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Uncovering collaboration and knowledge areas in lithium-ion battery recycling†

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The ongoing adoption of lithium-ion batteries (LIBs) in electric vehicles (EVs) and portable electronics has created an urgent need to address the looming challenge of managing the drastic increase in end-of-life batteries through effective recycling solutions. However, the battery recycling landscape remains complex due to the lack of a dominant recycling solution, primarily attributed to differences in battery chemistries and designs. This study contributes a comprehensive patent analysis in this field to track the evolving technological landscape across three time periods, spanning from 1990 to 2024, identify emerging trends and guide strategic decision-making in the rapidly growing battery recycling market. The patent analysis is structured as follows: first, a co-occurrence network analysis of patent assignees is performed to elucidate collaboration in the field. Second, key knowledge areas in LIB recycling are identified through clustering and subsequent natural language processing of co-occurring Cooperative Patent Classification (CPC) class networks. Third, these results are consolidated into two-mode networks to link each patent assignee to its knowledge stocks. The findings reveal a notable lack of international collaboration, which is particularly problematic for Western countries that currently hold minimal presence in the patent landscape. The results also assist in pinpointing the knowledge stocks of different patent assignees and may facilitate the discovery of new research topics and potential collaborators or competitors.

Broader context

In the face of climate challenges, lithium-ion batteries (LIBs) emerge as a pivotal technology for advancing clean energy solutions and accelerating the transition to sustainable economies. As global demand for LIBs soars, the environmental and economic implications of their end-of-life management pose substantial challenges. The ability to effectively recycle LIBs is not only crucial for mitigating resource scarcity and pollution but also for ensuring a resilient supply chain. Despite the essential role of recycling, the current landscape lacks comprehensive strategies that integrate technological, economical and collaborative dimensions. In this context, data science has become indispensable for sustainable battery management: it offers practical approaches to track technological developments, monitors how materials are managed across the battery lifecycle, and highlights areas where incremental improvements in recycling or policy could be most effective. By combining data science methods with patents – a rich yet underutilised source of information – this study reveals critical insights into LIB recycling trends and innovations. By mapping global collaboration networks and pinpointing key areas of expertise, our research uncovers opportunities to foster international partnerships and drive forward-thinking policies. This holistic approach is essential for bridging the gap between current practices and future needs, ultimately paving the way for effective and sustainable battery lifecycle management. These insights hold potential for policymakers, industry leaders and researchers committed to the sustainable transformation of the transport sector.

1. Introduction

Anthropogenic climate change is widely recognised as one of the most urgent challenges of our time and its consequences are already affecting ecosystems, economies and societies around the world.[1,2] Its direct impacts, such as extended droughts, record-breaking floods, destructive forest fires and rapidly melting ice caps, underscore the need for immediate action.[3] In response, governments all over the world have committed to ambitious goals, including limiting the global temperature increase to below 2 °C compared to pre-industrial levels,[4,5] achieving net-zero emissions by utilising clean energy,[6–8] implementing carbon taxes[9–11] and transitioning from a linear to circular economy.[12–14]

Battery energy storage, particularly the use of lithium-ion batteries (LIBs), is a critical technology that can accelerate the realisation of these goals.[15] Different types of LIBs are key for decarbonising important sectors such as mobility, stationary storage and portable electronics due to their efficiency and

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scalability.[16–18] As a result, demand for LIBs is growing rapidly, with projections estimating a significant increase in global demand to up to 3500 GWh by 2030.[19,20] However, this surge presents both opportunities and challenges.

Upstream, the growing demand for LIBs is putting immense pressure on the supply chains for critical raw materials such as lithium, cobalt and nickel.[21,22] Although global lithium reserves are abundant,[23] the exploration and construction of new mines is trailing behind demand due to lengthy regulatory processes and environmental concerns.[24] In addition, geopolitical conflicts like those affecting nickel supplies from Russia[25] and ethical issues, such as child labour in some cobalt mines in the Democratic Republic of Congo,[26,27] further complicate the stability of the supply chain. The International Energy Agency (IEA) estimates that approximately 50 new lithium mines, 60 nickel mines and 17 cobalt mines would need to be established worldwide to meet projected demand by 2030.[28]

Downstream, the disposal and recycling of LIBs pose substantial environmental and economic challenges.[29,30] It is projected that more than 11 million tons of spent LIBs will accumulate worldwide by 2030, representing a major source of pollution and a potential threat to public health.[31] Addressing this issue is critical to minimising the negative impacts of battery waste and promoting sustainability.

Given these complex upstream and downstream challenges, LIB recycling emerges as a pivotal solution for addressing the environmental impact of battery waste. Efficient recycling of LIBs can alleviate raw material shortages, reduce pollution and improve supply chain resilience by decreasing resource dependencies. This aligns with the broader goals of a circular economy, supporting climate action goals effectively.[32–36] Consequently, research on LIB recycling has gained momentum in academic, industry and policymaking, underscoring the need for innovative and comprehensive strategies to manage the full lifecycle of batteries in a sustainable way. Prior research has focused on incrementally improving specific steps in the value chain of important recycling technologies (*e.g.* hydrometallurgical, pyrometallurgical or direct recycling),[37–41] designing LIBs for recycling from the get-go,[42] or reviews focused on summarising major current findings.[43–46] However, patents have hardly been considered in LIB recycling research. This is a problem because patents, as a major source of information on technological development and a common proxy for innovation activity, hold huge potential for providing insights into emerging trends, identifying key technological advancements and uncovering competitive dynamics within the industry.[47] Applying data science methods to this rich patent landscape provides a systematic and scalable approach to reveal such insights and better inform the sustainable management of battery technologies.

To address this gap and support stakeholders in the battery recycling landscape in their decision-making, this study analyses the extensive data from LIB recycling patents using a multidimensional approach. By examining global patent data spanning over three decades, this research aims to uncover critical insights into the evolution of LIB recycling, including key knowledge areas, the collaboration between different organisations and the specific knowledge stocks of patent assignees involved in this field. This study claims three contributions: first, it reveals the evolving landscape of LIB recycling over different time periods, focusing on the distribution of patents by country or region, key patent assignees and major Cooperative Patent Classification (CPC) classes. Second, a temporal analysis of patent assignee co-occurrence networks, broken down by country and type of patent assignee (public *vs.* private), sheds light on the intricacies of collaboration in this sector. This will allow practitioners to better understand the collaboration dynamics in the field and more specifically, pinpoint key collaborators. Third, a temporal co-occurrence network analysis of CPC classes is performed, followed by an established clustering methodology to find central clusters. By generating a set of central descriptive keywords using a natural language processing method and then interpreting them manually, this study identifies key knowledge areas in LIB recycling. These findings provide an accessible overview of past and present research foci and assist in decisions about future battery recycling. Fourth, a temporal analysis of two-mode networks, linking major patent assignees to the knowledge clusters they are most active in, offers insights into players' technological priorities and strategic positioning. This may assist battery researchers in academia and industry with finding potential partners and identifying knowledge areas that are currently overlooked.

2. Patent insights and technological aspects of LIB recycling

2.1. Importance of patents in technological innovation and research

Technological innovation is a key driver for social welfare and long-term economic growth.[48,49] In competitive market environments, companies and universities seek to secure their innovations, typically through safeguarding their intellectual property.[47] The patent system, established to encourage research and development, enables this protection by granting inventors exclusive and prohibitive rights to their inventions for up to 20 years.[50] Because patent rights are typically nation-specific (with some pathways for streamlined international protection, such as European patents or the Patent Cooperation Treaty), companies and universities often file patents in multiple countries to protect their inventions in the relevant key markets.[51,52] To avoid duplication bias, the patents representing the same invention are grouped into patent families.[53]

Notably, patents protect inventions rather than innovations, as they only become innovations once applied and adopted – a step that is not always achieved.[54] In return for providing monopolistic rights, patent systems require that patents are openly published, making previously undisclosed intellectual property accessible to the public.[50] For this reason, some corporations may refrain from filing for patents, keeping their intellectual property as trade secrets.[55] Nevertheless, patents remain an accessible and somewhat structured resource, offering a unique opportunity for data collection and analysis. Their rich information can inform decision-making for governments and other organisations by providing insights into technological trends and patterns.[47] Although patents may not capture all research and development activities in a field, they still form a solid foundation for academic research.[56] In fact, around 80% of technical information on newly published inventions is only available in patents.[57]

Various approaches to utilise and analyse the data 'hidden' in patents exist. Basic analyses often examine the trajectory of patent applications in a field, key patent assignees, leading countries, or the most important CPC classes.[58] More advanced approaches use methods such as co-citation analysis (sometimes combined with link prediction),[59] technological impact factors,[60] or natural language processing.[61] Because CPC classes form the foundation of this study, they are discussed in more detail in the following section.

2.2. Relevance of CPC classes in patent categorisation

Patents vary substantially in length, sub-structure and complexity. The latter often arises due to the detailed nature of the invention described in the claims.[62] However, it can also be a deliberate strategy to obscure information, preventing competitors from fully understanding the patent and extracting valuable intellectual property for their own use.[63] Additionally, patents are frequently written in broad terms to encompass and protect as much intellectual property as possible.[64]

To address this complexity and improve accessibility for a broader audience, several classification systems have been introduced to categorise patent documents based on their technical field.[65] The most notable of these are the International Patent Classification (IPC) and the CPC. The CPC system can be seen as an evolution of the IPC system and was introduced jointly by the European Patent Office (EPO) and the United States Patent and Trademark Office. Its goal was to create a unified and internationally compatible system for classifying technical documents.[66]

Due to their standardised and global applicability, CPC classes provide an excellent basis for patent analyses. They offer a consistent and concise framework for categorising patents, making them particularly useful for techniques such as co-occurrence network analysis and natural language processing. This structured approach delivers valuable insights into emerging and underexplored fields, such as LIB recycling.

2.3 LIB technology and its recycling methods

To effectively interpret results from any patent analysis, it is essential to first understand the technology under investigation. This is particularly important for LIBs because of their wide range of possible cell chemistries, use cases and recycling methods.

At their core, all LIBs consist of two electrodes into which lithium cations (Li^+) can reversibly be inserted. Each electrode is connected to a current collector to allow the flow of electrons. Li^+-ions move through the electrolyte, typically a mixture of an organic solvent (*e.g.* ethylene carbonate–dimethyl carbonate mixture) and a lithium salt (*e.g.* $LiPF_6$). To prevent short circuits, enhance mechanical strength and provide thermal stability, LIB cells also require a porous separator. During discharge, Li^+-ions are extracted from the negative electrode (*e.g.* graphite) and inserted into the positive electrode (*e.g.* $LiFePO_4$ or $Li(Ni_xMn_yCo_{1-x-y})O_2$). The process is reversed during charging, with Li^+-ions migrating from the positive electrode back to the negative electrode, where they are reinserted.[29] In addition to the widely used cathode active materials like *lithium iron phosphate* and *lithium nickel cobalt manganese oxide*, other options include *lithium cobalt oxide*, *lithium manganese oxide* and *lithium nickel cobalt aluminium oxide*.[67]

Depending on the application, LIB cells are integrated into complex systems, ranging from mobile phones to electric vehicles.[45] This variability in design makes uniform recycling at the end-of-life particularly challenging, as battery cells first need to be separated from other components before critical materials such as lithium, nickel, or cobalt can be recovered. Larger applications, such as those used in electric vehicles, are often the most complex, as battery cells are part of modules or packs that vary strongly across manufacturers.[68]

There are three main types of LIB recycling technologies: hydrometallurgical, pyrometallurgical and direct recycling.[21] Due to the economic importance of cathode materials, recycling efforts typically focus on these components.[69] In hydrometallurgical recycling, end-of-life batteries must first be mechanically pre-treated, which can include sorting, disassembly and shredding.[70] Due to the variety of battery designs, this step can be quite complex.[21] The battery materials are then separated using a wet-chemical process, usually including leaching, separation and purification.[45] This process offers the advantage of selectively extracting high-value metals with relatively low energy consumption, although the chemicals involved can pose substantial environmental risks.[45] In pyrometallurgical recycling, the battery materials are melted at high temperatures and reduced to extract metals such as nickel and cobalt from the matte made up of alloys.[44] However, in this process, lithium extraction is often challenging.[35] While pyrometallurgy is relatively straightforward and less sensitive to variations in battery design, it is energy-intensive and produces lower-purity metals.[45] In contrast to other recycling methods, direct recycling seeks to recover the cathode material without reducing the metals, aiming to preserve the structural integrity of the existing cathode material to the highest possible extent. While this approach requires customised processes for different cell chemistries, direct recycling represents a promising alternative that could possibly allow economically viable recycling of lower-value cathode or even anode materials.[33,36]

Each of these established recycling technologies has its advantages and disadvantages and none of them can handle all types of batteries or materials. It is therefore pertinent to continue research and development of recycling technologies.

2.4. Patent analyses of LIB recycling

Recent years have seen a growing number of studies applying patent analytics to the battery recycling field, varying in scope, methodology, and the specific aspects of LIB recycling they address. Some studies examine battery recycling more broadly, while others focus specifically on LIBs. To facilitate clear methodological comparison and highlight the unique contributions of the present study, an overview of the reviewed literature is provided in Table 1.

Lee[71] provides a patent analysis on battery recycling technologies, focusing on China, South Korea and the United States, with an emphasis on corporate patent trends. His study identifies the technological priorities of each country by analysing each country's top five patent assignees, using measures such as top IPCs, citations per patent, patent impact index, technology strength and patent family size. Baum *et al.*[72] conducted a big data analysis focused on both patents and journal articles to provide an overview of techniques and trends for LIB recycling. Their study analyses the types of LIB materials recycled, reviews environmental and economic perspectives and provides an overview of established and planned recycling facilities as well as their planned capacities. Lim and Sohn[73] aim to identify future technological convergence of batteries *via* link prediction of multiplex networks based on battery patents. They first modelled three-layered multiplex co-occurrence networks representing combinations of battery recycling, storage and safety, utilising four established network models. After determining the best performing multiplex network model, the corresponding network is subjected to link prediction based on the exponentially weighted moving average of pair similarities. New links are then clustered *via* the Louvain clustering algorithm to characterise potential technological convergence between different technological areas represented by IPCs. Davis and Demopoulos[74] review hydrometallurgical recycling technologies for lithium nickel manganese cobalt oxide battery cathodes, incorporating selected patents alongside scientific literature. They conclude that hydrometallurgical recycling will be crucial moving forward, while emphasising the need to further develop direct recycling as a greener alternative. Lin *et al.*[75] offer a bibliometrics-based analysis of emerging publishing and research trends in journal articles and patents on the recycling of rechargeable batteries. In their study, they provide several quantitative overviews, such as the most influential authors, the highest cited journal articles and an

Table 1 Overview of core literature on patent data and LIB recycling

Source	Aim of the study	Focus on LIB?	Big data?	Patent focus?	Methodology
Lee (2024)[71]	Analyses national and corporate patent trends in battery recycling across Korea, China, and the US	No	Yes	Yes	Quantitative analysis of company patents using IPC classification and statistical tools to map trends in battery recycling by country
Baum *et al.* (2022)[72]	Examines LIB material recycling trends and facilities using patent and publication data	Yes	Yes	No	Bibliometric analysis of patents and publications; categorisation by recycling method; assessment of efficiency, economic/environmental impact, and facility data
Lim and Sohn (2024)[73]	Predicts technological convergence in Li-based batteries through multiplex patent network analysis	Yes	Yes	Yes	USPTO patent data modeled as three-layer multiplex IPC networks, with temporal snapshots; network embeddings, link prediction, and Louvain clustering for convergence analysis
Davis and Demopoulos (2023)[74]	Reviews recycling methods for NMC LIBs, focusing on hydrometallurgical processes	Yes	No	No	Systematic review of patents and industry news; extraction and comparative analysis of technical details for current hydrometallurgical recycling of NMC cathodes
Lin *et al.* (2022)[75]	Conducts bibliometric analysis of global rechargeable battery recycling research	No	Yes	No	Bibliometric analysis of patents and articles on battery recycling; classified by battery type/source; trend and policy correlation analysis
Martins *et al.* (2021)[76]	Reviews EV battery recycling impacts, future waste, and recycling pathways	Yes	No	No	Statistical trend analysis of global EV/HEV markets plus literature/patent review of recycling methods
Metzger *et al.* (2023)[77]	Assesses the evolution and circularity of the global battery patent landscape	No	Yes	Yes	Analysis of secondary battery patent families; IPC categorisation, temporal/geographic aggregation, and text mining for circular economy terms.
Piątek *et al.* (2021)[29]	Critically reviews LIB recycling technologies from a sustainability perspective	Yes	No	No	Systematic review of literature and patents with experimental details; compares conventional and sustainable LIB recycling approaches
Dong *et al.* (2024)[78]	Maps global trends and innovation hotspots in LIB recycling patents	Yes	Yes	Yes	Systematic patent retrieval; manual denoising; quantitative analysis of patent trends and innovation fields
This study	**Maps global LIB recycling patents over time, analysing collaboration, CPC clusters, and assignee knowledge stocks**	**Yes**	**Yes**	**Yes**	**Temporal network analysis of LIB recycling patents, mapping collaborations, CPC co-occurrence clusters, NLP-based keyword extraction, and assignee–knowledge links**

analysis of battery recycling literature by cell chemistry. Martins *et al.*[76] review the global demand for electric car batteries and their recycling approaches based on journal articles and patent literature, identifying key companies within the battery recycling sector and providing guidelines for future perspectives. Metzger *et al.*[77] conduct a large-scale patent analysis comprising over 90 000 battery patents to gain potential insights on current developments of batteries related to the circular economy. After providing a descriptive overview of the patent dataset, they employ k-means clustering to identify which countries are active in which type of battery chemistry research. Furthermore, they use *n*-grams to identify important current research avenues and examine the occurrence of circularity terms in battery patent titles and abstracts. In their review, Piątek *et al.*[29] take a holistic look at the chemistry and recycling of LIBs, critically assessing current LIB recycling technologies from a sustainable perspective to determine whether they can truly be considered "green". Dong *et al.*[78] apply patent analysis to systematically identify global trends in LIB recycling development, the main players and key fields in LIB recycling.

While prior research has leveraged a variety of patent analytics tools, approaches such as temporal network analysis of assignee collaborations, dynamic clustering of CPC codes, and two-mode mapping of assignees to knowledge areas have not yet been integrated within a single, unified framework (see Table 1). By combining these methodological advances, the present study addresses key analytical gaps in the literature.

3. Methodology

3.1. Data collection and clean-up

Relevant patent data was extracted from the curated Derwent World Patents Index,[79] a patent database managed by Clarivate Analytics. This subscription-based database offers translation services, enabling the inclusion of patents in multiple languages and features revised titles and abstracts that more accurately reflect the content of each patent. This improvement in data quality is particularly valuable, as patent abstracts are often low in informational value.[80] While utilising a subscription-based patent database poses barriers to reproducibility and accessibility, there are free alternatives like Espacenet[81] or Patentscope.[82]

Given the high-quality data, a keyword search approach targeting revised titles, abstracts and claims (the "CTB" field in Derwent), with no language restrictions due to the presence of reliable translations, was selected. The search was not restricted to primary CPC classes in LIB recycling to avoid bias in subsequent CPC class analyses. Keywords were derived from a bibliometric analysis of scientific literature on recycling methods of spent LIBs.[83] After adjusting the keywords with wildcard truncations ("*") to capture alternate word forms and manually standardising selected terms (*e.g.* li-ion and lithium-ion) to ensure consistency, the search focused on lithium-ion batteries (and synonyms) and recycling (including synonyms and relevant descriptions), and filtered for inventions dated from January 1st, 1990 onward. In total, 63 109 patent families were identified through this process. Hereafter, all references to patent numbers denote patent families. The complete list of keywords along with a more detailed explanation on patent extraction is available in Table S1 of the ESI.†

Further data processing and analysis were conducted using Python (v. 3.11) within the Spyder (v. 5.5.5) environment. Data clean-up was performed *via* a documented Python script (see shared Zenodo repository), which included removing duplicates based on application number, excluding patents with incomplete entries in core data fields, and normalising text to lowercase. To finalise data pre-processing, the number of patent families was substantially reduced to include only those relevant to LIB recycling, by retaining patents containing the term "recycl" in the revised title, abstract, or claims – capturing all forms (*e.g.* "recycle", "recycling", *etc.*) *via* Python substring matching. This yielded a final set of 1233 patent families that served as the data foundation for all subsequent analyses.

3.2. Temporal data analysis

A temporal analysis approach was employed by dividing the data into three periods: 1990–2004, 2005–2014 and 2015–2024. This established methodology[58,84,85] facilitates the identification of trends over time when it is combined with various analytical tools. The specific tools used for this analysis are detailed in the subsequent sections.

3.2.1. Network analysis

Methodological background. Network analysis is a powerful tool for data analysis and visualisation, widely applied across various scientific fields. Originating in the social sciences,[86] its purpose is to connect interacting actors (displayed as nodes) within a network, forming a web of connections that reveals otherwise hidden relationships. In its simplest form, network analysis involves a single class of nodes (also known as mode), where all nodes share similar characteristics.[87] Networks that feature only one type of node are therefore referred to as one-mode networks.

A typical network is constructed as follows: all nodes within the network are represented with varying sizes.[88,89] The size of each node can correspond to different characteristics, such as *weight* or *degree*. In this study, node size represents the *weight*, which indicates how often a specific node appears in the network. For example, in patent analysis, this could be the number of times a patent assignee has filed for a patent or the number of times a particular CPC class has been used to categorise patents. *Degree*, in contrast, measures how many other nodes a particular node is connected to.[89] Nodes are connected by *edges* if they interact within the dataset. In patent analysis, this would mean connecting two patent assignees if they have filed for a patent together or linking two CPC classes if they have appeared in the same patent. Similar to nodes, edge size represents the *weight* of the connection; a thicker edge indicates a stronger connection between nodes.[88]

Adding a second node type (or mode) creates a two-mode network, in which nodes, per definition, can only be connected to nodes of the opposite mode.[90,91] Therefore, characteristics like node weight and edge weight stay the same, while the interconnectedness of nodes changes. This added complexity allows for deeper analysis. In patent analysis, for instance, one mode could represent patent assignees (mode 1) and the other could represent CPC classes (mode 2). In such a network, it becomes possible to determine which patent assignees are active in specific areas of research, as represented by CPC classes. Additionally, indirect connections between two assignees through a shared CPC class can indicate overlapping research interests.

This methodology, involving weighted nodes and edges with one or multiple modes, allows for the visualisation of complex interconnections. Network analysis, thus, aids in understanding technological linkages and uncovering trends over different time periods. An overview of the basic structure of one- and two-mode networks is provided in Fig. S1 of the ESI.† All networks in this study were constructed using the Python library *networkx* and visualised with the software Gephi (v. 0.10).[92]

Types of networks used in this study. This work features two types of one-mode networks. The first is a co-occurrence network of CPC classes, where nodes representing CPC classes are linked if they appear together in the same patent. The second is a co-occurrence network of patent assignees, where assignee nodes are interconnected if they have jointly filed a patent. To add further detail, node shapes (squares or circles) indicate the type of patent assignee, while node colours represent the assignee's country of origin.

Additionally, a two-mode network was constructed. In this network, patent assignees (mode 1) are linked to key knowledge areas in LIB recycling (mode 2). Connections in this two-mode network are based on whether the assignees have filed for patents categorised under CPC classes relevant to these specific knowledge areas.

3.2.2. Leiden clustering. In network analysis, grouping specific nodes into densely connected subgroups – known as communities or clusters – can simplify interpretation and reveal additional insights.[93] Consequently, various automatic clustering methods using algorithms[94,95] have been introduced to enable quick and efficient analysis of huge amounts of data. Depending on the use case and goal of analysis, the specific choice of algorithm must be taken seriously since it will lead to different results.[96] One well-known unsupervised algorithm that can quickly cluster nodes in large networks is the Louvain algorithm.[96] However, Louvain can generate communities that are internally disconnected or contain weakly connected components, potentially leading to misleading cluster assignments. To address this limitation, the Leiden algorithm was developed as an improved alternative.[97]

Leiden was chosen for this study because its refinement phase ensures that communities remain internally connected, reducing the risk of fragmented or misleading clusters that can arise with other community detection methods, such as Louvain.[97] This advantage is particularly valuable for capturing coherent knowledge areas in large CPC co-occurrence networks, where clear community structure is essential for meaningful interpretation. Furthermore, Leiden's computational efficiency enables practical analysis of large patent datasets, and its increasing adoption in recent literature supports its reliability and robustness as a state-of-the-art community detection method.[98–100]

Like the Louvain algorithm, the Leiden algorithm tries to maximise the modularity quality function to find an optimal number of clusters.[97] In this context, modularity is defined by comparing the actual number of edges within clusters to the number of edges that would be expected in a randomised network.[101] *Via* integration in Python, the library leidenalg uses eqn (1) to calculate the modularity of the weighted patent networks.[102]

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(\sigma_i, \sigma_j) \tag{1}$$

Here, m represents the total edge weight of the graph, A_{ij} is the adjacency matrix of nodes i and j, k is the weighted degree of a node and σ is the specific cluster to which a node belongs to. The delta function δ returns a value of 0 if nodes i and j are in different clusters and 1 if they are in the same cluster.

The Leiden algorithm involves three phases:[97] after initially placing all nodes into their own clusters, it iteratively moves individual nodes from one cluster to another to improve modularity. Then, a refining step is carried out to make sure that clusters are internally connected. Finally, the algorithm creates an aggregated network based on the refined partition. In the aggregated network, nodes are assigned to different clusters based on the non-refined partition. These phases are repeated until no further improvements in modularity can be made.

In this study, Leiden clustering is carried out for the CPC co-occurrence networks, where CPC classifications categorise patents by knowledge areas, resulting in clusters termed "key knowledge areas" of LIB recycling. To create representative descriptions for each knowledge area, the following section introduces an established methodology for finding important keywords within bodies of text.

3.2.3. Term frequency-inverse document frequency. To efficiently handle large text datasets, different automated natural language processing methods have been developed, ranging from simpler methods like term frequency-inverse document frequency (TF-IDF) to more sophisticated algorithms or artificial intelligence.[103,104] The goal of this study is to utilise the uncomplicated and structured descriptions of CPC classes to extract fitting keywords for the CPC-clusters identified as described above. This makes TF-IDF a fitting option for analysis.

In essence, TF-IDF combines the two measures term frequency and inverse document frequency. These are multiplied to assign each word a score that ranks its relevance within a document compared to all documents in a dataset.[105] Term frequency is calculated by dividing the number of times a term appears in the document by the total number of terms in the document.[106] Thus, terms that appear more often are ranked higher. Contrary to this, inverse document frequency is computed as the logarithm of the ratio of total documents in the dataset to the number of documents containing the term.[107] This leads to a ranking system that ranks terms higher if they appear in only a small number of documents. Finally, by multiplying these two measures, the TF-IDF score is received which emphasises terms that occur frequently but are confined to a limited number of documents.

In this study, the TfidfVectorizer module from the scikit-learn library[108] is used to conduct a TF-IDF analysis for CPC class descriptions within clusters across three distinct periods. All hyperparameters of the module, including *n*gram range, document frequency thresholds, and normalisation, were left at their default values (see Table S3 and section S4 of the ESI† for a detailed discussion). Prior to TF-IDF vectorisation, stopwords were removed during preprocessing using the nltk library. To clarify, one TF-IDF analysis was performed per period, with clusters of each period representing one document each. Preparations for analysis included downloading official CPC descriptions in XML format from the Cooperative Patent Classification website,[109] importing them into Python and matching them with CPC symbols in the patent dataset. With clusters already established for CPC classes, it was straightforward to assign descriptions to clusters. Cluster descriptions were tokenised and to account for varying frequency, were weighted according to the corresponding CPC class's node weight in the network.

The TF-IDF analysis then extracted the top ten keywords for each cluster, serving as the foundation for concise manual summaries of the top ten clusters in each period. The resulting TF-IDF keyword lists were assessed for interpretability by the expert reviewers during this process, with preliminary iterations used to refine preprocessing and stopword lists to optimise output quality. To enhance the accuracy and objectivity of these summaries, two independent experts each generated brief descriptions for every cluster. In most cases, the experts' summaries were consistent. When discrepancies did arise, they were resolved through collaborative discussion, during which both experts compared rationales, clarified interpretations, and jointly arrived at consensus descriptions that best captured the essence of each cluster. This iterative process ensured that the final summaries of the clusters were both accurate and comprehensive. An overview of the workflow discussed in this chapter is provided in Fig. 1.

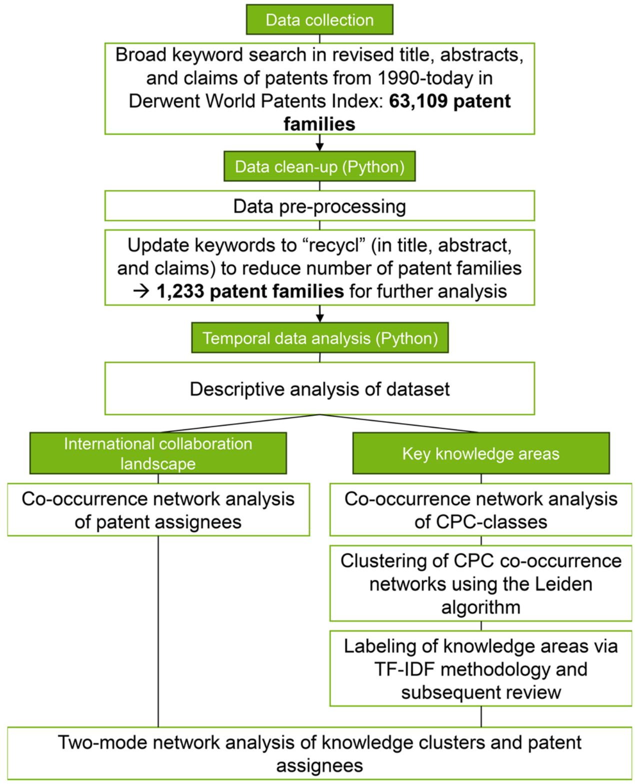

Fig. 1 Overview of the research methodology.

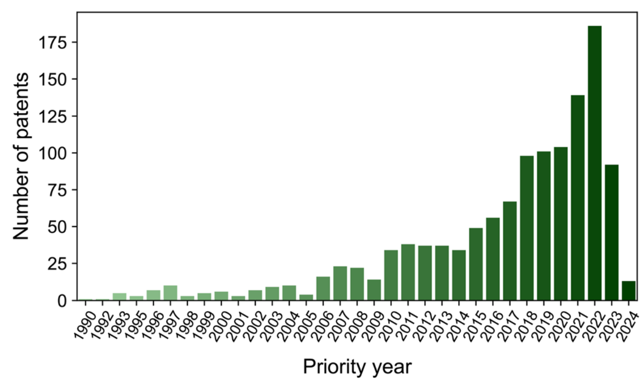

Fig. 2 Number of LIB recycling patents published per year.

4. Results and discussion

4.1. Descriptive analysis of patent dataset

The number of patent families related to LIB recycling has grown exponentially over the past decade (Fig. 2), mirroring trends in overall LIB patent filings and reflecting the technology's increasing importance.[71,75,77] The dip in 2023 and 2024 results from the typical 18-month delay between patent filing and publication.[58,110]

As illustrated in Fig. 3, China dominates LIB recycling patent filings, with the US and Japan following, while European countries lag significantly. Analysis across three periods (see Fig. 4) shows China's leadership has intensified: while the US and Japan led prior to 2004, China rapidly overtook them between 2005–2014 and now holds a pronounced lead. The US maintains steady growth, Japan's pace is moderate, and Europe continues to trail, underscoring the strategic need for Europe to bolster LIB recycling research investment.

The most frequent CPC classes (see Fig. 5) correspond to core themes in LIB recycling, with all major classes showing marked increases since 2015. The top three, including *Y02W 30/84* (recycling of batteries or fuel cells), *H01M 10/54* (reclaiming serviceable parts of waste accumulators) and *Y02E 60/10* (energy

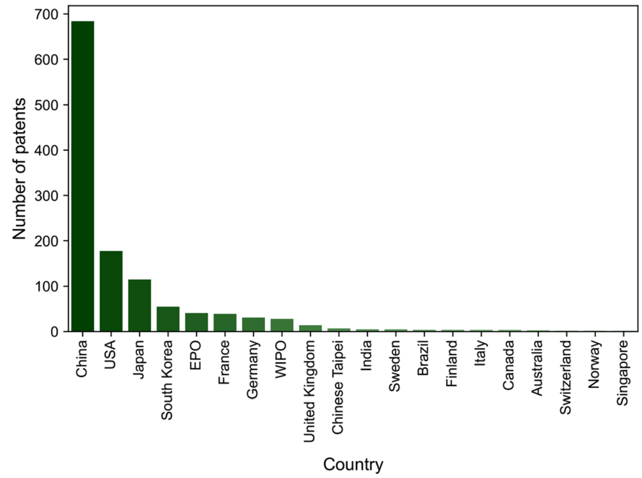

Fig. 3 Geographical distribution of filed LIB recycling patents.

storage using batteries), reflect the focus of the keyword-based search operator on battery recycling. Additional CPC classes like *H01M 10/0525*, *C22B 26/12*, or *H01M 10/052* (see Table S2 in the ESI† for full descriptions) confirm the lithium-based focus of the dataset. Taken together, the diversity of CPC classes ranging from obtaining raw materials and specific lithium oxides to wet processes, analytical methods and recycling, captures the complexity of the entire LIB value chain and provides first insights into possible key knowledge areas.

The final descriptive analysis (see Fig. 6) identifies the top 20 patent assignees, showing continued growth and reinforcing China's dominance with leading institutions such as the Chinese Academy of Science, Central South University, and Contemporary Amperex Technology (CATL). There is a near-equal distribution of patents between state-run universities and private firms, indicating the field's research-driven character and strong governmental engagement. Leading multina-

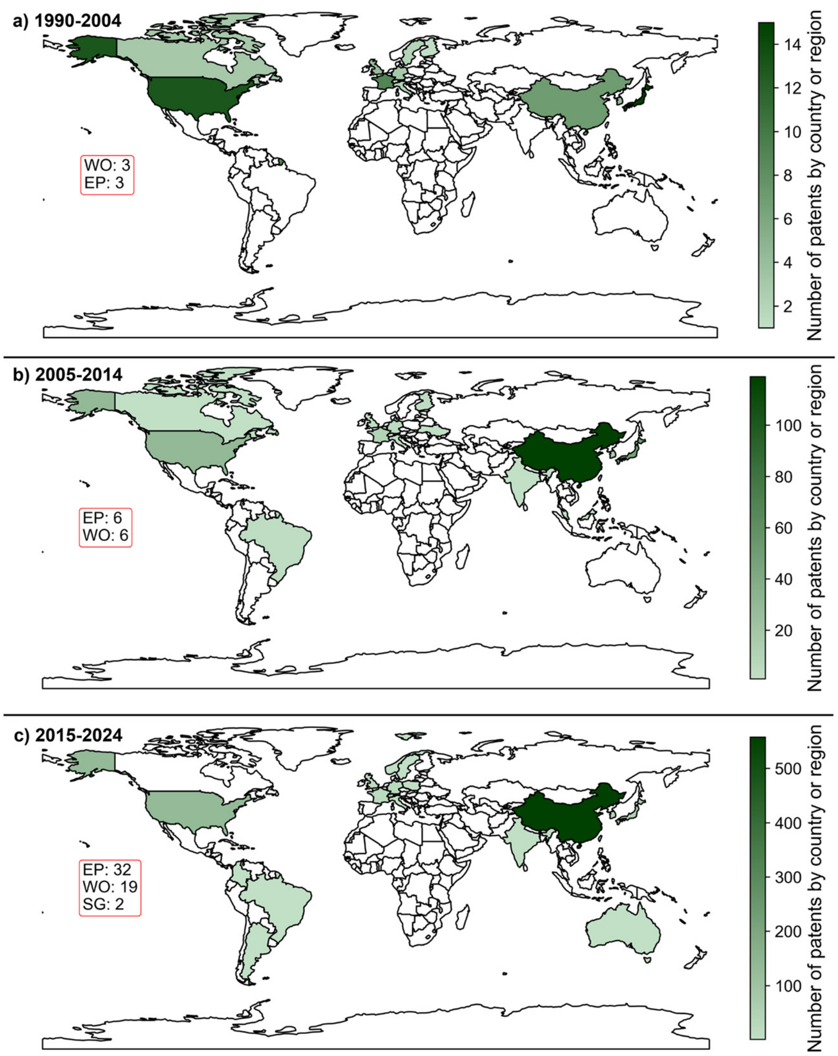

Fig. 4 Number of LIB recycling patents published per country and period. (a) 1990 to 2004, (b) 2005 to 2014, and (c) 2015 to 2024. Entries in the red boxes show the number of patents per region or country that are not marked within the world map (EP: European patent; WO: International patent application (under the PCT); SG: Singaporean patent).

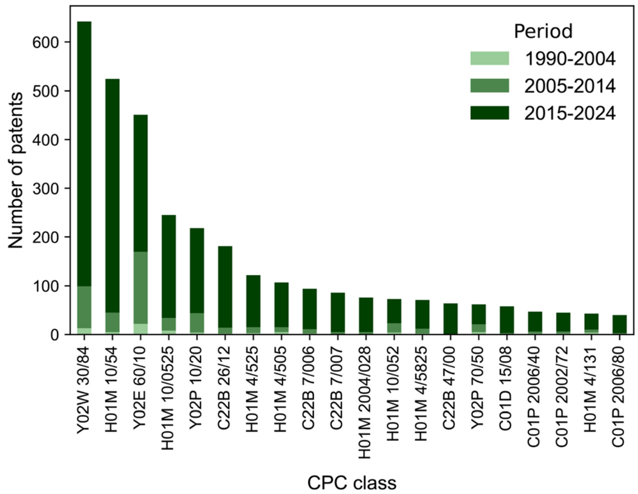

Fig. 5 Distribution of top 20 overall most frequent classification codes in LIB recycling patents by period. See Table S2 in the ESI† for more information.

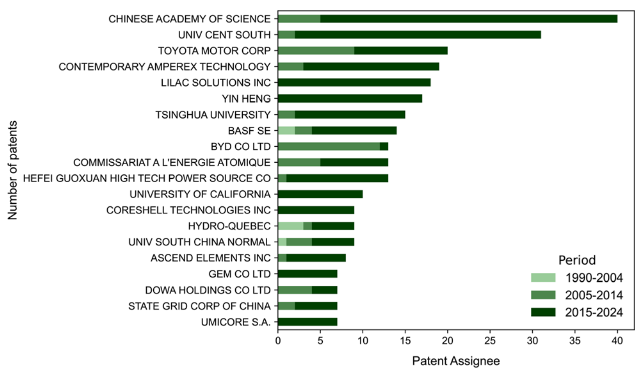

Fig. 6 Distribution of top 20 overall most frequent patent assignees in LIB recycling by period.

tional corporations like Toyota, BYD, and BASF also feature among top assignees.

4.2. International collaboration dynamics in LIB recycling patents

To better understand the national and international collaborations of patent assignees, a co-occurrence network analysis was conducted for three distinct time periods (Fig. 7). In these networks, node shape distinguishes universities from other organisations, node size represents each assignee's patent count, node colour indicates country of origin, and connections denote shared patent filings, signifying collaboration.

From 1990 to 2004, collaborations were limited, reflecting the overall low patent counts. Most collaborating entities originated in the corporate sector, with only two university participants. During this period, Japan, South Korea, and Italy were the most prominent countries, and some international collaborations are observable.

In 2005 to 2014, the number of collaborators increased to about 2.5 times the previous period and non-university assignees continued to predominate. The data reveal the first signs of China's growing presence, as more Chinese assignees began to participate and lay the foundation for the substantial role China would later assume. Japan remained a key player. Notably, international collaboration declined proportionally, with most co-filed patents originating from assignees within the same country.

The final period from 2015 to 2024 shows a more extensive and complex collaboration network, predominantly consisting of Chinese players. This undeniable presence can be attributed to several factors. China has been particularly proactive in implementing coordinated government policies and funding mechanisms (*e.g.* the "Electric vehicle battery recycling technology policy" (2016) or "Recovery of traction battery used in electric vehicle" (2024))[111] to support LIB recycling, resulting in a robust regulatory framework. In contrast, the US and Europe have only recently begun to introduce comparable policies (*e.g.* the European "New batteries regulation" (2023) and the "Critical raw materials act" (2023) or the American "Inflation Reduction Act" (2022) and "Lithium Battery Recycling Regulatory Status and Frequently asked questions" (2023)).[111,112] Due to less centralised governmental structures in Europe and the US, policy implementation and impact can be slower and more fragmented. Moreover, with 1.1 million tons per year, China's LIB recycling capacity far exceeds that of North America (144 000 tons per year) and Europe (200 000 tons per year).[111] Combined with extensive expertise across the established Chinese LIB value chain, this provides access to a large pool of skilled professionals and further strengthens China's competitive advantage.[21,111–113] Furthermore, China is rapidly developing competencies in battery research and development for future battery technologies and corresponding waste management (*e.g.* in defective material recycling).[112,114] Instead of smaller, isolated clusters of up to three assignees, this network features larger sub-networks. Some of these sub-networks are composed of multiple patent assignees with similar influence (*e.g.* University of Montpellier and the University of Rouen), while others center around a dominant player, such as the Chinese Academy of Science or Central South University, with numerous smaller connections. These central assignees can be expected to hold the most knowledge in the field and might even play a central role in creating knowledge spillovers.[115,116] This type of information could help battery researchers identify potential partners for future projects. Another clear trend is the further reduction of international collaboration. In this period, almost all collaborations take place between patent assignees of the same country, a trend that might not have been expected in times of globalisation. While collaboration is often encouraged, there are several reasons why stakeholders may hesitate to engage internationally. These include organisational and cultural differences, high administrative costs, misaligned objectives, and competitive concerns – such as the fear of unintentionally aiding potential rivals in technological development.[117] Similar

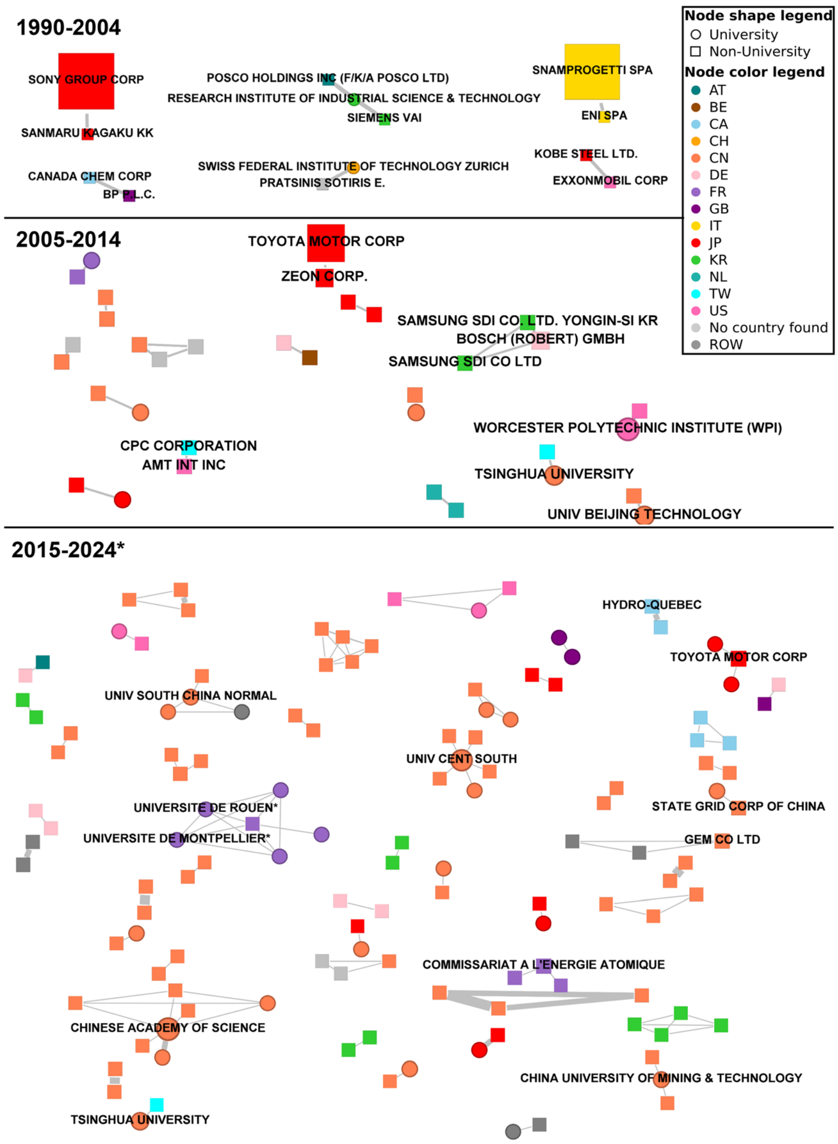

Fig. 7 Overview of full patent assignee co-occurrence networks over three periods. Only the 10 nodes with the highest weights are labelled. *Despite not ranking in the top 10, the universities of Rouen and Montpellier are labelled for clarity due to their discussion in the text.

trends have been reported in a global value chain analysis of LIBs, which found that the largest players tend to focus on independent innovation, while smaller or less dominant countries are more likely to seek international partnerships.[118] As a result, the concentration of patents among a few dominant Chinese institutions may accelerate national technological development but could also limit global diffusion of new recycling solutions if not accompanied by greater international engagement.

In summary, the evolution of the collaboration networks illustrates strong growth in both patent activity and the concentration of innovation within specific countries, particularly China. This trend, also reflected in the geographical split shown in Fig. 4, has been shaped by early and targeted policy interventions, large-scale investment, and the development of comprehensive expertise along the LIB value chain. However, despite the increasing number of active assignees, international collaboration remains limited – especially among dominant stakeholders – due to institutional, strategic, and competitive factors. Overcoming these barriers will be crucial to accelerate technological advancement and to ensure progress towards global sustainability and climate targets.

4.3. Key knowledge areas of LIB recycling

4.3.1. CPC co-occurrence networks. CPC classes, with their concise and standardised descriptions, provide an effective data source for identifying specific knowledge areas within a field of interest. The first step in this process involves constructing CPC co-occurrence networks in which co-occurring CPC classes are connected to each other. The resulting net-

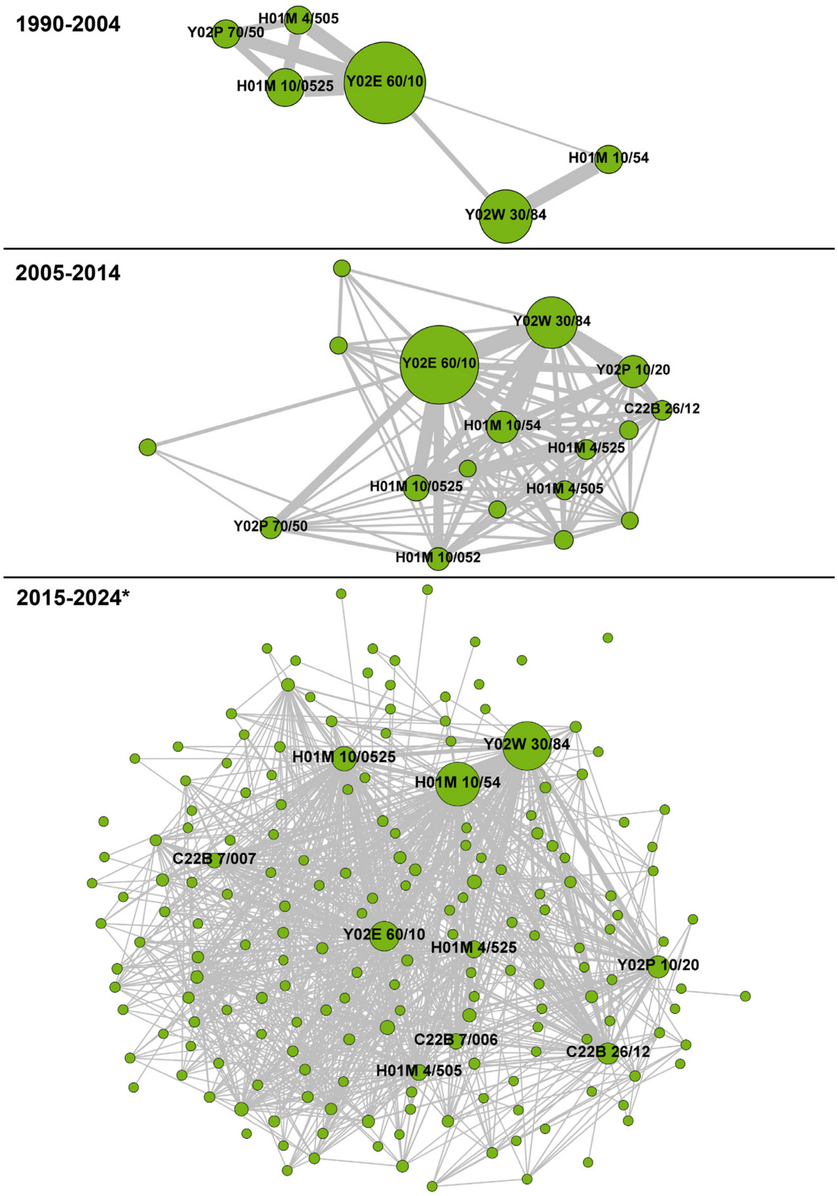

Fig. 8 Overview of CPC co-occurrence networks for three periods. Only nodes with weight ≥5 are shown. Only the 10 nodes with the highest weights are labelled. *To increase readability, edges with weights below five are filtered out.

works across the three time periods are illustrated in Fig. 8. To reduce clutter and complexity, network visualisations display only nodes with a weight of five or more, thereby highlighting the most prominent CPC classes. This threshold is applied solely at the visualisation stage and does not affect any prior analyses. The full, unfiltered networks are available in Fig. S5 of the ESI† for reference and reproducibility.

The trends seen in earlier analyses continue: the first period (1990–2004) features a limited number of relevant CPC classes and a small network, but network size and diversity increase sharply in subsequent periods. During 2015–2024, a broader range of CPC classes emerges, and node weights for many of these classes increase compared to previous years. The most prevalent CPC classes throughout all periods – *Y02W 30/84*, *H01M 10/54*, and *Y02E 60/10* – align with prior findings (see Fig. 5). By exploring the network structure, it is possible to identify frequently co-occurring motifs that highlight relevant fields of knowledge. For instance, from 2015 to 2024, a strong connection appears between *H01M 10/54* (reclaiming serviceable parts of waste accumulators) and *H01M 4/505* (of mixed oxides or hydroxides containing manganese for inserting or intercalating light metals, *e.g.* $LiMn_2O_4$ or $LiMn_2O_xF_y$), indicating that this type of battery material has likely been examined for recycling.

4.3.2. Leiden clustering of CPC co-occurrence networks. Leiden clustering is an efficient method for grouping related nodes, reducing complex networks into a smaller number of clusters where nodes share similar characteristics. Fig. 9 pre-

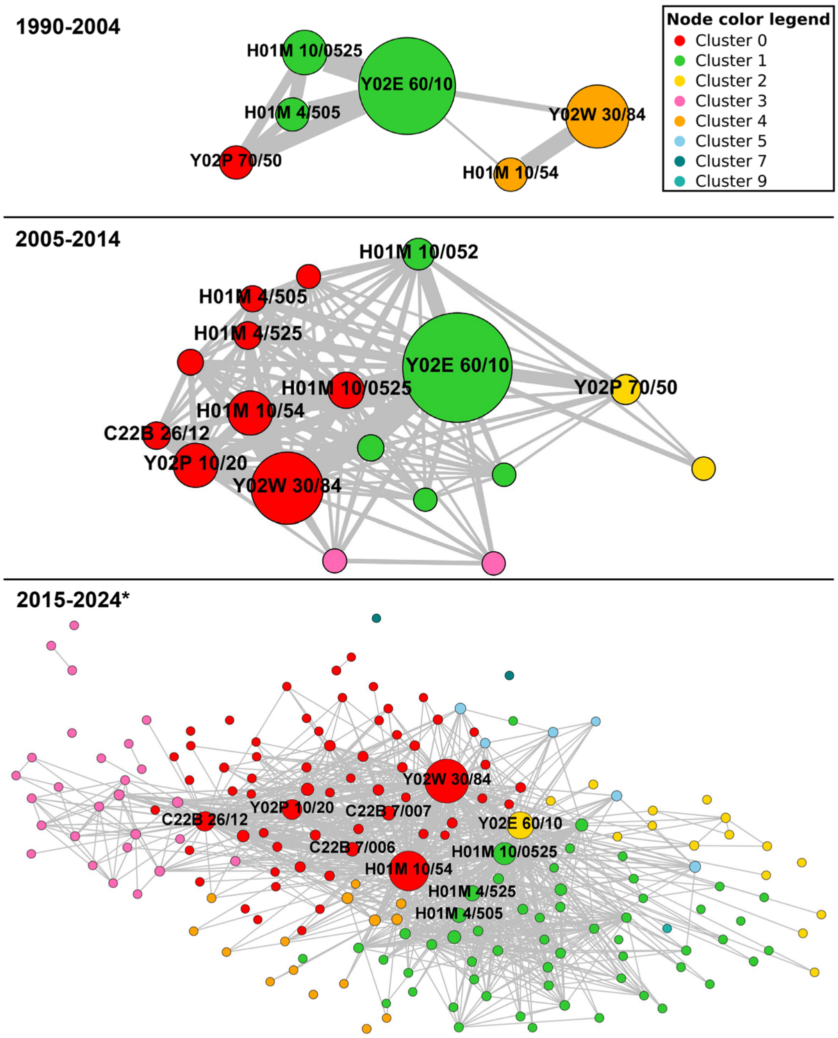

Fig. 9 Overview of clustered CPC co-occurrence networks for three periods. Only nodes with weight ≥5 are shown. Only the 10 nodes with the highest weights are labelled. *To increase readability, edges with weights below five are filtered out.

sents the clustering results for all periods, showing only nodes with a weight of five or more to improve clarity (full results are shown in Fig. S7 of the ESI†).

The network structure is unchanged from the previous CPC co-occurrence analysis, with no new connections observed and no impact on co-occurrence patterns or their interpretation. Visual differences stem mainly from changes in network orientation and slight repositioning of nodes, due to the Gephi layout algorithm. The main difference here is the colouring of each node, now indicating its cluster affiliation.

The number of clusters has increased over time, reflecting the rising diversity of CPC classes: 29 clusters were identified for 1990 to 2004, 38 for 2005 to 2014, and 44 for 2015 to 2024. The uniform colouring in each network demonstrates that the algorithm grouped nodes effectively by modularity, a measure derived from edge connectedness. Outliers in these visualisations are attributable to the layout algorithm, not the clustering process itself.

Although manual inspection of clusters could provide further detail, at this stage, the clusters mostly indicate node affiliation. To extract broader insights and generate descriptive labels for each cluster, thereby linking them to specific knowledge areas, a TF-IDF analysis is conducted in the following section.

4.3.3. TF-IDF analysis of CPC clusters. TF-IDF is a natural language processing technique used to identify key keywords within a set of documents. Here, each cluster acts as a document and keywords are drawn from the weighted CPC descriptions. Interpreting these keywords allows for the identification of knowledge areas within LIB recycling.

Because clusters are ordered by size and therefore importance, the top clusters are analysed in detail. Tables 2–4 present the top ten clusters per period, along with manual summaries, while comprehensive keyword extraction results for all clusters are included in Tables S3–S5 of the ESI.†

From 1990 to 2004, the top knowledge areas focus on topics related to batteries, including oxide manufacturing, intercala-

Table 2 Matching of clusters to central keywords received from TF-IDF for the period 1990 to 2004. A manual summary for the top 10 clusters is based on the independent evaluations of two experts

Cluster-Id	Central keywords	Manual summary
0	['oxides', 'thereof', 'salts', 'oxide', 'final', 'manufactured', 'nanometer', 'manufacturing', 'production', 'product']	Oxide manufacturing
1	['batteries', 'energy', 'storage', 'oxides', 'electrodes', 'hydroxides', 'mixed', 'inserting', 'intercalating', 'intercalation']	Batteries, intercalation
2	['catalysts', 'plates', 'catalytically', 'step', 'product', 'fuel', 'gases', 'feed', 'active', 'cells']	Catalysts
3	['ligands', 'groups', 'containing', 'carbon', 'separation', 'hydroxy', 'including', 'bonds', 'comprising', 'catalysts']	Chemical complexes
4	['recycling', 'cells', 'batteries', 'fuel', 'accumulators', 'reclaiming', 'serviceable', 'waste', 'parts', 'processes']	LIB recycling
5	['joined', 'joining', 'several', 'parts', 'form', 'articles', 'least', 'ir', 'reciprocating', 'welding']	Joining parts
6	['work', 'film', 'separating', 'apparatus', 'plastics', 'single', 'subclass', 'part', 'recycling', 'means']	Separating parts
7	['manufacture', 'processes', 'inorganic', 'diluents', 'nanobatteries', 'electrolytes', 'impregnation', 'solution', 'paste', 'electrode']	Inorganic electrolyte manufacturing
8	['meth', 'acrylate', 'containing', 'polyethylene', 'glycol', 'moiety', 'alcohol', 'treatment', 'methoxy', 'acrylic']	Chemical substances/treatments
9	['filter', 'ultraviolet', 'filtrate', 'measuring', 'flow', 'devices', 'membrane', 'filters', 'rate', 'irradiation']	Filtering

Table 3 Matching of clusters to central keywords received from TF-IDF for the period 2005 to 2014. A manual summary for the top 10 clusters is based on the independent evaluations of two experts

Cluster-Id	Central keywords	Manual summary
0	['batteries', 'recycling', 'fuel', 'cells', 'reclaiming', 'serviceable', 'waste', 'lithium', 'hydroxides', 'parts']	LIB recycling
1	['storage', 'batteries', 'energy', 'active', 'phosphates', 'silicates', 'polyanionic', 'borates', 'oxygenated', 'metallic']	Battery materials
2	['final', 'manufactured', 'product', 'manufacturing', 'processes', 'characterised', 'production', 'manufacture', 'electrodes', 'form']	Product manufacturing (electrodes)
3	['batteries', 'battery', 'controller', 'systems', 'data', 'state', 'electromobility', 'transfer', 'several', 'sequentially']	Battery management system
4	['alloys', 'si', 'based', 'electrodes', 'metals', 'silicon', 'solutes', 'making', 'battery', 'electrolyte']	Electrodes, silicon
5	['gasification', 'removing', 'carbon', 'water', 'recovery', 'cogeneration', 'pressure', 'dioxide', 'distributors', 'electrolysis']	Gasification, carbon removal
6	['hydroxy', 'aromatic', 'amino', 'carbon', 'groups', 'ring', 'rings', 'bound', 'skeleton', 'atom']	Aromatic, hydroxy, amino
7	['nitrogen', 'ligands', 'atom', 'complexing', 'least', 'one', 'ring', 'comprising', 'ruthenium', 'complexes']	Chemical complexes
8	['treatment', 'biological', 'waste', 'anaerobic', 'sewage', 'processes', 'water', 'temperature', 'alcohol', 'sludge']	Biological waste treatment
9	['portion', 'mould', 'moulding', 'preform', 'runner', 'injected', 'flange', 'variable', 'components', 'two']	Molding process

Table 4 Matching of clusters to central keywords received from TF-IDF for the period 2015 to 2024. A manual summary for the top 10 clusters is based on the independent evaluations of two experts

Cluster-Id	Central keywords	Manual summary
0	['recycling', 'serviceable', 'reclaiming', 'fuel', 'batteries', 'accumulators', 'cells', 'parts', 'waste', 'obtaining']	LIB recycling
1	['batteries', 'electrodes', 'hydroxides', 'oxides', 'inserting', 'intercalating', 'mixed', 'intercalation', 'insertion', 'lithium']	Electrode intercalation
2	['batteries', 'storage', 'energy', 'cells', 'battery', 'testing', 'systems', 'measuring', 'circuits', 'arrangements']	Battery testing systems
3	['solutions', 'inorganic', 'salt', 'processes', 'hydroxides', 'oxides', 'filtration', 'generated', 'extraction', 'exchangers']	Inorganic solutions, extraction processes
4	['li', 'diagram', 'sem', 'electric', 'two', 'obtained', 'properties', 'type', 'oxides', 'hydroxides']	Material characterisation
5	['manufactured', 'micrometer', 'compositional', 'purity', 'final', 'product', 'manufacturing', 'production', 'metal', 'characterised']	Micrometre scale production
6	['catalysts', 'one', 'least', 'atoms', 'compounds', 'type', 'hydroxy', 'ring', 'addition', 'groups']	Catalysts
7	['electrolysis', 'water', 'sources', 'production', 'hydrogen', 'gases', 'hydride', 'catalysts', 'containing', 'carbon']	Water electrolysis
8	['screens', 'separator', 'devices', 'screen', 'denying', 'egress', 'oversize', 'disintegrating', 'mechanisms', 'screening']	Filtering using separators
9	['diaphragms', 'membranes', 'characterised', 'material', 'separators', 'waste', 'processing', 'separation', 'choice', 'metal']	Filtering using membranes/diaphragms

tion and inorganic electrolyte manufacturing. LIB recycling features prominently, as expected due to the search operator. Other knowledge areas, such as chemical substances and component separation, are broader and less specific – a limitation often seen in natural language processing, which may overlook semantic nuances.[119]

For 2005 to 2014, LIB recycling remains the top area. More specific knowledge areas emerge, including battery management systems, (silicon) electrodes, battery materials, and certain chemical compounds.

In 2015 to 2024, LIB recycling continues as the central knowledge area. Additional topics, including electrode intercalation, battery testing systems, and separators, are closely tied to battery technology, while broader domains like inorganic solutions, material characterization, and micrometre-scale production are evident.

Overall, the extracted knowledge areas reflect critical aspects of the LIB recycling value chain. While these knowledge areas often align with policy priorities (such as material recovery or advanced battery management) and evolving industrial strategies, they represent broad research domains rather than specific scientific or technical challenges (*e.g.* lithium recovery efficiency or environmental trade-offs). This constraint arises from the limited granularity of CPC-based clustering and keyword analysis, which is well suited to reveal overarching trends but not to resolve individual technical bottlenecks.

Other methodological limitations also warrant consideration. Although meaningful descriptions were assigned to the clusters, they may not fully capture each cluster's multifaceted nature. Additionally, the analysis assumes consistent interpretation of keywords, which may not always reflect the underlying data complexity. The predetermined limit of 10 keywords per cluster may also influence results. Despite these limitations, the analysis yields valuable insights into the LIB recycling patent landscape and is particularly effective when paired with patent assignee data, as explored in the following section. Furthermore, this approach is highly efficient, substantially simplifying the analysis of complex, multidimensional research domains.

4.4. Key knowledge stocks of important patent assignees

Building on previous results, this section connects patent assignees to knowledge areas using two-mode networks, enabling identification of key knowledge stocks for each assignee, a critical insight for policymakers, researchers, and competitors. The resulting two-mode networks, filtered to only include nodes with a weight of two or more for improved clarity are shown in Fig. 10. Full networks can be found in Fig. S9 in the ESI.†

These networks capture multidimensional patterns: node shapes differentiate "clusters" (knowledge areas) from "patent assignees", node size reflects weight, edge thickness shows the frequency of an assignee publishing in a particular knowledge area, and node colour indicates assignee country. Since clusters typically contain several CPC classes and many assignees fall below the node weight threshold, some clusters appear without linked assignees in the filtered networks – a pattern not seen in the unfiltered versions.

In 1990–2004, the filtered network contains few patent assignees, reflecting the field's early stage. Countries are represented evenly, with no single country leading. One primary subnetwork links patent assignees and clusters indirectly, suggesting similarity among those with shared knowledge areas. Among the more active companies, Hydro-Quebec stands out for activity across several clusters ("oxide manufacturing", "batteries, intercalation", "inorganic electrolyte manufacturing"), indicating early diversification. Rhodia S.A., not tied to the main subnetwork, is linked to two related knowledge areas which may be a sign of diverse chemical research interests.

The 2005–2014 network is much larger and more interconnected, pointing to increased patenting and overlapping knowledge stocks. China, Japan, and the US dominate in assignee count. The most connected knowledge areas are broader battery-specific clusters, such as Cluster 0 ("LIB recycling", 23 connections) and Cluster 1 ("battery materials", 30 connections), followed by more specialized fields like Cluster 4 ("electrodes, silicon", 7 connections). Toyota appears under two entities (Toyota Industries Corporation and Toyota Motor Corp) and is linked to six knowledge areas (including Clusters 0, 1, 2 ("product manufacturing (electrodes)"), 3 ("battery management system"), 4 and 14 ("inorganic electrode compounds")), highlighting its focus on electrode materials, especially in recycling. Other strongly connected patent assignees include Panasonic, the French Alternative Energies and Atomic Energy Commission and LG Chem.

The 2015–2024 two-mode network is the largest and most interconnected, involving numerous industry and academic players and many links to knowledge areas. Again, some clusters lack connections due to the node weight threshold. China now leads overwhelmingly both in number of assignees and publication counts. The most strongly connected knowledge areas are Cluster 0 ("LIB recycling", 136 connections), Cluster 1 ("electrode intercalation", 87 connections) and Cluster 2 ("battery testing systems", 77 connections). The Chinese Academy of Science (weight: 35), Central South University (weight: 29) and Lilac Solutions (weight: 18) have published the most patents and maintain strong connections to multiple knowledge areas. The Chinese Academy of Science is linked to the seven Clusters 0, 1, 2, 3 ("inorganic solutions, extraction processes"), 4 ("material characterisation"), 5 ("micrometre scale production") and 7 ("water electrolysis"), depicting its wide range of competencies. Central South University shares this cluster linkage, indicating a similar knowledge base. Meanwhile, Lilac Solutions is connected to Clusters 0, 2, 3 and 5.

In summary, the two-mode network analysis provides crucial insights: it helps identify central companies across time periods, uncovering both newcomers and established players, which could be valuable for other fields, particularly due to its high degree of automation. Additionally, it highlights similar patent assignees, easing the selection of collaboration partners based on network proximity and research portfolios indicated by their knowledge areas. Existing knowledge areas can also guide competitors and researchers toward underdeveloped research topics within the field. While this methodology offers numerous advantages, it has limitations and room for improvement. As discussed earlier, knowledge areas may occasionally be vague or nonspecific and results depend heavily on the natural language processing technique employed. Future analyses could benefit from using more advanced models, like Latent Dirichlet Allocation[120] based on patent abstracts, to enhance outcomes. Nevertheless, this analysis serves as a robust starting point due to its simplicity and the lack of comparable studies.

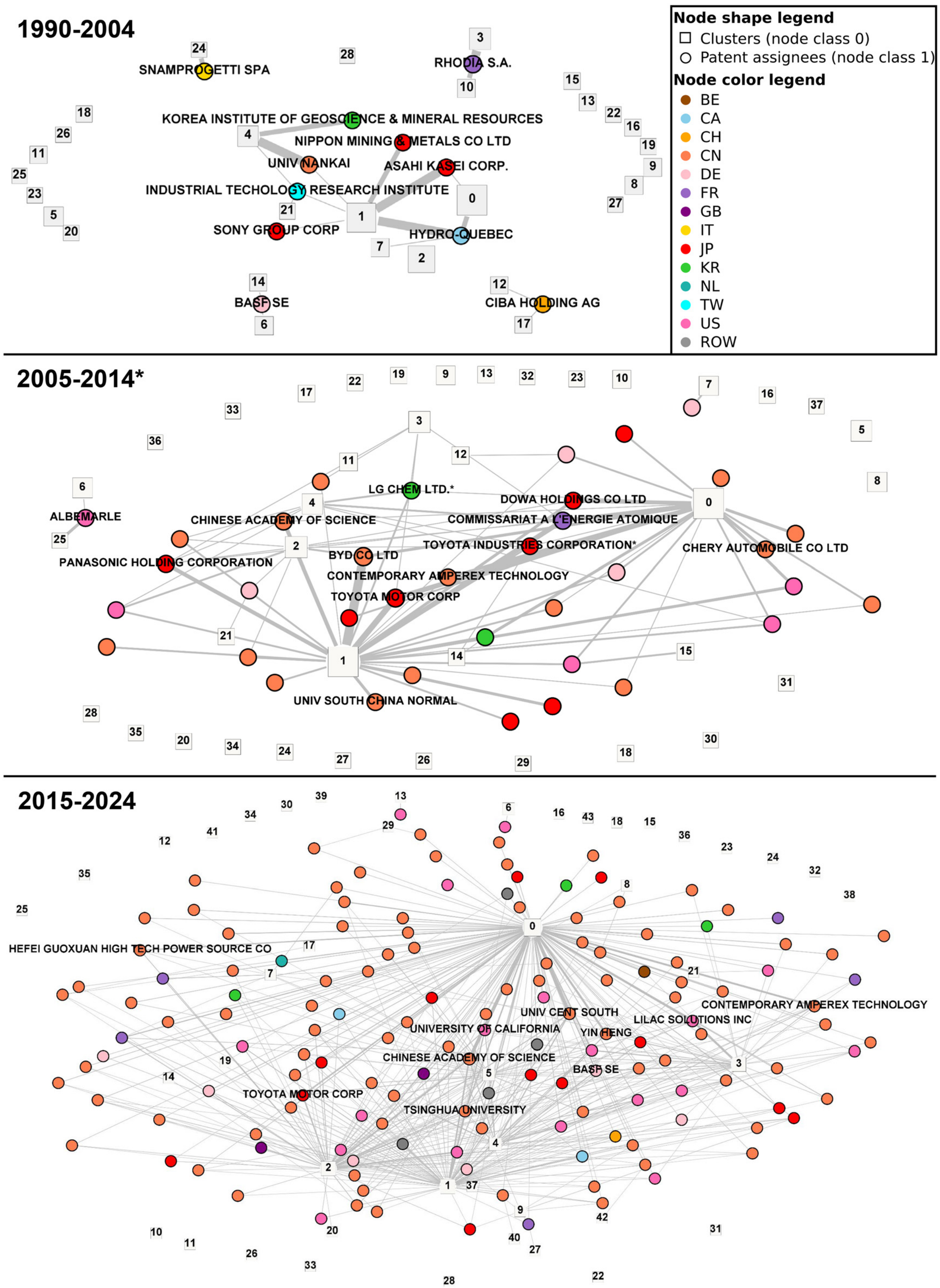

Fig. 10 Overview of two mode networks (knowledge areas and patent assignees) over three periods. To improve readability, only nodes with a weight of two or more are displayed, and only the top 10 patent assignees by weight are labelled. *Despite not ranking in the top 10, LG Chem and Toyota Industries Corp. are labelled for clarity due to their discussion in the text.

5. Conclusion

With the expected end-of-life volume of spent LIBs exceeding 11 million tons by 2030, effective recycling of these batteries is crucial for meeting international climate goals.[31] To aid with this endeavour, this study provides a comprehensive, large-scale patent analysis on LIB recycling across three time periods, aiming to understand both historical developments and potential future trends.

The insights of this study are as follows: first, the analysis confirms China's overwhelming presence in LIB recycling research and indicates that a significant portion of this work is still carried out by universities, suggesting that the technology is in its early development stages.

Second, our analysis highlights that international collaboration in LIB recycling remains limited, with expertise concentrated in regions like China while Europe remains comparatively underrepresented. Policymakers could address this by incentivising transnational research alliances – such as the EU's Battery 2030+ (ref. 121) or the Global Battery Alliance[122] – through targeted grants, tax benefits, or streamlined regulations for cross-border projects. For industry, forming joint ventures or international consortia can accelerate knowledge exchange, as seen in recent collaborative initiatives between Asian and European firms (*e.g.* joint venture announcements between CATL and Stellantis,[123] or Orano and XTC New Energy[124]). However, policy incentives that have proven effective in China may require adaptation in other regions due to differing market conditions and regulatory environments.

Third, the combination of Leiden clustering and TF-IDF analysis applied to CPC co-occurrence networks enabled the identification of meaningful knowledge areas that reflect past and current research trends. Our results show that LIB recycling research is organised around both established domains, such as material recovery and battery testing, as well as evolving areas like advanced electrode design and process optimisation. The presence of distinct clusters focused on material characterisation and production at finer scales suggests that industry and academia are increasingly emphasising quality, purity, and efficiency throughout the recycling process. For policymakers and industry leaders, this indicates the necessity of supporting a range of innovations: from ensuring robust testing standards for recycled batteries to encouraging investment in new material processing methods that can enable higher-value recovery and extend battery lifecycles.

Finally, by mapping knowledge areas to patent assignees, this study highlights the specific technological strengths and strategic focus areas of leading organisations across the LIB recycling landscape. This transparency allows policymakers to better target incentives or support mechanisms toward emerging or underrepresented fields and to encourage collaboration between organisations with complementary expertise. For industry and academia, these insights facilitate more informed decisions when identifying potential partners for joint development, benchmarking competitors, or exploring gaps where new research and innovation could have the greatest impact.

Ultimately, fostering stronger international collaboration by reducing existing barriers and encouraging more cross-border partnerships, will be essential to unlock the full global potential of LIB recycling innovation and to achieve international sustainability and climate objectives.

Building on this study, future research could address methodological limitations to achieve deeper insights into LIB recycling. Employing advanced natural language processing techniques could enhance the precision and detail of identified knowledge areas, especially when analysing patent abstracts rather than CPC descriptions. Additionally, because patent co-ownership does not capture all forms of international collaboration, as many partnerships may not result in jointly filed patents and ownership may be solely assigned to companies for contractual reasons, future research could complement patent analysis with alternative indicators of collaboration. Addressing shorter time periods may also reveal more nuanced insights into knowledge shifts within LIB recycling. Incorporating patent quality assessments, alongside quantity, would allow for more nuanced analysis by highlighting the impact of patents.

Author contributions

SS and AH conceived the idea. SS designed the research. SS conceived the illustrations. SS performed the analysis. SvD guided and supervised the project. SS and SvD wrote and revised the manuscript. AH reviewed the manuscript.

Conflicts of interest

The authors declare no competing interests.

Data availability

The data supporting this article have been included as part of the ESI,† except the patent raw data, which are not available due to licensing restrictions but can be obtained from the Derwent World Patents Index using the search string presented in the ESI.† The Python code is available on Zenodo (**https://zenodo.org/records/15631938**).

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