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Exploring the characteristics of technological knowledge interaction dynamics in the field of solid-state batteries: A patent-based approach

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ABSTRACT

This study provides a novel patent-based analysis framework for identifying the latent knowledge structure of technological domains by adopting dynamic perspectives. It uses patent data collected between 2010 and 2018 to systematically examine and visualize promising knowledge interactions that could foster the advancement of solid-state battery technology. Moreover, solid-state battery technology is compared with lithium-ion battery technology to demonstrate the difference in development focus. Based on different metrics and methodological designs, the results indicate that solid-state batteries are an emerging field driven by the uptake of electric vehicles. The results also reveal that a critical factor for desirable cell performance in lithium-based solid-state batteries is improvement to electrode–electrolyte interface stability, while the most critical factor for lithium-ion batteries is electrode materials. Additionally, materials, advanced manufacturing, battery engineering and automotive sectors must work together to establish a dominant design and corresponding value chain. Moreover, like with lithium-ion batteries, Asian manufacturers are dominating the patent space. The proposed framework is expected to add a new empirical perspective to the discussion of sustainable technology development and provide insight on innovation areas where key players can coordinate their activities to ramp up R&D operations.

1. Introduction

To accelerate the clean energy transition and to mitigate the impact of climate change by reaching carbon neutrality by 2050, considerable efforts are being made to increase the proportion of renewable energy sources (Gielen et al., 2019). Leading tech-companies such as Apple, General Motors, Google and LG have joined the global initiative, RE100, which pushes the participating companies to switch to 100% renewable electricity in business activities (Peirce, 2021). Accordingly, high importance is attached to developing sophisticated energy storage solutions to integrate more renewable energy sources into the electrical grid (Argyrou et al., 2018). Effective use of energy storage systems can contribute to higher renewable energy-penetration levels and the decarbonization of electricity production (Arbabzadeh et al., 2019; Hoang et al., 2021). Hence, the demand for sustainable, affordable and high-performance electrical energy storage technologies has increased considerably over the last decade (Acar, 2018). To reach the next milestone in battery technology, a single battery chemistry will not be able to satisfy the diverse facets of battery performance such as energy density, safety, sustainability, cyclability and cost (Manthiram, 2017). The battery systems designed to be the successors to lithium-ion batteries (LIBs) and have the potential to meet the requirements of energy-intensive products are referred to as post-lithium-ion batteries (PLIBs) (Choi and Aurbach, 2016). Solid-state-batteries (SSBs) are a kind of PLIB in which solid electrolytes are used instead of liquid electrolytes (Chen et al., 2020). SSBs are attracting interest as a promising electrochemical energy storage technology to expand the battery capacity of electric vehicles (EVs) (H. Shen et al., 2019).

Because the speed and scope of the research and development (R&D) landscape are changing at a fast pace, it is crucial for researchers to be aware of the key research streams that could accelerate the development of next-generation batteries (Zeng et al., 2019). An understanding of the R&D landscape can help create a clearer picture of the evolving characteristics of technological innovations and assess the influence of specific knowledge interactions in the technical domain (Aaldering et al., 2019a; Yuan and Li, 2021). In this regard, the analysis of patent

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information is indispensable for establishing sound innovation strategies and discovering new development opportunities for scientists and R&D managers. Patent data are regarded as one of the most important standardized technical resources because they reflect technological advancements and reveal the state of global technological collaboration structures (de Paulo and Porto, 2018; Yin et al., 2020). Especially in the early stages of technology development, patent-based metrics can play a key role in delivering the intelligence required to innovate with confidence (Fischer et al., 2020).

However, limited attention has been paid to exploring the technological development path of SSBs and their key technology nodes based on objective technological profiling. A previous patent analysis did not include SSBs in its investigation of the PLIB technological development trajectory (Aaldering and Song, 2019). Other recent studies have focused on the manufacturing compatibility of post-lithium-ion technologies with the existing lithium-ion production infrastructure (Duffner et al., 2021) or the related challenges of key performance parameters to achieve desired research outcomes (Randau et al., 2020). Moreover, patent data in raw form are complex and require an appropriate analysis framework. When combined with an appropriate analytical method, it is possible to leverage the data and deliver some actionable insights. Thus, this paper aims to identify and compare the patent landscape of SSBs against that of LIBs using an exploratory research approach to provide broad-scoped insights.

To this end, a novel patent-based analysis framework is proposed and applied to generate an inclusive view of the technological development path of SSBs and to compare their knowledge interaction pattern with that of LIBs. This framework uses a modified patent co-classification analysis to not only quantify interaction changes over time but also to map out interacting knowledge areas that could be perceived as driving forces for the advancement of SSB technology. While previous research efforts have been geared towards creating a static snapshot of past technology landscapes, the proposed framework is capable of representing how the interaction dynamics between co-occurring knowledge areas have evolved and might shift in terms of significance over time. The combination of static and dynamic perspectives is more suitable for monitoring innovation-driven technology landscapes, and the inclusion of direct and indirect interaction profiles via interaction analysis and distance-based analysis can reveal a differentiated perspective on the technological development trend.

In terms of its theoretical contributions, the proposed analysis framework can help extend the currently available list of patent analysis methods by offering an additional way of handling complex patent data. Combined with other data-driven analytical methods (Aaldering et al., 2019b; Baumann et al., 2021; Mejia and Kajikawa, 2020), this study can enhance the overall transparency of post-lithium-ion battery research to interested members of the scientific community. Moreover, its findings confirm the emerging importance of SSBs in the adoption of EVs because SSBs are regarded as a promising candidate for leveraging the limits of conventional LIBs (Lee et al., 2020). This study also has important practical contributions for both R&D planners and policy makers in the field of environmental and sustainability research. It is a valuable reference point capable of visualizing the ongoing R&D landscape, guiding policy planning debates and improving the market perception of scientists and R&D managers so that they can determine their optimal portfolio mix. Furthermore, this study responds to the call for more patent-based empirical research studying the direction of technological development in PLIB technologies (Aaldering and Song, 2019). Although SSBs have attracted considerable interest as potentially safe and stable high-energy storage systems compared to the LIBs in academia and industry (Balaish et al., 2021; Janek and Zeier, 2016), a corresponding discussion on their technological progress in consideration to underlying R&D activities is not available. Thus, this study can help broaden the scholarly literature on the analysis of next-generation energy storage systems using patent data. Additionally, the findings of this study contribute to a complementary view of solid-state batteries, which might have a profound impact on the acceleration of the sustainable development and deployment of clean energy and green chemistry solutions.

The remainder of this paper is organized as follows: Following this introduction, Section 2 briefly reviews the literature on the operating principle of solid-state batteries and the significance of patent-based trend analysis for monitoring the evolutionary trajectories of technological innovation. Section 3 outlines the data collection procedure and the associated empirical methods. In Section 4, we present the empirical findings by highlighting the different knowledge interaction patterns between LIBs and SSBs. Conclusions and outlook for future research and policy implications are summarized in Section 5.

2. Background

2.1. *Significance of solid-state batteries*

With a growing global energy consumption and government agendas accelerating the transition to a zero-carbon economy, ensuring a high penetration rate of renewable energy sources into the power grid is one of the most important and challenging issues of our time (Chen et al., 2019; Karunathilake et al., 2018). As a result, innovations in electrochemical energy storage devices, which store and release electricity on demand, have gained considerable significance in establishing sustainable energy infrastructure. The effective use of energy storage systems enables cleaner electricity to penetrate a wide range of applications, including the areas of electric mobility and grid-scale storage (Hoang et al., 2021).

Currently, LIBs are considered to be the most prominent type of rechargeable battery and are well-established for various commercial uses (Rallo et al., 2020). Since their introduction to the market in the early 90s, LIBs have revolutionized modern society and the way our lives work (Manthiram, 2020; Xie and Lu, 2020). LIBs have been the primary power source choice for portable electronic devices. They also have been integral to the successful market introduction and commercialization of EVs due to their high energy densities and long-life span compared to other rechargeable batteries (Placke et al., 2017). The main cell components of a LIB are the cathode, the anode, the liquid electrolyte and the separator, which spatially and electrically isolates the cathode from the anode and allows ion permeability (Liu et al., 2020). Typical active materials used for the cathode are layered transition metal oxides ($LiMO_2$, M = Ni, Mn, Co, Al) (Myung et al., 2017) whereas artificial and natural graphite are widely used as the anode materials (Blomgren, 2017). To fully exploit the energy storage capabilities of LIBs, changes in cell component materials and cell design are critical factors (Kwade et al., 2018; Park et al., 2021; Wu et al., 2020; Zhang et al., 2021). In particular, considerable attention has been given to improving electrolyte and electrode materials as they play a crucial role in affecting battery performance (Schmuch et al., 2018; Wang et al., 2020).

Despite the positive attributes of LIBs and their dominance in the current market, there are concerns with their effectiveness, such as the limited driving range of EVs, and safety (Sun, 2020). Further energy density advancements are necessary to meet the ever-growing demand for high-performance energy devices, but LIB technology is approaching its theoretical performance limit (Grey and Hall, 2020). Only incremental advances are expected in the near future due to the inherent trade-off between reactivity and stability of materials at the electrolyte/electrode interface (Ge et al., 2020; Liu et al., 2019). Therefore, designing batteries with improved safety, energy density, energy efficiency and energy retention rates are necessary for the development of next-generation energy storage technologies (Randau et al., 2020).

Based on this perceived necessity, research into PLIB technologies has been triggered by substantial efforts to offer high-energy and long-duration battery storage capabilities (Walter et al., 2020). Among these PLIB technologies, SSBs represent a potential successor to LIBs (Kim et al., 2021). This study focuses only on lithium-based SSBs (LSSBs) to enable a comparison with lithium-based battery technologies. In Table 1, the key differences between LIBs and LSSBs are summarized.

Unlike LIBs, LSSBs rely on a solid electrolyte (Chen et al., 2020; Janek and Zeier, 2016). This makes the production of safer batteries possible due to the absence of highly flammable liquid electrolytes (Li et al., 2018; Wu et al., 2021). LSSBs can demonstrate improved stability and increased safety due to its solid structure as the electrolyte maintains its form even if it is damaged by an external impact and it cannot be leaked upon temperature changes. Furthermore, the solid electrolyte adopts the properties of a separator so it also serves as the separator in a battery cell (Janek and Zeier, 2016). Hence, short-circuits caused by lithium metal dendrite formation and growth from the anode through the separator to the cathode can be suppressed (Famprikis et al., 2019). LSSBs have more space for active materials and have increased energy density per unit area providing improved packaging efficiency to battery modules. Moreover, LSSBs enable the full potential of lithium metal anodes, resulting in higher energy densities compared to conventional LIBs (Wu et al., 2021; Yu et al., 2017). According to Lee et al. (2020), their recent LSSB prototype based on a lithium metal anode would enable an EV to travel up to 800 km on a single charge. Typically, high-energy long-cycling SSBs are based on lithium metal anodes as they have the potential to improve the energy density of the batteries through their high theoretical specific capacity, safety and recyclability, and they potentially have a lower cost compared to advanced Li-ion systems (Albertus et al., 2021; Zeng et al., 2019). Currently, when considering electrochemical performance in terms of energy efficiency, power and cycle life, LSSBs are still quite far behind LIBs (Schmuch et al., 2018). For example, additional research is needed to improve the ionic conductivity of solid electrolytes and to optimize the interfacial stability (Wu et al., 2021; Yu et al., 2017). Finally, the question of when LSSBs will catch up to LIBs in terms of performance and cost also raises the question of whether the technologies are moving in similar directions. Hence, this study aims to provide more clarity to this question by exploring the trajectory of interactions between the technology areas of LSSBs and LIBs.

Table 1
Comparison of key features between LIBs and LSSBs (Adapted from Choi and Aurbach (2016) and Duffner et al. (2021)).

	Lithium-ion batteries	Lithium-based solid-state-batteries
Characteristics	Liquid electrolyte Separator required	Solid electrolyte Electrolyte acts as a separator film
Advantages	High technological maturity High volumetric energy density Longer life span	Higher energy density and safety with lithium metal Much wider viable range of working temperatures
Disadvantages	Availability and costs of selected materials Environmental impact of raw materials	Applied stack pressure to inhibit delamination during cycling Promising chemistries are under investigation Uncertain material and processing costs
Nominal voltage	3.2–3.85 V	3.7–3.8 V
Operating voltage window	3.0–4.2 V	2.5–4.25 V (often above RT)
Areal electrode capacity	3–5 mAh cm^{-2}	0.5–14 mAh cm^{-2}
Power (cell)	1–20 kW kg^{-1}	0.01–3 kW kg^{-1} (temperature dependent)
Gravimetric energy density	264-435 Wh kg^{-1}	100-450 Wh kg^{-1}
Volumetric energy density	733-1,200 Wh l^{-1}	200-820 Wh l^{-1}
Cycle life	1,000–6,000	100–1,000
Energy efficiency	High (>90%)	Low (50–76%)
Self-discharge	Low	Low

2.2. Patent data as a unique source of information on technological innovations

The pace of technological change has increased dramatically in the last several decades with new sectors emerging and several others converging (Stucki and Woerter, 2019). Technological development trends have experienced an immediate acceleration and gain in significance in a relatively short period of time. In this context, patents represent a unique source of information on inventive activities and their main technological features (Bregonje, 2005). Besides serving as legal instruments to confer exclusive rights to an owner, patents illustrate a well-structured document that enables the exploration of various analytical approaches to highlight technological progress (Clarke, 2018). In addition to the full technical description and claims of an invention, patents contain a wide variety of metadata from which critical patent metrics for making evidence-based business decisions can be computed (Choi et al., 2020; Suominen et al., 2017). The prevailing view is that 80 percent of the latest technical information can be found exclusively in patent documents (Asche, 2017). Hence, patent data can provide valuable insights by analyzing the competitive landscape, assessing patentability and preparing freedom-to-operate opinions (Holgersson and Wallin, 2017). Patent data have been widely accepted as a standard approach for measuring innovation and technology trends. In the field of technology and innovation management, the generation of competitive intelligence using patents and monitoring the dynamics of emerging technologies have been vital for supporting national R&D policy planning and technology project selections (Stephan et al., 2019). For example, scholars have adopted a series of different data-driven approaches to capture the relative technological specialization (Shubbak, 2019), to identify emerging topics (Mejia and Kajikawa, 2020) and to measure innovation cycles (Ahn and Yoon, 2020). In particular, patent citation analysis provides a direct link to study the pattern of knowledge development paths and spillovers (Lai et al., 2021), while the co-occurrence of patent classification codes can be used to explore converging technology areas (Feng et al., 2020). In several studies, the use of international patent classification (IPC) codes has been highlighted as an effective means to analyze complex technological relationships through co-classification-based analyses in combination with the visualization of their relations as a network (Lim and Park, 2010). Patent co-classification analysis is a useful method for outlining the intellectual structure of technological capabilities and measuring the interdisciplinarity between disciplines at various technology levels (Geum and Kim, 2020). Recently, co-classification analysis has been adopted to help operationalize a patent's bridging characteristic (Moehrle and Frischkorn, 2021) as well as to derive technological sub-domains by calculating technologically similar overlapping classes (Mun et al., 2019). In addition to patent data, scientific publications could also be considered as an indicator for technical change (Spreafico and Russo, 2021). However, patent data are appropriate data for revealing the development and status of technological progress with a strong link to practical applications while scientific publications cover basic research that has no proven usage cases for monetization (Huang et al., 2012). Moreover, scientific publications offer a smaller variety of metadata, which limit the options for technology trend analysis. Hence, this study considers patent data as a suitable option to investigate technological development and interconnectedness.

3. Methods

The proposed analysis framework consists of four analysis steps (Fig. 1). It builds on the co-classification-based approach to characterize the technological development of LSSB, enabling an in-depth analysis of the underlying knowledge interaction pattern. After giving an introductory overview of this framework, each step will be explained in a more detailed fashion.

In the first step, the raw patent data were collected and pre-processed

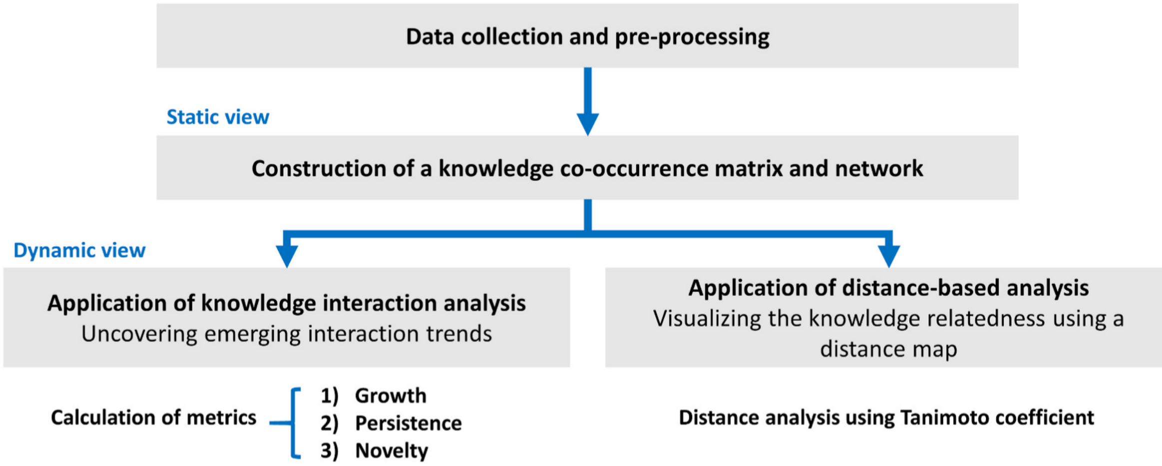

Fig. 1. Overview of the proposed analysis framework.

to remove noisy data and transform them into a suitable format for further analysis (see Subsection 3.1). The second step involves the construction of the co-occurrence matrix from a static view and the corresponding interaction network to visualize the interrelation of technological knowledge areas (see Subsection 3.2). The subsequent steps capture the interaction dynamics of technological knowledge areas by analyzing the variation in interaction rate over defined time intervals. The applied knowledge interaction analysis reveals the evolving dynamics of direct interactions. Three metrics were introduced to quantify the intensity and significance of the direct relationships between interacting pairs of knowledge areas. This is especially suitable for identifying emerging, persistent and relevance-gaining interactions, thereby measuring the direct impact of knowledge areas on the R&D landscape (see Subsection 3.3). The applied distance-based analysis computes the relative proximity between knowledge areas, thereby revealing the possible influence of knowledge areas on the progress of underlying technological fields (see Subsection 3.4). In contrast to the interaction analysis, the distance-based analysis evaluates the indirect relationship between distinct knowledge areas based on their shared set of knowledge areas. Hence, the focus in the latter method considers the dynamics of whole interaction profile of knowledge areas while the former method only considers the direct relational link. As a result, these distinct perspectives give the opportunity for different contextual interpretations of the technological environment. This is because knowledge areas with a strong direct relationship can appear rather distant from each other when considering the whole interaction profile. Such relationships could pave a new way for detecting vacant technology development opportunities as the distance-based analysis also considers the surrounding environment in which a technology is embedded.

3.1. Data collection and pre-processing

We extracted the relevant patent data from the Derwent Innovations Index (DII), which represents an aggregate database of over 80 million individual patent documents drawn from 59 patent-issuing authorities worldwide. The patent data from DII are organized in patent families where each patent family is grouped around a priority patent that refers to the same basic invention. Hence, a patent family is a set of patents filed with different patenting authorities along with continuations or divisions linked by a common priority. This feature is particularly helpful in finding a comprehensive view of the global patent landscape because duplicated records can be filtered out for the patent analytics. Moreover, DII adds valuable metadata, such as Derwent Manual Codes (DMC) or DWPI Abstracts, abstracts rewritten in plain English without the inclusion of complex legal jargon, to the patent record providing access to curated and enriched patent data sources (See Section 3.4 for further explanation on DMC).

Although a keyword-based patent search is the most widely adopted means of identifying patents, it has two limitations. First, there is a risk of retrieving irrelevant patents to the interested technology domain if there is insufficient expertise on the research subject. Second, there is a lack of proper key terms for emerging technological domains to detect all relevant patents. Hence, in this study, patent retrieval was done by selecting suitable cooperative patent classification (CPC) codes for LSSBs and LIBs (Table 2). The classification-based search query was partly adopted from the work of Aaldering et al. (2019a) and IEA (2020), which relied on patent classification codes for patent retrieval and defined the characteristic CPC codes for LIB and LSSB technologies. Similar to the IPC scheme, CPC is an extended classification system based on hierarchical structures that categorizes patent documents based on their technical field of invention. With more than 250,000 subdivisions, CPC is designed to harmonize the global classification system for patent documents and provide the granularity needed to cover and classify the details of patent content (Table 3). To capture the relevant patents, Boolean operators such as “AND” and “OR” were combined to specify the queries. For example, the query for LSSB was designed by extending the base classification codes for LIB (which consist of CPC=(H01M0010052 OR H01M00100525 OR Y02E0060122 OR Y02T00107011)) with the representative code “H01M-10/0562” (Lithium-accumulators – Electrolyte – Solid materials) for LSSB. The patent retrieval took place in March 2021.

The analysis time frame was from 2010 onwards to capture the latest developments. The R&D activity of LSSB remained low compared to LIBs until now because LIBs have achieved remarkable energy densities in recent decades. Therefore, setting the starting year to 2010 permits better comparability between the considered technologies. Lastly, the collected data were preprocessed and stored in a well-defined format to facilitate further analytical processing.

Table 2
Patent search query. (PRDS: Priority date, CPC: CPC codes.)

Technology domain	Search query
Lithium-based solid-state batteries	CPC=((H01M0010052 OR H01M00100525 OR Y02E0060122 OR Y02T00107011) AND (H01M00100562)) AND PRDS>=(20100101);
Lithium-ion batteries	CPC=(H01M0010052 OR H01M00100525 OR Y02E0060122 OR Y02T00107011 OR H01M0004013) AND PRDS>=(20100101);

Table 3
Definition of CPC codes. (Note: The CPC scheme is updated regularly to keep in line with the latest filing trends and technology advances. Therefore, some CPC codes are present in the documents, but are not actively used anymore to improve patent searching.)

CPC	Description
H01M-10/052	Lithium-accumulators with non-aqueous electrolyte
H01M-10/0525	Lithium-accumulators - Rocking-chair batteries, i.e. batteries with lithium insertion or intercalation in both electrodes; Lithium-ion batteries
H01M-10/0562	Lithium-accumulators – Electrolyte – Solid materials
H01M-04/013	Electrodes for lithium-accumulators
Y02E-60/122	Lithium-ion battery technologies with an indirect contribution to GHG emissions mitigation
Y02T-10/7011	Lithium-ion battery technologies related to road transport of goods or passengers

3.2. *Construction of co-occurrence matrix and technological knowledge interaction network*

In this step, a co-classification approach was applied to investigate the interconnectedness of the LSSB and LIB knowledge areas. The co-classification approach measures the co-occurrence of distinct classification codes assigned to individual patents (Karvonen and Klemola, 2019; Park and Yoon, 2017). Depending on the nature of a patented invention, various patent classification codes can be simultaneously assigned to a patent document. As each code can denote a specialized technological knowledge area, the presence of multiple classification codes indicates a dependency between these codes (Song et al., 2017). This dependency is assumed to produce knowledge flows or knowledge spillovers among technology areas. Hence, both obvious and non-obvious patterns of knowledge interactions can be revealed by looking at their degree of connectedness. (Note: In this study, a knowledge area is equivalent to a classification code according to the DMC indexing system). DMC are used to create the co-occurrence matrix. DMC are an alpha-numeric classification scheme designed by experts at Clarivate Analytic and are broadly used to categorize patents in 21 subject areas related to “Chemical”, “Engineering”, and “Electronic and Electrical Engineering”. The DMC classification system represents a customized taxonomy indicating the novel technical aspects of an invention and has a hierarchical indexing system, where the addition of an extra letter or number denotes moving down the hierarchy and specificity (Table 4). Past research has shown that the use of DMC was helpful in revealing the detailed aspects of a technological area covered by a patent (Aaldering and Song, 2019; Li et al., 2021; Wei et al., 2017).

The resulting co-occurrence matrix was then used as the input for the construction of a corresponding knowledge interaction network (Fig. 2). The network visualization of the interacting knowledge areas helps highlight different relational aspects around a single node, which are otherwise difficult to examine using a matrix illustration. Information visualization in business is a crucial component for making sense of complex systems and generating insights on high-dimensional data (Basole, 2019). Network visualization is a specific area in the field of information visualization. In a network, each node denotes a technological knowledge area and each link specifies the degree of interaction between a pair of technological knowledge areas. Previous studies have shown that a network analytic perspective provides a particular lens for quantitatively measuring the degree of connectivity between diverse disciplines and categorizing the strategic positioning of sectors within the ecosystem network (Aaldering et al., 2018; Basole, 2016; Basole et al., 2019). Furthermore, the calculation of quantitative network measures can enhance the understanding of the internal structure of the network. Among the various modes of measuring network characteristics, centrality-based metrics are commonly used to measure the degree of interconnection and influence of nodes in the network (Wang, 2020).

Table 4
Exemplary illustration of the hierarchical structure of DMC system.

Hierarchy	DMC	Explanation
Section	X	Electric Power Engineering
Class	X16	Electrochemical storage
Group	X16-B	Rechargeable or secondary cells
Subgroup - main	X16-B01	Cells
Subgroup – lower level (I)	X16-B01F	Non-aqueous cells
Subgroup – lower level (II)	X16-B01F1	Lithium-based
Subgroup – lower level (III)	X16-B01F1C	Solid electrolyte

To rank the relative importance of nodes and examine their roles in information exchange, we considered betweenness, closeness and eigenvector centrality measures. Betweenness centrality indicates the extent to which a node is positioned on the shortest geodesic path between other pairs of nodes in the network (Leydesdorff, 2007). Hence, it is a measure of bridging others and serves as a control point of interactions. A node with high betweenness centrality is different from having many direct contacts and is about being in between a node that tries to reach another node. It reflects the intermediary location between indirectly tied pairs of nodes. The betweenness centrality of a node $C_B(i)$ can be calculated as follows:

$$C_B(i) = \sum_{k=1}^{n} \sum_{j=1}^{n} \frac{g_{jk}(i)}{g_{jk}}, i \neq j \neq k \tag{1}$$

where $g_{jk}(i)$ describes the number of shortest paths between a pair of nodes j and k that pass through node i and g_{jk} represents the total number of shortest paths between nodes j and k.

Closeness centrality represents the average distance of one node to all other nodes in the network by measuring its summed lengths of shortest paths to other nodes (Freeman, 1978). It explains a node's ability to reach many other nodes by traversing relatively small distances. A node with high closeness centrality can easily contact all other nodes within the network due to its strong proximity. Thus, closeness centrality explains a node's ability to access or absorb information from one node to another nearby node, resulting in a high degree of indirect influence on other nodes. The closeness centrality of a node $C_C(i)$ can be calculated as follows:

$$C_C(i) = \frac{N-1}{\sum_j^n d_{ij}} \tag{2}$$

where d_{ij} describes the shortest path between the considered node i and another node j. N stands for the number of reachable nodes.

Eigenvector centrality indicates the degree to which a node is connected to other central nodes in the network (Basole, 2016). It captures the direct and indirect relational connectivity because the influence of a node is determined by the number and influence of its adjacent nodes. This metric enables assessment of how prominent a node is. In this study, a classification code with high eigenvector centrality is connected to many other codes, which are themselves connected to many other prominent codes. The eigenvector centrality of a node $C_E(i)$ can be calculated as follows:

$$C_E(i) = \frac{1}{\lambda} \sum_{j=1}^{n} A_{ij} x_j \tag{3}$$

where A_{ij} represents the network's adjacency matrix, n is the total number of nodes in the network, x_j is the relative centrality score and λ is the corresponding eigenvalue (Bonacich, 2007). Hence, $C_E(i)$ is the summation of its neighbor's centralities. By considering these centrality metrics, this study aims to detect key knowledge areas exerting a significant influence on the development of LSSBs and LIBs. This will allow for new insights into the functional roles played through specific

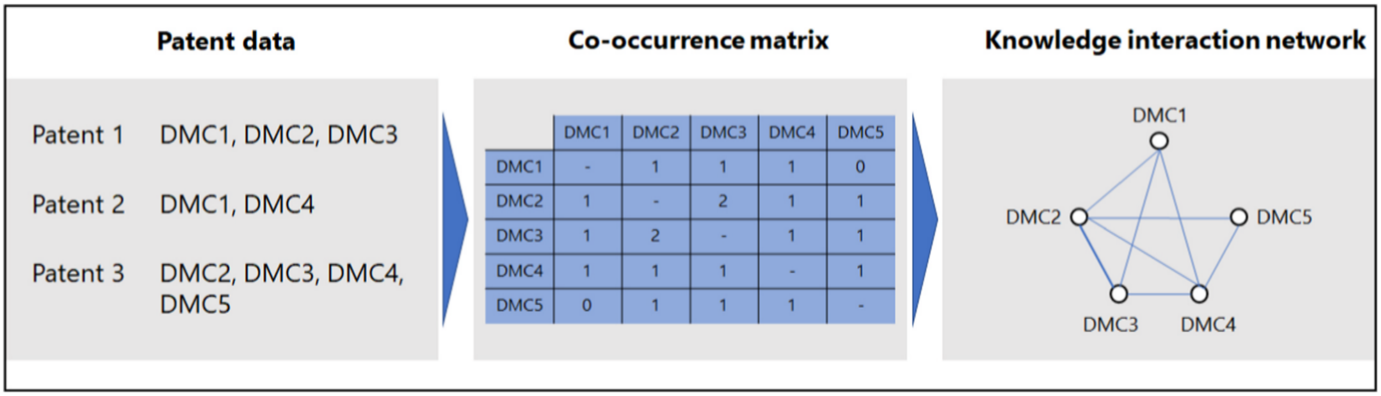

Fig. 2. Conceptual process of computing the co-occurrence matrix and the transformation into a knowledge interaction network.

knowledge areas.

3.3. Dynamics of interacting knowledge areas

While the previous step was oriented towards the description of the interaction network and its node properties from a static perspective, it is of equal importance to identify the emerging and ever-evolving interacting pairs of knowledge areas from a dynamic point of view. This is especially true if the underlying technology landscape is in a constant state of flux. To highlight the interacting pairs of knowledge areas with promising potential, we proposed an integrated procedure, which includes the introduction of three new metrics. For this purpose, the interval-specific co-occurrence matrices were constructed to track the variation in interaction rate over different time intervals. Here, the frequency of interactions has been normalized by the number of patents in each time period to ensure comparability. The resulting proportional interaction frequency is defined as follows:

$$prop\_freq_{(x,y)j} = \frac{freq_{(x,y)j}}{num\_pat_j} \tag{4}$$

where *freq(x,y)* indicates the absolute number of interaction frequencies of an interaction pair (x,y), *j* denotes the corresponding interval and *num_pat* stands for the number of patents. The most promising interaction pairs were identified by considering the metrics of growth, persistence and novelty.

Growth measures the change in the interaction rate between two interacting knowledge areas over the examined intervals. $Growth_{(x,y)}$ is dependent on the proportional interaction frequency and can be defined as follows:

$$Growth_{(x,y)} = \sum_{j=2010}^{2018} \left(prop\_freq_{(x,y)j} - prop\_freq_{(x,y)j-1} \right) \tag{5}$$

According to Equation (5), $Growth_{(x,y)}$ is the sum of all proportional interaction frequency differences between period *j* and *j-1*. Hence, growth is useful for highlighting the interacting knowledge areas that received more attention from the R&D community considering a dynamic perspective. To ensure that a significant growth is due to a consistent R&D performance, the evaluation metric of persistence is considered. $Persistence_{(x,y)}$ analyzes whether a certain interaction has been continuously manifested and can be defined as follows:

$$\begin{cases} Persistence = if \left(\sum_{j=2013}^{2018} \left(freq_{(x,y)j} > 0 \right) = 6 \right) \\ No\ persistence = if \left(\sum_{j=2013}^{2018} \left(freq_{(x,y)j} > 0 \right) \neq 6 \right) \end{cases} \tag{6}$$

According to Equation (6), $Persistence_{(x,y)}$ is the sum of the interaction presence appearing in the last six years of the considered study period. This metric is helpful in stressing the interacting pairs that are sustained over time and is a useful feature for separating a trend from a fad.

The last metric novelty is capable of highlighting the interacting pairs that have experienced significant growth in the most recent year, thus demonstrating a high potential for future relevance. $Novelty_{(x,y)}$ can be calculated with the following formula and is represented as a percentage:

$$Novelty_{(x,y)} = \left(\frac{prop\_freq_{(x,y)k}}{\sum_{j=2013}^{2018} prop\_freq_{(x,y)j}} \right) * 100 \tag{7}$$

where *k* is equal to the most recent period. $Novelty_{(x,y)}$ can be determined by setting a cut-off value. In this study, the cut-off value was set to 25%. Based on the proposed metrics, it is possible to offer further insights into which interacting pairs have contributed to the growth of the underlying technological fields and to filter out the promising pairs.

3.4. Calculation of a distance metric

In this step, distance-based measurements were applied to quantify the relationship between two distinct knowledge areas. While the preceding analysis revealed the emerging trends by looking at the direct linkages, a distance-based analysis is capable of establishing references between knowledge areas through common intersections. For example, the distance measurement via computing proximity in high-dimensional data can take place by considering the ratio of the intersecting set of knowledge areas. To this end, an adapted co-occurrence matrix was relied upon to examine how closely two different knowledge areas are related. This matrix provides additional insights into the degree of similarity between distinct knowledge areas. The corresponding conceptual process is depicted in Fig. 3.

To ensure a comprehensive overview of the most relevant developments and to avoid sparse matrix handling, only the top 50 frequently occurring knowledge areas are included in the matrix. Moreover, the analysis period was divided into three equal time intervals to study the evolutionary change in growing or decaying similarity between knowledge areas. Accordingly, the adapted co-occurrence matrices are generated and the distances are calculated using the Tanimoto coefficient, which is based on pairwise similarity measures (Cha, 2007; Ertl, 2020). The distance d_{tani} can be calculated as follows:

$$d_{tani} = 1 - \frac{\sum_{i=1}^{n} \max(x_i y_i) - \min(x_i y_i)}{\sum_{i=1}^{n} \max(x_i y_i)}$$

where *x* and *y* represent the distinct knowledge areas, *i* describes the index position within the row vector of the matrix and *n* stands for the

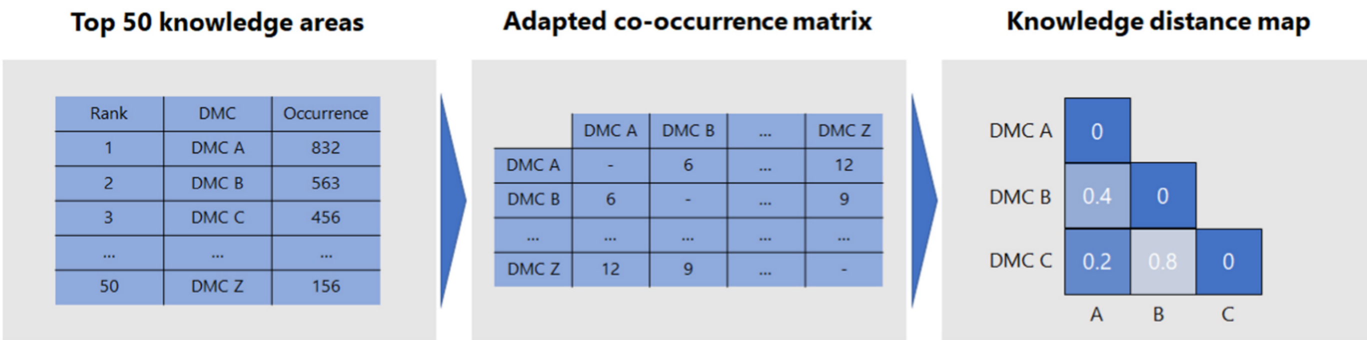

Fig. 3. Conceptual procedure for performing the distance analysis.

lengths of the matrix. The distance values can range from 0 to 1. A value of 0 states that the two knowledge areas are indistinguishable whereas a value of 1 indicates that the two knowledge areas do not share any common interactions. Finally, the results are visualized as a heat map that uses color intensities to reflect the degree of varying distance for each interval.

4. Results and discussion

4.1. Descriptive statistics

This subsection provides a descriptive overview of the key characteristics of the collected patent data. Fig. 4 shows the number of LSSB patent families by priority year between 2010 and 2020. In total, 3164 patent families were identified for this time frame after the initial pre-processing. In the initial pre-processing step, patent documents were excluded if they did not have information on the priority date or Derwent Manual Codes because these are essential features for conducting the analysis. The number of patent families in the field of LSSB has steadily grown until 2018. According to a recent technology report by the International Energy Agency (IEA), patent filing activities in batteries and other electricity storage technologies grew at an average annual rate of 14% worldwide from 2008 to 2018 (IEA, 2020). This number is four times higher than the average patent filing rate in other technology fields. A similar growth rate can be witnessed in this study's data. The sudden drop in the number of patent families after 2018 can be explained by the fact that the patent applications are usually published with a delay of 18 months after the priority date in most patent offices. Subsequently, this could create a false impression of declining research productivity although the actual number of patents for the years 2019 and 2020 would be higher. Hence, this study considers only the time interval between 2010 and 2018 to avoid possible bias in interpreting the results and to ensure comparability over time. Ultimately, 2669 patent families are included in the subsequent analysis steps. In the case of LIBs, 63198 patent families remained for further analysis after pre-processing. Table 5 provides a summary of these data.

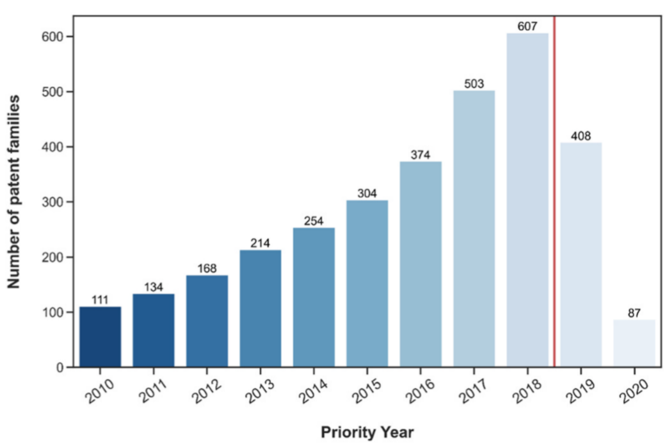

Fig. 4. Historical patent development trend sorted by priority year (LSSB).

Interestingly, the development pattern of LSSBs shown in Fig. 4 is in contrast to the patent development trend of LIBs, which is characterized by stagnant growth (Fig. 5). This contrast could indicate that LSSBs show promise for advancing EV development as they are capable of tackling issues related to performance, safety and costs (Lim et al., 2020).

A brief overview of the most prominent classification codes for LSSB is illustrated in Fig. 6. The data set contains 1459 different classification codes with varying degrees of prominence. Compared to other preceding studies, the classification codes were analyzed at their most detailed hierarchy level to provide a comprehensive overview about the underlying technological trajectory. The high number of individual codes shows how diversified the LSSB technology area is.

The first three most common classification codes "L03-E01C3" (Solid electrolytes), "X16-B01F1C" (Lithium-based solid electrolyte) and "L03-E01B5B" (Lithium electrodes) represent essential parts of LSSBs (Note: A more detailed explanation of individual codes can be downloaded as a supplementary file. Moreover, the readers can look up the description of codes individually by accessing the following website: https://clarivate.com/derwent/dwpi-reference-center/mcl/.). These are classification codes related to solid-state battery cell components and their production processes. Apart from them, another cluster of classification codes were identified that underscore the potential of LSSBs for the electric vehicle market and moving towards clean mobility. For example, "L03-H05" (Vehicles) represents the fourth most frequently occurring classification code. The assumption that LSSBs could become the new standard for EVs is strengthened by the presence of "X21-B01A" (Traction Battery) and "X21-A01F" (Electric vehicles). Furthermore, the code "L03-H03A" (Data storage units, computers) indicates the potential application of LSSBs as a solution for wearable and portable electronics (Yadav et al., 2019). The remaining classification codes refer to the advancement of electrodes, which are usually made up of active materials, conductive additives and binders. The strong focus on these components seems plausible because the energy density is largely dependent on the active material loading in the composite electrode (Shi et al., 2020).

Next, the geographical distribution of patents by country of origin

Table 5
Number of collected patents for LSSBs and LIBs after first and second pre-processing.

Technology domain	Number of patent families after initial pre-processing	Number of patent families after second pre-processing (limiting the time interval)
Lithium-based solid-state batteries (LSSB)	3164	2669
Lithium-ion batteries (LIB)	72900	63198

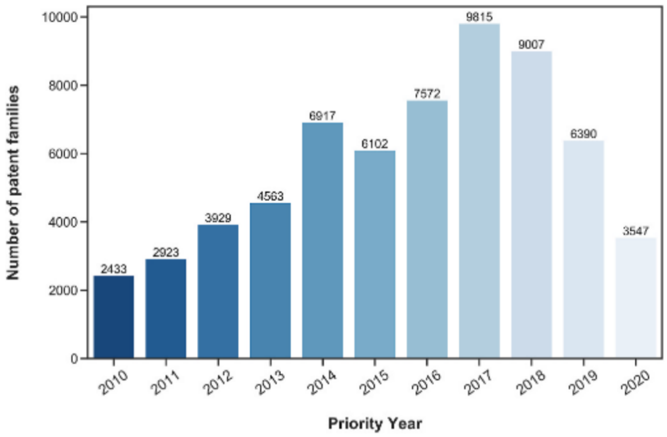

Fig. 5. Historical patent development trend sorted by priority year (LIB).

was examined. The breakdown by country is shown in Fig. 7 where the intensity of the color spectrum is proportional to the number of priority patents. The related R&D activities are concentrated in a few geographic areas with the majority of the patents originating from Japan, USA, South Korea and China, which rank high on the international intellectual property (IP) filling activity list (WIPO, 2020).

The analysis shows that Japan (Count: 1030) has filed by far the most patent applications, making it the dominant country for LSSB technologies, followed by United States (Count: 597), South Korea (Count:408) and China (Count: 290). The high focus of R&D in these countries can be explained by their expertise in LIB production and related operations (Golembiewski et al., 2015) as well as government policies pushing the EV market globally into the mainstream (Kapustin and Grushevenko, 2020). In this context, leading Japanese manufacturers have teamed up with the government in a program to develop SSBs. For example, the consortium, Lithium Ion Battery Technology and Evaluation Center (LIBTEC), aims to set global standards for SSBs by being first to commercialize the technology and to develop an SSB that doubles the

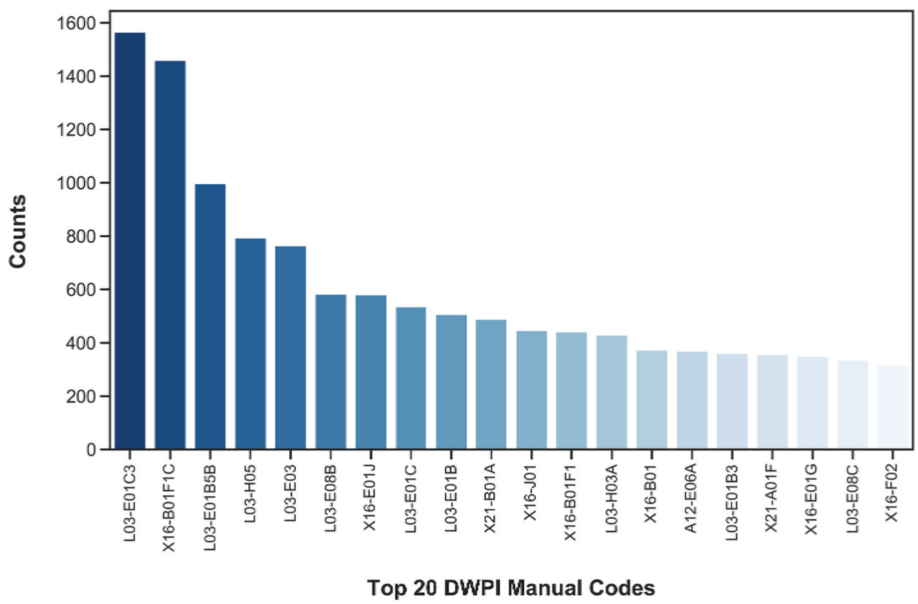

Fig. 6. Distribution of top 20 frequently classification codes (LSSB).

Fig. 7. Geographic distribution of patent families by country of origin (LSSB).

range of EVs from 400 km to 800 km (Bindra, 2020). From a manufacturing perspective, LSSBs can be industrialized in a similar way to conventional LIBs by driving down the processing costs with additional manufacturing competencies regarding the fabrication of a solid electrolyte separator layer and the integration of a lithium metal anode (Schnell et al., 2018).

Next, the patent assignee information was analyzed at the organizational level to gain further insight into patent ownership. Fig. 8 reveals the top 20 patent-holding organizations out of the 715 distinct patent holders operating in the public and private sectors. To clarify patent ownership, we relied on Optimized Assignee, which provides a normalized company name by considering the latest reassignment and company hierarchy.

The results show that Toyota Motor Corporation holds by far the most patents, followed by well-known companies such as Panasonic, Bosch and LG. It is interesting to note that automobile manufacturers, such as Toyota and Hyundai Motor, conventional battery manufacturers, such as Panasonic, LG Chemistry and Samsung Electronics, and hardware manufacturers, such as Murata Manufacturing and IBM, are involved in speeding up the industrial production of LSSBs. This could indicate that knowledge sharing between the automotive, battery, and materials manufacturers is crucial. The relevant actors from LIBs are turning their attention towards the development of LSSBs (Bindra, 2020). Although no established value chain for LSSBs exists to date, the value chain of conventional LIBs may serve as a guide to better coordinate the actions of key players (European Commission, 2021). The relatively high presence of academic institutions, such as Chinese Academy of Science and Ulsan National Institute of Science & Technology, indicates the necessity of collaborative R&D efforts to overcome processing issues for solid composite electrolytes as well as to upscale manufacturing capacities for batteries (European Commission, 2021). As EV makers remain the key drivers behind the development of LSSBs, the overall design of the supply chain for LSSBs could depend on their requirements and the potential to set up an integrated ecosystem around materials, advanced manufacturing, battery engineering and the automotive sectors.

4.2. *Visualization of technological knowledge interaction network*

A co-classification approach was adopted to delve deeper into the underlying technological interrelations of the knowledge areas. The analysis of co-occurring patent classification codes is a useful method for quantifying the strength of knowledge relationships and spillovers (Aaldering and Song, 2019). While the exploitation of citation information (i.e. studying technological follow-up relations among patents) can help trace the knowledge diffusion pattern at an individual patent level (Jiang et al., 2020), the approach adopted here aims to provide a bird's-eye view of the knowledge linkages at a detailed technology level. To this end, the constructed co-occurrence matrix was converted into a network graph object. The resulting knowledge interaction network is outlined in Fig. 9, whereby each node refers to a specific knowledge area and each link indicates the interaction dynamics between a connected pair of technological knowledge areas. To provide a more thorough picture of the knowledge distributions and interaction patterns, the lowest DMC index level was used for representation. This holistic perspective enables a more comprehensive examination of the patterns of knowledge interaction dynamics, and is capable of highlighting interdisciplinary knowledge structures. To highlight the evolving nature of the technological landscape, the analysis period was divided into three equal time intervals (2010–2012; 2013–2015; 2016–2018) to better capture the evolution trend of LSSB innovation. However, due to the high degree of interconnectedness, a threshold-value had to be set to reduce the complexity of network visualization (Note: To obtain a better view on the node connections, readers can download the source file from the journal's website.). A threshold-value of 5% was selected, indicating that only the top 5% of the most frequent interactions are highlighted to keep the complexity to a manageable level. The interaction strength between two knowledge areas is proportional to the edge weight within the network.

The network development for LSSBs over time in Fig. 9 shows that both the number of knowledge areas and the number of interactions increased significantly over time. This observation is supported by the calculated network properties shown in Table 6 and it implies that the knowledge scope and depth of LSSB technologies have continuously expanded. The interaction network was visualized with the Fruchterman-Reingold layout, which is a force-directed algorithm. It positions the more strongly connected sets of nodes together by minimizing the topological distance between them (Fruchterman and Reingold, 1991). Hence, highly connected nodes are clustered close to the center. The decreasing network density over time further indicates that the interaction dynamics are mainly concentrated in a few core knowledge areas and the knowledge does not transmit efficiently across all nodes. Interestingly, the opposite pattern was observed in LIBs (Fig. 10).

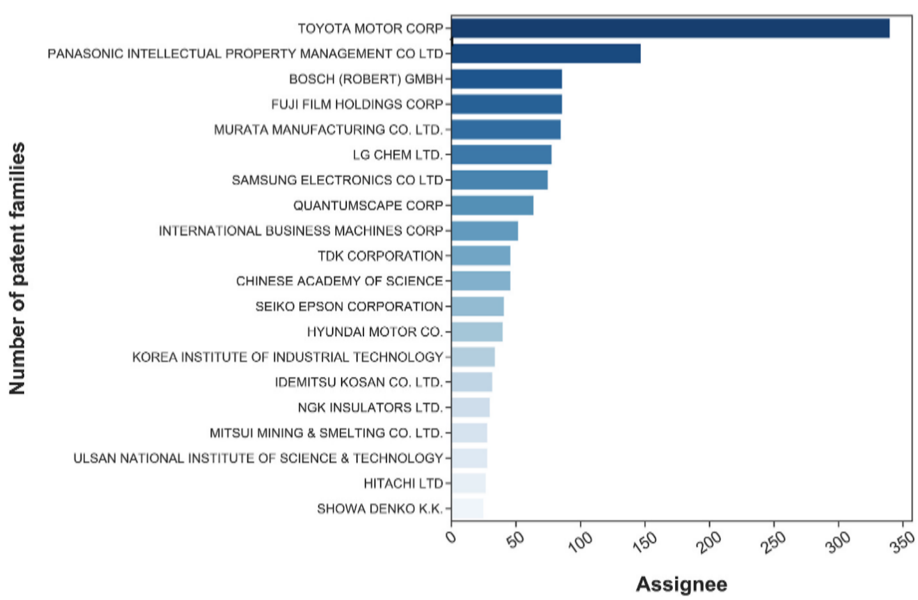

Fig. 8. Distribution of top 20 assignees for LSSB (Optimized assignee).

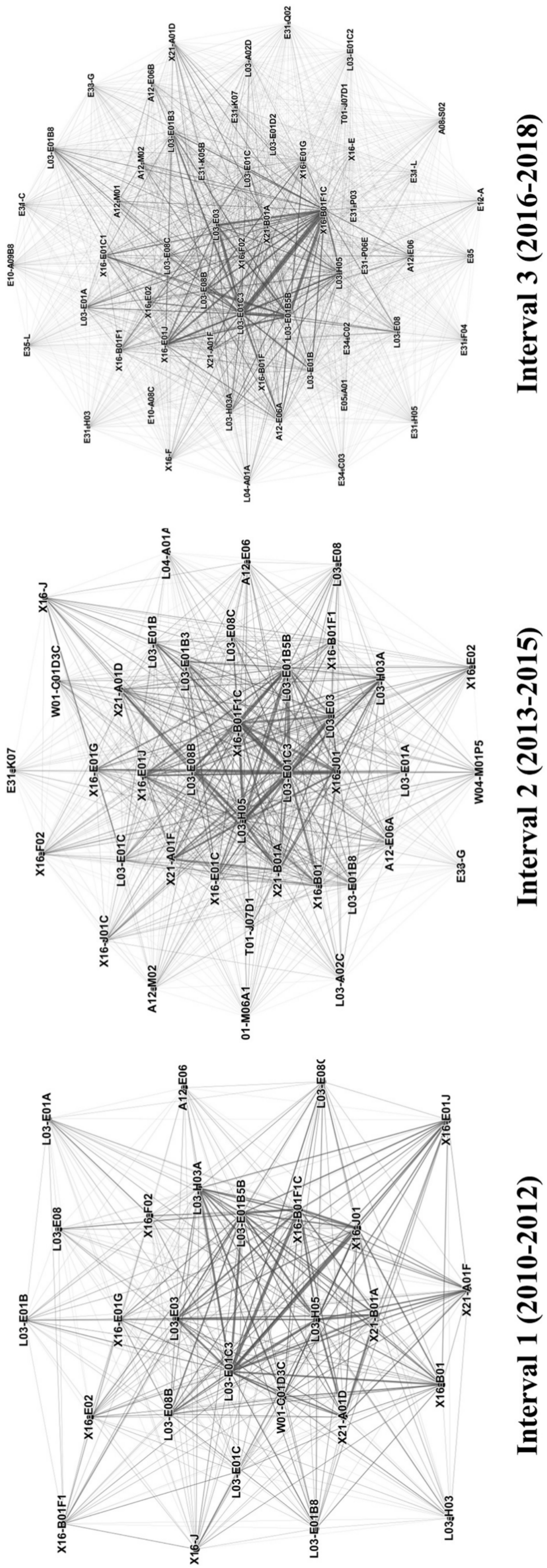

Fig. 9. Network visualization of interacting codes sorted by different time intervals - LSSBs (Threshold-value: 5%).

Table 6
Network properties of LSSB over time.

	Interval 1	Interval 2	Interval 3	All intervals
Number of interacting nodes	532	756	1103	1449
Number of edges	10589	15454	29641	43874
Density	0.0750	0.0541	0.0488	0.0418

The density for LIBs was similar across time intervals despite the increasing number of nodes, indicating that the information flow across knowledge areas is more flexible (Meagher and Rogers, 2004). This also suggests that LIBs represent a more mature technology, in which the degree of knowledge interconnectivity is more critical (Placke et al., 2017). As the development of LSSB is pulled by mobility applications and pushed by large research consortia, the knowledge integration and cross-linking of adjacent technological competencies will remain crucial for their successful uptake. Simultaneously, this growing complexity might cause coordination problems and require appropriate policy measures for shortening the time needed to bring solid-state batteries to market.

Next, a network centrality analysis identified the most influential classification codes in the network. The intervals were aggregated to provide a comprehensive view. The parameters calculated at the node level are called centrality scores, which are measures of a node's importance in the network. A brief overview of the most influential codes is given in Table 7. The centrality scores are sorted by eigenvector centrality. Each centrality score measures a node's importance from each different perspective and helps determine its characteristic role.

We observed that the different centrality measures strongly correlate with each other and thus rank classification codes in a similar manner with a few exceptional cases. Classification codes that have high global importance also play a brokering role in connecting otherwise distinct groups of knowledge areas. As could be expected, the two top-ranked codes are "L03-E01C3" (Solid electrolytes) and "X16-B01F1C" (Lithium-based solid electrolyte). Similar to the observed values in Fig. 6, the application field of "vehicles" had a strong influence on the overall interaction dynamics. Moreover, as solid electrolytes act as a mixed form of electrolyte and separator, there are a substantial number of classification codes related to solid–solid interfaces (Tateyama et al., 2019). The fact that the eigenvector centrality values lie close to each other indicates that the delineated codes in Table 7 are prominent and are mutually well-connected.

When comparing the most influential codes of LSSBs with those of LIBs in Table 8, it becomes evident that there is a similar composition of dominant classification codes. This finding suggests that the advancements of electrolytes and their application in the automobile industry are driving the global R&D efforts. Moreover, the code "X16-B01F1" (Secondary lithium cells) holds a critical position for knowledge diffusion due to its relatively high betweenness centrality score.

4.3. Systematic insights into interaction dynamics

To capture the dynamic aspects of knowledge interactions, we complemented the network visualization with an integrated procedure, which suggests three new metrics. In particular, we focused on revealing promising interaction pairs that showed persistent growth over time and gained notable significance in the latest year of investigation. Subsequently, nine different co-occurrence matrices were constructed for each time point and the corresponding metrics were calculated using Equations (4)–(7). As mentioned in Section 3.3, a threshold-value was assigned to filter out only the emerging signals. In case of the growth metric, the outcome must be a positive value. The persistence metric was checked as being present if there was a consistent interaction pattern from the year 2013–2018 (e.g. the last six years of the total study period). The threshold for the novelty metric was set to 25%, implying

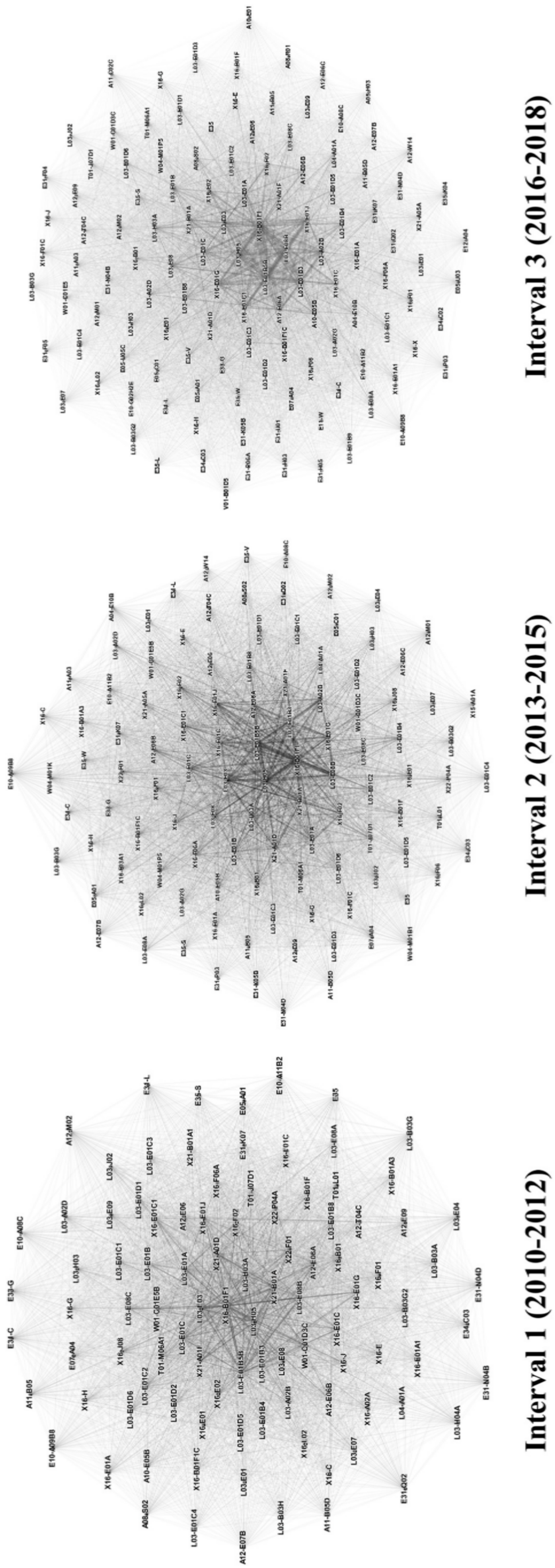

Fig. 10. Network visualization of interacting codes sorted by different time intervals - LIBs (Threshold-value: 5%).

Table 7
Selected summary of calculated network centrality metrics for LSSB (sorted by eigenvector centrality).

Derwent Manual Codes	Eigenvector centrality	Closeness centrality	Betweenness centrality	Rank
L03-E01C3	0.134	0.768	0.105	1
X16-B01F1C	0.133	0.754	0.098	2
L03-H05	0.125	0.692	0.049	3
L03-E01B5B	0.124	0.693	0.050	4
L03-E03	0.120	0.673	0.039	5
L03-E01B	0.112	0.656	0.041	6
L03-H03A	0.111	0.636	0.023	7
X16-E01J	0.108	0.630	0.020	8
X21-B01A	0.107	0.616	0.013	9
A12-E06A	0.106	0.622	0.017	10
X16-F02	0.106	0.630	0.024	11
L03-E08B	0.105	0.620	0.016	12
L03-E01C	0.104	0.626	0.028	13
X16-B01F1	0.103	0.632	0.041	14
A12-E06	0.103	0.623	0.027	15
L03-E01A	0.100	0.613	0.019	16
L03-E08C	0.100	0.615	0.021	17
X21-A01F	0.096	0.594	0.009	18
L03-E08	0.096	0.607	0.020	19
X16-J01	0.094	0.600	0.013	20

Table 8
Selected summary of calculated network centrality metrics for LIB (sorted by eigenvector centrality).

Derwent Manual Codes	Eigenvector centrality	Closeness centrality	Betweenness centrality	Rank
X16-B01F1	0.088	0.838	0.200	1
L03-H05	0.084	0.724	0.056	2
L03-E01B5B	0.082	0.695	0.039	3
L03-E03	0.078	0.649	0.020	4
L03-E08B	0.078	0.651	0.020	5
A12-E06A	0.077	0.642	0.017	6
L03-E08	0.077	0.651	0.024	7
L03-E01A	0.076	0.636	0.017	8
L03-E01C	0.075	0.630	0.018	9
L03-E01B3	0.075	0.633	0.014	10
X16-F02	0.075	0.635	0.019	11
L03-E01B	0.074	0.631	0.018	12
A12-E06	0.073	0.625	0.023	13
X16-E01J	0.073	0.617	0.010	14
X16-B01	0.073	0.643	0.046	15
L03-H03A	0.072	0.620	0.012	16
X21-B01A	0.072	0.624	0.015	17
L03-E08C	0.072	0.614	0.013	18
X16-E01G	0.071	0.621	0.016	19
X21-A01F	0.071	0.620	0.018	20

that at least 25% of the proportional interaction frequency must fall in the year 2018. In this manner, more weight can be assigned to the latest technology. Hence, interacting pairs with a high novelty score can be interpreted as important contributors to subsequent technological development patterns. In Table 9, the top 20 promising interacting pairs are listed according to the calculated metrics. In total, there were 43883 distinct unique interactions. The interactions deserving specific attention were highlighted with a bluish background color. The most promising relationships were finally ranked by the growth metric.

Overall, the significance of solid electrolytes in the development of LSSBs is confirmed by the fact that "L03-E01C3" (Solid electrolytes) and "X16-B01F1C" (Lithium-based solid electrolyte) are involved in almost every interaction. Achieving electrode–electrolyte interface stability on solid-state batteries is a major challenge to enhance the cell performance (Zahiri et al., 2021). Further advancements in electrolyte materials are crucial because an uneven charge distribution at the interface of the electrolyte and electrode can still cause lithium metal dendrite issues (Cao et al., 2020). Moreover, their relationships to "X12-D01C" (Carbon,

Table 9
Selected summary of calculated metrics for LSSBs (sorted by Growth).

Interacting pairs		Growth	Persistence	Novelty [%]
L03-E01C3	X12-D01C	0.0692	Yes	29.17
X12-D01C	X16-B01F1C	0.0659	Yes	30.14
L03-E03	X12-D01C	0.0527	Yes	32.20
X12-D01C	X16-E01J	0.0494	Yes	37.68
L03-E01B5B	X12-D01C	0.0461	Yes	37.85
E12-A	L03-E01C3	0.0379	Yes	31.18
A12-E06B	A12-M02	0.0297	Yes	27.97
E31-K07	X16-B01F1C	0.0281	Yes	26.31
L03-E01B	X16-E02	0.0264	Yes	26.83
E35-L	X16-B01F1C	0.0264	Yes	28.39
A12-E06B	A12-M01	0.0247	Yes	32.01
E31-K07	L03-E01B	0.0214	Yes	32.86
E35-V	L03-E01C3	0.0165	Yes	34.59
A12-M01	L03-E01B8	0.0165	Yes	28.58
E31-P06E	X16-B01F1C	0.0157	Yes	30.48
E35-W	X16-B01F1C	0.0148	Yes	33.19
E35-W	L03-E01C3	0.0132	Yes	29.73
E33-G	L03-E01B	0.0132	Yes	28.40
E31-Q08	X16-B01F1C	0.0132	Yes	30.61
L03-E08	X16-E01C1	0.0124	Yes	25.05

silicon, or other nonmetallic material; conductive polymers) and "E31-Q08" (Other Boron compound) point to the usage of chemical compounds that are highly ionic conductive, chemically inert and mechanically robust to stabilize the electrode-electrolyte interphase. This can enhance the performance as well as the lifetime of the battery (Cheng et al., 2019; Song et al., 2016). On the other hand, their interaction with "E35-W" (Nickel (Ni) compound) could be indicative of the interface problems between a solid electrolyte and a nickel containing cathode, which also plays a crucial role in the performance of the battery (Zahiri et al., 2021; Zhao et al., 2018). Furthermore, solid electrolyte containing chemical compounds, such as "E35-L" (Zirconium (Zr), hafnium (Hf) compound), could represent promising electrolyte materials as they help achieve a better compromise between ionic conductivity and stability (Murphy et al., 2020).

The calculated metrics for LIBs are shown in Table 10. From this comparison, it is evident that these two distinct battery chemistries also differed significantly in knowledge interaction patterns. While LSSBs have a strong focus on understanding the impacts of solid electrolyte interphase composition and stability, the R&D focus of LIBs lies predominantly on electrodes. This finding shows that both battery technologies have different key components to optimize and therefore have adopted distinct development trajectories. Moreover, the knowledge areas of "E11-W" (Environmentally friendly inventions (compositions/applications)) and "A12-W11" (Chemical engineering, pollution control) show that LIBs have a stronger engagement with the topic of sustainability, which is particularly required in the electric vehicles automotive industry. This might be because LIBs are a more mature technology compared to LSSBs and try to foster incremental innovation by converging with neighboring knowledge disciplines.

Table 10
Selected summary of calculated metrics for LIBs (sorted by Growth).

Interacting pairs		Growth	Persistence	Novelty
X16-E01C1	X16-E01J	0.0954	Yes	27.32
L03-E01B4	X16-E01C1	0.0485	Yes	25.91
A10-E05B	X16-E01J	0.0434	Yes	27.13
L03-A02G	X16-B01F1	0.0339	Yes	26.04
L03-A02G	X16-E01J	0.025	Yes	25.64
A10-E05B	X16-E01C1	0.024	Yes	28.14
X16-B01F1C	X16-E01J	0.0233	Yes	25.56
A12-E06A	X16-B01F1C	0.0216	Yes	27.35
E35-V	X16-E01C1	0.0157	Yes	27.93
E11-W	X16-B01F1	0.0155	Yes	37.22
A12-M02	X16-B01F1C	0.0155	Yes	27.08
A04-D05A	X16-B01F1	0.0139	Yes	29.27
E05-U05C	X16-B01F1	0.0136	Yes	25.07
A12-E06B	L03-E01C3	0.013	Yes	27.34
E35-W	X16-E01C1	0.0128	Yes	26.38
A12-W11	X16-B01F1	0.0128	Yes	33.89
A04-E08	X16-B01F1	0.0125	Yes	30.65
X16-B01F1	X16-F	0.0123	Yes	52.84
A12-W14	L03-E01B3	0.0123	Yes	26.38
A04-D05A	A12-E06A	0.0118	Yes	27.22

4.4. Distance analysis

The distance-based measure can help investigate whether specific knowledge areas have become more similar over time. In this study, the distance is calculated pairwise among all vector elements within the co-occurrence matrix using the Tanimoto coefficient. By quantifying the distance, it is possible to make further statements about the technological environment and visually communicate the vacant technology development opportunities. In general, the knowledge areas are assumed to have a smaller distance when they are in similar environments and a larger distance when they are in dissimilar environments. To provide an alternative view on analysis of technological development trends, the distance values are computed using the top 50 most prominent knowledge areas. The distances were calculated for three equally spaced time intervals (2010–2012; 2013–2015; 2016–2018) to characterize the dynamic pattern of knowledge relatedness. Based on the dynamic view of the distance measurement, the distance map for each time interval was outlined in Figs. 11–13. In the heat map visualization, the color intensity corresponds to the proximity or closeness of two knowledge areas. The darker the color, the shorter the distance between two areas. The probability of knowledge spillover can be assumed to be higher when two distinct knowledge areas are closer to each other.

Closer inspection shows that the R&D focus has shifted gradually. Although the overall proximity seems to have decreased over time, each interval has its own characteristic features. For example, while the "X16-F" (Constructional details of cells or batteries) had a relatively high distance to other knowledge areas until the second interval, its proximity to "L04-A01A" (Silicon) has decreased drastically in the last interval. This reflects the current research on silicon anodes, which are regarded as a promising material having a high volumetric energy density and invulnerability to dendrite formation (Cangaz et al., 2020). Another example is the decreased distance between "X16-E01C1" (Electrode material -Oxides) and "X16-E01G" (Manufacturing of electrode active material). This shift is in line with the observation that LSSB production based on oxide solid electrolytes is regarded as a promising candidate, and further studies in scaling-up their fabrication are deemed necessary (Schnell et al., 2018, 2019). On the contrary, "L03-H03" (Electric communications techniques) has increased its proximity to most of its neighboring knowledge areas in the last interval. This might be because recent research efforts are more geared towards application in the automotive sector as sustainable transportation based on electric vehicles has a high policy priority (Qiu et al., 2019).

Table 11 summarizes the interacting knowledge pairs that most continuously decreased their distance over the examined intervals. The decreased distance could indicate that there is a synergistic effect of knowledge spillover between the interacting knowledge areas. Overall, "X16-F" (Constructional details of cells or batteries) is present in almost every interaction pair outlined in Table 11. The application of a solid-state electrolyte that is roughly as conductive as a liquid but resists dendrite formation can address a number of limitations inherent to conventional LIBs. However, the R&D community has not yet found suitable materials capable of meeting these requirements. Hence, many classes of electrolyte/separator materials have been tested. This trend is reflected in the extensive research efforts directed at finding a dendrite-free design for solid-state batteries (Boaretto et al., 2021) The strongest decline in distance occurred between "L04-A01A" and "X16-F", followed by "X16-E01C", "W01-C01D3C" (Portable; hand-held mobile phone)

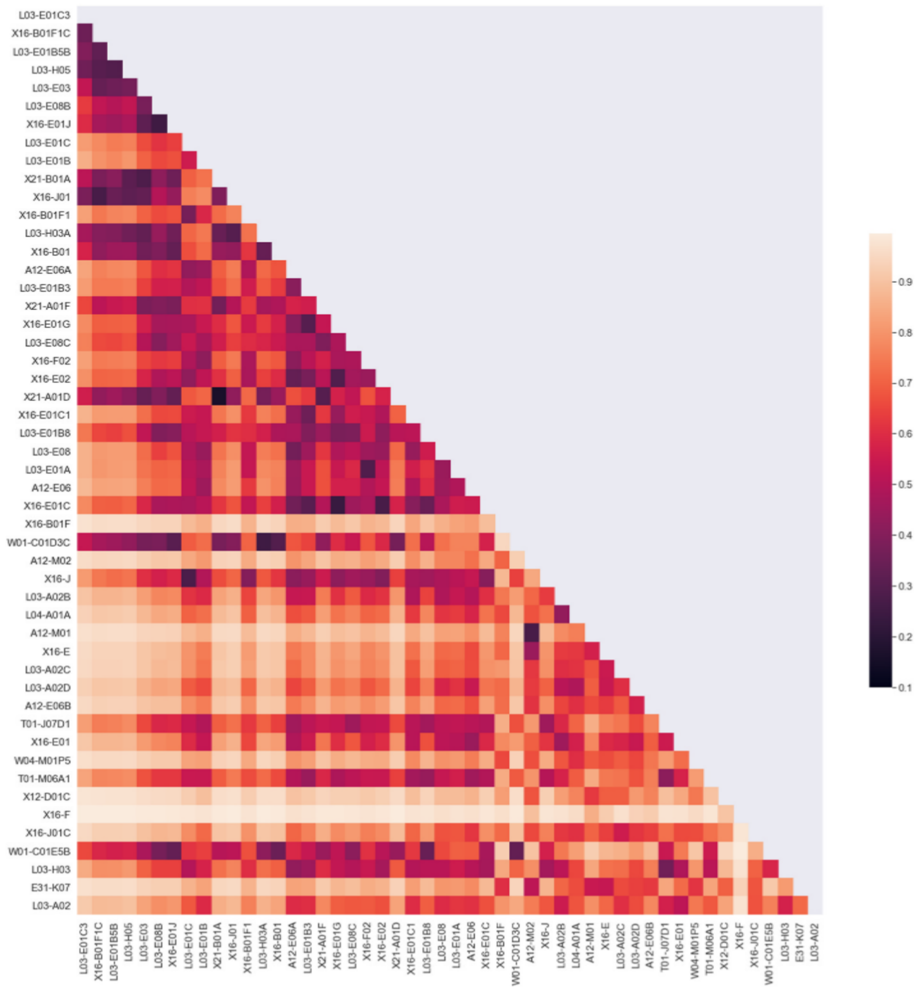

Fig. 11. Distance map among the top 50 most occurring knowledge areas. (Interval 2010–2012).

and "X21-A01D" (Hybrid vehicle). These findings could indicate the expansion of LSSBs adaptability to power portable electronic devices. Hence, it is necessary to cross the traditional knowledge boundaries to accelerate the commercial breakthrough of LSSBs and engage in value chain coordination at an early stage.

In the case of LIBs, a different interaction trend was observed (Note: The corresponding figures and values can be found in Appendix A-2, A-3, A-4 and A-5.). For example, the distance between "A10-E05B" (Chemical modification by carbonization) and "X16-E01C" (Electrode material - Oxides) has reduced the most. This interaction might show the recent research efforts to develop porous carbon membranes that can be integrated into high-value electrode materials without severe volume expansion during intercalation (W. Shen et al., 2019). Moreover, "L03-H03A" (Data storage units, computers) and "L03-H05" (Vehicles) have also significantly reduced their distances. This further supports the findings from the previous sections that vehicles and large-scale energy storage systems are the main application fields of LIBs and drive their technological advancements. On the contrary, "X16-J" (Electrolytes) has increased its distance to most of its interacting neighbors, thereby being less significant for the innovation of LIBs. This further strengthens the growing importance of solid-state electrolytes and batteries in changing the battery production landscape (Wang et al., 2021).

5. Conclusion

As our society moves towards a low-carbon economy, secure and high-performing energy storage systems become more important for meeting the increasing demands from large-scale application markets and decarbonizing the electricity supply. A rapid advancement in battery technology will play a major role not only in clean energy transitions but also in accelerating EV deployment. Although the currently commercialized LIBs have allowed EVs to enter the market, LSSB technologies show great promise in accelerating the transition to electric mobility (Albertus et al., 2021). Despite the significance of this issue, there has been no research systematically investigating the underlying technological development trajectory of LSSB and the proximity between interacting knowledge areas. This study analyzed and highlighted the patent landscape of LSSBs and compared their technology profile against that of LIBs by proposing a novel analysis framework. After reviewing the descriptive statistics of the collected patent data, a modified co-classification approach was applied to quantify knowledge interactions and detect emerging interaction trends by quantifying significant changes in interaction rates. In particular, three novel metrics were introduced with the aim of highlighting promising relations that might serve as innovation drivers. Furthermore, this study introduced a distance map, which visualizes the relatedness of knowledge areas. By comparing the technology development of LSSBs with LIBs, this study was able to reveal their distinct development paths and driving forces. Hence, the proposed approach can further contribute to enhanced policy planning and help R&D managers optimize their portfolio mix through an increased awareness of patent intelligence. The main line of this research is based on the provision of combined static and dynamic perspectives to investigate the technological development trends in solid-state battery research. In particular, this research extended 1) the

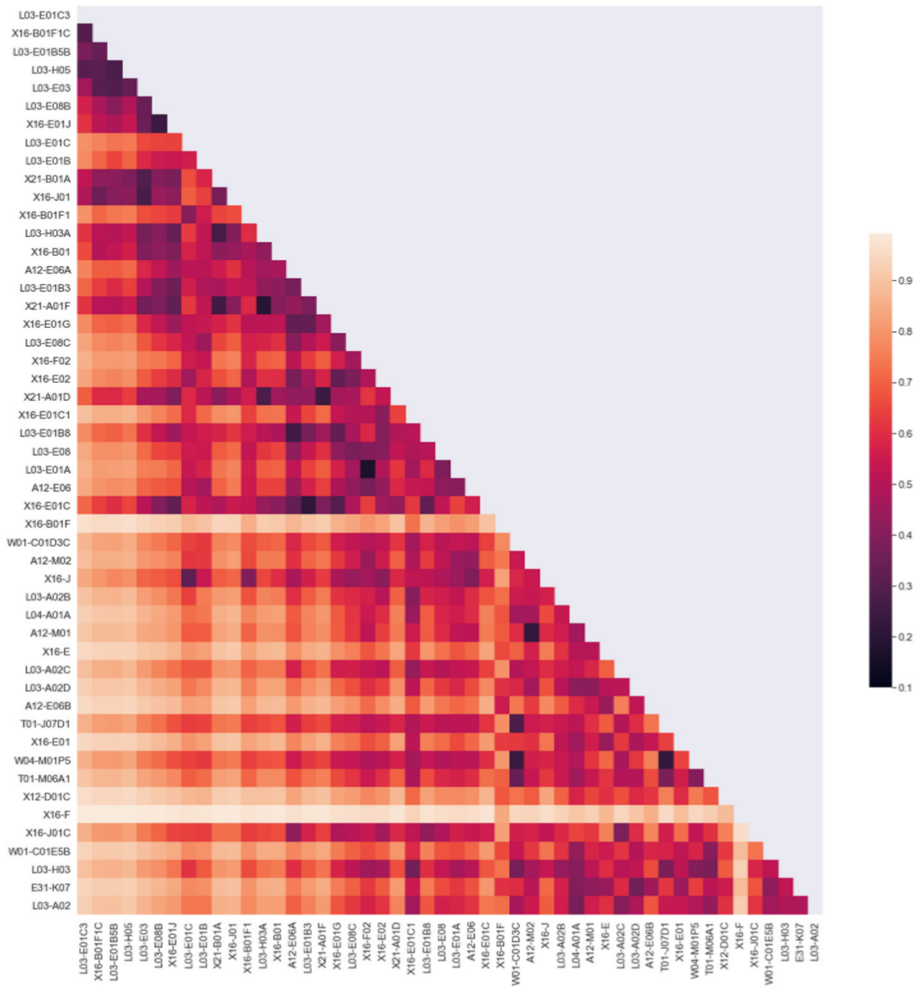

Fig. 12. Distance map among the top 50 most occurring knowledge areas. (Interval 2013–2015).

conventional co-occurrence approach by introducing new quantifiable metrics for assessing interaction dynamics and 2) revealed the usefulness of including indirect interactions by adopting distance-based measurements. The following paragraph pinpoints the individual contributions in more detail. This study is characterized by following theoretical and managerial contributions.

With regard to its theoretical contributions, this study extends the currently available methods for patent analysis by introducing a novel framework. The novel analysis framework combines several data-driven analytical methods to transform complex patent data into high value map representations. Thus, the ongoing advancements of considered battery technologies can be comprehensively quantified and visualized. Secondly, we responded to the call for the development of a dynamic perspective to detect relationships that could become more relevant in the future by introducing novel metrics (Feng et al., 2020). The introduced metrics allowed evaluation of knowledge interactions according to emerging trend characteristics, whereby a threshold value can be set to filter out the most relevant interactions. These metrics can help strengthen the interpretability of emerging interactions. Moreover, this study was able to broaden the view of emerging trends between knowledge areas of LSSBs and LIBs by considering both direct and indirect interaction dynamics. The distance measurement can provide an alternative quantifiable perspective on how to shape the ecosystem structure based on data-driven insights. Lastly, this study extended the limited literature on the analysis of next-generation energy storage system based on patent mining.

In terms of managerial implications, this work contributed to promoting the overall transparency of the technological landscape of battery research. The insights derived from this study can become a valuable point of reference for R&D managers and policy makers designing competitive strategic initiatives to help accelerate the transition of solid-state batteries from the lab to the market, and link different industrial disciplines to maximize cross-sectoral learning. Simultaneously, research scientists can use the distance map as a guideline to coordinate their research efforts and patenting behavior.

Despite its contributions, this study is not without limitations. First, the findings should be interpreted with caution, as they are largely dependent on the scope and depth provided by the patent data used. Hence, this study should be viewed as a complement to previous qualitative analyses to support the decision making of research scientists and R&D managers. To remedy this, future research could combine additional industry data sources to gain a more comprehensive picture of the technological landscape. Second, the robustness of the newly proposed metrics should be tested using additional case data. To validate its usefulness, the proposed framework can be applied to non-lithium based or non-electrical energy storage systems. Third, the changing knowledge dynamics could be captured along and across battery value chain steps to monitor potential shifts in value creation activities. Hence, systems thinking in value chain might lead to improved outcomes and help judge the strengths, opportunities, challenges and risks presented in a collaborative research environment. Moreover, this study made use of data derived from a commercial database, which is not publicly accessible. This could make the replication of the data creation step difficult. Furthermore, the collected data might not fully reflect the patent

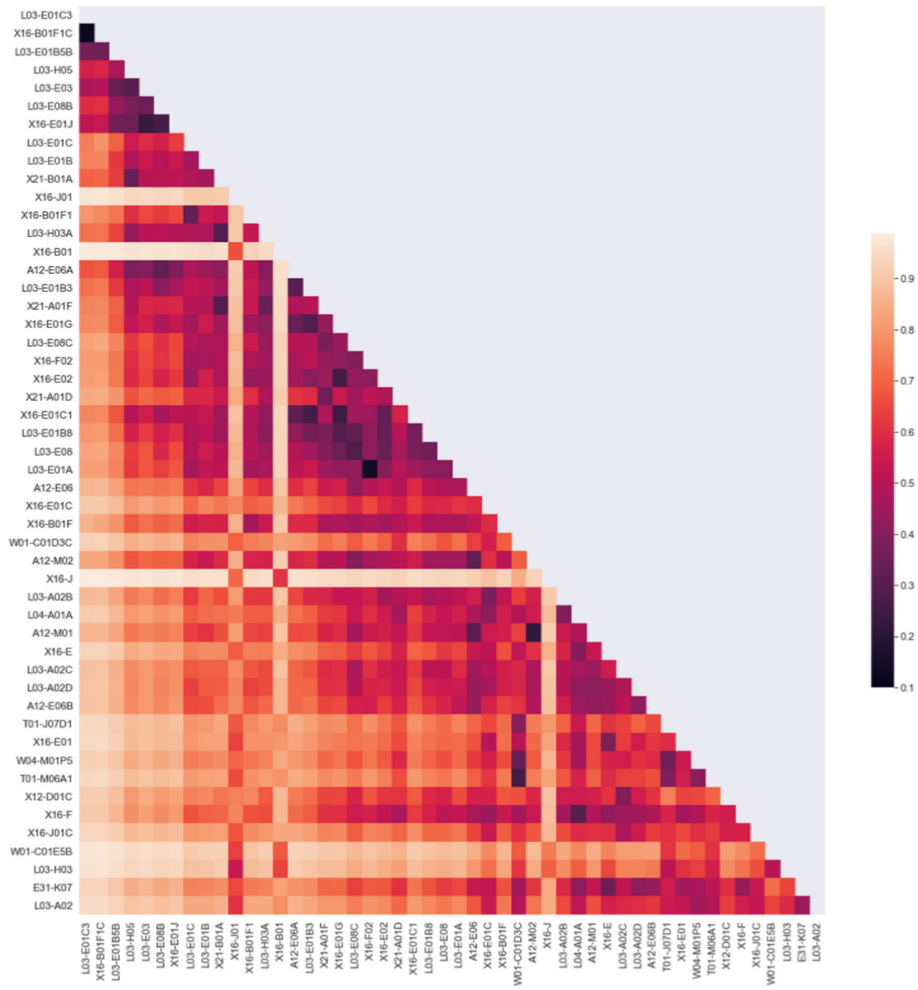

Fig. 13. Distance map among the top 50 most occurring knowledge areas. (Interval 2016–2018).

Table 11
Top 20 continuously distance-decreasing knowledge interaction pairs (LSSBs).

Interacting knowledge pairs		Amount of change in distance
L04-A01A	X16-F	−0.653
W04-M01P5	W01-C01D3C	−0.600
X16-F	X16-E01C	−0.539
X16-F	W01-C01D3C	−0.523
X21-A01D	X16-F	−0.522
X16-F	L03-A02B	−0.509
X16-F	X16-E01	−0.507
X16-F	L03-A02C	−0.504
E31-K07	X16-F	−0.501
X16-E	X16-F	−0.495
A12-E06	X16-F	−0.491
L03-A02D	X16-F	−0.481
W01-C01D3C	E31-K07	−0.477
A12-E06	A12-M01	−0.475
L03-E08C	A12-M02	−0.467
W04-M01P5	X16-F	−0.466
X16-E02	X16-F	−0.457
W04-M01P5	T01-J07D1	−0.454
X16-F	L03-E08	−0.447
A12-E06	X16-F	−0.446

landscape of examined technologies due to the chosen search strategy. Hence, the search strategy could be extended by assigning keywords for a more precise definition of the technology domains (Moehrle and Caferoglu, 2019). The search for appropriate keywords can be accompanied by a manual review of the patents to ensure that novel technical terms are included. To get a more comprehensive view of the technological landscape, the original input data could be extended with publications data. However, this step requires an in-depth understanding on how to merge those two different data sets as publication data do not come with a hierarchical classification scheme. Lastly, future research could consider integrating text mining to extend the research toolkit as well as to uncover the primary topics related to selected technology components from the claims of the patents.

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CRediT authorship contribution statement

Anton Block: Conceptualization, Methodology, Visualization, Software, Investigation, Project administration, Writing – original draft. **Chie Hoon Song:** Conceptualization, Methodology, Investigation, Supervision, Project administration, Writing – review & editing.

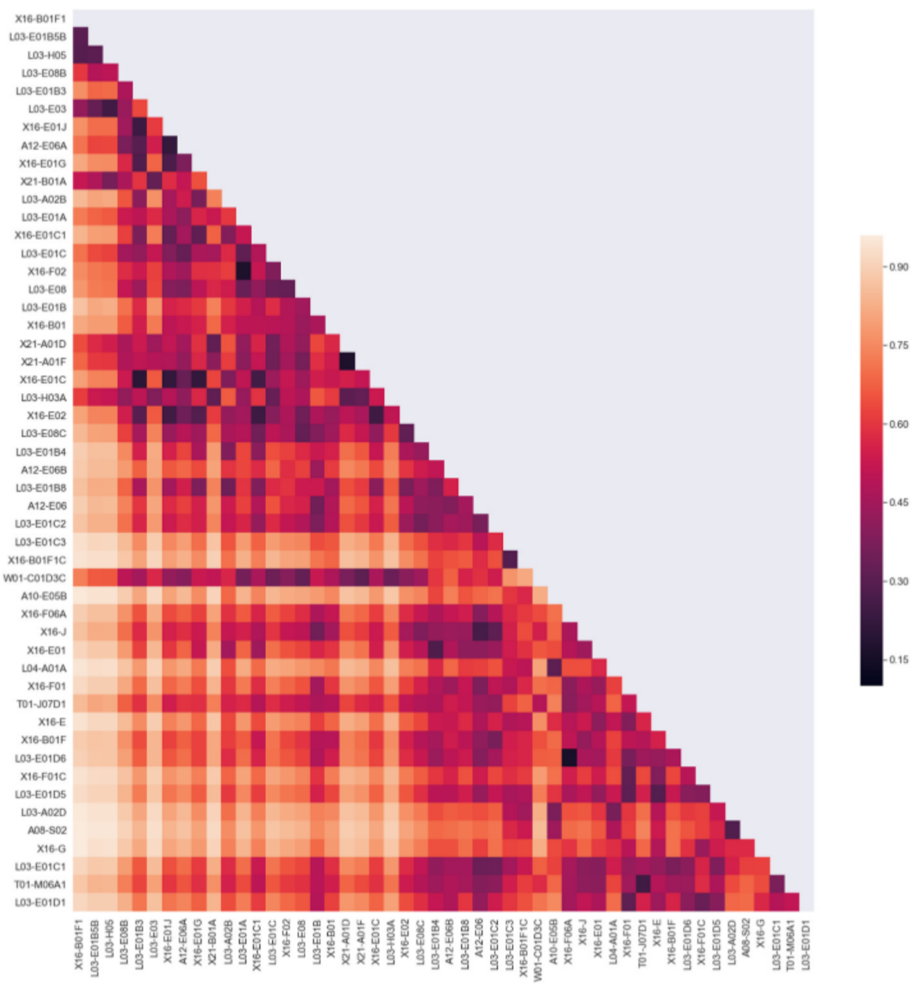
Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

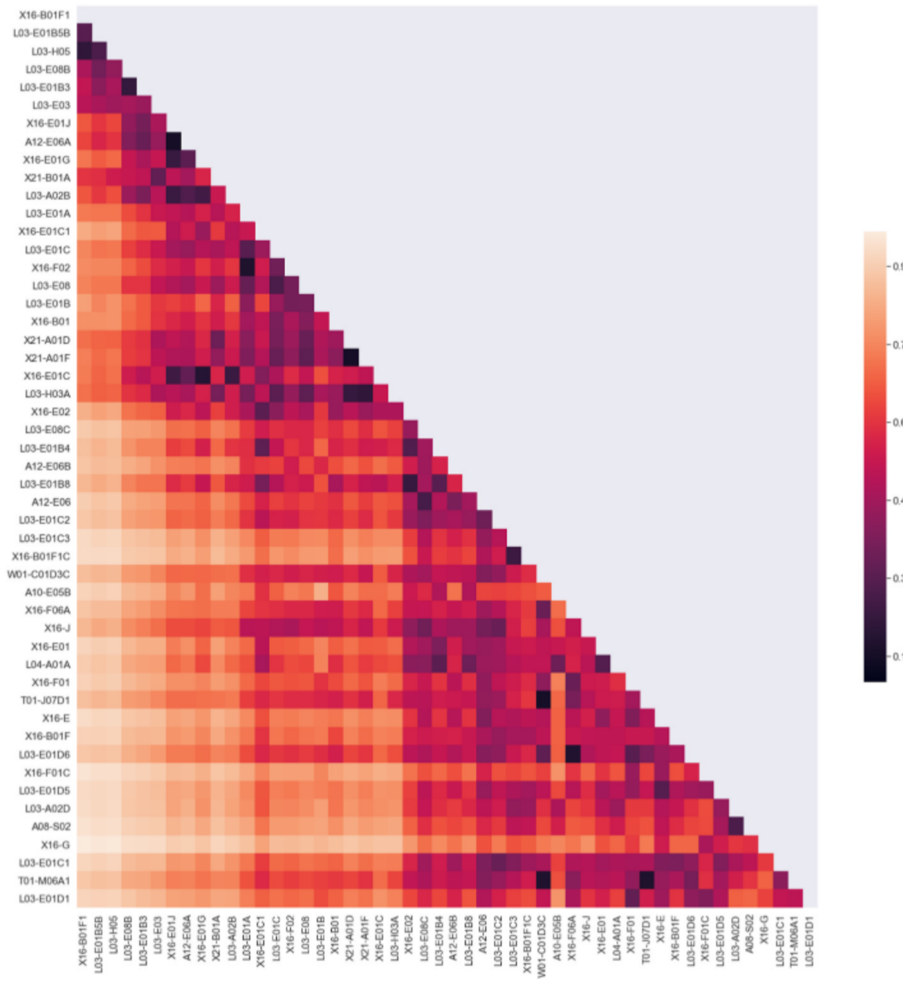
Appendix

Appendix A-1
Network properties of LIB over time.

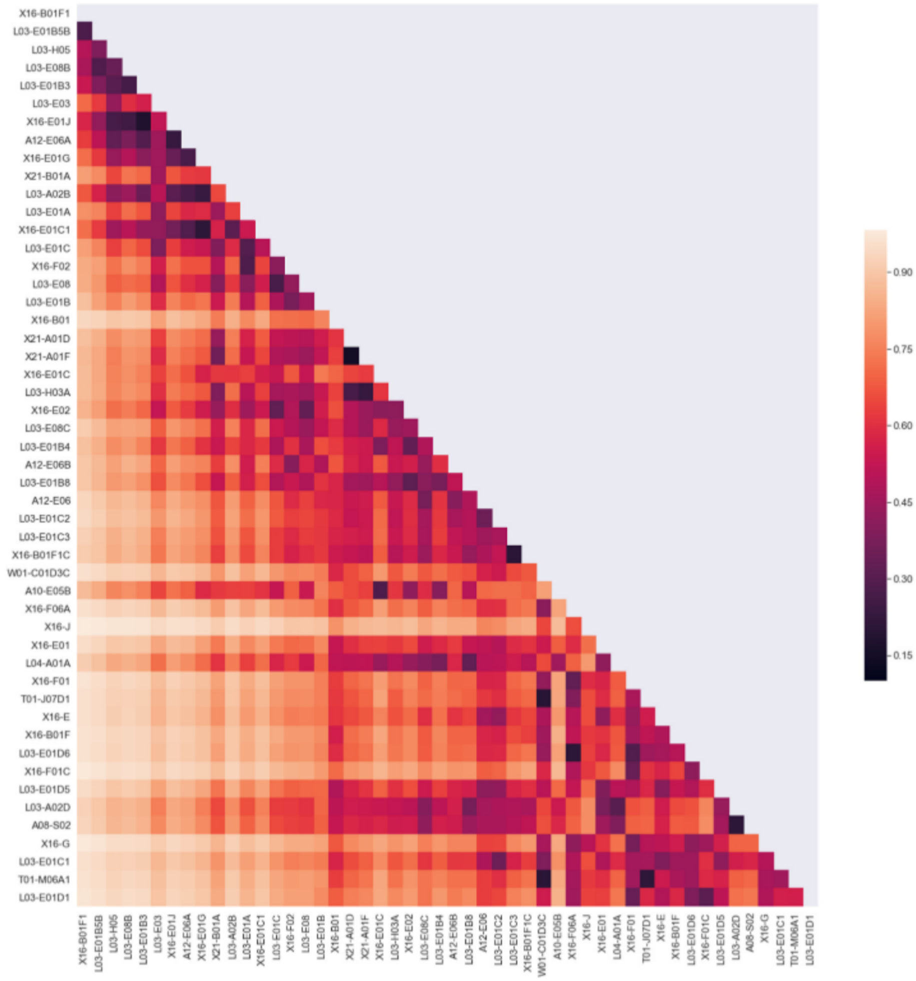
	Interval 1	Interval 2	Interval 3	All intervals
Number of interacting nodes	3201	3551	4048	5567
Number of edges	124554	160921	203238	337778
Density	0.0240	0.0260	0.0250	0.0220



Appendix A-2. Distance map among the top 50 most occurring knowledge areas for LIBs (Interval 2010–2012).



Appendix A-3. Distance map among the top 50 most occurring knowledge areas for LIBs. (Interval 2013–2015).



Appendix A-4. Distance map among the top 50 most occurring knowledge areas for LIBs. (Interval 2016–2018).

Appendix A-5
Top 20 continuously distance-decreasing knowledge interaction pairs (LIBs).

Interacting knowledge pairs		Amount of change in distance
A10-E05B	X16-E01C	−0.496
L03-H05	X16-E01J	−0.433
L03-A02B	L03-H05	−0.402
L03-H05	L03-E01B3	−0.393
T01-M06A1	W01-C01D3C	−0.377
L03-H03A	X16-B01F1C	−0.371
L03-H03A	L04-A01A	−0.368
X16-G	W01-C01D3C	−0.357
L03-A02D	L03-H03A	−0.352
L03-H03A	A08-S02	−0.352
L03-E08C	A08-S02	−0.346
X16-E02	A10-E05B	−0.344
X21-A01D	L04-A01A	−0.337
X16-E01C1	L03-H05	−0.336
X21-A01F	X16-B01F1C	−0.333
X16-B01F1C	X21-A01D	−0.331
X21-A01D	L03-A02D	−0.318
L03-A02D	L03-E08C	−0.317
X16-E01G	L03-H05	−0.316
L03-E01C	A10-E05B	−0.311

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.131689.

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