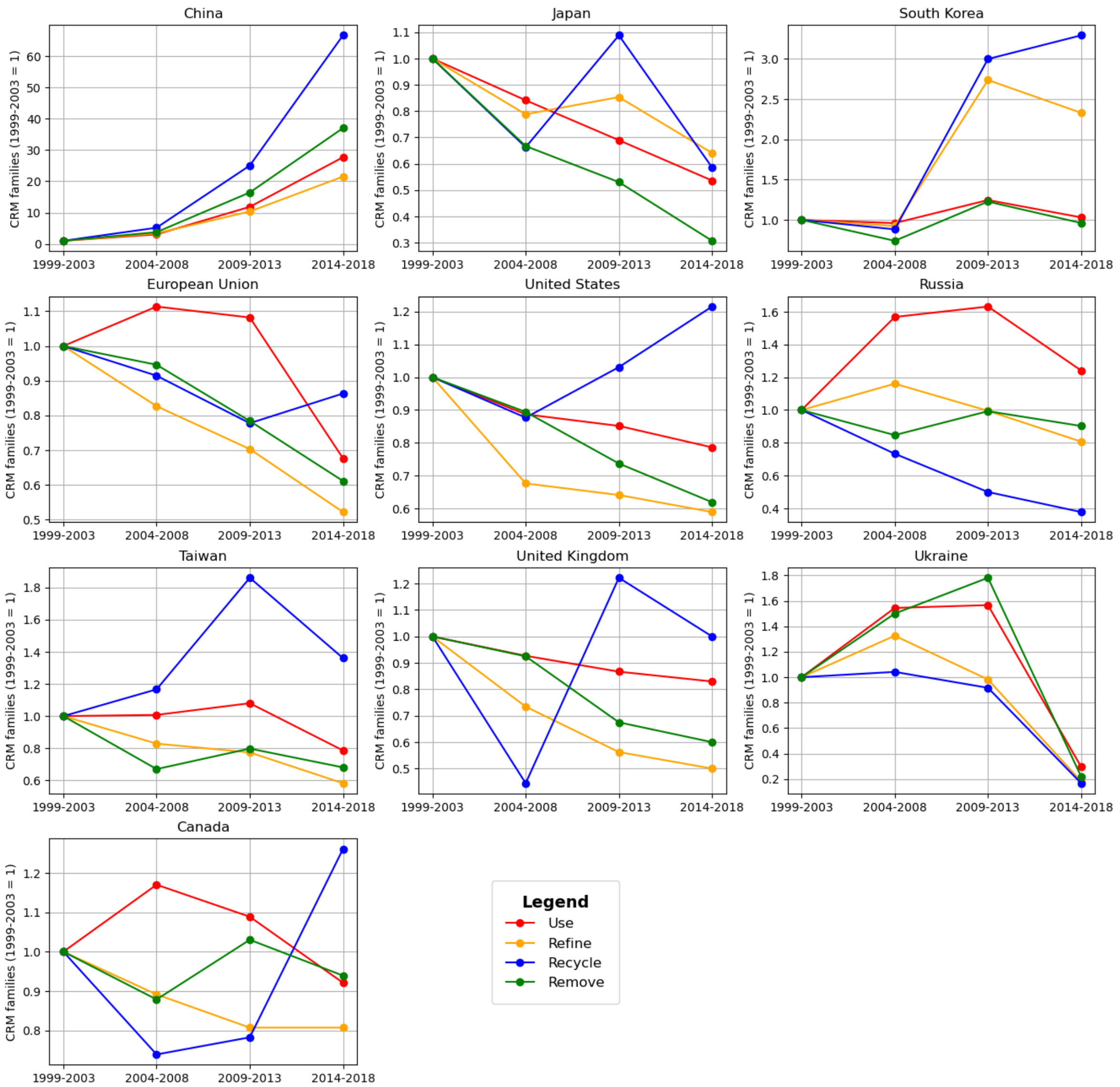

Figure 5: Evolution of CRM-related patent families across functions in the top 10 countries–see Table 8. The number of CRM-related patent families is computed in four distinct 5-year intervals (1999-2003, 2004-2008, 2009-2013, 2014-2018) and their evolution is relative to the first period 1999-2003.

for the resource-rich countries—Ukraine and Russia—their relatively high shares in refining, observed in Table 8, present an initial growth phase, followed by a decline after 2008. In Russia's case, CRM-related innovation increases slightly in the use function alone, going from 7,327 patent families in 1999-2003 to 9,095 in 2014-2018. Western countries—such as the EU27, United States, United Kingdom, and Canada—show a general decline in CRM use-related patenting over time. However, in the most recent time-window, the US, the UK, and Canada record modest growth in recycling-related innovations, suggesting a partial shift in innovation focus toward circularity-oriented strategies, though at lower absolute levels compared to leading countries.

Summing up, the geographic analysis reveals distinct national trajectories in CRM-related innovation. China has rapidly expanded its innovation capacity across all functions, establishing itself as the dominant and most diversified actor. Other countries show more selective patterns: Japan's early leadership has faded; Russia and Ukraine remain narrowly focused on CRM refining; and Western economies, despite lower patent volumes, exhibit a late pivot toward recycling and circularity. These trajectories reflect underlying differences in industrial structure, resource endowments, and strategic positioning within global supply chains.

5.3 Functional interdependencies in critical raw material innovation

We examine functional interdependencies in CRM innovation, assessing how advancements in recycling, refining, and removing technologies relate to downstream innovation in CRM use. To test this relationship, we estimate a panel fixed effects regression model using data from 20 countries over the period 1999–2018.

5.3.1 Model specification

To build our panel, we select only the top 20 countries in CRM patenting over the period 1999-2018.[11] Cumulatively, this group of countries covers the 99.2% of total CRM patent families over the entire period—i.e., 1,857,984 out of the total 1,873,724. For each country and year, we compute the number of patent families in the functional categories *use*, *recycle*, *refine*, and *remove* for all the CRMs investigated–as detailed in Table 2–for a total of 12,400 observations comprising 20 countries, 20 years, and 31 CRMs. To assess how innovation in *recycle*, *refine*, and *remove* functions relates to innovation in CRM use, we estimate the following panel fixed-effects model.

$$\begin{aligned}\log(\text{Use}_{cmt}) = &\ \beta_1 \log(\text{Recycle}_{cmt}) + \beta_2 \log(\text{Refine}_{cmt}) + \beta_3 \log(\text{Remove}_{cmt}) \\ &+ \gamma X_{cmt} + \delta_t + \mu_{cm} + \varepsilon_{cmt}\end{aligned} \tag{1}$$

where c indexes countries, m critical raw materials, and t years. The dependent variable, $\log(\text{Use}_{cmt})$, is the log-transformed number of patent families classified under the *use* function for CRM m in country c and year t. The key explanatory variables–i.e. $\log(\text{Recycle}_{cmt})$, $\log(\text{Refine}_{cmt})$, and $\log(\text{Remove}_{cmt})$–are the log-transformed counts of patent families associated with the *recycle*, *refine*, and *remove* functions for the same country-CRM-year unit. The model includes year fixed effects (δ_t) to control for global shocks and trends common across all units, and country–CRM fixed effects (μ_{cm}) to capture unobserved time-invariant heterogeneity specific to each country–CRM pair. X_{cmt} denotes a set of time-varying controls: country GDP per capita (GDP_{ct}), R&D expenditures ($R\&D_{ct}$), and total patenting volume ($PatentVolume_{ct}$), all measured at the country–year level; the inflation-adjusted price of CRM m ($Price_{mt}$); a dummy variable ($Active_{cmt}$) equal to one if country c has non-zero innovation activity in any non-*use* function for CRM m in year t; and a production dummy ($Producer_{cmt}$) equal

[11] The country selection is based on the number of CRM patent families over the period 1999-2018, and includes China, Japan, South Korea, United States, Russia, Germany, Taiwan, France, United Kingdom, Ukraine, Canada, India, Netherlands, Italy, Switzerland, Spain, Belgium, Australia, Austria, and Sweden.

to one if country c produces any quantity of CRM m in year t. Standard errors are clustered at the country–CRM level to account for serial correlation within units over time.

We apply a log-transformation to patent counts for the four functional categories to address the substantial skewness in the distribution of innovation activity across countries, materials, and years. A potential concern in our empirical specification is endogeneity, particularly in the form of reverse causality. In principle, innovation in *use* could influence subsequent innovation in *recycle*, *refine*, or *remove* functions, just as improvements in secondary functions could facilitate greater material use. Moreover, unobserved factors—such as technology-specific demand shocks or shifts in regulatory frameworks—could simultaneously drive both *use* and other innovation activities, leading to omitted variable bias. However, we emphasise that the objective of our analysis is not to establish causal relationships but rather to identify robust patterns of association across functions.

To further assess the directionality and robustness of the observed relationships, we conduct additional regressions, including models that invert the direction of analysis (regressing *recycle*, *refine* and *remove* on *use*) as well as alternative estimation strategies such as Poisson and OLS models (see Appendix C). These checks confirm the stability of our main results across specifications, while also suggesting that the reverse relationship—from *use* to other functions—is weaker and less systematic. Table 9 summarises the descriptive information of the variables in our panel.

	mean	sd	min	max
Log(Use)	2.82	2.017	0	10.9
Log(Recycle)	0.212	0.598	0	5.96
Log(Refine)	0.515	0.932	0	6.57
Log(remove)	0.342	0.787	0	7.57
GDP per capita	38036	15813	2524	75222
R&D expenditure	2.00	0.848	0.449	4.52
Patent volume	83743	277673	1373	3.06e6
CRM real price	5.61e5	2.62e6	24.2	2.03e7
Active dummy	0.431	0.495	0	1
Producer dummy	0.284	0.451	0	1
Observations	12400			

Table 9: Summary statistics.

5.3.2 Regression results

Table 10 presents the results of four fixed-effect regression specifications assessing the relationship between CRM use innovations vis-à-vis *recycle*, *refine*, and *remove* innovations. Column (1), our baseline model, reports our main specification estimating log-log relationships between functional patent counts. Column (2) replaces continuous patent counts–for *recycle*, *refine*, and *remove*–with binary indicators for the presence of patenting activity in each function. Columns (3) and (4) introduce a one-year and five-year lag of the main explanatory variables respectively, to better capture temporal dynamics and address concerns about reverse causality. All specifications include year fixed effects to control for global trends, and country–CRM fixed effects to control for unobserved heterogeneity. Standard errors are clustered at the country–CRM level. Adjusted R-squared values (R^2) range from 0.30 to 0.39, and the number of observations varies between 10,087 in columns (1) and (2), 9,577 in column (3), and 7.558 in column (4), depending on the lag construction.

Across all specifications, innovation in *recycle*, *refine*, and *remove* is positively associated with innovation in CRM use. In the baseline model (column 1) a 1% increase in refining-related patents is associated with a 0.2% increase in use-related patents. The *recycle* and *remove* functions also display positive and statistically significant effects, with elasticities of approximately 0.09 and 0.14, respectively. These findings suggest that upstream and circular innovations are complementary to CRM use innovation, with refining playing the most substantial enabling role.

The dummy specification in column (2) provides additional insights by examining whether the mere presence of innovation activity–rather than its intensity–correlates with use innovation. All three functional dummies remain positive and highly significant, confirming the direction of association. Notably, the coefficient for the recycling dummy is larger than in the continuous baseline model, This suggests threshold or activation effects, whereby the onset of even minimal recycling activity may yield disproportionate returns in CRM use innovation—a dynamic potentially relevant for emerging economies and nascent technological domains.

Columns (3) and (4), which introduce one-year and five-year lags of the functional variables respectively, help address concerns of reverse causality and better capture the time structure of innovation effects. In the one-year lag model (column 3) all three functions are positive and statistically significant, although the magnitude of the corresponding coefficients is lower than in the baseline model. This supports the robustness of our main findings, while also indicating that the influence of recycling, refining, and removing on use-related innovation appears strongest in the short term. In the five-year lag model (column 4), the coefficient for *refine* remains positive and significant, while those for *recycle* and *remove* lose significance—pointing to a time-decay pattern. This suggests that circular innovation effects may be more time-sensitive, while refining exerts a more durable enabling role. It is important to note, however, that introducing longer lags reduces the effective sample size and may contribute to noisier estimates. While the five-year results should therefore be interpreted with caution, the overall patterns are robust: *refine* consistently supports CRM use innovation over time, while *recycle* and *remove* appear to exert shorter-term influences. Taken together, these results point to a pattern of functional interdependence within CRM innovation, with varying temporal profiles across functions.

Our findings highlight a robust association between CRM use innovation and upstream (*refine*), circular (*recycle*), and mitigation (*remove*) functions, even after accounting for CRM-country production statuses and innovation intensities, as well as for potential distributional biases. This underscores the systemic nature of CRM-related technological change: progress in circularity and resource efficiency can reinforce rather than substitute core technological development. In particular, the strong and persistent role of refining underscores its importance as a technological enabler, while the positive but shorter-lived effects of recycling and removal innovations suggest that circular economy strategies can align synergistically with innovation-oriented goals. These findings carry important policy implications: supporting circularity and material efficiency through targeted innovation strategies may not trade off against advancing technological competitiveness in critical raw materials. Rather, both objectives can be mutually reinforcing, offering integrated pathways toward sustainable and resilient CRM governance.

	(1) Log(Use)		(2) Log(Use)		(3) Log(Use)		(4) Log(Use)	
Log(Recycle)	0.0878***	(0.0185)						
Log(Refine)	0.201***	(0.0224)						
Log(Remove)	0.142***	(0.0168)						
GDP	0.161	(0.0825)	0.179*	(0.0834)	0.209*	(0.0841)	0.370**	(0.120)
R&D	0.169***	(0.0335)	0.221***	(0.0356)	0.184***	(0.0336)	0.307***	(0.0409)
Patent volume	0.249***	(0.0142)	0.347***	(0.00812)	0.258***	(0.0121)	0.255***	(0.00987)
CRM real price	0.0166	(0.0127)	0.0214	(0.0126)	0.0180	(0.0111)	0.0207	(0.0156)
Active dummy	-0.0117	(0.0212)	-0.000957	(0.0254)	0.144***	(0.0194)	0.153***	(0.0239)
Producer dummy	0.0233	(0.0485)	0.0233	(0.0501)	-0.00415	(0.0489)	-0.0510	(0.0603)
Recycle dummy			0.125***	(0.0197)				
Refine dummy			0.134***	(0.0208)				
Remove dummy			0.108***	(0.0218)				
Log(Recycle)$_{lag1}$					0.0571**	(0.0175)		
Log(Refine)$_{lag1}$					0.178***	(0.0201)		
Log(Remove)$_{lag1}$					0.102***	(0.0161)		
Log(Recycle)$_{lag5}$							0.0256	(0.0156)
Log(Refine)$_{lag5}$							0.0523***	(0.0152)
Log(Remove)$_{lag5}$							0.0322	(0.0169)
Constant	2.502***	(0.0769)	2.498***	(0.0814)	2.551***	(0.0742)	2.381***	(0.0857)
N	10087		10087		9577		7558	
r2_a	0.389		0.362		0.375		0.303	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Regression of CRM use on recycle, refine, and remove. Column (1) baseline model; (2) dummies; (3) 1-year lag; (4) 5-year lag.

5.3.3 Interaction between CRM innovation functions

We further explore the interrelationships among CRM functions by examining whether innovation activities in *recycle*, *refine*, and *remove* functions complement or substitute for one another in driving CRM use innovation. To test this, we estimate models that include interaction terms between functional variables, allowing us to assess whether innovation in one function modifies the marginal effect of another on *use*. Table 11 presents the results. Columns (1) to (3) report models with interaction terms between *recycle* and *refine*, *recycle* and *remove*, and *refine* and *remove*, respectively. The results show that the interactions between *recycle* and *refine* (column 1) and between *recycle* and *remove* (column 2) are negative and statistically significant. This suggests that when both functions are simultaneously active, their marginal contributions to *use* innovation partially offset each other, indicating a degree of functional substitutability. One interpretation is that technological improvements in refining may reduce the need for recycling-based strategies (and vice versa), or that resource constraints induce countries to prioritise one innovation pathway over another. In contrast, the interaction between *refine* and *remove* (column 3) is negative but statistically insignificant.

	(1) Log(Use)		(2) Log(Use)		(3) Log(Use)	
Log(Recycle)	0.128***	(0.0200)	0.109***	(0.0207)	0.0940***	(0.0190)
Log(Refine)	0.214***	(0.0233)	0.206***	(0.0229)	0.207***	(0.0250)
Log(Remove)	0.156***	(0.0179)	0.158***	(0.0192)	0.155***	(0.0217)
Log(Recycle)*Log(Refine)	-0.0246**	(0.00838)				
Log(Recycle)*Log(Remove)			-0.0181*	(0.00736)		
Log(Refine)*Log(Remove)					-0.00825	(0.00744)
GDP	0.157	(0.0823)	0.161	(0.0826)	0.160	(0.0825)
R&D	0.166***	(0.0332)	0.167***	(0.0333)	0.168***	(0.0334)
Patent volume	0.262***	(0.0145)	0.256***	(0.0139)	0.252***	(0.0141)
CRM real price	0.0168	(0.0129)	0.0167	(0.0128)	0.0163	(0.0127)
Active dummy	-0.0348	(0.0216)	-0.0259	(0.0223)	-0.0227	(0.0234)
Producer dummy	0.0210	(0.0480)	0.0223	(0.0481)	0.0225	(0.0483)
Constant	2.696***	(0.0723)	2.688***	(0.0728)	2.683***	(0.0727)
N	10087		10087		10087	
r2_a	0.390		0.390		0.389	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Regression of CRM use on the interaction of other functions. Column (1): recycle and refine interaction; (2) recycle and remove interaction; (3) refine and remove interaction

In conclusion, these findings highlight the systemic complexity of CRM-related innovation. While innovation efforts in individual functions reinforce *use* innovation when considered separately, pursuing multiple functions simultaneously may be associated with diminishing returns. This may reflect overlapping technological scopes, competition for limited R&D resources, or strategic trade-offs in national innovation priorities. From a policy perspective, the results underline the importance of coordinating innovation support across CRM functions to maximise synergies and avoid unintended crowding-out effects in core technological applications.

6 Conclusions

The governance of critical raw materials has shifted from a technical niche concern to a pressing global issue, now occupying front-page headlines. Recent geopolitical tensions, exemplified by the debate on rare earths in Ukraine and broader concerns about the resilience of the CRM supply chain, have underscored the profound strategic, environmental, and technological risks linked to material dependencies. As clean energy, digital technologies, and green infrastructures become central to economic competitiveness, the foundational role of CRMs in enabling these systems has intensified. Their limited substitutability, geographic concentration, and high environmental and social costs of extraction raise complex challenges across industrial, environmental, and strategic domains. This growing awareness has brought new urgency to understanding how innovation systems engage with CRMs, not just in terms of securing supply, but in shaping the technological trajectories upon which future sustainability and competitiveness depend.

Understanding how innovation systems respond to mounting material and strategic pressures requires moving beyond questions of CRM presence in patented inventions to examine the functional roles these materials play across the technological value chain. To this aim, our study introduces a novel, function-sensitive methodology to systematically map CRM-related innovation across supply chain stages, technologies, and geographies. Building on recent advances in AI-based text analysis and patent mining (Aroyehun et al., 2025; Madani and Weber, 2016; Zhang et al., 2022), we propose a hybrid empirical strategy that combines keyword-based filtering with large language model classification to map how CRMs are functionally embedded in technological innovation. First, we identify CRM-related patents in the PATSTAT database through a targeted keyword search. This yields nearly 4 million CRM–patent abstract associations during the period 1999–2018. Second, to move beyond sheer material mentions, we apply a LLM-based classifier to assign each CRM–patent pair to one of the four functional categories of CRMs in each invention: *use*, *refine*, *recycle*, and *remove*. Each of these functional categories is connected to one or more stages of the CRM supply chain, either in the upstream extraction and processing, downstream manufacturing, or circular end-of-life recovery. A fifth category, *wrong*, is used to detect false positives introduced in the initial keyword filtering, improving the accuracy and robustness of the CRM-patent classification. By clarifying the roles critical raw materials play in technological innovation, this function-sensitive framework enables us to provide comparative and temporal insights across materials, technological domains, geographies, and supply chain stages. It offers a dynamic and granular lens on how innovation systems are adapting to material constraints, capturing not only the scale of CRM-related innovation but also its strategic orientation—interpreting patented inventions as signals of how these systems respond to the sustainability, security, geopolitical, and material challenges shaping the global governance of CRM supply chains.

Our empirical analysis points to several key findings. Firstly, we explore how CRM innovation is distributed across functions, materials, and technology domains. At the function-level, while CRM use-related inventions dominate in absolute patent counts, there is a notable and growing diversification towards circular and sustainability-oriented functions, particularly *recycle* and *remove*. This trend suggests that, albeit in small volumes, CRM innovation is evolving towards greater material efficiency and resilience, responding to emerging environmental and supply chain pressures. At the material level, lithium, graphite, rare earth elements, and copper emerge as the most frequently mentioned CRMs in patented inventions—reflecting their central role in the green and digital transitions, especially through applications in electrification and energy storage. These patterns are further reinforced by our analysis of CPC classifications. Use-related patents span a wide range of technology applications, while innovation in *refine*, *recycle*, and *remove* functions is more narrowly concentrated in technical domains linked to material processing, recovery, and battery systems. For instance, lithium and graphite recycling and refining patents are strongly rooted in battery-related subclasses–such as H01M and Y02W 30/84–underscoring the pivotal role of battery innovation as a driver of circular and enabling CRM strategies.

Secondly, we investigate the distribution of CRM function-specific innovations across countries. The geographic distribution of CRM-related innovation reveals an increasingly polarised global landscape, characterised by high spatial concentration and distinct national specialisation profiles. Between 1999 and 2018, China advanced throughout the CRM supply chain and consolidated its global leadership in CRM innovation, recording exponential growth in patenting activity across all functional categories. Hand in hand with its strategic efforts to secure dominance in CRM extraction and refining, the breadth and pace of China's functional diversification indicate a deliberate attempt to position itself at the technological frontier of CRM-intensive innovation, especially in green and digital technologies. In contrast, Western countries, including the EU and the US, exhibit declining trends in *use*-oriented CRM innovation and only recently modest growth in the *recycling* and *remove* functions, potentially reflecting a slow but strategic move away from CRM-intensive technologies, or a lag in adapting their technology base, raising concerns about their long-term competitiveness in critical technology domains.

Thirdly, to better understand the functional interdependencies between upstream, circular, and use-related innovations, we examine how patenting in CRM refining, recycling, and removing is linked to CRM use. Employing a fixed-effects panel estimation–with patenting activity in the *use* function as the dependent variable and observations indexed by CRM, country, and year—we find that innovation in the *refine*, *recycle*, and *remove* functions is positively associated with *use*-related innovation. This suggests that upstream and circular efforts tend to reinforce, rather than substitute for, core technological development, indicating that CRM innovation often unfolds through system-wide, integrated advances rather than isolated breakthroughs. However, the analysis also reveals significant interaction effects—most notably a negative and statistically significant interaction between *recycle* and *refine*—indicating that these functions may partially offset each other in their contribution to CRM *use* innovation. This suggests that the benefits of combining innovation efforts across functions may be limited. When two functional areas like *recycle* and *refine* are both highly active, their joint impact on *use*-related innovation is smaller than expected—possibly because they target similar technological challenges or follow competing innovation paths. While pursuing multiple innovation pathways can create synergies, these findings point to potential trade-offs when allocating effort across functions.

These findings carry several implications for innovation and industrial policy. Despite growing academic and policy attention to circularity, particularly regarding recycling and reuse, our analysis reveals that use-oriented innovations still dominate CRM-related patenting. Although recycling, refining, and removing activities are expanding—especially since 2010—their absolute volumes remain modest, signalling that market forces alone are unlikely to deliver the scale of circular and upstream progress envisioned in policy goals without targeted policy support. However, our results show that supporting innovation in circularity functions should not be viewed as counter to industrial competitiveness; rather, advancing recycling, refining, and removing capabilities are foundational to securing the technological bases necessary for CRM *use*-related inventions, and therefore to strengthening the broader innovation ecosystem. At the same time, the observed mix of complementarity and partial substitutability among CRM functions underscores the importance of coordinated policy frameworks that account for functional interdependencies and minimise potential crowding-out effects. Finally, the geographic concentration of CRM innovation, particularly China's cross-functional leadership, highlights the limitations of policy approaches that focus narrowly on supply diversification and domestic extraction. Broader technological sovereignty and supply chain resilience objectives must be in fact aligned with efforts to reduce dependence on primary extraction and mitigate its socio-environmental impacts, through sustained investment in circular and less CRM-intensive innovation pathways and the development of robust frameworks for responsible sourcing. This alignment is particularly urgent in the European context, where the near-total reliance on external sources amplify strategic vulnerabilities and poses a significant obstacle to the EU's sustainability and autonomy goals.

Although our study introduces a novel empirical framework for analysing CRM innovation dynamics, several limitations should be acknowledged, many of which point to promising directions for future research into how material constraints shape technological trajectories. Our functional classification offers a realistic representation of critical raw material supply chains within patents, however, it could be further refined by introducing additional categories such as CRM *mining*, *substitution*, and *reduction*. Expanding the CRM functional categories would help further disentangling the strategic orientation of patented inventions around material constraints and sustainability challenges, particularly within the dominant *use* category. Furthermore, while we map the main CRM-related innovations across patent domains and our primary objective is to demonstrate the potential of our hybrid text-analysis methodology to capture aggregate functional patterns across countries and materials, future research should undertake a more fine-grained analysis of how CRM functions evolve within strategic technological domains, especially renewable energy, digital infrastructure, and defence, in order to deepen our understanding of the key technological trajectories of CRM innovation. Finally, our econometric analysis provides robust evidence of associations between CRM functions. However, it does not establish causal relationships, such as the impact of innovations in recycling or refining on downstream technology adoption, which would require more advanced identification strategies, which could leverage exogenous variation from material supply shocks or regulatory changes. Although such analysis lies beyond the scope of this paper, future research may integrate function-sensitive patent mapping with causal inference to obtain more actionable policy insights, particularly by examining the distribution of CRM functions within strategic technological domains.

The CRM economy illustrates how sustainability imperatives, innovation dynamics, and international competition are increasingly interconnected. Far from being passive inputs, CRMs actively shape the direction and intensity of technological change, as supply pressures reconfigure not only the pace of innovation but also its underlying trajectories (Li et al., 2024). Therefore, as innovation systems shift their material foundations and become increasingly exposed to resource constraints, understanding the role of CRMs within technological change is essential for anticipating the evolution of technological capabilities. Our function-sensitive, large language model-based approach contributes to this task by offering a novel and scalable framework for capturing the evolving role of CRMs in patented inventions, enabling more systematic monitoring of innovation responses across supply chain stages, materials, and geographies. By making visible the functional interdependencies between upstream, downstream, and circular innovation, this methodology provides critical insight for designing more coherent and forward-looking policy frameworks. Ultimately, building resilient, sustainable, and fair CRM supply chains will be crucial not only for achieving climate and digital goals, but also for shaping the global distribution of technological capabilities and economic power. In an era of profound technological and geopolitical transformation, addressing these interlinked challenges calls for integrated governance approaches that align environmental targets with technological, industrial, and strategic objectives.

A Labelled Dataset for Functional Role Classification

To train the classification model on functional roles, we use a manually validated dataset of CRM–patent abstract pairs, each labelled according to one of the five functional categories described in Section 4.2: *use*, *refine*, *recycle*, *remove*, or *wrong* (false positives). The sample is based on the manually annotated dataset used for a robustness analysis in de Cunzo et al. (2023). Each example links a specific CRM mention in a patent abstract to its function within the invention. For each pair, we also retain metadata on the detected keyword(s) and the associated CPC codes. The original sample includes 4,044 INPADOC patent family IDs, corresponding to 11,564 CRM–abstract pairs.[12]

As approximately 90% of the original examples fall under the *use* category, we apply a data augmentation strategy to improve the balance across functional roles. We use a back-translation method to increase the number of examples for the less frequent functions—*refine*, *recycle*, *remove*, and *wrong*.[13] This process involves translating each text from English to another language X, and then back to English. A new CRM–abstract pair is then created using the back-translated abstract and the original CRM keyword. Table 12 reports the number and share of examples in each functional category before and after data augmentation.

Function Category	**Examples before data augmentation (Share)**	**Examples after data augmentation (Share)**
Use	10205 (88.2%)	10205 (55.6%)
Recycle	357 (3.1%)	2142 (11.7%)
Refine	528 (4.6%)	3168 (17.2%)
Remove	198 (1.7%)	1188 (6.5%)
Wrong	276 (2.4%)	1656 (9.0%)

Table 12: Function composition of the training sample before and after the data augmentation procedure

B Functional Innovation Patterns across CPC Technology Classes

Studying how CRM-related inventions map onto the CPC system across functional categories provides insights into the technological directions of innovation for specific materials. More specifically, understanding which CPC domains are associated with particular CRM–function pairs helps reveal where innovation is concentrated, which areas are maturing, and where efforts remain nascent. Figure 6 presents a heatmap of patent family counts for the top 10 CRMs across functions and CPC sections.

[12]The CRM list differs slightly from that used in this paper. de Cunzo et al. (2023) relies on the 2020 EU CRM list (European Commission, 2020*a*), while we adopt the 2023 update (European Commission, 2023*a*). However, most CRMs in the training sample are retained in the updated list.

[13]We use Helsinki-NLP's OPUS-MT models Tiedemann et al. (2023), implemented with the MarianMT architecture Junczys-Dowmunt et al. (2018).

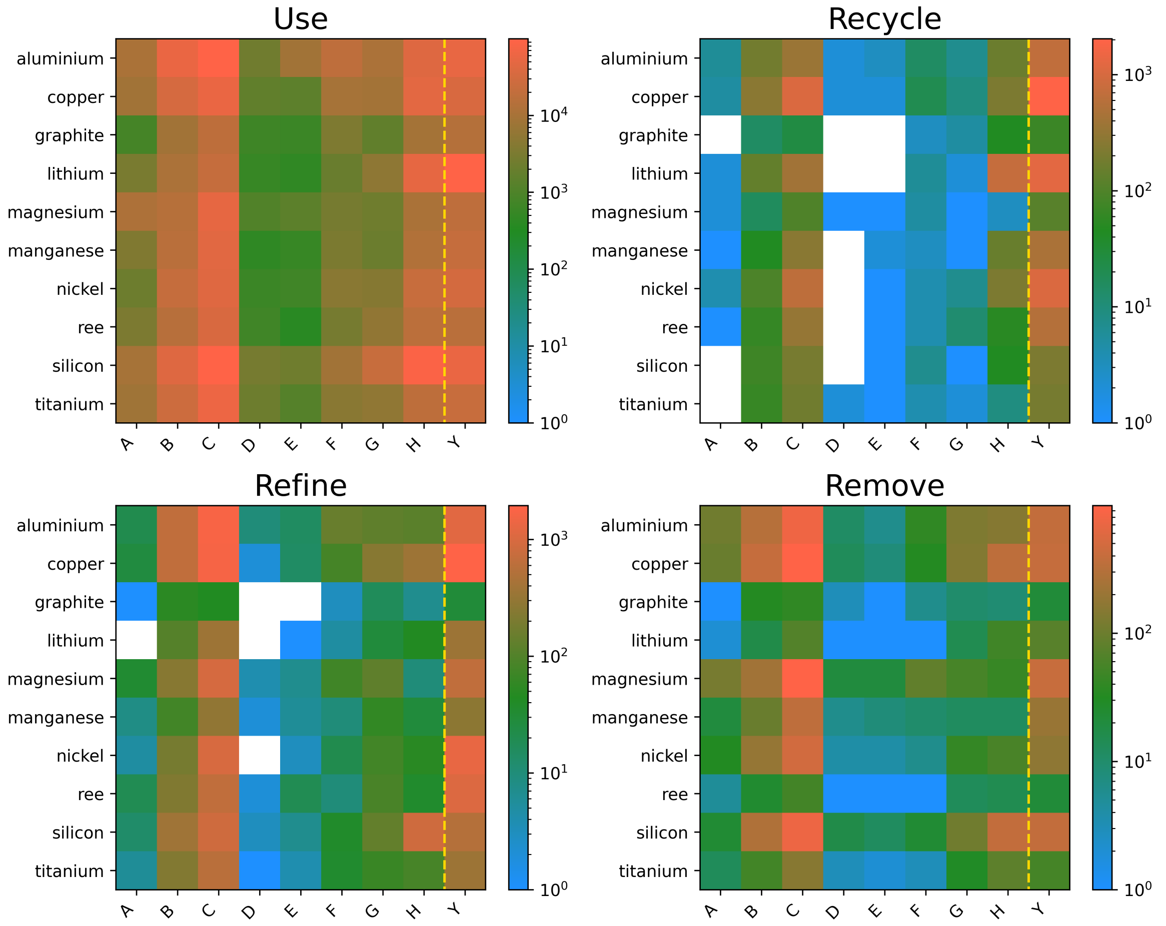

Figure 6: Heatmap of INPADOC family counts by CRM function across CPC sections reported on the x-axis. Colour intensity follows a log scale—compressing large values and revealing low-frequency cells—while white denotes zero occurrences. The dashed yellow line separates sections A–H from section Y, which is reserved for climate change adaptation and mitigation technologies.

As shown in the figure, CRM-related innovations are predominantly located in CPC sections C (*Chemistry; Metallurgy*), H (*Electricity*), and Y (*General tagging of new technological developments*). The signal in section Y is almost entirely concentrated in the Y02 class, which covers *Climate change mitigation and adaptation technologies* (CCMT). In contrast, sections such as D (*Textiles; Paper*) and E (*Fixed Constructions*) show almost no CRM-related patents. Other sections—A (*Human Necessities*), F (*Mechanical Engineering*), and G (*Physics*)—contain CRM patents primarily within the *use* function, and only for the selected sub-set of materials shown in the figure. These findings suggest that CRM innovation, whether aimed at new devices, separation processes, or end-of-life recovery, is overwhelmingly linked to chemical, metallurgical, electrical, and sustainable technology domains.

Functional patterns vary: *use*-related patents are widely distributed across CPC sections, reflecting how deeply embedded CRMs are in the development of finished technologies, from batteries to electronics. In contrast, circular functions (*recycle*, *remove*) and enabling functions (*refine*) are more narrowly concentrated in specific technological areas and materials. For example, rare earths show recycling and refining activity primarily within specialised metallurgical and chemical processing codes, consistent with their complex recovery challenges. Manganese removal patents cluster in chemical-processing domains, while lithium recycling is concentrated in electrochemical (H-section) technologies. Notably, graphite—despite being among the fastest-growing CRMs in patenting activity–see Figure 2–shows very limited patent presence outside the *use* function, highlighting its strongly application-driven role in energy storage and conductive technologies. Together, these patterns map the intersection of material-specific challenges with functional innovation strategies, showing how some CRMs are moving toward circular and enabling innovations, while others remain focused on direct application and device integration.

To provide a more granular view of the most CRM-intensive technology domains by function, we disaggregate the data to the CPC subclass level. Figures 7 and 8 present the most frequently associated CPC subclasses for the top 10 CRMs across four functions for non-green (A–H) and green (Y02) technologies, respectively.

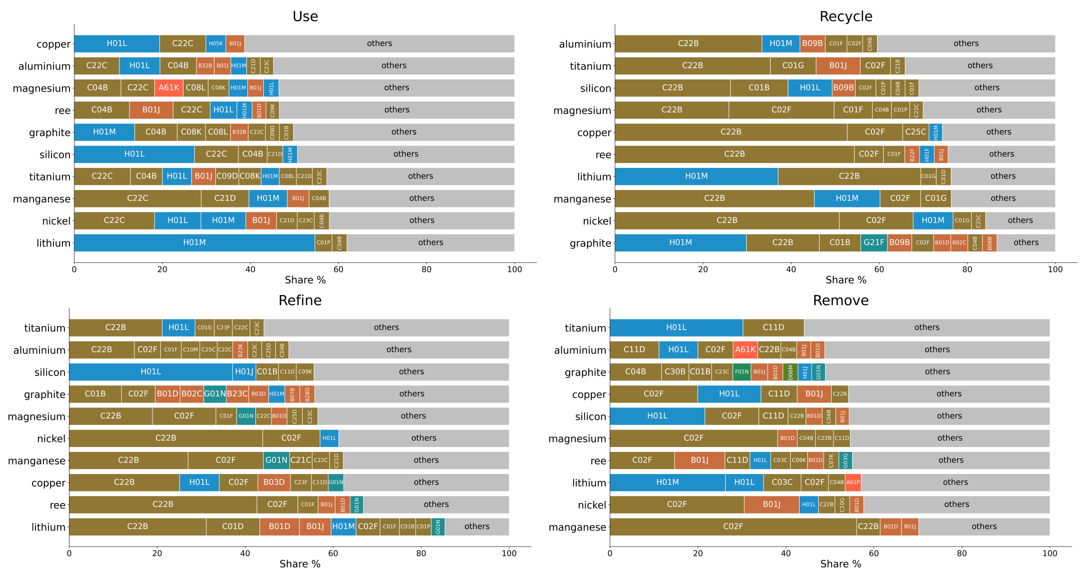

Figure 7: Stacked bar chart of the top 4-digit CPC subclasses (A–H) by CRM function. Only subclasses exceeding 5% share are labelled; all remaining codes are grouped under “Others”. Bar colours denote their parent CPC A-H section.

Focusing on non-green technologies (Figure 7), clear CRM–technology patterns emerge. Refining patents are concentrated in subclass C22B (*production and refining of metals*), reflecting efforts to improve purification processes. A notable exception is silicon, whose refining patents cluster in H01L (*semiconductor devices*), consistent with its role in photovoltaics and microelectronics. Recycling patents largely mirror this structure: C22B dominates for most CRMs, indicating the centrality of chemical recovery methods. However, lithium and graphite diverge from this pattern, clustering in H01M (*electrochemical cells*), which highlights battery-oriented processes such as hydrometallurgical leaching. Removal patents are more varied. Manganese, magnesium, copper, and nickel frequently appear in C02F (*water treatment*), while silicon and titanium removal patents cluster in H01L, reflecting etching and cleaning in semiconductor processes. Lithium again aligns with H01M, consistent with battery-related purification steps. For the *use* function, the technological spectrum is broader. Key subclasses include C22B, H01M, H01L, and C04B (*construction ceramics*), showing that CRMs are embedded in a wide array of applications—from energy storage and permanent magnets to semiconductors and construction materials.

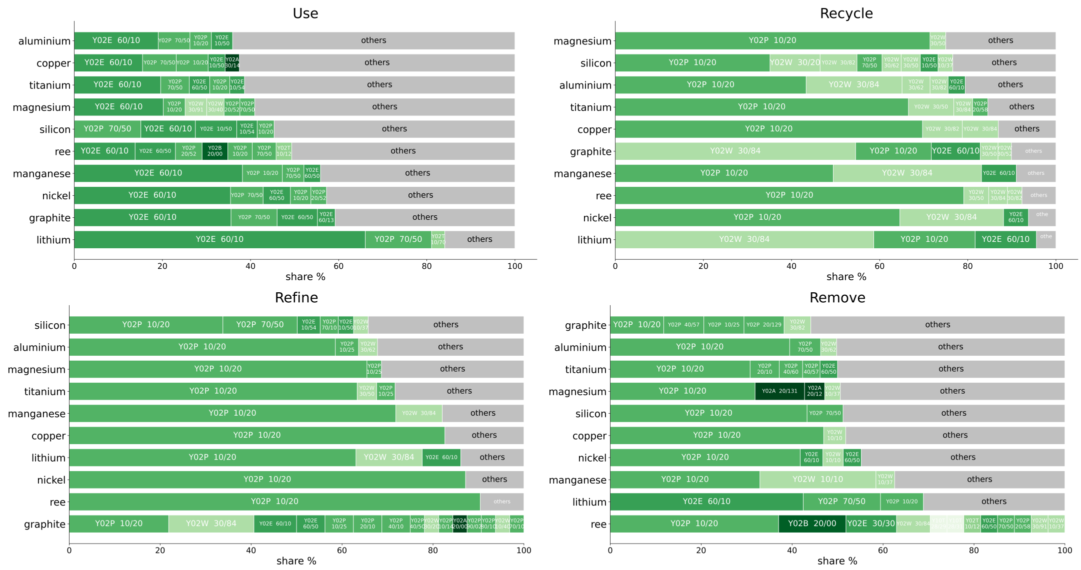

Figure 8: Stacked bar chart of the top 8-digit CCMT CPC codes by CRM function. Only codes exceeding 5% share are labelled; all remaining codes are grouped under "Others". Bar colours denote their parent CPC Y02 subclass.

Turning to green technologies (Figure 8), we observe a strong dominance of the Y02P subclass (*processing of goods*) in the circular (*recycle*, *remove*) and enabling (*refine*) functions. A large share of CRM-related innovation in these functions falls under Y02P 10/20, which captures *technologies related to metal processing and recycling*. The predominance of this category suggests that technical know-how for purification and recovery is closely intertwined, highlighting metal recovery from waste as a key enabling step for low-carbon transitions. Beyond Y02P, additional signals emerge in more specialised areas. In recycling, graphite and lithium are particularly prominent in Y02W 30/84 (*recycling of batteries or fuel cells*), reflecting the growing role of end-of-life battery technologies in driving targeted recovery innovations. For the *remove* function, lithium also appears in Y02E 60/10 (*energy storage using batteries*), suggesting emerging links between purification efforts and battery-specific applications. Notably, the same Y02E 60/10 subclass also captures the majority of CRM use patents, underscoring the integration of materials such as lithium, cobalt, and nickel into next-generation energy storage systems. Silicon stands out with a different profile: its top use patents fall under Y02P 70/50 (*manufacturing processes characterised by the final product*), likely reflecting its central role in high-efficiency photovoltaics and LED technologies. Taken together, these patterns reveal a highly focused technical orientation in refining and removal under the Y02P "metal recovery" umbrella, while use-related innovations diversify into Y02E energy storage systems and Y02W battery-specific recovery pathways for the selected materials.

C Econometric Robustness Checks

This section presents additional econometric specifications that complement those discussed in Section 5.3, providing further robustness to our main results.

Table 13 examines the potential for reverse influence—whether innovation in CRM use is associated with increased patenting in the other CRM-related functions. Specifically, we regress patenting activity in the *recycle*, *refine*, and *remove* categories on *use*, shown respectively in columns (1), (2), and (3). The model controls for the same covariates as Equation 1, including GDP, R&D, CRM prices, patent volumes, and country-level production and activity dummies. Across all models, *use*-related patenting shows a positive and statistically significant association with subsequent innovation in each of the other functions. However, these associations are generally weaker than the corresponding effects of *recycle*, *refine*, and *remove* on *use* found in the main analysis (Table 10), suggesting that feedback effects exist but may be secondary in strength and consistency.

	(1)		(2)		(3)	
	Log(Recycle)		Log(Refine)		Log(Remove)	
Log(Use)	0.0450***	(0.0100)	0.131***	(0.0160)	0.0838***	(0.0118)
Log(Recycle)			0.199***	(0.0252)	0.160***	(0.0327)
Log(Refine)	0.156***	(0.0230)			0.0529*	(0.0243)
Log(Remove)	0.139***	(0.0283)	0.0584*	(0.0261)		
GDP	0.00574	(0.0487)	0.0842	(0.0508)	-0.0293	(0.0431)
R&D	0.120***	(0.0237)	0.150***	(0.0237)	0.0292	(0.0202)
Patent volume	0.189***	(0.0212)	0.146***	(0.0146)	0.141***	(0.0211)
CRM real price	-0.00968	(0.0132)	0.0138	(0.0141)	0.00886	(0.00915)
Active dummy	0.0203	(0.0246)	0.498***	(0.0184)	0.208***	(0.0254)
Producer dummy	-0.0512	(0.0315)	0.0275	(0.0416)	0.0117	(0.0307)
Constant	-0.278***	(0.0598)	-0.351***	(0.0814)	-0.0604	(0.0606)
N	10087		10087		10087	
r2_a	0.421		0.466		0.317	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Regression results of other functions on *use*. The dependent functions are *recycle* in column (1), *refine* in column (2), and *remove* in column (3).

Table 14 presents robustness checks using alternative estimation strategies. Column (1) reports our baseline fixed-effects model excluding China, testing whether China's dominant patenting volumes disproportionately shape the results. Column (2) presents results from a standard OLS regression. Column (3) reports estimates from a Poisson model, which better accommodates the count nature of the dependent variable. Across all three models, coefficients on the functional variables remain positive and statistically significant, reinforcing the direction and robustness of our main findings.

	(1)		(2)		(3)	
	Log(Use)		Log(Use)		Number of Use families	
Log(Recycle)	0.0400*	(0.0158)	0.365***	(0.0287)	0.118***	(0.0196)
Log(Refine)	0.158***	(0.0262)	0.625***	(0.0226)	0.186***	(0.0189)
Log(Remove)	0.0802***	(0.0169)	0.264***	(0.0243)	0.226***	(0.0279)
GDP	0.139	(0.0865)	-0.279***	(0.0173)	0.734***	(0.163)
R&D	0.119***	(0.0322)	0.578***	(0.0220)	0.00172	(0.0659)
Patent volume	0.883***	(0.193)	0.121***	(0.0154)	0.174***	(0.0125)
CRM real price	0.0185	(0.0129)	0.103***	(0.0101)	0.00271	(0.00926)
Active dummy	0.0315	(0.0202)	1.077***	(0.0322)	-0.102**	(0.0310)
Producer dummy	0.00639	(0.0478)	-0.0410	(0.0306)	-0.0511	(0.0637)
Constant	2.633***	(0.0759)	0.764***	(0.0689)		
N	9517		10087		9952	
r2_a	0.127		0.637			

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Additional regression specifications. Column (1): baseline fixed effects model without China; Column (2): OLS model; Column (3): Poisson regression.

Acknowledgments

F.d.C, A.P., A.S., and A.T. acknowledge the financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 1409 published on 14.9.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union – Next Generation EU – Project Title "Triple T – Tackling a just Twin Transition: a complexity approach to the geography of capabilities, labour markets and inequalities" – CUP F53D23010800001 –Grant Assignment Decree No. 1378 adopted on 01.09.2023 by the Italian Ministry of Ministry of University and Research (MUR).

A.P., A.S., and A.T. acknowledge the financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 104 published on 2.2.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union – NextGenerationEU– Project Title "WECARE – WEaving Complexity And the gReen Economy" – CUP 20223W2JKJ by the Italian Ministry of Ministry of University and Research (MUR).

References

Ambrose, H. and Kendall, A. (2020), 'Understanding the future of lithium: Part 2, temporally and spatially resolved life-cycle assessment modeling', *Journal of Industrial Ecology* **24**(1), 90–100.

Arendt, R., Bach, V. and Finkbeiner, M. (2022), 'The global environmental costs of mining and processing abiotic raw materials and their geographic distribution', *Journal of Cleaner Production* **361**, 132232.

Aroyehun, S. T., Marzo, G. D., Fenoaltea, E. M., Santoro, F. and Tacchella, A. (2025), 'Using large language models to uncover emergent technological dynamics', *In preparation* .

Arts, S., Appio, F. P. and Van Looy, B. (2013), 'Inventions shaping technological trajectories: do existing patent indicators provide a comprehensive picture?', *Scientometrics* **97**(2), 397–419.

Bae, H. and Kim, Y. (2021), 'Technologies of lithium recycling from waste lithium ion batteries: a review', *Materials advances* **2**(10), 3234–3250.

Baum, Z. J., Bird, R. E., Yu, X. and Ma, J. (2022), 'Lithium-ion battery recycling–overview of techniques and trends', *American Chemical Society Energy Letters* **7**(2), 712 – 719.

Beales, E. J., Brøske Danielsen, J., Grytli, T. and Simas, M. (2021), Environmental and social consequences of mineral extraction for low-carbon technologies: Cobalt, lithium and nickel extraction, impacts and relation to the sdgs, Technical report, SINTEF AS.

Beltagy, I., Lo, K. and Cohan, A. (2019), Scibert: A pretrained language model for scientific text, *in* 'Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)', Association for Computational Linguistics, pp. 3615–3620.
URL: *https://aclanthology.org/D19-1371*

Berman, N., Couttenier, M., Rohner, D. and Thoenig, M. (2017), 'This Mine is Mine! How Minerals Fuel Conflicts in Africa', *American Economic Review* **107**(6), 1564–1610.

Blum, U., Borg, G., Kropp, N., Liventseva, H. and Rozhkova, I. (2023), 'Die rohstoffe der ukraine und ihre strategische bedeutung–eine geopolitische analyse', *SIRIUS–Zeitschrift für Strategische Analysen* **7**(3), 257–276.

Bonds, E. and Downey, L. (2012), 'Green? technology and ecologically unequal exchange: the environmental and social consequences of ecological modernization in the world-system', *Journal of World-Systems Research* pp. 167–186.

Chandra, M., Yu, D., Tian, Q. and Guo, X. (2022), 'Recovery of cobalt from secondary resources: a comprehensive review', *Mineral Processing and Extractive Metallurgy Review* **43**(6), 679–700.

Church, C. and Crawford, A. (2018), Green Conflict Minerals: The fuels of conflict in the transition to a low-carbon economy, Technical report, International Institute for Sustainable Development (IISD).

Cobalt Institute (2023), Cobalt market report 2022, Technical report, Cobalt Institute.

Conde, M. (2017), 'Resistance to mining. a review', *Ecological economics* **132**, 80–90.

Davis, G. A. and Tilton, J. E. (2005), 'The resource curse', *Natural Resources Forum* **29**(3), 233–242.

de Cunzo, F., Consoli, D., Perruchas, F. and Sbardella, A. (2023), Mapping Critical Raw Materials in Green Technologies, Papers in Evolutionary Economic Geography (PEEG) 2322, Utrecht University, Department of Human Geography and Spatial Planning, Group Economic Geography.

De Oliveira, R., Benvenuti, J. and Espinosa, D. (2021), 'A review of the current progress in recycling technologies for gallium and rare earth elements from light-emitting diodes', *Renewable and Sustainable Energy Reviews* **145**, 111090.

de Rassenfosse, G., Dernis, H., Guellec, D., Picci, L. and van Pottelsberghe de la Potterie, B. (2013), 'The worldwide count of priority patents: A new indicator of inventive activity', *Research Policy* **42**(3), 720–737.

de Rassenfosse, G., Kozak, J. and Seliger, F. (2019), 'Geocoding of worldwide patent data', *Scientific Data* **6**(1).

Dechezleprêtre, A., Glachant, M., Haščič, I., Johnstone, N. and Ménière, Y. (2011), 'Invention and transfer of climate change–mitigation technologies: a global analysis', *Review of Environmental Economics and Policy* **5**(1), 109–130.

Diemer, A., Iammarino, S., Perkins, R. and Gros, A. (2022), 'Technology, resources and geography in a paradigm shift: the case of critical and conflict materials in ICTs', *Regional Studies* pp. 1–13.

Dou, S., Xu, D., Zhu, Y. and Keenan, R. (2023), 'Critical mineral sustainable supply: Challenges and governance', *Futures* **146**, 103101.

Dowling, C. and Otero, G. (2025), 'Mirages or miracles? lithium extraction and the just energy transition', *Energy Research & Social Science* **119**, 103862.

European Commission (2020*a*), 'Communication from the commission to the european parliament, the council, the european economic and social committee and the committee of the regions critical raw materials resilience: Charting a path towards greater security and sustainability', https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0474.

European Commission (2020*b*), *Study on the EU's list of Critical Raw Materials (2020), Factsheets on Critical Raw Materials*, Publications Office of the European Union.

European Commission (2023*a*), 'Proposal for a regulation of the european parliament and of the council establishing a framework for ensuring a secure and sustainable supply of critical raw materials and amending regulations (eu) 168/2013, (eu) 2018/858, 2018/1724 and (eu) 2019/1020', https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52023PC0160.

European Commission (2023*b*), Study on the critical raw materials for the EU - final report, Technical report, European Commission, Brussels.

European Commission (2023*c*), *Supply chain analysis and material demand forecast in strategic technologies and sectors in the EU: a foresight study.*, Publications Office of the European Union, LU.

European Commission (2024), 'Regulation (eu) 2024/1252 of the european parliament and of the council of 11 april 2024 establishing a framework for ensuring a secure and sustainable supply of critical raw materials and amending regulations (eu) no 168/2013, (eu) 2018/858, (eu) 2018/1724 and (eu) 2019/1020', https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L_202401252.

European Patent Office (2021), *Data Catalog PATSTAT Global 2021*, European Patent Office: Spring Edition.

European Raw Materials Alliance (2021), Rare earth magnets and motors: A european call for action, Technical report, EIT RawMaterials.
URL: *https://erma.eu/reports*

Fusillo, F., Manera, M., Orsatti, G., Quatraro, F. and Rentocchini, F. (2025), The exposure of EU inventive efforts to critical raw materials: Evidence from an AI-based patent indicator, JRC Technical Report JRC141261, European Commission, Joint Research Centre (JRC), Seville.

G7 Leaders (2023), 'G7 hiroshima leaders' communiqué', https://www.consilium.europa.eu/media/64497/g7-2023-hiroshima-leaders-communiqu%C3%A9.pdf. G7 Summit, Hiroshima, May 19–21, 2023. Accessed April 2025.

G7 Ministers' Meeting on Climate, Energy and Environment (2023), 'G7 five-point plan for critical minerals security', https://www.meti.go.jp/information/g7hirosima/energy/pdf/Annex005.pdf. Annex to the G7 Ministers' Meeting, Sapporo, Japan, 15–16 April 2023.
URL: *https://www.meti.go.jp/information/g7hirosima/energy/pdf/Annex005.pdf*

Gielen, D. (2021), 'Critical minerals for the energy transition', *International Renewable Energy Agency (IRENA), Abu Dhabi* .

Giglio, E. (2021), 'Extractivism and its socio-environmental impact in south america. overview of the "lithium triangle"', *América Crítica* **5**(1), 47–53.

Gong, H. and Andersen, A. D. (2024), 'The role of material resources for rapid technology diffusion in net-zero transitions: Insights from ev lithium-ion battery technological innovation system in china', *Technological Forecasting and Social Change* **200**, 123141.

Graedel, T. E., Harper, E. M., Nassar, N. T. and Reck, B. K. (2013), 'On the materials basis of modern society', *Proceedings of the National Academy of Sciences* **112**(20), 6295–6300.

Grandell, L., Lehtilä, A., Kivinen, M., Koljonen, T., Kihlman, S. and Lauri, L. S. (2016), 'Role of critical metals in the future markets of clean energy technologies', *Renewable Energy* **95**, 53–62.

Griliches, Z. (1998), Patent statistics as economic indicators: a survey, *in* 'R&D and productivity: the econometric evidence', University of Chicago Press, pp. 287–343.

Harper, G., Sommerville, R., Kendrick, E., Driscoll, L., Slater, P., Stolkin, R., Walton, A., Christensen, P., Heidrich, O., Lambert, S., Abbott, A., Ryder, K., Gaines, L. and Anderson, P. (2019), 'Recycling lithium-ion batteries from electric vehicles', *Nature* **575**(7781), 75–86.

Herrington, R. (2021), 'Mining our green future', *Nature Reviews Materials* **6**(6), 456–458.

Hofmann, M., Hofmann, H., Hagelüken, C. and Hool, A. (2018), 'Critical raw materials: A perspective from the materials science community', *Sustainable Materials and Technologies* **17**, e00074.

Huang, B., Pan, Z., Su, X. and An, L. (2018), 'Recycling of lithium-ion batteries: Recent advances and perspectives', *Journal of power sources* **399**, 274–286.

Hund, K., La Porta, D., Fabregas, T., Laing, T. and Drexhage, J. (2020), Minerals for climate action: The mineral intensity of the clean energy transition, Technical report, The World Bank Group, 1818 H Street NW Washington, DC 20433, USA.

International Energy Agency (2021), The role of critical minerals in clean energy transitions, Technical report, International Energy Agency, Paris.

International Energy Agency (2023*a*), 'Critical minerals market review 2023', https://www.iea.org/reports/critical-minerals-market-review-2023. All rights reserved.

International Energy Agency (2023*b*), Energy technology perspectives 2023, Technical report, IEA, Paris.

International Energy Agency (2024), 'Global critical minerals outlook 2024', https://www.iea.org/reports/global-critical-minerals-outlook-2024.

International Renewable Energy Agency (2023), 'Geopolitics of the energy transition: Critical materials'.

IRP (2019), *Global Resources Outlook 2019: Natural Resources for the Future We Want*, International Resource Panel, United Nations Environment Programme, Nairobi.
URL: *https://www.resourcepanel.org/reports/global-resources-outlook*

Jerez, B., Garcés, I. and Torres, R. (2021), 'Lithium extractivism and water injustices in the salar de atacama, chile: The colonial shadow of green electromobility', *Political geography* **87**, 102382.

Jin, S., Mu, D., Lu, Z., Li, R., Liu, Z., Wang, Y., Tian, S. and Dai, C. (2022), 'A comprehensive review on the recycling of spent lithium-ion batteries: Urgent status and technology advances', *Journal of Cleaner Production* **340**, 130535.

Jowitt, S. M. (2022), 'Mineral economics of the rare-earth elements', *MRS Bulletin* **47**(3), 276–282.

Jowitt, S. M., Werner, T. T., Weng, Z. and Mudd, G. M. (2018), 'Recycling of the rare earth elements', *Current Opinion in Green and Sustainable Chemistry* **13**, 1–7.

Junczys-Dowmunt, M., Grundkiewicz, R., Dwojak, T., Hoang, H., Heafield, K., Neckermann, T., Seide, F., Germann, U., Fikri Aji, A., Bogoychev, N., Martins, A. F. T. and Birch, A. (2018), Marian: Fast neural machine translation in C++, *in* 'Proceedings of ACL 2018, System Demonstrations', Association for Computational Linguistics, Melbourne, Australia, pp. 116–121.
URL: *http://www.aclweb.org/anthology/P18-4020*

Junne, T., Wulff, N., Breyer, C. and Naegler, T. (2020), 'Critical materials in global low-carbon energy scenarios: The case for neodymium, dysprosium, lithium, and cobalt', *Energy* **211**, 118532.

Kowalski, P. and Legendre, C. (2023), 'Raw materials critical for the green transition: Production, international trade and export restrictions', *OECD Trade Policy Papers* **269**.

Lanjouw, J. O., Pakes, A. and Putnam, J. (1998), 'How to count patents and value intellectual property: The uses of patent renewal and application data', *The Journal of Industrial Economics* **46**(4), 405–432.

Leader, A., Gaustad, G. and Babbitt, C. (2019), 'The effect of critical material prices on the competitiveness of clean energy technologies', *Materials for Renewable and Sustainable Energy* **8**(2), 8.

Lee, J. C. and Wen, Z. (2017), 'Rare earths from mines to metals: comparing environmental impacts from china's main production pathways', *Journal of Industrial Ecology* **21**(5), 1277–1290.

Li, G. Y., Ascani, A. and Iammarino, S. (2024), 'The material basis of modern technologies. a case study on rare metals', *Research Policy* **53**(1), 104914.

Liventseva, H. (2022), 'The mineral resources of ukraine', *Tierra y Tecnología. URL: https://www. icog. es/TyT/index. php/2022/05/the-mineral-resources-of-ukraine/(date of access: 08.10. 2023)* .

Madani, F. and Weber, C. (2016), 'The evolution of patent mining: Applying bibliometrics analysis and keyword network analysis', *World Patent Information* **46**, 32–48.

Mancini, L., Eslava, N. A., Traverso, M. and Mathieux, F. (2021), 'Assessing impacts of responsible sourcing initiatives for cobalt: Insights from a case study', *Resources Policy* **71**, 102015.

Manera, M., Fusillo, F., Orsatti, G. and Quatraro, F. (2025), Addressing the identification of Critical Raw Material Patents Using Pretrained and Large Language Models, Department of Economics and Statistics Cognetti de Martiis. Working Papers 202505, University of Turin.
URL: *https://ideas.repec.org/p/uto/dipeco/202505.html*

Marín, A. and Goya, D. (2021), 'Mining—the dark side of the energy transition', *Environmental Innovation and Societal Transitions* **41**, 86–88.

Marin, A. and Palazzo, G. (2025), 'Civic power in mining conflicts: Barrier or catalyst for a just energy transition?', *Environmental Research Letters* .

Mertens, J., Dewulf, J., Breyer, C., Belmans, R., Gendron, C., Geoffron, P., Goossens, L., Fischer, C., Du Fornel, E., Hayhoe, K. et al. (2024), 'From emissions to resources: mitigating the critical raw material supply chain vulnerability of renewable energy technologies', *Mineral Economics* **37**(3), 669–676.

Mudali, U. K., Patil, M., Saravanabhavan, R. and Saraswat, V. (2021), 'Review on e-waste recycling: part ii—technologies for recovery of rare earth metals', *Transactions of the Indian National Academy of Engineering* **6**(3), 613–631.

München, D. D., Stein, R. T. and Veit, H. M. (2021), 'Rare earth elements recycling potential estimate based on end-of-life ndfeb permanent magnets from mobile phones and hard disk drives in brazil', *Minerals* **11**(11), 1190.

Norgate, T. and Haque, N. (2010), 'Energy and greenhouse gas impacts of mining and mineral processing operations', *Journal of Cleaner Production* **18**(3), 266–274.

OECD (2019), *Global Material Resources Outlook to 2060: Economic Drivers and Environmental Consequences*, Organisation for Economic Co-operation and Development, OECD Publishing, Paris.
URL: *https://doi.org/10.1787/9789264307452-en*

Pommeret, A., Ricci, F. and Schubert, K. (2022), 'Critical raw materials for the energy transition', *European Economic Review* **141**, 103991.

Que, S., Wang, L., Awuah-Offei, K., Chen, Y. and Yang, W. (2018), 'The status of the local community in mining sustainable development beyond the triple bottom line', *Sustainability* **10**(6), 1749.

Safirova, E. (2024), The mineral industry of russia [advance release], Technical report, U.S. Department of the Interior, U.S. Geological Survey.
URL: *https://pubs.usgs.gov/myb/vol3/2020-21/myb3-2020-21-russia.pdf*

Safirova, E. (2025), The mineral industry of ukraine [advance release], Technical report, U.S. Department of the Interior, U.S. Geological Survey.
URL: *https://pubs.usgs.gov/myb/vol3/2020-21/myb3-2020-21-ukraine.pdf*

Scrosati, B. and Garche, J. (2010), 'Lithium batteries: Status, prospects and future', *Journal of Power Sources* **195**(9), 2419–2430.

Smith, B. J., Riddle, M. E., Earlam, M. R., Iloeje, C. and Diamond, D. (2022), Rare earth permanent magnets: supply chain deep dive assessment, Technical report, US-DOE Office of Policy (PO), Washington DC (United States).

Sovacool, B. K., Ali, S. H., Bazilian, M., Radley, B., Nemery, B., Okatz, J. and Mulvaney, D. (2020), 'Sustainable minerals and metals for a low-carbon future', *Science* **367**(6473), 30–33.
URL: *https://doi.org/10.1126/science.aaz6003*

Swain, B. (2017), 'Recovery and recycling of lithium: A review', *Separation and Purification Technology* **172**, 388–403.

Tiedemann, J., Aulamo, M., Bakshandaeva, D., Boggia, M., Grönroos, S.-A., Nieminen, T., Raganato, A., Scherrer, Y., Vazquez, R. and Virpioja, S. (2023), 'Democratizing neural machine translation with OPUS-MT', *Language Resources and Evaluation* **58**, 713–755.

U.S. Geological Survey (2022), Mineral commodity summaries 2022: Cobalt, Technical report, U.S. Geological Survey.
URL: *https://pubs.usgs.gov/periodicals/mcs2022/mcs2022-cobalt.pdf*

Van den Brink, S., Kleijn, R., Sprecher, B. and Tukker, A. (2020), 'Identifying supply risks by mapping the cobalt supply chain', *Resources, Conservation and Recycling* **156**, 104743.

Vikström, H., Davidsson, S. and Höök, M. (2013), 'Lithium availability and future production outlooks', *Applied Energy* **110**, 252–266.

Wang, S. and Yang, L. (2024), 'Mineral resource extraction and resource sustainability: Policy initiatives for agriculture, economy, energy, and the environment', *Resources Policy* **89**, 104657.

Wang, X., Gaustad, G., Babbitt, C. W. and Richa, K. (2014), 'Economies of scale for future lithium-ion battery recycling infrastructure', *Resources, Conservation and Recycling* **83**, 53–62.

Zeng, A., Chen, W., Rasmussen, K. D., Zhu, X., Lundhaug, M., Müller, D. B., Tan, J., Keiding, J. K., Liu, L., Dai, T. et al. (2022), 'Battery technology and recycling alone will not save the electric mobility transition from future cobalt shortages', *Nature communications* **13**(1), 1341.

Zeng, X., Mathews, J. A. and Li, J. (2018), 'Urban mining of e-waste is becoming more cost-effective than virgin mining', *Environmental science & technology* **52**(8), 4835–4841.

Zhang, Y., Huang, Y., Chiavetta, D. and Porter, A. L. (2022), 'An introduction of advanced tech mining: Technical emergence indicators and measurements', *Technological Forecasting and Social Change* .

Zhou, W., Crochet, V. and Wang, H. (2023), 'Demystifying china's critical minerals strategies: Rethinking 'de-risking'supply chains', *World Trade Review* pp. 1–25.