Identifying Vibrant Actors in Technology Development Through Their R&D Activity and Persistence

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Abstract

Identifying vibrant actors in technological development is crucial for understanding innovation ecosystems and driving sustained advancements across industries. While traditional methods for identifying key contributors often focus on quantitative metrics such as patent counts and citation frequencies, they may overlook the persistence of R&D efforts—a critical factor in evaluating longterm technological impact. This study proposes a novel framework that incorporates both activity and continuity indicators to assess the sustained contributions of key actors in technology development. By applying a sliding window approach over a three-year period, this framework enables the identification of vibrant assignees who demonstrate consistent and impactful R&D engagement. The empirical analysis focuses on solid-state electrolyte technology for lithium batteries, a rapidly evolving field crucial to energy storage innovations. The study analyzed patent data from the United States Patent and Trademark Office (USPTO) from 2002 to 2021, identifying 981 relevant patents attributed to 223 assignees. The results reveal that while some assignees exhibit high patent counts, only a subset demonstrate persistent innovation over time, as captured through the proposed continuity index. Vibrant assignees, such as Samsung Electronics and LG Energy Solution, maintain consistently high continuity values, highlighting their strategic commitment to technological progress. In contrast, several non-vibrant assignees, despite holding substantial patent portfolios, lack sustained contributions, emphasizing the need to consider persistence in addition to patent volume when evaluating influence within an innovation ecosystem. The study's findings have significant implications for policymakers, industry stakeholders, and academic institutions, offering a more comprehensive approach to tracking and fostering technological leadership. Moreover, the proposed framework can be extended to various industries beyond energy storage, such as artificial intelligence and biotechnology, to analyze vibrant actors across different technological domains. Additionally, future research can apply this methodology to academic research institutions by analyzing journal publication data to evaluate the sustained contributions of universities and research organizations. Furthermore, the approach can be refined to assess individual inventors and authors, providing insights into their long-term impact and influence in their respective fields. In conclusion, this study advances the understanding of technological development by emphasizing the importance of persistence in R&D efforts. The proposed framework offers a robust tool for identifying vibrant actors, enabling more strategic resource allocation and fostering sustainable innovation in both industrial and academic settings.

Introduction

Understanding the key actors in technological development and R&D processes across various industries is crucial for deciphering the dynamics of innovation ecosystems. These actors serve as pivotal drivers of technological advancements, shaping industry trajectories and contributing to economic growth. Accurately identifying such contributors provides essential insights that inform policy decisions, guide investment strategies, and foster strategic collaborations among stakeholders. The identification of these key contributors is not only pertinent to academic research but also has practical implications for business strategies, government policies, and industry innovation planning (Valkokari et al., 2016).

Existing Approaches to Identifying Key Actors

A variety of methodologies have been employed to identify key actors within technology development processes, with patentometrics emerging as a particularly prominent approach. Valkokari et al. (2016) employed a design science framework to analyze the interactions between actors, resources, and activities within innovation ecosystems. Their study underscored the multifaceted roles that stakeholders play in driving innovation and highlighted the importance of coordinated efforts among diverse entities.

Dolphin and Pollitt (2020) advanced this field by applying machine learning techniques to UK patent data, enabling the identification of innovative entities within the electricity supply industry. Additionally, numerous studies have leveraged metrics such as patent citations, co-patenting networks, and technological classifications to delineate the ecosystem of influential R&D performers (Cohen, Fernandes, & Godinho, 2024). These approaches have significantly enhanced our understanding of the structural and collaborative dimensions of innovation ecosystems.

While these methods have provided valuable insights, they often rely heavily on quantitative indicators such as patent counts and citation frequencies, which capture only a snapshot of innovative activity. Such methods may overlook the critical element of persistence—an actor's sustained contributions over time—which is essential for assessing their true influence and long-term role in technological development.

Research Gap: The Importance of Persistence in R&D

Despite the advances in identifying key actors, a significant gap remains in the current methodologies: the insufficient emphasis on the persistence of R&D output. Innovation is not solely characterized by sporadic contributions or singular breakthroughs; rather, it requires continuous effort, adaptability, and sustained impact over time. Many traditional approaches fail to consider this longitudinal dimension, which is crucial for recognizing vibrant actors who actively and persistently shape technological landscapes (Cohen, Fernandes, & Godinho, 2024). For example, reliance on patent counts may undervalue actors who produce fewer patents but contribute disproportionately to breakthrough innovations or foundational technologies (Griliches, 1990). Similarly, citation-based metrics, while

indicative of influence, may not capture the durability and continuity of an actor's contributions (Narin, Noma, & Perry, 1987; Fleming & Sorenson, 2004). Without incorporating persistence into the analysis, existing methods risk overlooking key players who are instrumental in sustaining technological progress over extended periods (Breschi, Malerba, & Orsenigo, 2000).

Objectives and Contribution of This Study

This study aims to address the identified gap by incorporating the persistence of R&D output as a critical factor in identifying vibrant actors in technological development. By evaluating not only the quantity and immediate impact of R&D contributions but also their consistency over time, we seek to establish a more comprehensive framework for assessing influence within innovation ecosystems (Cohen, Fernandes, & Godinho, 2024).

Our approach integrates traditional patentometric methods with novel metrics designed to capture the longitudinal dimension of R&D activity. This combination allows for a more nuanced understanding of innovation ecosystems, identifying actors who consistently contribute to technological advancements and are likely to continue driving innovation in the future (Narin, Noma, & Perry, 1987).

In doing so, this study offers both theoretical and practical contributions. Theoretically, it enriches the literature on innovation ecosystems by highlighting the importance of persistence as a determinant of influence (Griliches, 1990; Fleming & Sorenson, 2004). Practically, it provides policymakers, industry leaders, and academic researchers with a robust tool for identifying key contributors, enabling more informed decisions regarding resource allocation, collaboration opportunities, and strategic investments (Breschi, Malerba, & Orsenigo, 2000).

Literature Review

Technology Development Dominated by Few Actors

Technology development across various industries is often driven by a limited number of key actors who play a crucial role in advancing innovation and shaping industry trends. Studies have shown that a small number of firms hold a significant share of patents in specific technological sectors, underscoring their pivotal influence on technological progress (Cohen, Fernandes, & Godinho, 2024). Notably, multinational corporations such as IBM, Samsung, and Siemens are frequently cited as leading innovators in their respective fields. The concentration of technological expertise within these dominant players highlights the importance of accurately identifying and analyzing their contributions to better understand the dynamics of innovation ecosystems (Valkokari, Amitrano, Bifulco, & Valjakka, 2016).

The dominance of a few key actors has significant implications for industry structure and competition. Breschi, Malerba, and Orsenigo (2000) found that a handful of firms control the majority of patents in the biotechnology and pharmaceutical sectors, exerting substantial influence on the direction of technological change. This concentration of power can create high entry barriers for new entrants, potentially stifling competition and leading to monopolistic market conditions. Smaller firms

and startups may face challenges in accessing critical technologies, limiting their ability to innovate and compete effectively.

Moreover, these dominant actors often have the capacity to influence standard-setting processes, regulatory policies, and industry norms, further solidifying their critical role in technological development (Blind, 2012). Their control over intellectual property can result in significant negotiation power, influencing licensing agreements and collaborative ventures. As a result, understanding the long-term influence of these key actors is essential for policymakers aiming to create balanced and inclusive innovation policies.

In addition, dominant players in technological development tend to form alliances and strategic partnerships that further strengthen their positions. Such collaborations enable resource-sharing and risk mitigation but can also result in knowledge silos, where technological advances remain confined to a select group of companies, limiting the broader diffusion of innovation. Therefore, examining how these firms sustain their dominance and identifying emerging challengers are crucial aspects of understanding the evolving innovation landscape.

Patentometrics for Identifying Key R&D Actors

Patentometrics has emerged as a powerful tool for identifying key R&D actors by utilizing quantitative measures derived from patent data to evaluate the innovation activities and impact of various entities. Valkokari et al. (2016) emphasized the importance of managing actors, resources, and activities within innovation ecosystems using a design science approach. Dolphin and Pollitt (2020) advanced this field by applying machine learning techniques to UK patent data, successfully identifying innovative entities within the electricity supply industry. Similarly, Hall, Jaffe, and Trajtenberg (2002) demonstrated the utility of patent citations as indicators of technological significance and innovation impact.

Further research has expanded on these methodologies to provide more nuanced insights. For instance, Huang, Notten, and Rasters (2011) employed network analysis to map co-patenting activities, revealing the collaborative networks that drive technological development. Such analyses help identify central actors who play key roles in fostering innovation and pinpoint potential areas for intervention to encourage broader participation in innovation ecosystems.

Additionally, Lerner and Seru (2017) explored patent text analysis to uncover the thematic focus of R&D activities, offering a deeper understanding of specific technological areas under development. Patent data, when analyzed in conjunction with text-mining techniques, enables researchers to detect emerging technological trends, forecast potential breakthroughs, and identify the interdisciplinary nature of innovation.

The integration of various patentometric approaches allows for a comprehensive analysis of innovation ecosystems. Love and Roper (2015), for example, combined patent citations, co-patenting networks, and patent text analysis to assess the impact of government R&D subsidies on firm-level innovation. This multi-dimensional approach provides a richer understanding of how different factors influence R&D

performance and supports the identification of key actors who contribute to technological advancement.

Despite the advantages of patentometrics, certain limitations should be acknowledged. Patent data may not fully capture informal innovation activities, and reliance on patent counts alone can overlook actors who contribute through open innovation or collaborative research without seeking formal intellectual property rights. Therefore, combining patentometrics with alternative indicators such as publication data, funding records, and industry collaborations may provide a more holistic view of innovation dynamics.

Patent Data as a Tool for Studying Technology Development

Patent data serves as a critical resource for studying technology development, offering valuable insights into the processes of invention, diffusion, and commercialization across industries. The systematic analysis of patent data allows researchers to map technological trajectories and identify emerging innovation trends (Cohen et al., 2024). Furthermore, patent data provides insights into collaborative networks and knowledge flows between actors, presenting a holistic view of the innovation ecosystem (Wang et al., 2025).

The utility of patent data spans across various disciplines. Griliches (1990) highlighted its value as an economic indicator, offering insights into firms' productivity and technological capabilities. Similarly, Trajtenberg, Henderson, and Jaffe (1997) employed patent citation analysis to trace the diffusion of knowledge across different sectors, demonstrating the interconnected nature of technological advancements.

In addition to technological insights, patent data can shed light on the geographical distribution of innovation activities. For instance, Carlino, Chatterjee, and Hunt (2007) examined the spatial concentration of patenting activities in the United States, identifying key innovation hubs and the factors contributing to their success. Such geographic analyses assist policymakers and researchers in understanding regional variations in technological development and designing targeted strategies to promote innovation. These insights are particularly relevant in crafting regional innovation policies, ensuring balanced economic growth, and preventing regional disparities in technological development.

Moreover, patent data has proven invaluable in assessing the role of universities and research institutions in technological progress. Studies by Mowery, Nelson, Sampat, and Ziedonis (2004) and Thursby and Thursby (2002) demonstrated the significant role of university patents in fostering industry-academia collaborations and driving technological innovation. These collaborations often facilitate the commercialization of cutting-edge technologies and the emergence of new industries.

Patent data also provides an opportunity to analyze technology life cycles, helping businesses and policymakers identify periods of rapid innovation and subsequent maturity phases. Understanding these patterns allows stakeholders to anticipate market shifts, allocate resources efficiently, and prioritize research efforts in areas with the highest potential impact.

Furthermore, patent analytics can be used to evaluate cross-sectoral innovation, examining how technologies from different industries converge to create new applications and business opportunities. This interdisciplinary approach is crucial in understanding emerging fields such as artificial intelligence, biotechnology, and clean energy, where technological convergence plays a pivotal role in shaping future developments.

Summary and Research Implications

In summary, the literature on technology development emphasizes the dominance of a select group of key actors who drive innovation and influence industry trajectories. Studies leveraging patentometric methodologies have effectively identified these influential entities, utilizing patent data to provide comprehensive insights into their R&D activities and impact. Various approaches, including patent citations, copatenting networks, and patent text analysis, have been employed to map technological advancement and reveal collaborative networks that underpin innovation ecosystems.

Furthermore, patent data has been recognized as a valuable tool for tracking technology development, offering a wealth of information on invention processes, market diffusion, and commercialization efforts. The systematic analysis of patent data not only aids in tracing technological trajectories but also enhances the understanding of regional innovation dynamics and the contributions of universities and research institutions.

This review underscores the critical need to incorporate the persistence of R&D output into future analyses to ensure a more holistic evaluation of key actors in technological development. Recognizing actors who consistently contribute to innovation over extended periods is essential for accurately capturing their long-term influence and impact on technological progress.

A Novel Method for Identifying Vibrant Actors in Technology Development

This study introduces a novel approach to identifying vibrant actors in technology development by assessing their performance across two key dimensions: activity and continuity. Given the dynamic nature of R&D performance, which cannot be accurately captured by a single indicator at a fixed point in time, this study proposes an approach that calculates annual indicator values to provide a more comprehensive assessment of performance trends.

To mitigate potential misinterpretations arising from short-term fluctuations, the study employs a sliding window approach, which utilizes a three-year performance span to generate annual indicator values. This approach ensures a more stable and reliable evaluation of actors' sustained contributions over time. To achieve this objective, two key indicators are introduced: the Activity Index and the Continuity Index, which are defined and explained as follows:

Activity index

The activity indicator measures the activity level of actor i in a specific field j in year y. This indicator is measured using a sliding window approach, with a window size

of 3 years, counting the research outputs in the filed during 3 years (*y*, *y*-1, and *y*-2). The formula for calculating the activity indicator is as follows:

$$A_i^j(y) = P_i^j(y) + P_i^j(y-1) + P_i^j(y-2)$$
 (1)

where

y represents the observed year.

i represents the observed actor.

j represents the research field.

 $P_i^j(y)$ represents the number of research outputs by actor i in field j in year y.

 $A_i^j(y)$ represents the activity indicator for actor i in field j in year y.

Continuity index

The research continuity of actors is a critical indicator of innovation sustainability. In this study, an actor's annual research output is represented by binary values: 0 for no output and 1 for output produced. The cumulative continuous output is then calculated yearly. An actor demonstrating consistent output for three consecutive years is considered to have a high level of continuity. The corresponding calculation formula is explained as follows:

Boolean Variable $B_i^j(y)$

The Boolean variable $B_i^j(y)$ represents whether actor i in field j has research output in year y. The definition of is as follows:

$$B_i^j(y) \begin{cases} 1 , P_i^j(y) \neq 0 \\ 0 , P_i^j(y) = 0 \end{cases}$$
 (2)

Where $P_i^j(y)$ represents the research output by actor i in field j in year y. A value of 1 indicates the presence of research output, while 0 indicates its absence.

A. Continuous Research Output Count $n_i^j(y)$

The variable $n_i^j(y)$ captures the number of consecutive years in which actor i has research outputs in field j up to year y. The initial condition is defined as:

$$n_i^j(y_0) = B_i^j(y_0) (3)$$

This implies that the consecutive research output for the initial year y_0 is equivalent to the value of $B_i^j(y_0)$. For subsequent years, $n_i^j(y)$ is determined as follows:

$$n_i^j(y) = \begin{cases} n_i^j(y-1) + B_i^j(y) & \text{if } B_i^j(y) \neq 0 \\ 0 & \text{if } B_i^j(y) = 0 \end{cases}$$
 (4)

Where

 y_0 Initial year of observation.

 $B_i^j(y)$ Boolean variable indicating whether research output was in year y.

Continuity Indicator $C_i^j(y)$

To capture broader trends in research output continuity, we define the continuity indicator $C_i^j(y)$, which incorporates a sliding window of three years (SW=3). The formula for calculating the continuity indicator is as follows:

$$C_i^j(y) = n_i^j(y) + \frac{n_i^j(y-1) + n_i^j(y-2)}{2}$$
 (5)

Where:

 $C_i^j(y)$ represents the continuity indicator for actor i in field j in year y.

 $n_i^j(y)$ represents the number of consecutive years of research outputs.

This formulation balances recent activity $n_i^j(y)$ with the historical continuity of the preceding two years $n_i^j(y-1)$ and $n_i^j(y-2)$.

Identifying Vibrant Actors

This study introduces the concept of vibrant actors, who must exhibit activity and continuity in R&D output that surpass the average performance of all actors within the field. Therefore, they must meet the following three conditions:

1. The activity index of actor *i* in field *j* during year *y* must be greater than the average activity index of all actors in year *y*. Formula is as follows:

$$A_i^j(y) > \frac{\sum_{l=1}^I A_i^j(y)}{I(y)} = \overline{A_i^J(y)}$$
 (6)

Where I(y) represents the total number of actors in year y.

2. The continuity index of actor i in field j during year y must be greater than the average continuity index of all actors in year y. Formula is as follows:

$$C_i^j(y) > \frac{\sum_{i=1}^{I} c_i^j(y)}{I(y)} = \overline{C_i^J(y)}$$
 (7)

3. The conditions (1) and (2) must be satisfied for at least three consecutive years (SW=3). Formula is as follows:

$$\forall y \in [y_0, y_0 + sw - 1], \left(A_i^j(y) > \overline{A_i^J(y)}\right) \cap \left(C_i^j(y) > \overline{C_i^J(y)}\right) \tag{8}$$

This indicates that during the period from y_0 to $y_0 + SW$ -1, both $A_i^j(y)$ and $C_i^j(y)$ must be greater than their respective averages, and this condition must be met for at least y + SW - 1 consecutive years.

The following example illustrates the process of selecting vibrant assignees in this study, as shown in Table 1. The annual number of patent applications filed by Assignee i is represented as $P_i^j(y)$, from which the annual Activity performance values $A_i^j(y)$ can be calculated. Comparing these values with the average Activity performance of all assignees in the field, $\overline{A_i^j(y)}$, it can be observed that Assignee i's $A_i^j(y)$ values exceed the average $\overline{A_i^j(y)}$ in the year.

Regarding Continuity performance, the Boolean value $B_i^j(y)$ indicates whether Assignee i produced patents in a given year, while the cumulative number of consecutive years with patent applications is represented as $n_i^j(y)$. Using a three-year performance span, the annual Continuity performance values $C_i^j(y)$ can be calculated. Comparing these values with the average Continuity performance of all assignees in the field, $\overline{C_i^j(y)}$, it can be observed that Assignee i's $C_i^j(y)$ values exceed the average $\overline{C_i^j(y)}$ in the year.

Finally, when evaluating whether Assignee i consistently meets the threshold of having both $A_i^j(y)$ and $C_i^j(y)$ values above the field average for at least three consecutive years, it is found that Assignee i satisfies this requirement during the periods 2003–2005 and 2014–2020. Therefore, this study identifies Assignee i as a vibrant assignee based on its performance.

'02 '03 '04 '05 '06 '08 '09 10 11 12 *'13* 14 15 16 17 18 19 *'20* **'21** $P_i^j(y)$ 5 2 0 0 0 0 1 1 3 0 1 0 0 1 1 1 1 0 $A_i^j(y)$ $B_i^j(y)$ 1 1 1 1 0 $n_i^j(y)$ 0 0 0 2 0 0 1 2 5 0 **2.5 4.5 2.5 1.5** 0 <u>1</u> <u>2.5</u> <u>1.5</u> <u>1</u> <u>1</u> <u>2.5</u> <u>4.5</u> <u>6.5</u> <u>8.5</u> <u>10.5</u> <u>12.5</u> <u>6.5</u> <u>3.5</u> $C_i^j(y)$ 0 1.57 1.73 1.63 1.46 1.35 1.41 1.24 1.38 1.58 1.36 1.09 1.13 1.32 1.54 1.63 1.65 1.81 2.13 1.84 1.39 $\overline{A_i^J(y)}$ $1.00\, 1.05\, 0.93\, 1.02\, 1.13\, 1.12\, 0.94\, 0.84\, 1.21\, 1.29\, 0.89\, 0.90\, 0.93\, 1.08\, 1.09\, 1.15\, 1.23\, 1.46\, 1.09\, 0.89\, 0.90\, 0.91\, 1.09\, 1.10\, 1.09\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10\, 1.10$ $C_i^J(\overline{y})$

Table 1. Sample of a Vibrant Assignee.

An Empirical Study on Solid-State Electrolyte Technology for Lithium Batteries

This study focuses on solid-state electrolyte technology for lithium batteries as the subject of its empirical analysis, recognizing its transformative impact on battery

innovation. Solid-state electrolyte technology addresses critical limitations of conventional lithium-ion batteries, particularly in terms of environmental sustainability and safety, positioning it as a key driver of technological progress and sustainable development. With the global push for carbon neutrality and the growing demand for renewable energy—especially in applications such as electric vehicles and energy storage systems—solid-state electrolyte technology is emerging as a crucial enabler. It enhances battery performance and safety, minimizes environmental impact, and accelerates the adoption of green technologies, thereby supporting global emission reduction targets and advancing renewable energy initiatives (Li et al., 2022).

By analyzing the R&D activities of vibrant actors within this domain, this study aims to identify the key contributors driving technological advancements. Furthermore, it categorizes the various subfields within solid-state electrolyte technology and conducts an in-depth patent analysis to examine the technological strategies adopted by leading companies. This comprehensive approach provides valuable insights into future development trajectories and the evolving competitive landscape of this pivotal technology.

Patent Data Collection

The patent data used in this study was sourced from the United States Patent and Trademark Office (USPTO). Following the research framework of Karabelli, Birke, and Weeber (2021) and the definition of CPC codes (Cooperative Patent Classification, 2024), the study focused on patents related to solid-state electrolyte technology for lithium batteries. Using the query string:

@*AD*>=20020101<=20211231 AND ((lithium OR ion) AND solid* AND electrolyte*) AND (H01M10/052*.CPC. AND H01M10/056*.CPC.) NOT (Y02E60/50.CPC. OR H01M10/0563.CPC. OR H01M10/0566.CPC. OR H01M10/0567.CPC. OR H01M10/0569.CPC.)

Patents with application dates from 2002 to 2021 were retrieved, resulting in a total of 2,690 patents.

The patent search and filtering process was conducted systematically to identify relevant patents related to lithium battery solid-state electrolytes. Initially, patent data was retrieved from the United States Patent and Trademark Office (USPTO) database, yielding a total of 2,690 patents. To refine the dataset, a set of filtering criteria was applied to ensure the selection of patents closely aligned with the research focus. The filtering process involved examining the independent claims to determine whether the solid-state electrolyte was explicitly mentioned and verifying its application in lithium batteries. In cases where the independent claims did not provide explicit information, the patent specifications were reviewed to assess whether they described technological advancements related to solid-state electrolytes. Through this rigorous filtering process, a total of 981 relevant patents were identified, representing 223 assignees. These selected patents provide a robust foundation for the subsequent analyses in this study. These patents were further

categorized into five sub-fields within solid-state electrolyte technology for lithium batteries.

Patent Activity and Vibrant Assignee Distribution across Solid-State Electrolyte Subfields

As summarized in Table 2, the analysis of patenting activity across five sub-technical fields of solid-state electrolytes for lithium batteries provides valuable insights into the distribution of patents, assignees, and vibrant assignees within each category. Among these subfields, organic polymer solid electrolytes stand out as the most extensively studied, with a total of 293 patents and 126 assignees. This reflects substantial research and commercialization efforts in this domain. However, despite the high level of activity, the proportion of vibrant assignees—those demonstrating sustained and impactful R&D contributions—remains at only 10%, underscoring the need for persistent innovation to maintain competitiveness in this rapidly evolving field.

Table 2. Summary of Solid-state Electrolytes for Lithium Batteries.

sub-technical field	Patents	Assignees	Vibrant Assignees
Halides solid electrolytes	134	30	4(0.13)
Mixed inorganic/organic solid electrolytes	99	48	4(0.08)
Organic polymers solid electrolytes	293	126	12(0.10)
Oxides solid electrolytes	236	80	8(0.10)
Sulfide solid electrolytes	219	62	7(0.11)

In contrast, halide solid electrolytes, with 134 patents and 30 assignees, exhibit the highest vibrant assignee ratio at 13%. This indicates a more concentrated distribution of key contributors who consistently drive technological progress. Despite having a lower overall patent volume, this field benefits from a dedicated group of persistent innovators, highlighting the strategic importance of long-term R&D commitment in advancing the technology.

Conversely, mixed inorganic/organic solid electrolytes have the lowest proportion of vibrant assignees at 8%, with 99 patents and 48 assignees. This indicates a more fragmented innovation landscape, where numerous entities contribute to the field, but relatively few sustain a long-term, high-impact presence. The lower ratio of vibrant assignees suggests that consistent innovation efforts are less prevalent in this category, potentially hindering the field's long-term development trajectory and competitiveness.

Oxide and sulfide solid electrolytes, with 236 and 219 patents respectively, demonstrate similar characteristics, exhibiting vibrant assignee ratios of 10% and 11%. These fields strike a moderate balance between the volume of patents and the persistence of key players, indicating steady and ongoing contributions to technological advancement. Notably, the slightly higher vibrant assignee ratio for

sulfide solid electrolytes suggests a more committed group of researchers and institutions, which may further drive consistent progress in this domain.

Overall, the data highlights the critical role of sustained R&D engagement in fostering meaningful and lasting contributions to technological development. While certain subfields, such as halide solid electrolytes, exhibit a strong core of persistent innovators, others—particularly mixed inorganic/organic solid electrolytes—show a broader distribution of participants but may benefit from a more concentrated focus on long-term research efforts. These insights offer valuable guidance for stakeholders aiming to identify key areas of opportunity and strategically invest in the future of lithium battery solid-state electrolyte technologies.

Identifying Vibrant Assignees in Organic Polymers Solid Electrolytes

The persistence of R&D activity among vibrant assignees in the organic polymer solid electrolyte sub-technical field from 2002 to 2021 is a critical aspect of this study, as summarized in Table 3. This analysis captures two key indicators—A values and C values, representing different dimensions of innovation performance. Notably, the C value is of particular significance, as it reflects the sustained and cumulative impact of an assignee's R&D efforts over time. The boxed periods in the table highlight instances where both A and C values exceeded 1 for at least three consecutive years, providing clear evidence of persistent, long-term contributions—one of the core focuses of this research.

A key finding from the data is that vibrant assignees consistently achieve higher and more sustained C values over time compared to their non-vibrant counterparts. For instance, Samsung Electronics and LG Energy Solution, two of the most prominent vibrant assignees, display consistently high C values across multiple years, with extended boxed periods indicating a strong, continuous impact on technological development. These companies not only achieve notable innovation output in specific years but also maintain a steady pace of impactful contributions over the long term. Their persistence underscores a strategic commitment to R&D and an ability to continuously innovate, reinforcing their position as key players in the organic polymer solid electrolyte sector.

In contrast, non-vibrant assignees, despite holding a higher number of patents, often demonstrate fluctuating and less sustained C values, suggesting that their contributions are more sporadic and reactive rather than proactive. For example, assignees such as General Motors and Hydro-Quebec, while possessing relatively high patent counts, lack the consistent upward trend in C values observed among vibrant assignees. Their intermittent bursts of activity, without sustained periods of high C values, suggest that their influence on the technological development of solid-state electrolytes may be transient rather than enduring. This distinction highlights the critical role of persistence—while patent quantity is important, the true measure of technological influence lies in consistent, long-term contributions, as evidenced by the sustained C values of vibrant assignees.

Table 3. Performance of Vibrant and Non-vibrant Assignees in Organic polymers solid electrolytes.

4 70 4		Solid circularytes.
Application Year		02 '03 '04 '05 '06 '07 '08 '09 '10 '11 '12 '13 '14 '15 '16 '17 '18 '19 '20 '21
BOSCH (12)	A	0.920.880.760.650.62
	C	1.12 0.560.54 0.93 0.46 1.3 2.03 3.08 2.29 1.69
CNRS (5)	A	0.740.920.88 1.3 1.852.42 1.1 0.47
	C	0.780.560.56 0.93 2.3 3.912.03 1.03
HITACHI (5)	A	0.580.61 2.052.222.13 0.81 0.63 0.74 0.92
	C	0.960.54 1.472.221.34 1.06 0.83 0.39 0.56
HON HAI PRECISION (3)	A	1.842.652.27 0.65
	C	1.122.781.62 0.93
LG ENERGY SOLUTION (21)	A	1.621.451.26 3.02 3.9 3.692.426.06 6.1 5.971.44
	C	1.06 0.59 0.41 1.08 2.32 1.38 1.74 2.03 3.08 2.29 1.69
MURATA (3)	A	0.76 1.3 1.85 1.21 0.55
	C	1.08 2.324.142.17 1.22
NIPPON SODA (5)	A	$0.58 \frac{1.222.052.221.42}{0.81} 0.740.920.88$
	C	0.96 <mark>2.684.425.783.13</mark> 2.13 0.780.560.56
NISSHINBO (3)	A	0.64 <mark>1.161.221.37</mark> 0.740.71
	C	1 2.391.611.960.440.45
NITTO DENKO (7)	A	0.580.61 1.37 1.48 1.42 1.62 2.18 1.89 1.47 0.92 0.88 0.76
	C	0.960.54 <mark>1.472.221.342.132.961.24</mark> 0.78 <mark>1.12</mark> 0.560.54
SAMSUNG ELECTRONICS (24)	A	3.18 4.05 4.9 2.05 0.74 0.73 1.26 1.47 0.92 0.88 1.51 4.55 4.31 5.45 3.31 2.81 1.63 0.72
	C	1 2.394.822.45 1.33 1.192.071.171.121.11 2.7 4.185.987.388.528.565.95 3.95
SANYO ELECTRIC (4)	A	1.221.37 2.221.421.62 0.73
	C	1.07 0.49 1.33 2.24 1.59 1.19
SEEO (14)	A	0.81 2.182.532.95 1.84 1.76 1.51 1.3 3.08 3.03 3.31 1.41 1.09 0.72
	C	1.06 2.963.725.063.933.33 2.7 1.391.842.173.654.45 3.2 2.25
HYDRO-QUEBEC (9)	Α	1.272.322.451.37
	C	1.00 2.39 1.61 0.98 1.06 0.59 0.41 1.11 0.54 1.39 0.46 1.30 2.03 1.03 0.92
CALIFORNIA (7)	A	1.27 1.16 1.22 0.68 0.74 1.42 0.81 0.73 0.92 0.88 1.51 0.65 1.23 0.61 0.55
	C	1.000.480.540.980.44
KUREHA (6)	A	0.61 0.68 0.74
	C	1.07 0.49 0.44
COMMISSARIAT A L'ENERGIE ATOMIQUE(5)	A	1.511.301.231.821.651.41
	C	1.08 0.46 0.46 0.87 0.41 0.34
GENERAL MOTORS (5)	A	0.920.880.76
	C	1.12 <mark>0.560.54 </mark>

^{*}A: The value of $A_i^j(y)/\overline{A_i^j(y)}$ for the assignee.

^{**}C: The value of $C_i^j(y)/\overline{C_i^j(y)}$ for the assignee.

^{***}Patent Count of the assignee.

^{*****}**Italicized assignee name:** The top 2 non-vibrant assignees by patent count.

^{******}**Boxed:** The period during which both A and C values were greater than 1 for at least three consecutive years.

Furthermore, the analysis reveals that even among vibrant assignees, the timing and duration of high C values vary, offering insights into different innovation strategies. Some companies, such as SEEO, demonstrate a late but steady rise in C values, indicating their evolving role within the field. This trend suggests that certain companies may transition from being non-vibrant to vibrant assignees by gradually increasing their sustained impact over time, reinforcing the importance of monitoring persistence as an indicator of future influence.

Another key observation is that the relationship between patent counts and sustained impact is not always direct. Some vibrant assignees with relatively fewer patents, such as Murata and Hon Hai Precision, exhibit strong C value performance over multiple years, emphasizing their focus on high-impact, enduring innovations rather than high-volume patenting strategies. This finding underscores the significance of persistence over sheer quantity in assessing an assignee's long-term technological footprint.

Overall, the findings reinforce the central argument of this study—persistent innovation efforts, as captured through high and sustained C values, provide a more accurate reflection of an assignee's true influence in the organic polymer solid electrolyte sector. Vibrant assignees distinguish themselves not merely by patent output but by their ability to maintain a consistent and meaningful presence in the technological landscape over time. These insights offer valuable guidance for policymakers, investors, and industry stakeholders in identifying and supporting long-term contributors to innovation, ensuring that resources are directed towards entities that demonstrate sustained, impactful R&D efforts.

Conclusion

This study presents a novel framework for identifying vibrant actors in technological development by emphasizing the persistence of their R&D efforts alongside their overall activity. The findings reveal that traditional patentometric approaches—primarily focused on patent counts and citation frequencies—often fail to capture the critical dimension of sustained innovation. By developing and applying the activity and continuity indices, this study effectively distinguishes vibrant assignees, who demonstrate consistent and impactful contributions over time, from non-vibrant assignees, who may achieve high patent output but lack sustained engagement.

The empirical analysis of solid-state electrolyte technology for lithium batteries further reinforces the importance of persistence in driving technological advancements. The results indicate that vibrant assignees, such as Samsung Electronics and LG Energy Solution, consistently achieve high continuity values, reflecting their long-term commitment to R&D and strategic positioning within the industry. Conversely, non-vibrant assignees, despite holding extensive patent portfolios, often exhibit fluctuating continuity values, suggesting sporadic involvement and a lack of sustained impact.

These findings offer valuable insights for policymakers, industry stakeholders, and investors, helping them better identify and support key contributors to technological innovation. By integrating persistence as a core factor in R&D evaluation, decision-

makers can optimize resource allocation, foster strategic partnerships, and strengthen the overall innovation ecosystem.

Moreover, the proposed framework provides a more comprehensive approach to tracking technological leadership and identifying potential emerging players. By considering both the frequency and sustainability of contributions, this approach offers a deeper understanding of innovation dynamics, supporting more informed decision-making processes in policy and investment planning.

Future Research

Future research can build upon the proposed framework by applying it across various industries to examine the persistence of R&D efforts in diverse technological landscapes. While this study focuses on solid-state electrolytes for lithium batteries, the methodology can be effectively adapted to other high-impact sectors. Analyzing the sustained performance of key players in different industries can provide deeper insights into how persistent innovation drives long-term technological leadership and competitiveness.

Beyond corporate assignees, the framework can be extended to academic research institutions by analyzing journal articles and publication data. Evaluating the sustained contributions of universities and research organizations can offer valuable insights into their research impact and long-term influence across scientific domains. This extension can assist funding agencies, policymakers, and institutional leaders in better understanding and fostering innovation within the academic ecosystem, ultimately guiding strategic decision-making and resource allocation.

Additionally, the framework can be refined to assess individual-level vibrant performance, focusing on inventors and authors. By tracking personal research trajectories based on persistence in patenting or publishing, it becomes possible to identify prolific innovators and thought leaders who consistently contribute to technological and scientific advancements. Such insights can support talent management strategies, facilitate targeted collaborations, and help organizations recognize and retain top-performing researchers.

Expanding the application of this framework across industries, academic institutions, and individual contributors will not only enhance its versatility but also provide a more comprehensive understanding of innovation ecosystems. Future research efforts can focus on developing sector-specific benchmarks, refining the methodology to accommodate discipline-specific nuances, and leveraging advanced analytics to further enhance the precision and applicability of vibrant performance evaluations.

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