MDSAA

Master Degree Program in
Data Science and Advanced Analytics

ELECTRIC VEHICLES BATTERIES: EXAMINING KNOWLEDGE TRACKS THROUGH PATENTED AND PUBLISHED TECHNOLOGIES

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Master Thesis

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

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Instituto Superior de Estatística e Gestão de Informação
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by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Business Analytics

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July, 2024

Electric vehicles batteries: Examining knowledge tracks through patented and published technologies

This document was created with the (pdf/Xe/Lua)LaTeX processor and the NOVAthesis template (v7.1.5) (Lourenço, 2021).

Acknowledgements

I would like to express my deepest gratitude to my supervisors, Professor Bruno Damásio and Professor Sandro Mendonça, for their support, guidance, and feedback. The last academic thanks goes to Professor Carolina Vasconcelos.

I would like to thank my family and friends. Their love and support helped me with the motivation to achieve my goals.

A special thanks goes to Miguel, whose patience, understanding, and company during countless adventures have brought happiness and balance to my life.

Lastly, I would like to thank Renato for being a constant source of comfort and joy.

Abstract

Climate change and technological advances are driving the rise of electric vehicles (EVs), with batteries at their core, influencing cost, range, charging time, and lifespan. As sustainable EV battery development is vital for widespread adoption, investigating innovation in this field allows us to assess the landscape of battery-related inventions. This study uses a two-fold approach: (1) patent analysis and (2) bibliometric methods, exploring battery developments from 2000 to 2022. It contributes to the literature by comparing two different approaches to innovation: to patent it and protect it or to publish it and disseminate it. Using data from PATSTAT and Web of Science, the study analyses around 20 000 international patent families and more than 20 000 publications. We find continuous growth in the innovation output, particularly from 2010 onwards and identify productive countries, notably Asian nations, as leading patent and scientific research contributors. By comparing the G7 and BRICS outputs, we find that the first group leads in patent applications, while the second recently leads in scientific studies. An analysis of keywords uncovers an evolutionary shift in battery chemistries, for example from lead acid to Li-ion. We also identify a shift towards the integration of energy storage into larger systems and applications. We present a systematic analysis of technology trends to guide market players, researchers, and policymakers in promoting EV adoption.

Keywords: Electric car batteries, patent, data science of science, innovation

Resumo

As alterações climáticas e os avanços tecnológicos alimentam o crescimento dos veículos eléctricos (VE), com as baterias no seu cerne, influenciando o custo, a autonomia, o tempo de carregamento e a vida útil. Uma vez que o desenvolvimento sustentável de baterias para VE é vital para a sua adoção generalizada, a investigação da inovação neste domínio permite-nos avaliar o panorama das invenções relacionadas com as baterias. Este estudo utiliza uma abordagem dupla: (1) análise de patentes e (2) métodos bibliométricos, explorando o desenvolvimento de baterias entre 2000 e 2022. Contribuímos para a literatura ao comparar duas abordagens diferentes à inovação: patenteá-la e protegê-la ou publicá-la e divulgá-la. Utilizando dados do PATSTAT e do Web of Science, o estudo analisa cerca de 20 000 famílias de patentes internacionais e mais de 20 000 publicações. Constatamos um crescimento contínuo da inovação, sobretudo a partir de 2010, e identificamos os países mais produtivos, nomeadamente os asiáticos, como os principais contribuidores de patentes e investigação científica. Comparando os resultados do G7 e dos BRICS, verificamos que o primeiro grupo lidera em pedidos de patentes, enquanto o segundo lidera recentemente em estudos científicos. Uma análise das palavras-chave revela uma mudança evolutiva nos tipos de baterias, por exemplo, de chumbo-ácido para ião-lítio. Identificamos também uma mudança no sentido da integração do armazenamento de energia em sistemas e aplicações de maior dimensão. Apresentamos uma análise sistemática das tendências tecnológicas para orientar os intervenientes no mercado, os investigadores, e os decisores políticos na promoção da adoção de VE.

Palavras-chave: Baterias de carros elétricos, patente, ciência de dados da ciência, inovação

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Acronyms

BCU Battery Control Unit *(p. 7)*
BEV Battery Electric Vehicle *(pp. 5–7, 14, 17, 27)*
BMS Battery Management System *(pp. 2, 6, 10, 12, 21, 41–43, 46)*

CD Charge-Depleting *(p. 6)*
CPC Cooperative Patent Classification *(pp. 16, 19, 21)*
CRISP-DM Cross-Industry Standard Process for Data Mining *(p. 17)*
CS Charge-Sustaining *(p. 6)*

EC Electric Car *(pp. xi, 18)*
EES Electrochemical Energy Storage *(p. 12)*
EPO European Patent Office *(pp. 15, 16, 18, 19)*
EV Electric Vehicle *(pp. xi, xiii, 1–3, 5–12, 14, 15, 17–19, 21, 22, 27–33, 35, 38, 39, 41–47, 52–55, 57)*

FCEV Fuel Cell Electric Vehicle *(pp. 5, 11)*
FCV Fuel Cell Vehicle *(p. 14)*

HEV Hybrid Electric Vehicle *(pp. 5–7, 11)*
HHI Herfindahl-Hirschman Index *(pp. xi, 23, 31, 32)*

ICE Internal Combustion Engine *(pp. 5, 6, 8, 12)*
IEA International Energy Agency *(p. 15)*
IPC International Patent Classification *(pp. xi, xiii, 14, 16, 18, 19, 21, 22, 81–83)*
IPF International Patent Family *(pp. xi, xiii, 2, 15, 16, 20, 21, 23, 27–34, 38, 41, 44, 46, 47, 57)*

LEV Low-Emission Vehicle *(p. 14)*
Li-ion Lithium-ion *(pp. 2, 7–9, 12, 44, 53)*

MCU Module Control Unit *(p. 7)*

Na-ion Sodium-ion *(p. 9)*
Ni-Cd Nickel-Cadmium *(p. 8)*
Ni-MH Nickel-Metal Hydride *(pp. 8, 53)*

PHEV Plug-in Hybrid Electric Vehicle *(pp. 5–7, 27)*

R&D Research and Development *(pp. 10, 13, 27, 30)*

SOC State of Charge *(p. 6)*

USPTO United States Patent and Trademark Office *(pp. 14, 16, 18)*

VAR Vector Autoregressive *(pp. 24, 25, 28, 33, 34)*

WIPO World Intellectual Property Organisation *(p. 16)*
WoS Web of Science *(pp. 2, 17, 18, 44, 57, 58)*

ZEBRA Zero Emission Battery Research Activity *(p. 8)*

1 | Introduction

Climate change is a global challenge that threatens the stability and well-being of humans and all life forms on Earth, referring to long-term shifts in temperatures and weather patterns (UN, 2023). The increase in greenhouse gas emissions is the leading cause of this phenomenon, namely carbon dioxide, methane, and nitrous oxide, which can result in, for example, a higher risk of species losses, heat-humidity risks to human health, or food production impacts (IPCC, 2023).

In 2015, the Paris Agreement on global climate change solidified the unanimous aspiration of nations worldwide to restrain global warming to levels significantly below 2 degrees Celsius, to limit the temperature rise even further to 1.5 degrees Celsius (UNCC, 2023a). This historic agreement also laid the foundation for nations to make formal commitments to reduce emissions.

Furthermore, during the Climate Change Conference (COP26) in Glasgow, a consensus was reached on key objectives aligned with this agreement, including reducing the reliance on fossil fuels or promoting the sale of new vehicles with zero emissions by 2040 (Smith et al., 2022). More recently, the Climate Change Conference (COP28), in Dubai, closed with an agreement of the "beginning of the end" of the fossil fuel era, recognising the need to triple the renewable energy capacity and to double the efficiency improvements by 2030 (UNCC, 2023b).

One of the significant contributors to atmospheric pollution is the transportation sector (according to Eurostat, 2023b, in the first quarter of 2023, the transportation and storage sectors of all 27 countries of the European Union emitted 96 492.036 thousand tonnes of greenhouse gases, which accounts for, approximately, 10% of all greenhouse gases emissions), which heavily relies on fossil fuels, thus necessitating a transition towards greener alternatives.

Electric Vehicles (EVs) have become increasingly popular in recent years to help address these problems, due to environmental awareness, technological innovation, as well as government incentives (Vilchez et al., 2019), as they emit zero emissions when powered by electricity from renewable sources. In 2021, the number of electric passenger cars ascended to 1 928 307 in the European Union, which represents an increase of 3 599%, since 2013 (Eurostat, 2023a).

EV technology is evolving rapidly, driven by advances in battery technology, power electronics, electric motors, and materials science. This constant evolution creates a fertile ground for research opportunities.

However, as the EV industry gains momentum, it is essential to recognise that with this paradigm shift comes challenges, opportunities, and obstacles. EVs face a common critique regarding the availability of charging infrastructure (Mutarraf et al., 2022) and their range limitations, as the battery technology has yet to offer the same energy density as gasoline (the energy stored per pound is much lower) (Wouk, 1971). There are also concerns that the adoption of electric mobility could result in an increased electricity demand, which could have limited benefits in terms of reducing CO_2 emissions if the electricity generation relies heavily on non-renewable sources (US EPA, 2023).

The battery is the most important component of EVs and is crucial for their performance, range, and overall viability (Totev & Gueorgiev, 2021). It is the device that stores and delivers electrical energy to power the electric motor, thus affecting the cost, weight, size, range, charging time, and lifespan of EVs.

Battery technology is advancing rapidly, tied to ongoing transformations in the automotive sector (IEA, 2023). The European Union adopted the Strategic Action Plan for Batteries, which focuses mainly on battery development for EVs, but also on other aspects such as battery second use and recycling (European Economic and Social Committee, 2019). The two biggest companies supplying batteries and battery metals in passenger EVs, Contemporary Amperex Technology Co. and LG Energy Solution, experienced an explosive growth from 2016 to 2020, with growth rates of 3 400% and 1 193% in their market share, respectively (Ulrich, 2021).

Therefore, in light of this landscape, it is valuable to recognise the importance of tracking and assessing the pace and trajectory of EV battery advancements. Hence, we aim to answer a question to fill the research gaps found: *How have advancements in EV battery technology evolved?* We aim to know where does innovation in this field take place and how does it flow. This master thesis will answer the previous research question by adopting both a quantitative science study and a patent analysis approach. Through these approaches, we look to demonstrate the influence and impact of the institutions, uncover the drivers of innovation. We want to fill the existing gap of researches studying EV battery technologies separately (i.e. using either publications or patents) by adopting a comparative approach.

For this study, two different datasets were built, one containing 22 105 scientific articles on EV battery technologies and another containing 20 219 IPFs. The analysed time frame is 2000 to 2022, and the raw data was extracted respectively from WoS and PATSTAT Online (edition: Autumn 2023).

We found that the activity on both fields is trending upwards between 2000 and 2022, especially after 2010, when the intensity started to increase. The most productive countries are the Asian, but European countries are more prolific if we account for the size of the countries, namely using population measures. In the analysis of the content of papers' and patents' abstracts, we can see the different trends of technologies, for example, recently, lead acid batteries falling behind Lithium-ion batteries, or Battery

Management System technologies becoming more relevant. In the same analysis, we can see new technologies arriving, such as battery swapping.

The remainder of this thesis is organised as follows. Chapter 2 contains the theoretical framework of this essay, including a literature review, with some basic concepts regarding EV batteries, innovation, and how to measure it; Chapter 3 contains the description of the used data and methods, while Chapter 4 contains the results and discussion of the analysis made. Finally, some conclusions are presented in Chapter 5, including limitations and future work and steps that can be done in this area.

2 | Theoretical Framework

2.1 Electric car batteries

2.1.1 Electric cars

An EV is a transportation device designed for propulsion, employing one or more electric or traction motors (Khan et al., 2021). The main subsystems of an EV are energy storage (battery and charging), electric propulsion (electric motor and power electronics), body, chassis and auxiliaries (Chan, 2002).

According to Enyedi (2018), there are four main types of EVs: Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Fuel Cell Electric Vehicles (FCEVs).

A BEV is a fully electric car that relies solely on electricity stored in a battery pack to power an electric motor. This vehicle must be plugged into an electrical outlet or charging station to recharge its batteries. The primary limitation of this vehicle lies in its current battery technology since the batteries tend to be heavy and offer limited storage capacity, resulting in comparatively shorter driving ranges, as mentioned previously.

A HEV integrates both an electric motor and a traditional Internal Combustion Engine (ICE) (Corbo et al., 2011). These vehicles are designed to generate electrical energy through the combustion engine, which in turn charges the battery and powers the electric motor. While this configuration enhances fuel efficiency beyond that of standard vehicles, it introduces increased complexity, elevates costs, and potentially reduces reliability due to the inclusion of an additional engine.

A PHEV integrates both an ICE and an electric motor alongside a battery pack. It functions in all-electric mode for a restricted range before transitioning to the ICE, which can result in diminished environmental benefits if drivers primarily use the ICE.

A FCEV generates electricity through a fuel cell, which powers an electric motor. Most of these vehicles use hydrogen but can also use ethanol. This vehicle emits only water vapour as a byproduct and offers long driving ranges, but the main limitation is the availability of hydrogen refuelling infrastructure. The batteries from this type of vehicle serve a different purpose compared to those in a BEV.

EVs use a regenerative braking system, a technology employed to recapture some of the kinetic energy, that would otherwise be lost during braking, and store it in the battery for future use. When the regenerative braking torque alone is insufficient to achieve the desired deceleration rate, conventional hydraulic braking torque is applied, functioning similarly to traditional vehicles (Chau, 2014). Thus, the regenerative braking system is crucial in optimising the energy efficiency of EVs.

As previously noted, HEVs and PHEVs use two types of power trains, integrating both an internal combustion engine and an electric motor. These can be set in different configurations, namely series, parallel and series-parallel, offering distinct operational modes and advantages (Yong et al., 2015). In a series setup, the ICE solely powers a generator, which generates electricity to power an electric motor. Therefore the ICE has no direct connection to the transmission or wheels. Conversely, in a parallel configuration, both the electric motor and the ICE are mechanically connected to the wheels, enabling dynamic power distribution based on driving conditions and power demand. Lastly, a series-parallel configuration combines elements of both, leveraging the strengths of each, at the expense of increased complexity and cost.

In the case of PHEVs, the operation can be divided into two main modes: Charge-Depleting (CD) mode and Charge-Sustaining (CS) mode (Emadi, 2011). In CD mode, the vehicle relies on its electric propulsion system, drawing power from the battery until its charge level drops to a predefined threshold, a minimum State of Charge (SOC). This happens in shorter trips, where the electric range is enough to cover the entire journey. Subsequently, the vehicle transitions to CS mode, where the ICE takes over as the primary power source and provides the necessary propulsion. On the other hand, BEVs, exclusively propelled by electric motors, operate solely in CD mode, reflecting their all-electric configuration.

2.1.2 Batteries

Each battery cell contains two key components: an anode and a cathode. Usually, the anode is composed of a carbon-based material, however, recently, manufacturers have been using silicon to increase the energy density (IEA, 2023). The cathode can be made of multiple materials, namely sodium-ion, lithium iron phosphate, lithium nickel manganese cobalt oxide, or nickel cobalt aluminium oxide. These two elements serve as sources for chemical reactions and are separated by an electrolyte solution and a porous barrier, which prevents direct contact between the anode and cathode, thereby preventing a short circuit (Castelvecchi, 2021).

Additionally, a Battery Management System (BMS) is responsible for monitoring, controlling, and optimising the performance of the vehicle's battery pack, playing a central role in ensuring the safe and efficient operation of the battery (Mutarraf et al., 2022). The BMS calculates the SOC, which indicates how much energy is remaining in the battery, to guarantee the long-term health of the battery.

One of the key functions of the BMS is temperature management, especially needed in Li-ion batteries, as they cannot be overcharged or used outside of their acceptable operating temperature range. Offer et al. (2020) identify three types of thermal management systems, namely, air cooling, liquid cooling, and phase-change cooling, each with advantages and disadvantages. Therefore, every cell in a module needs to be monitored (namely for temperature), hence a Module Control Unit (MCU) is used to control these modules. Multiple MCUs are connected in a battery pack, forming the Battery Control Unit (BCU) (Castelvecchi, 2021).

Contrary to what happens in HEVs, the batteries of BEVs and PHEVs can be charged from the grid. Battery chargers work by converting alternating current (AC) from the electrical grid into direct current (DC) which is stored inside the vehicle's battery pack (Yong et al., 2015). This conversion is usually performed by a power electronic device called a rectifier or a converter. Charging standards play a vital role, providing a common framework for charging infrastructure and ensuring interoperability among different EVs and chargers. Some of the most prominent charging international standards are Society of Automotive Engineers (SAE), International Electromechanical Commission (IEC) and CHAdeMO EV standards (Foley et al., 2010).

The voltage of EV battery packs varies depending on several factors, including the chemistry of the used batteries, the cells' configuration inside the pack, and the design of the vehicle itself, usually operating at voltages ranging from 120V to 450V ("EV Specifications", 2024). However, the next generation of EVs, especially those with extended driving ranges, use battery packs ranging from 600V to 800V, which require fewer cells to achieve the same energy capacity, thus reducing weight and size. Therefore, new chargers are appearing in the innovation landscape to accommodate the needs of the new EVs.

EV batteries can use various materials in their construction, and the choice of materials depends on the battery technology, therefore examining the batteries'composition reveals a complex interaction between materials and technologies. According to Tie and Tan (2013), Yong et al. (2015), and Un-Noor et al. (2017), there are five groups of batteries: lead-acid batteries (lead-acid, advance lead acid, valve regulated lead acid, metal foil lead acid), nickel batteries (nickel-zinc, nickel-iron, nickel–cadmium, nickel-metal hydride), ZEBRA batteries (sodium-nickel chloride, sodium-sulfur), lithium batteries (lithium–iron sulphide, lithium–iron phosphate, lithium-ion polymer, lithium-ion, lithium–titanate), and metal-air batteries (aluminium-air, zinc-air, zink-refuelable, lithium-air).

Lead-acid batteries are one of the oldest types of batteries used in EVs (Rajashekara, 2013). They rely on a chemical interplay between lead dioxide (serving as the positive active material) and sponge lead (acting as the negative active material) to generate energy, ultimately by transforming both materials into lead sulfate (Caumont et al., 2000). Lead-acid batteries are relatively inexpensive compared to some other battery technologies and find widespread use in ICE vehicles, in systems dedicated to starting, lighting, and ignition (May et al., 2018). Despite the technological advances inherent drawbacks persist, mainly related to their height, as lead-acid batteries tend to be heavier than alternative battery types. Moreover, these batteries exhibit a limited energy density compared to newer technologies like lithium-ion batteries (35–40 Wh/kg against 150–180 Wh/kg) (May et al., 2018).

On the other hand, we have Nickel-Metal Hydride (Ni-MH) batteries, which are becoming more popular as a replacement for Nickel-Cadmium (Ni-Cd) batteries, as the last ones were outlawed by the European Commission in 2006 due to toxicity concerns (Directive 2006/66/EC, 2006). These batteries are composed of a nickel hydroxide compound, as the positive electrode, and a metal hydride alloy, as the negative electrode. They dominated the hybrid market in 2012, being used in the most popular hybrid vehicle model, the Toyota Prius, however, they also cannot compete with the energy density of lithium-ion batteries (50–80 Wh/kg against 100–150 Wh/kg) (Rajashekara, 2013). These batteries' high self-discharge rate, which means that they may gradually lose charge when not in use, and their high heat production during charging are two other major drawbacks (Kopera, 2004).

"Zero Emission Battery Research Activity" or ZEBRA batteries are made of sodium nickel chloride and use beta alumina as a solid electrolyte. These batteries run at a high temperature, usually between 270 and 350°C, for the beta alumina solid electrolyte to function properly (Dustmann, 2004). These batteries outperform existing technologies in a variety of ways, including long cycle life (because of their ability to sustain numerous cycles of charge and discharge without experiencing appreciable performance degradation) and inexpensive cost (due to their lack of dependency on hazardous elements, such as cadmium). Nevertheless, they waste energy due to the elevated operating temperature, despite having no loss during charge and discharge cycles (100% coulombic efficiency). The running cycle affects this heat loss, thus if the battery is not used at all, the heat loss may be as much as 10% daily (Sudworth, 2001).

Lithium-ion (Li-ion) batteries are one of the most prevalent battery technologies used in EVs and a wide range of portable electronic devices due to their high energy density, reliability, and relatively low self-discharge rates (Prajapati & Bhatnagar, 2023). These batteries charge by moving lithium ions from the cathode to the anode when an external voltage is applied, while discharging occurs as lithium ions move from the anode to the cathode, releasing energy in the form of an electric current (Nzereogu et al., 2022). Li-ion batteries are valued for being lighter and more compact than alternative battery technologies, and for having a relatively low memory effect, meaning they do not require full discharges before recharging (Z. Wang et al., 2023). However, they are sensitive to temperature extremes, and their performance can degrade over time. Additionally, lithium mining for EV battery production raises several concerns, namely, environmental impact (water usage, land disruption, and chemical pollution), human rights considerations involving land rights disputes or labour conditions, as well as recycling challenges due to complex industrial processes (Luong et al., 2022). On the other hand, lithium-iron phosphate batteries use this material as the cathode and are known for their stability and safety, yet compromising their energy density when compared to some other Li-ion battery chemistries, meaning that they have lower capacity and energy storage capability per unit of weight (Kumar & Revankar, 2017).

Moreover, the metal-air battery uses a metal as one electrode and oxygen from the air as the cathode material resulting in high energy density, cost-effectiveness and, potentially, lower toxicity (T. Liu et al., 2020). The zinc-air battery exhibits higher energy density when compared to lithium batteries, despite grappling with challenges such as limited life cycle and lower specific power (Kopera, 2004). The lithium-air battery stands out as the most extensively researched technology among the metal-air batteries, as it is the one with higher theoretical energy density, potentially surpassing that of traditional Li-ion batteries (Girishkumar et al., 2010). While lithium-air batteries hold substantial promise for EV applications, several challenges prevent their widespread adoption. Some of these challenges are also common to other lithium technology batteries (X. Liu et al., 2015), such as safety concerns linked to overheating and potential thermal runaway induced by dendrites formed on the surface of lithium electrodes during the charging process. Other obstacles relate to chemical instabilities, such as the interaction between O_2^- and the carbonate solvents or the formation of Li_2O_2 versus the carbon electrode, leading to degradation and reduced performance (Armand & Tarascon, 2008). Additionally, a lack of basic knowledge of reaction kinetics, particularly oxygen reduction reaction (ORR) and oxygen evolution reaction (OER) (Lu et al., 2013), poses a challenge. Despite these hurdles, lithium-air battery technology is considered the future of electric mobility, exemplified by IBM's Battery 500 Project, which intends to develop a lithium-air battery technology that can enable a conventional vehicle to drive 500 miles or more between charges (IBM, 2011).

Sodium-ion (Na-ion) batteries operate in similar principles to their Li-ion counterparts and have been developed approximately over the same time as them. These batteries are growing in popularity due to sodium's abundance and widespread presence in the Earth's crust, making them potentially less expensive and less environmentally harmful compared to Li-ion batteries (Larcher & Tarascon, 2015). Sodium, like lithium, is an alkali metal and they share key properties such as ionicity, electronegativity, and electrochemical reactivity (F. Wang et al., 2018), which translates into similarities in operating principles and electrode materials between the two battery types. Among the advantages of Na-ion batteries is their reduced sensitivity to temperature variations and their high charge/discharge rate (Sundaram et al., 2023). However, further research is needed to refine and develop these technologies before they can emerge as a true contender to replace the prevalent Li-ion battery technology (Dixit et al., 2023).

All the components mentioned in this section are structured together and work jointly to form the battery system. Beyond batteries themselves, these systems encompass crucial elements such as BMSs, thermal management systems, charging infrastructure, and control algorithms. Thus, in addition to examining only EV batteries themselves, this study aims to investigate the broader landscape of battery systems. This includes exploring the previously mentioned components, seeking to gain insights into the research gaps, the opportunities, the innovations surrounding these components, and uncovering their role in improving the performance, efficiency and sustainability of EVs.

2.2 Innovation

Innovation refers to the process of conceiving, developing, and implementing new ideas to create value or solve problems, introducing novel and improved solutions. According to Kline and Rosenberg (1986), innovation is not a solitary event but rather a series of interlinked activities and processes that contribute to the development and diffusion of new technologies and products. Consequently, innovation is a dynamic and cumulative process where one innovation often builds upon earlier innovations (Caraça et al., 2009).

Innovation research can be categorised into different levels of analysis: micro, meso, and macro (Fulvio Castellaci & Wibe, 2005). At the micro level, studies focus on the innovative processes within firms and their organisational structures. The meso level examines sectoral differences, highlighting the heterogeneity of innovation across industries and regions. At the macro level, research investigates the broader economic impacts of innovation on national economies, including growth and employment trends.

Measuring and quantifying innovation is important as it can help to identify patterns in the innovation process and map the research's conceptual framework, which can inform policies and strategies for economic growth (Naeini et al., 2022). Furthermore, innovation metrics can be used to compare different regions and assess the contributions of different actors in terms of innovation performance, allowing for benchmarking and identification of best practices (Park et al., 2022).

In addition to various other metrics in the realm of science and technology, such as Research and Development (R&D) spending, personnel data, or innovation surveys, patents stand out as a remarkably comprehensive and precise data source for tracking inventive endeavours (OECD, 2009b).

2.3 Publications as an indicator of innovation

2.3.1 Bibliometric methods

Different definitions of the term bibliometrics have been presented. The first author using the term bibliometrics was Pritchard and Groos (1969), who stated that bibliometrics is "the application of mathematics and statistical methods to books and other media of communication". Broadus (1987) consider that bibliometrics is "the quantitative study of physical published units, or of bibliographic units, or of the surrogates for either". According to Hood and Wilson (2001), bibliometrics is a quantitative analysis technique used to study patterns and trends involving statistical analysis of bibliographic data (information about research papers, journal articles, conference proceedings, etc.).

McBurney and Novak (2002) identify two dimensions of bibliometrics: descriptive and evaluative. Descriptive bibliometrics involves quantifying aspects like the volume of articles an organisation produces, offering an overview and tracking publishing trends. Evaluative bibliometrics examines the impact and influence of scholarly works, providing insights beyond publication counts. This includes citation analysis, which highlights the influence of journals, organisations, and countries on academic topics.

Authors or organisations can choose to patent rather than publish their research findings (Martin, 2019), consequently it is useful to complement the bibliometric approach with the patent approach, to better understand the real-world uses, emerging technologies, and commercialisation of EV batteries.

2.3.2 Literature on bibliometric analysis

Bibliometric analysis help in mapping the existing research landscape, identifying key areas, trends, and gaps, enabling researchers to understand the evolution of the field and its current state. Bibliometric methods are used to identify key contributors, analyse collaboration networks, and understand the impact of the work on policymakers and investors. These methods have been used to study general trends in EV innovation, namely by Zhang et al. (2015) who examine the development status and the essential characteristics of different energy management strategies for HEVs. These technologies play a crucial role in optimising fuel efficiency and overall performance of HEVs. Then, Alvarez-Meaza et al. (2020) chose another type of EV to study, the FCEV. The authors construct two distinct maps: the scientific map, derived from citation relationships (offers insights into author productivity, co-authorship patterns, and influential journals), and the technology map, derived from patent analysis (provides an overview of key technologies, jurisdictions, and technological fields). The findings reveal Chinese universities as the most productive in terms of scientific output, yet Japanese car manufacturers lead in technological advancements. Two studies examine the rentability of EVs when compared to ICE vehicles. Another paper reviewed 42 articles on life cycle cost analysis of EVs, revealed that the high cost of batteries prevents EVs from being competitive with traditional ICE vehicles (Ayodele & Mustapa, 2020). They also find that the different life cycle costs of different EVs are mainly due to different policies and incentives that the governments apply in different nations. Soares et al. (2023) analyses the EV supply chain, focusing, for example, on the supply of critical materials of EV batteries and their environmental impact. Finally, Ullah et al. (2023) present a global bibliometric analysis of EV research. The findings reveal China, the US, and the UK as leaders in EV research and applications, with China having the most productive institutions and authors in the area. Key research themes include BMS, energy storage, and charging infrastructure, all of them related to batteries which are one of the most important components of EVs.

Then, other studies apply bibliometric methods to study the evolution of battery technologies, not exclusive to EVs. The main focus of Cabeza et al. (2020) is to identify the research gaps and trends in battery thermal management systems, revealing a significant research void in thermal management of batteries across different types of batteries, emphasising that the existing focus predominantly revolves around Li-ion technology. With a more technical approach, Su et al. (2023) use bibliometric data to study the advances in a specific type of battery, the zinc-ion battery, which is being explored for large-scale energy storage applications, particularly in grid storage systems. With the current popularity of Li-ion batteries and their wide use, X. Wang et al. (2023) examine the research landscape concerning the thermal hazards associated with Li-ion batteries using bibliometric analysis. The authors identify the weakness of the Chinese research on Li-ion thermal hazards and its initial stage, as their publications are less cited than the ones from European and American countries. Finally, L. Wang et al. (2024) present a comprehensive review of Electrochemical Energy Storage (EES). The study reveals an increase in EES publications, with China and the US as leading contributors but with developing economies such as India, Iran and Saudi Arabia growing in importance. They categorise the development history into three stages: initial, rapid, and boom. Research hotspots include fundamental theories (lead acid batteries), storage performance enhancement (thanks to Li-ion batteries and market expansion driving up demand for battery energy storage), and large-scale commercialisation.

Regarding the study of battery technologies in EVs, there are two papers worth mentioning. Battery state estimation is crucial for determining the available charge as well as the overall health of a battery. Consequently, Swarnkar et al. (2022) provide a bibliometric analysis of EV battery state estimation, showing that China is the leading contributor to this field. Li-ion batteries are the predominant choice for EVs due to their efficiency, high energy density, and declining costs. Chen et al. (2023) provide a bibliometric analysis of Li-ion batteries in EVs, discussing the importance of these batteries in the transition towards clean energy and their role in the future of transportation.

2.4 Patents as an indicator of innovation

2.4.1 Patents

A patent is a legal document that provides a monopoly on an invention's use, production, and sale, granting the inventor exclusive rights to that invention for a limited period (WIPO, 2023b). In exchange for the exclusive rights, the inventor must provide a detailed and publicly available description of the invention, ensuring that the state of knowledge in the field can advance and that innovation in the area is encouraged.

To patent an invention, it should be "directed to patentable subject matter, novel, inventive, and capable of industrial application" (OECD, 2009b, p. 19). A patent is issued either by a national patent office or through a regional authority. Currently, a global or international patent granting system does not exist, nonetheless, inventors can secure patent rights in multiple jurisdictions by filing separate applications in each desired location.

Patent data can be used as a valuable indicator of innovation, offering quantifiable insights into inventive activity within an industry (each patent represents a unique technological advancement and a higher number of patents can suggest a higher level of inventive activity) (Dang & Motohashi, 2015). Companies often invest significant resources in R&D to create patented innovations, therefore, an increase in patent filings by a company can indicate a commitment to innovation.

Patent data primarily emphasises the outputs of the innovation process, offering details about inventors' and organisations' names, as well as comprehensive descriptions of the patented innovations (Griliches, 1990). Moreover, patents can be categorised into distinct technological domains and the countries where these technologies are applied, making them an ideal choice for analysis when compared to traditional R&D expenditures. Therefore, patents shed light on who invests in R&D, where innovation occurs, and which organisations lead in patent fillings. This information is valuable for businesses, investors, and policymakers, providing a comprehensive view of the competitive landscape, market trends (emerging contenders or industry leaders), and potential areas for investment or strategic partnerships.

However, there are limitations to using patents as a definitive measure of innovation. Not all patents are of equal value (OECD, 2009b), as some patents represent groundbreaking innovations, while others may be incremental improvements or even defensive patents filed to deter competitors. Furthermore, the distribution of patent values is usually skewed (Harhoff et al., 2003), with the bulk of patents having relatively low or limited value and a small fraction of patents accounting for a considerable share of the overall value.

The number of patents granted can vary significantly by country, industry, and technology field, as some countries may grant more patents than others due to differences in patent policies and practices. For example, Japan is known for having a low number of patents granted for a given invention (Dechezleprêtre et al., 2011). Also, the strength and effectiveness of a country's intellectual property laws and enforcement mechanisms can influence the propensity to patent, therefore countries with robust patent protection systems are likely to see more patent filings since investors and businesses have confidence in the legal framework (Kortum & Lerner, 1999). Since patents are only one way of safeguarding innovations, alongside strategies such as preserving industrial secrecy or deliberately crafting intricate specifications, many inventions never result in patent filings (Cohen et al., 2000), as some inventors and companies may choose to keep their innovations as trade secrets rather than disclosing them through patents.

2.4.2 Literature on patent analysis

Many researchers are using patent data to investigate innovation trends and technological trajectories in the EV market. This trend is mostly influenced by the work of Griliches (1990), which has been built upon over the past few decades. Mendonça et al. (2021) review nearly 2 000 articles that cite Griliches' seminal paper, illustrating the diverse applications and developments in patent-based research.

For instance, Pilkington et al. (2002) concentrate the analysis in EV technology at a firm level. Their findings are limited to the patent office considered (USPTO) and to the created dataset. Hoed (2005) analysed automotive patent data comprising the three main types of Low-Emission Vehicles (LEVs). His objective was to study the development of FCVs. Oltra and Jean (2009) focus their research on the various technological trajectories of the automotive industry, therefore their research is not focused specifically either on batteries or on EVs. Wesseling et al. (2014) focus on the study of the four identified waves of development. Their research has a downside, as they use keywords to identify the desired technologies instead of taking advantage of the IPC codes present in the patent documents. More recently, Feng and Magee (2020) divided their study into the four domains of EVs, namely power electronics, charging and discharging, battery, and electric motor. Although this article improves the findings previously uncovered, it does not concentrate exclusively on batteries and is also limited to the US. They explored the improvement rate of each domain and performed a main path analysis. Yuan and Li (2021) use different measures and indicators on a patent dataset to compute the technological diffusion of BEV. They find that BEV innovation is concentrated in five countries, namely Japan, China, the US, Korea, and Germany, however, the technological diffusion is uneven, with proximity between China and the US, and between China and Germany. Finally, Li and Yuan (2023) use BEV technology as a case study to examine the complexity and overlap of patent thickets (dense webs of interrelated patents that cover various aspects of a particular technology or innovation). Their presence can pose challenges for companies or researchers aiming to develop new products as they may need to navigate and potentially license multiple patents from different patent holders to avoid infringement.

Several studies have examined broader technological aspects of batteries beyond just vehicles. Different studies focus on lithium-ion batteries, namely Stephan et al. (2019) who examined how inter-sectoral knowledge spillovers in the value chain of these batteries impact innovation, using regression analysis of global patent data, or Malhotra et al. (2021) who investigated the relationship between use environment shifts and knowledge trajectories, by analysing patents covering this technology and their respective networks. Metzger et al. (2023) go further in the topic of batteries and explore the role of secondary battery innovation in the transition to a circular economy. Their work is related to the published report from the European Patent Office (EPO) and the International Energy Agency (IEA), that use patent data to provide decision-makers insights on the innovation trends of batteries and electricity storage technologies (IEA, 2020). Lastly, Silva et al. (2023) use patent applications to investigate technological advancements and to map the patterns of innovation in battery technology, specifically focusing on the pace and direction of technical evolution.

Despite the diversity of studies, research specifically dedicated to the foundational technology of EVs, i.e., batteries, remains notably sparse. Golembiewski et al. (2015) divided their analysis into 4 pieces, each one corresponding to one step of the battery value chain, namely, raw materials, cell components, battery system and, finally, vehicle. Despite the findings, their time frame only covers 2000 to 2011, and the database they used may not provide the global coverage that PATSTAT offers. Some research is being done in China as well, with J. M. Liu et al. (2015) using patent data of Chinese EV batteries to analyse the transition from growth to maturity of China in innovation in this field. More recently, Yuan and Wu (2020) analysed the pure EV power battery technology trends in the country, focusing only on the patent counts and differentiating between patentees.

2.4.3 International Patent Families

A patent family is a collection of related patents that have been granted for the same invention in different countries or regions, sharing a common priority application (Kim et al., 2021). By counting at the family level, it is possible to reduce duplication, because a single invention may be patented in multiple countries, which prevents overestimation of the number of unique new technologies (Duch-Brown & Costa-Campi, 2015).

Moreover, if the patent families counted are restricted to the ones containing applications filed in two or more countries, we get International Patent Family (IPF). On the other hand, singletons refer to patents that do not share priority with any other patent, meaning that they are patent families with only one patent (Dechezleprêtre et al., 2017). We can control patent quality and value by assessing the IPFs, as patents protected in numerous countries may be considered more valuable (Martínez, 2011). Therefore, instead of analysing patents themselves, we will analyse IPFs.

2.4.4 International Patent Classification

The International Patent Classification (IPC), administered by the World Intellectual Property Organisation (WIPO), is a standardised system for categorising and classifying patents based on the technical content and subject matter of the inventions they describe (WIPO, 2023a). This system is organised hierarchically into sections, classes, subclasses, groups, and subgroups, allowing for a precise classification and a systematic breakdown of technological areas. Each IPC classification is represented by an alphanumeric code as depicted in Table 2.1.

Table 2.1: Main characteristics of IPC codes (example). Adapted from OECD (2009b)

Hierarchy level	**IPC code**	**Title**
Section	*H*	Electricity
Class	*H01*	Electric Elements
Subclass	*H01M*	Processes or means, e.g. Batteries, for the direct conversion of chemical energy into electrical energy
Main group	*H01M 10/00*	Secondary cells; Manufacture thereof
Subgroup	*H01M 10/05*	* Accumulators with non-aqueous electrolyte
	H01M 10/052	** Li-accumulators
	H01M 10/0525	*** Rocking-chair batteries, i.e. batteries with lithium insertion or intercalation in both electrodes; Lithium-ion batteries

The Cooperative Patent Classification (CPC) is a patent classification system jointly developed between two major patent offices, the EPO and the United States Patent and Trademark Office (USPTO). This collaboration aimed to create a unified and internationally recognised system for categorising patents, facilitating more efficient and consistent patent information retrieval across different jurisdictions. The CPC is fully compatible with the IPC, ensuring smooth interoperability between the two systems.

3 | Data and Methods

This Chapter provides an in-depth exploration of the methodological approach and research strategy adopted in this study. The followed methodology was the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, which is a widely recognised methodology for guiding the entire data analysis process. CRISP-DM provides a comprehensive approach to handling data projects, offering a clear structure that encompasses business understanding, data understanding, data preparation, modelling, evaluation, and deployment (Kelleher et al., 2015). By adhering to the principles and stages outlined in CRISP-DM, we aim to provide a transparent and structured account of our data analysis, enabling both the replication of the work and a deeper understanding of the methodologies employed.

3.1 Data collection

Given the dynamic and rapidly evolving nature of EV battery technology, it is essential to choose a time frame that includes the recent period in which significant innovations and advancements have occurred. Therefore, we opt for a comprehensive time frame, starting in 2000, which coincides with the industry's initial stages of development, as discussed in Chapter 1, and ending in 2022. Furthermore, a vital transition occurred around 2006 with the emergence of BEVs, marking the onset of a new phase in EV technology evolution characterised by the significant participation of new entrants in the automotive industry, which actively embarked on BEV production (Wesseling et al., 2014).

3.1.1 Publications

Regarding the data collection for the bibliometric analysis, we decided to use WoS and Scopus databases. Martín-Martín et al. (2018) find that Google Scholar outperforms WoS and Scopus in capturing citations across various subject areas. While a substantial portion of citations overlap between the three databases, Google Scholar identifies a significant number of unique citations that are not covered by the other two databases. However, since around half of these unique citations come from non-journal sources (theses, books, conference proceedings, unpublished materials), they exhibit lower scientific impact compared to those found on both databases. Therefore, only WoS was used to retrieve the needed observations, complemented by information from Scopus.

The query used to retrieve information from WoS is presented in the Appendix A. The framework for data collection in WoS is presented and summarised in Figure 3.1.

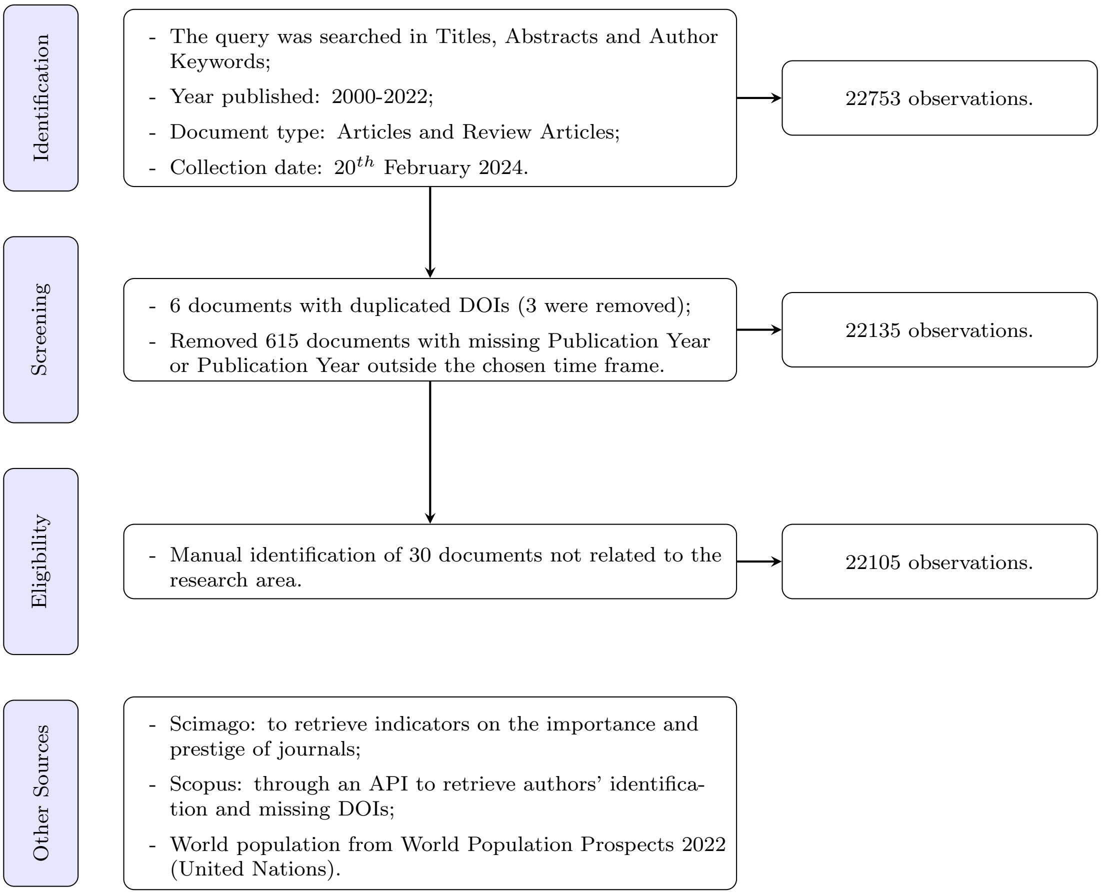


Figure 3.1: Scheme to identify publications associated with EC batteries. Adapted from Bortoletto et al. (2023).

3.1.2 Patents

Data on patent applications in EV battery technologies was retrieved from PATSTAT, which is a comprehensive database of patent information, managed and provided by the EPO, containing detailed information on patents granted by various patent offices around the world (EPO, USPTO, and other national and regional patent offices).

The framework for data collection in PATSTAT, adapted from Braun et al. (2011), was the following: first, it is necessary to identify the technological components of batteries, involving an extensive review of standard literature and publications from internationally recognised research institutions, associations, and manufacturers of EV batteries; the subsequent step is to review the IPC and pinpoint the pertinent patent classes relevant to EV batteries; to further refine the set of IPCs, the initial set can be cross-referenced with the components identified in the systematic analysis. This will be an iterative process to refine the dataset and tailor it to the specifics of the technology being studied. To validate the accuracy and completeness of this refined IPC set, the EPO's world patent search engine is used as an additional tool, including keyword searches within patent names and abstracts. Figure 3.2 comprehends the collection process.

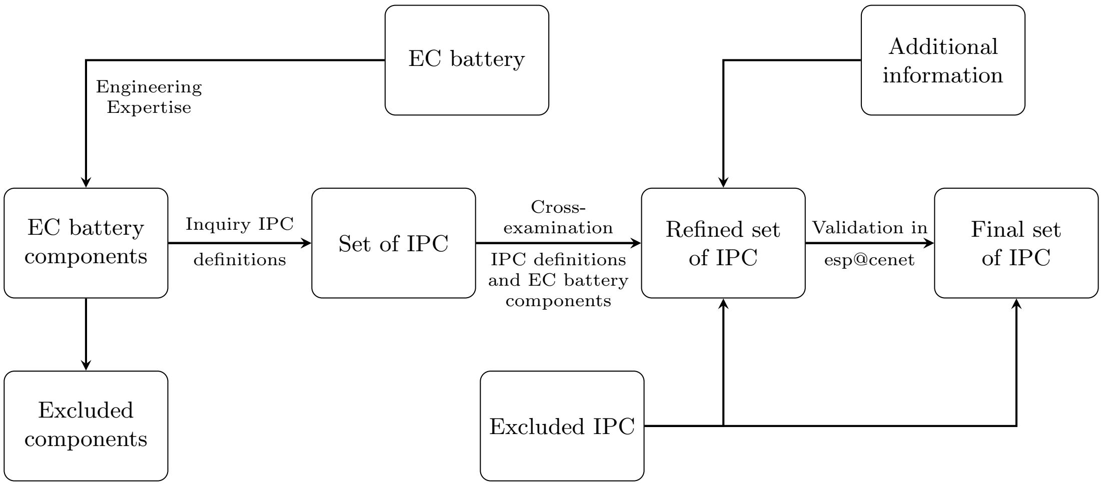


Figure 3.2: Scheme to identify IPC codes associated with EV batteries. Adapted from Braun et al. (2011).

When working with patents, there are usually two ways of retrieving the data: either take advantage of the standard classification that is present in the patent documents, namely IPC or CPC codes, or use a text search approach, using relevant keywords, such as 'battery' or 'cell'. In this study, PATSTAT data was retrieved exclusively using IPC codes.

While CPC codes offer a more detailed structure for data retrieval, their global adoption remains inconsistent. Japan and China, two significant players in the battery field, have low CPC adoption rates (Japan: 26.7% and China: 31.7% USPTO & EPO, 2018). Additionally, the complexity of CPC-based queries results in high computational costs beyond PATSTAT online capacities. Therefore, a balanced strategy was adopted: initial data extraction using IPC codes from PATSTAT, followed by further filtration using CPC codes.

3.2 Data description

Table 3.1 provides an overview of the publications dataset, while Table 3.2 provides an overview of the patents dataset.

Table 3.1: Summary of publications database.

Metric	Value
Time-span	2000 : 2022
Sources	1 898
Documents	22 105
Annual Growth Rate %	22.71
Document Average Age	5.73
Average citations per doc	49.6
Average citations per year per doc	6.584
References	447 452

Table 3.2: Summary of patents database.

Metric	Value
Time-span	2000 : 2022
Patent Applications	1 523 721
Patent Families	951 757
IPFs	180 026
IPFs Growth Rate %	383.4
Patent Grants	859 119
Countries Involved	73
Tagged Patents	266 443
Tagged IPFs	20 219

3.3 Data preparation

3.3.1 Publications

Author-level scientometric indicators are essential instruments for evaluating the impact of individual authors within the scientific community. These metrics provide insights into the productivity and influence of researchers based on their publications and citations (Hirsch, 2005). However, author ambiguity occurs when individuals share identical or similar names, leading to confusion in accurately attributing publications to specific authors (Abdulhayoglu & Thijs, 2017). This issue is compounded by heteronymous names, such as "Tom Mitchell" and "Tom M. Mitchell", which may be considered the same author by databases (Shin et al., 2014). Additionally, synonym problems arise when authors are referenced under various names. For instance, the German surname "Müller" may also appear as "Muller" or "Mueller" (Rehs, 2021).

Given that author ambiguity undermines the accuracy and reliability of citation analysis and the identification of influential researchers, we implemented a solution leveraged by the Scopus API. By retrieving detailed information on author names and affiliations, we conducted more robust analyses of authorship patterns, collaborations, and research trends.

To ensure accuracy and consistency in our analysis, we took additional preprocessing steps. We normalised keywords by standardising terms and merging synonyms (and plurals). Authors' affiliations were classified into academic and non-academic categories, through keyword searches in the institutions' names. We also standardised country names, grouped countries into regions, and matched these with population data.

3.3.2 Patents

Rigorous checks were performed to ensure data integrity and quality. Firstly, we checked if the earliest publication dates of the applications fell within the desirable range (between 2000 and 2022). Second, we verified if the column representing the size of each patent family was consistent with the actual number of observations for each patent family.

As stated before, the primary emphasis of this analysis is on IPFs, given that patents filed in multiple countries typically hold greater value for applicants seeking protection in various jurisdictions (Martínez, 2011). Therefore, we implemented a harmonisation process to guarantee consistent information regarding the earliest publication dates across all observations belonging to the same patent family. Additionally, we introduced a tagging system for patent families. Based on the definitions of IPF and singletons presented before, we classified the observations in the dataset into one (or none) of these categories. 18.91% of the patent families in the dataset are IPFs, and these were the ones used for the analysis.

Furthermore, we developed another tagging system to identify the three main groups of technologies in the study: charging technologies, BMS technologies, and EV batteries technologies. First, we identified the relevant classifications for each technology category. Then, we searched for these classifications in both the IPC and CPC columns. Figure 3.3 provides a summary of the preprocessing steps and the final used classifications for tagging patents. A more detailed description of the classifications used can be found in Appendix C.

The use of these categories was motivated by Feng and Magee (2020), as they use 4 categories to aggregate their dataset: power electronics, charging & discharging, battery, and electric motor. Since our focus is on batteries, we decided to use the categories of charging technologies, BMS technologies, and EV batteries technologies. By isolating BMS technologies, we could more accurately assess innovations that enhance battery performance and safety, a key area of interest.

It is worth noting that, regarding the classifications of EV batteries, patents containing the IPC code *H01M 8* (related to fuel cells and their manufacture) were included

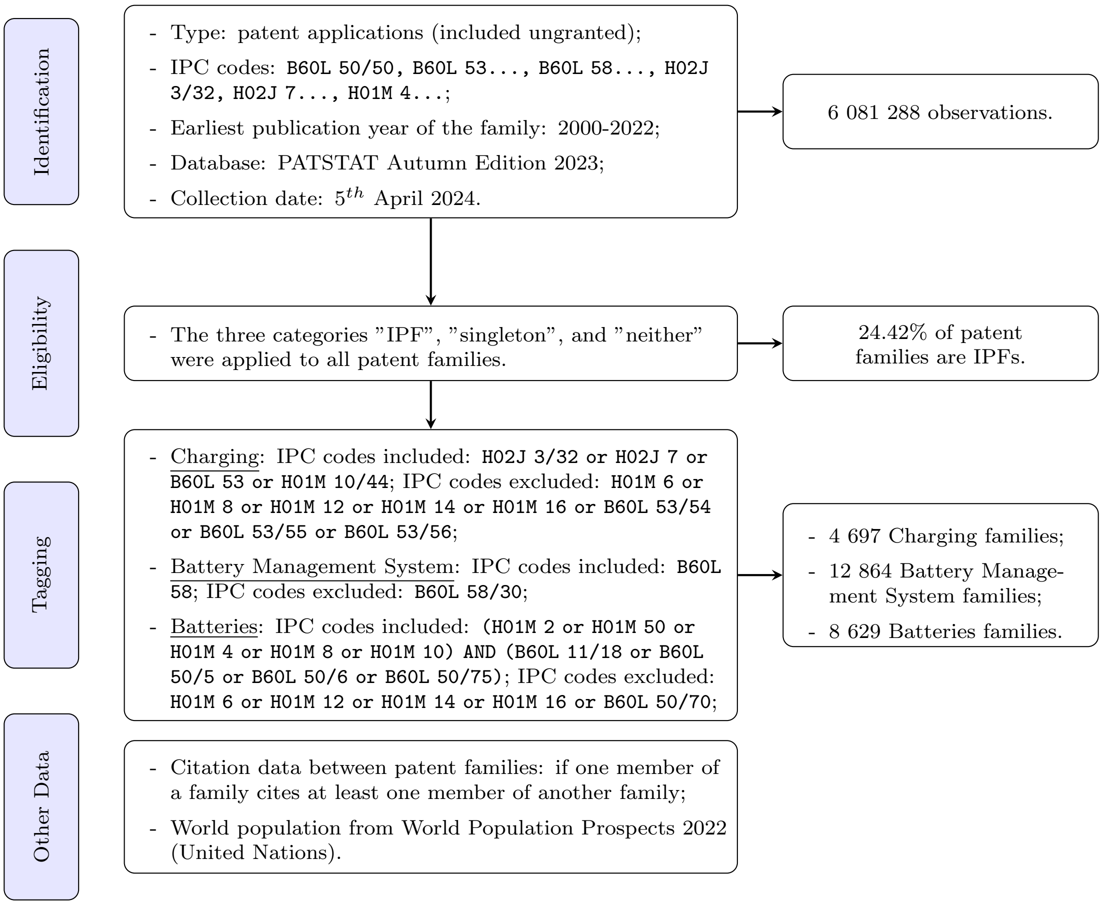


Figure 3.3: Scheme to identify the steps taken during data preprocessing of patents database.

only when they also contained the IPC code *B60L 50/75*. Fuel cells generate electricity through electrochemical reactions between a fuel and an oxidant (usually hydrogen and oxygen, respectively), converting chemical energy directly into electrical energy (Kanuri & Motupally, 2013). However, integrating fuel cells with batteries can optimise energy efficiency, performance, and range in EVs, leading to an overlap between these technologies (Lindorfer et al., 2020). The IPC code *B60L 50/50* relates to electric propulsion systems for vehicles using power supplied by batteries or fuel cells, specifically excluding those solely using fuel cells (*B60L 50/70*). By including patents with both *H01M 8* and *B60L 50/50* IPC codes, the dataset captures innovations integrating fuel cells with batteries (hybrid systems), while excluding technologies focused exclusively on fuel cells.

3.4 Modelling

3.4.1 Counts

Regarding the analysis of publications, for country counts, we attribute the first author's affiliated country to the publication of the country.

For the patent analysis, we followed the same methodology as in IEA (2020) and Metzger et al. (2023), where the considered dates were the earliest publication dates for each IPF. And when an IPF had more than one inventor, a fraction of the counts were assigned to each inventor and to each inventor's country to compute the geographic distributions.

The retrieved data from PATSTAT contains several columns to identify the patent applicants, some of them partially harmonised. Attribute `han_name` contains for many applicants the names as harmonised by the OECD HAN (Harmonised Applicant Name) project. However, since the harmonisation is not complete we can find in the dataset records ″HARUN, YETKIN″ and ″YETKIN, HARUN″ with different IDs, but in reality corresponding to the same applicant. Entries like this will, not only affect the counts but also prevent us from analysing the field at affiliation level since it is not possible to correctly match all the applicants' names to the correct companies with these problems in the data.

3.4.2 Network analysis

The degree of a node measures the number of connections a country has in the network, therefore countries with a higher degree centrality are more interconnected within the network (Freeman, 1978).

The betweenness of a node quantifies the extent to which a country serves as an intermediary between other countries in the network, meaning that higher betweenness means that the country plays a central role in connecting different parts of the network (Freeman, 1978).

The closeness measure assesses how quickly a country can interact with other countries in the network, so countries with higher closeness can reach the other countries in the network more efficiently (Sabidussi, 1966).

3.4.3 Concentration measures

The Herfindahl-Hirschman Index (HHI) is a market concentration and can be used to assess the level of competition within an industry (Yang et al., 2010). Higher values indicate a higher level of market concentration and lower competition, as the index ranges from 1 (least concentrated) to 10 000 (most concentrated).

$$\text{HHI} = \sum_{i=1}^{N} \left(\frac{X_i}{X} \right)^2 = \sum_{i=1}^{N} S_i^2 \tag{3.1}$$

where S is the number of citations (X_i) received by each paper divided by the total number of citations (X) received by papers published within a certain period, and N is the number of cited papers.

3.4.4 Title and abstract mining

N-grams are sequences of n-items (or terms) in a text. These items can be characters, words, or other linguistic units (Schonlau et al., 2017). Examples of n-grams used in this study include unigrams, bigrams, and trigrams. We analysed these expressions after filtering the stopwords, which are common words that are filtered out before preprocessing text data as they do not carry meaningful information, and they can introduce noise in the analysis.

We computed n-grams counts of the annual occurrences, as well as n-grams intensities, which are the counts divided by the number of abstracts' or titles' of the respective year. The presented results in section 4.6 are sorted in descending order of increase of the difference between the last and the first year of the analysed time frame. Other representations were computed: (1) the same sort but in ascending order to see the expressions that have decreased, (2) sort the results in descending order according to the sum of year-to-year difference too see the expressions that have experienced the biggest changes.

3.4.5 Time series analysis

Vector Autoregressive (VAR) models generalise single-variable autoregressive models, as they capture linear interdependencies among multiple time series variables. A VAR model describes the evolution of a set of k endogenous variables over time (Lütkepohl, 2005). Each variable is modelled as a linear function of its own past values and the past values of all other variables in the system.

The VAR model of order p can be represented as:

$$\mathbf{y_t} = \boldsymbol{\nu} + \mathbf{A_1 y_{t-1}} + \cdots + \mathbf{A_p y_{p-1}} + \mathbf{u_t}, t = 0, \pm 1, \pm 2, \cdots \tag{3.2}$$

where $\mathbf{y_t} = (y_{1t}, \cdots, y_{Kt})'$ is a $(K \times 1)$ random vector, the $\mathbf{A_i}$ are fixed $(K \times K)$ coefficient matrices, $\boldsymbol{\nu} = (\nu_1, \cdots, \nu_K)'$ is a fixed $(K \times 1)$ vector of intercept terms allowing for the possibility of a non-zero mean $E(y_t)$. $\mathbf{u_t} = (u_{1t}, \cdots, u_{Kt})'$ is a K-dimensional *white noise*, that is $E(u_t) = 0$, $E(u_t u_t') = \Sigma_u$, and $E(u_t u_s') = 0$ for $s \neq t$

Choosing the correct lag length p is critical for the proper specification of a VAR model. Different criteria (Akaike, 1974; Hannan & Quinn, 1979; Schwarz, 1978) are typically used to determine the optimal lag length, namely the Final Prediction Error criterion, Akaike Information Criterion, Hannan-Quinn criterion, and Schwarz criterion. The lag length that minimises these criteria is generally selected as the optimal lag length.

$$\text{FPE}(m) = \left[\frac{T + Km + 1}{T - Km - 1}\right]^K \det \tilde{\Sigma}_u(m) \tag{3.3}$$

where m denotes the order of the VAR process fitted to the data, T is the sample size, and K is the dimension of the time series.

$$\text{AIC}(m) = \ln \left|\tilde{\Sigma}_u(m)\right| + \frac{2mK^2}{T} \tag{3.4}$$

$$\text{HQ}(m) = \ln \left|\tilde{\Sigma}_u(m)\right| + \frac{2 \ln \ln T}{T} mK^2 \tag{3.5}$$

$$\text{SC}(m) = \ln \left|\tilde{\Sigma}_u(m)\right| + \frac{\ln T}{T} mK^2 \tag{3.6}$$

Our objective with these estimations was to test Granger causality, which is a test used to determine whether one time series can predict another (Granger, 1969). Granger stated that causality could be measured by the ability of prior values of a time series to predict the future values of a different time series. The intuition is that if knowing the past values of time series X helps us to make better predictions about the future values of time series Y, then X is said to Granger-cause Y.

The test compares the performance of two models: (1) a model using only past values of Y to predict future Y; (2) a model using past values of both Y and X to predict future Y.

So, a statistical test is used to assess the significance of the improvement by adding the information of time series X. The null hypothesis (H_0) is that X does not Granger-cause Y, while the alternative hypothesis (H_1) is that X does Granger-cause Y. If the null hypothesis is rejected, it indicates that past values of X help predict Y, suggesting Granger causality.

One important limitation of this method is that it assumes linear relationships between the variables, and so, if the true relationship is nonlinear, the test might not detect it (Granger, 1969). Also, other limitations are related to questions regarding the nature of causality or temporal ordering vs. causality, as discussed in Maziarz (2015).

4 | Results and Discussion

The findings of the analysis are presented in this chapter, to identify the patterns of innovation associated with EV batteries, their historical evolution, notable authors, inventors, and institutions, and academic and technological trends in this field.

4.1 Research per year

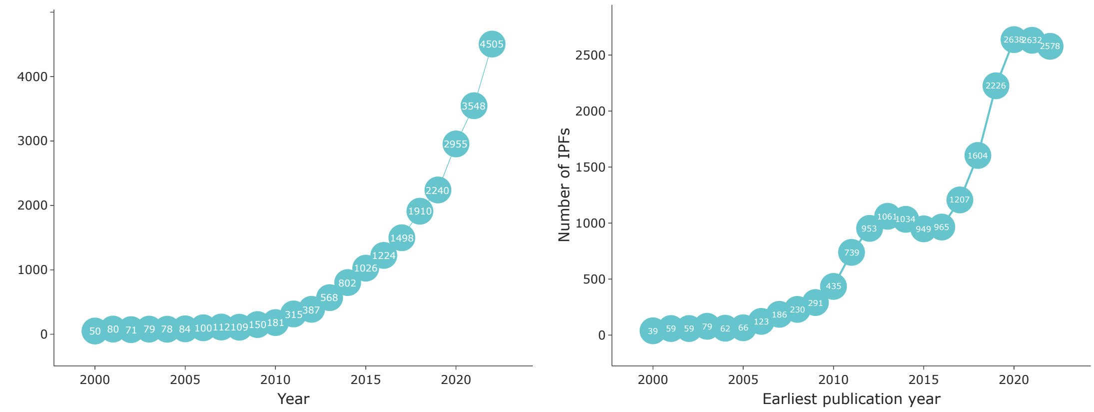
To answer the question ”How has the scientific and technical research on EV batteries evolved since 2000?”, a total of 22 105 publications published between 2000 and 2022 and 20 219 IPFs with the earliest publication year between 2000 and 2022 were analysed.

Until 2010, the number of publications had been stable, with around 100 publications per year, as shown in Figure 4.1a. After 2010, there was a steady increase with no sign of slowing down.

The overall trend in the number of IPFs suggests a significant and steady increase in the analysed period. It started with 39 IPFs in 2000 and reached the peak in 2020 with 2 638 applied IPFs. Again, between 2000 and 2010, there was a gradual increase in patent activity, and from 2011 onwards there was a marked acceleration in the number of applied patents. The highest increase is registered from 2010 to 2011 when the number of applied IPFs increased by approximately 70%. On average the increase from year to year was 24%.

The adoption of EVs was relatively low before this period, with limited market and infrastructure support. In the following years, there was a significant increase in EV sales and market share, reaching over 10 million sales worldwide by 2022 (IEA, 2023). This surge in demand for EVs not only reflects changing consumer attitudes but also triggers investment in R&D to meet growing market demands and technological advancements.

Before 2010, there were few government incentives, policies, and regulations promoting the adoption of EVs. In the United States, subsidies for PHEVs and BEVs began in 2010, offering 2 500$ to 7 500$ depending on the battery capacity; Japan introduced the ”Green Vehicle Purchasing Promotion Measures” in 2009, providing subsidies up



(a) Publications. (b) IPFs.

Figure 4.1: Number of research items analysed from 2000 to 2022.

to 100 000 Yen and tax reduction incentives; China launched the Electric Vehicle Subsidy Scheme in 2009, with updates in 2013, offering subsidies for both public and private EV purchases (Hao et al., 2014). This growing market demand for EVs, aligned with a growing global awareness of the importance of reducing greenhouse gas emissions and transitioning to cleaner transportation alternatives, likely spurred greater research interest and investment in EV battery technologies.

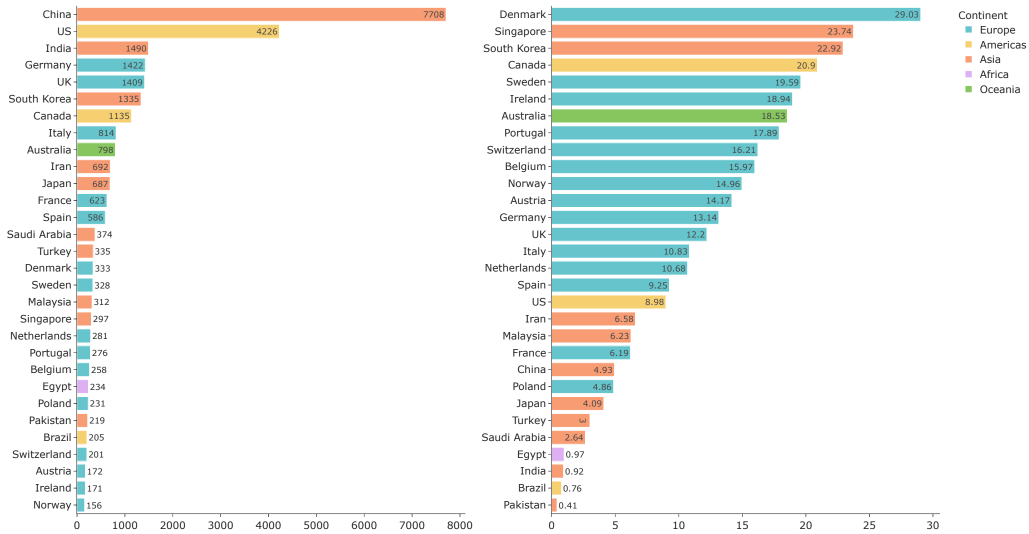
Moreover, there has been a notable increase in the number of journals publishing EV batteries-related research, surging from 22 journals in 2000 to 795 in 2022. Similarly, the scope of knowledge production in this field has expanded globally, with the involvement of 15 countries in 2000 and growing to encompass 103 countries by 2022. This proliferation reflects the collaborative efforts among researchers across borders, driven by diverse motivations such as strengthening economic or political ties, accessing specialised equipment or facilities that may be available in only a few locations worldwide, or fulfilling mandatory exercises outlined in bilateral agreements between institutions, government agencies, or science administrations (Glänzel, 2001).

A VAR model of order 3 was estimated, using the two time series, one with the number of IPFs applied in the analysed time frame, and the other with the number of published scientific papers in the same time frame. The model passed the Jarque-Bera test (for normality) and the Breusch-Godfrey test (for autocorrelation) with high p-values. Two Granger causality tests were performed, and the conclusions are interesting. The coefficients of the estimated lagged variables for the number of IPFs are jointly significant, and therefore, with a p-value of 0.08373, we reject the null hypothesis, meaning that we have statistical evidence for saying that the number of applied IPFs Granger-cause the number of published papers. The same does not happen for the inverse case.

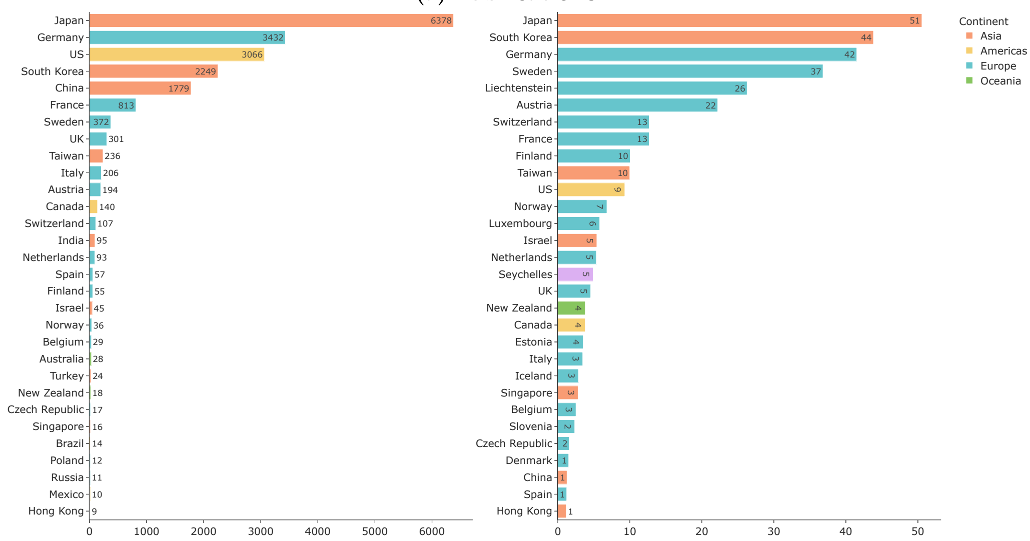
4.2 Major contributors

To answer the question "Who are the main authors/ inventors, journals, and countries that contribute to the EV battery field?" the data on authors/ inventors and publishers was analysed.

4.2.1 Countries



(a) Publications.



(b) IPFs

Figure 4.2: Research items analysed per country from 2000 to 2022. Absolute values (left) and normalised per 1M inhabitants (right).

Figure 4.2a presents the volume of research publications on EV batteries, with 103 countries involved. The countries were extracted from the authorship information of both the first author and the co-authors. The most productive authors were the Asian, with 11 637 papers published between 2000 and 2022, accounting for more than half of the published documents. We can see in the plot on the left that China emerges as the country with the highest number of published documents, with a total of 7 709 papers, followed by the US. These two countries account for nearly 44% of all publications.

These numbers should be complemented with the number of articles normalised by population for each country, which provides a more equitable comparison by accounting for the size of the country. Interestingly, when normalised by the population, we can see on the plot on the right of Figure 4.2a that Europe emerges as the continent with the highest number of articles per capita. Despite its prolific output, China's large population size means that its research output per capita does not rank as high when compared to smaller nations. In fact, on a per capita basis, China fails to even make it into the top 30 countries contributing to EV battery literature. These findings align with recent data showing that China has surpassed the US as the top-ranked country for contributions to research articles published in high-quality natural science journals (Baker, 2023).

Figure 4.2b presents the distribution and intensity of IPFs related to EV batteries per country. We can see Asian countries again leading in the total number of IPFs, with Japan having almost the same number of applied IPFs as the two next countries in the ranking (6 378 of Japan against 3 432 of Germany and 3 066 of the United States). When adjusting for population size, smaller countries like Liechtenstein, Switzerland, and Sweden show significantly high rates, suggesting highly concentrated innovative activities. Countries like China and India have significant absolute numbers, but they show lower figures on a per capita basis. As in the bibliometric analysis, although there is substantial innovation activity, their per capita engagement is diluted by the large populations.

Depicted in Figure 4.3a, we can see the US initially dominating the landscape with a higher share of first-author papers compared to China, accounting for approximately 31% of the total share in 2000 against the modest 4% share of the Asian country. As the years progressed, a shift occurred, with China steadily increasing its share after 2010, and surpassing the US after 2014. This trend confirms the repositioning in the global distribution of publications, with China emerging as the main contributor to this field.

The top 5 countries with the highest shares in terms of patents, shown in Figure 4.3b, indicate a clear dominance of Japan. At the beginning of the analysed time frame, Japan accounted for nearly 70% of all IPFs applied in the database. According to IEA (2008), Japan's budget for energy R&D was over USD 3.6 billion in 2006, a slight decline compared to the previous years. The share of funds allocated for power and storage technologies was increasing in the early 2000s, and this ambitious R&D policy might help explain the premature lead.

Over the years, Japan's share in the patent side has experienced a decline, falling to under 30% in 2022. This may be justified by the rise of other nations, namely Germany, China, South Korea, or the US, which started to catch up technologically, reducing

(a) Publications. (b) IPFs.

Figure 4.3: Share for top 5 countries with more research output from 2000 to 2022.

Japan's initial advantage. Germany continues to invest in energy storage applications for EVs, as the transport sector accounts for 29% of final energy consumption in Germany (Federal Ministry for Economic Affairs and Energy, 2018).

The overall trend in patents towards a more evenly distributed share among the most influential countries suggests an increase in global diversification in EV battery innovation.

The impact of scientists' work on the research paradigm can be measured through the citation count of their peer-reviewed articles. This proposition is built on the notion that high-quality work might receive more responses (citations) compared to lower-quality counterparts (Bornmann & Daniel, 2008). Looking at the citation patterns for each country in Figure 4.4, the US has the highest number of citations, closely trailed by China.

However, when normalising these citation metrics by the number of published articles, Israel emerges as the front-runner with 242 citations per paper. The US occupies the third place with an average of 88.2 citations per publication, and, in contrast, China ranks 22nd, recording 45.6 citations per article. This discrepancy suggests that China values publishing volume over quality, as F.-c. Liu et al. (2011) identify this phenomenon where Chinese mayors and governors are assessed on the rate of GDP increase "rather than on the quality" of their innovative contributions.

The Herfindahl-Hirschman Index can be calculated for countries to measure the concentration of research output among the different actors. Both Figures 4.5a and 4.5b present a decreasing trend in the HHI over the analysed time frame. This trend suggests a more evenly distributed research output across the involved countries and the scholarly community, which translates into a less concentrated landscape over time and a more competitive environment, as a larger number of countries is contributing to the research.

Despite the more significant decreasing trend in the IPF analysis, the values for the

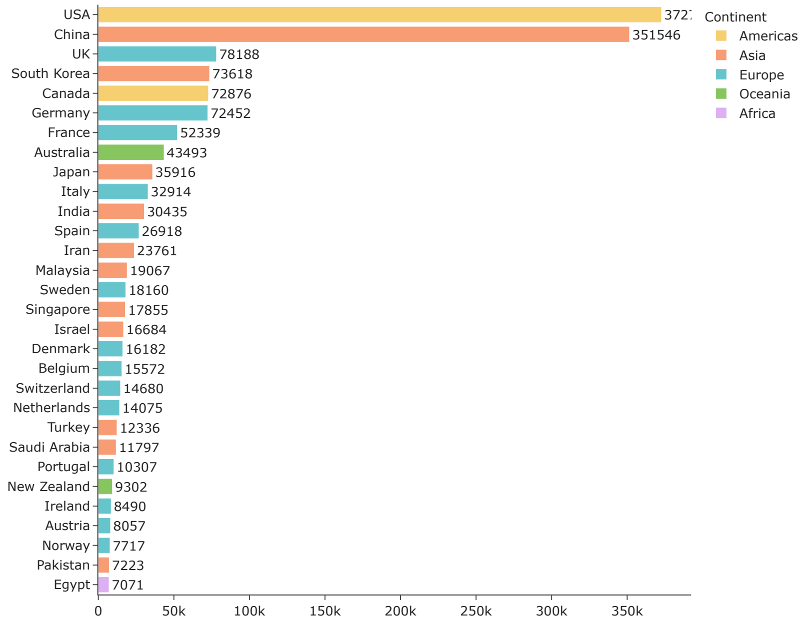


Figure 4.4: Total number of citations accruing from authors of a given country (Top 30) from 2000 to 2022.

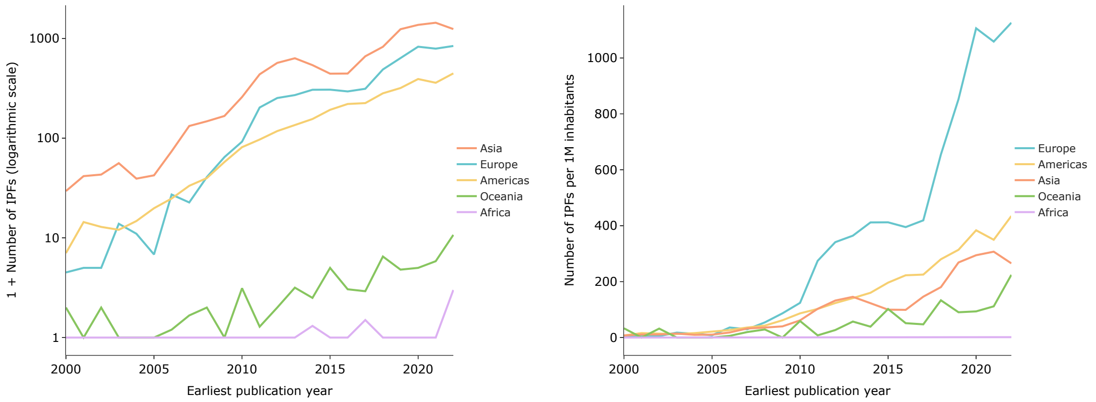
HHI remain significantly higher, indicating persistent concentration in patent applications with higher value.

(a) Publications.

(b) IPFs.

Figure 4.5: HHI for countries participating in EV batteries related articles from 2000 to 2022.

As mentioned before, Asian countries are the most productive ones: the Asian average yearly IPF output is 1.85 times higher than Europe's and 3.34 times higher than Americas'. Normalising the patent counts by population counts provides a more accurate comparison of patent activity between countries and continents because we are accounting for differences in population size and eliminating biases related to country size (OECD, 2009b). Figures 4.6 highlight the regional disparities in innovation, with Asia leading in total number of patents and Europe leading in per capita innovation. The average year-over-year increase for Asia and the Americas is similar, 22.26% and 22.61% respectively, while the average year-over-year increase for Europe is significantly higher, 39.92%.



(a) Logarithmic scale. (b) Per 1M inhabitants.

Figure 4.6: Number of IPFs applied from 2000 to 2022, separated by continent.

4.2.1.1 BRICS vs. G7

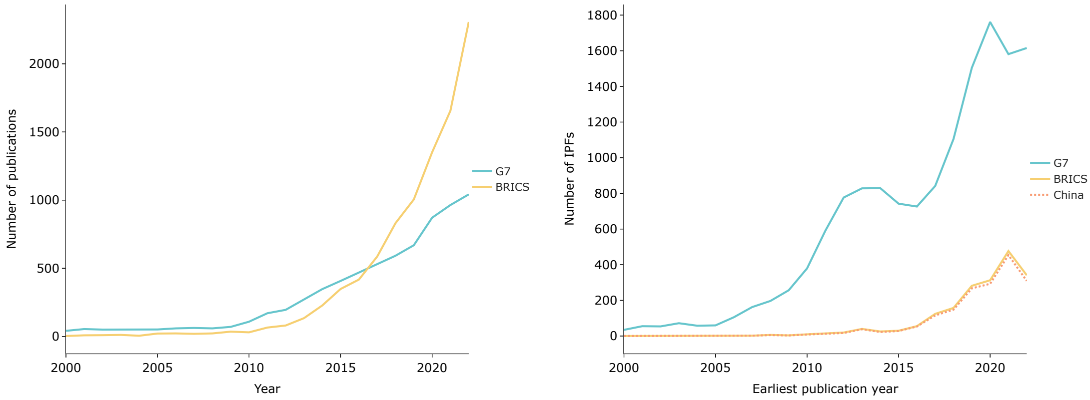
A detailed analysis can be made to compare the activity of BRICS countries and of G7 countries. The major emerging economies with rapidly growing innovation capabilities are BRICS countries: Brazil, Russia, India, China, and South Africa. On the other hand, we have the Group of Seven (G7) which consists of seven of the world's largest advanced economies: Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States.

Both G7 and BRICS countries face global challenges such as climate change and sustainable development, and comparing innovation activities can reveal how countries are addressing these challenges through research and technology, and how they can potentially collaborate on global solutions.

The two groups show an increasing trend in the number of publications. Initially, G7 countries are more productive than BRICS, however around 2016 the development of BRICS countries was more accelerated, with this group catching up and surpassing the other. These findings contrast with the ones found in (de Paulo et al., 2017), where the authors identify a clear dominance of the developed countries.

Contrary to what we see in the bibliometric analysis, G7 countries are leading the technical innovation in EV battery technologies. One fact worth noting is that the innovation in BRICS countries is clearly driven by Chinese patents, as we can see in Figure 4.7b.

We also performed time series analysis techniques to compare BRICS countries against G7 countries. We estimated two VAR models, one for the IPFs time series,



(a) Publications. (b) IPFs.

Figure 4.7: Research output from 2000 to 2022, separated by country group.

containing one time series for the number of IPF per year by BRICS countries and another time series for the number of IPF per year by G7 countries, and another for the publications time series (again, two time series, one for publications by BRICS another for publications by G7).

Based on the calculated values for the criteria mentioned in Subsection 3.4.5, both VAR models had order 4. Multivariate Jarque-Bera tests were performed, with the objective of assessing if the data follows a normal distribution, by examining skewness and kurtosis. For both models, the null hypothesis of the data following a normal distribution was not rejected at the usual levels of significance. Multivariate Breusch-Godfrey tests were performed as well, with the objective of detecting the presence of serial autocorrelation in the residuals of the two VAR models. Again, in both models, we did not rejected the null hypothesis of not having serial correlation in the residuals.

Finally, we tested for Granger causality in both models. On the analysis of the publications, we fail to reject the null hypothesis for both tests, with p-values of 0.8 and 0.2. Therefore we do not have statistical evidence for saying that nor publications of G7 countries Granger-cause publications of BRICS countries, nor vice-versa. On the patent analysis, the coefficients of the estimated lagged variables for the number of IPFs by BRICS countries are jointly significant, and therefore, with a p-value of 0.08218, we reject the null hypothesis for the Granger causality test, meaning that we have statistical evidence for saying that the number of IPFs by BRICS Granger-cause the number of IPFs by G7 countries. The same does not happen for the inverse case.

4.2.2 Journals - publications

Analysis of the top scientific journals, as depicted in Figure 4.8, reveals the twenty major scientific journals by publications count. Notably, all these journals fall within quartile Q1 or Q2 rankings, and their main focus areas are related to Chemistry, Energy, and Engineering. *Energies* emerges as the most prolific journal in absolute publication number, however, one of the lowest citations per paper metrics among this group of journals. Of particular interest is the *Renewable & Sustainable Energy Reviews*, distinguished by its significant impact, evidenced by an impressive average of 142 citations per paper, reflecting its contribution to knowledge dissemination in this field.

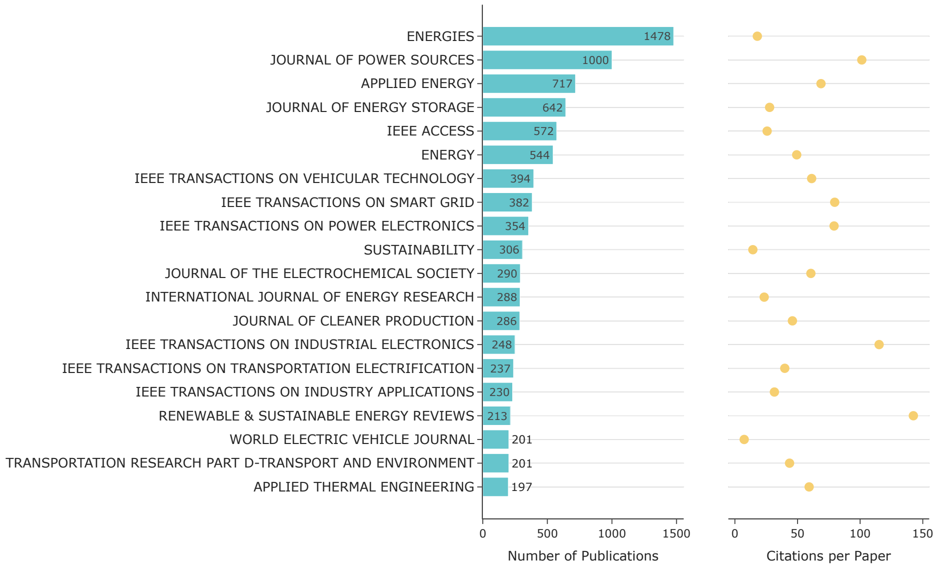


Figure 4.8: Most productive journals (Top 20) by number of articles (left) and their average number of citations per paper (right) from 2000 to 2022.

4.2.3 Authors - publications

In absolute terms, authors from China dominate the list, with 13 out of the top 20 contributors from this country, as it can be noted in Figure 4.9. Notably, Ouyang M. takes the lead as the most productive author, with 147 published articles, accounting for 0.6% of all selected publications.

However, when considering impact, measured by the number of citations on the left plot of Figure 4.9, authors from the US take the lead, with 9 authors among the top 20. Interestingly, the distribution of countries among both the most productive and impactful authors is heavily concentrated around these two countries. While citations serve as an indicator of acknowledgement and recognition from peers, they do not necessarily capture the broader influence. This discrepancy can be attributed to the time it takes for citations to accumulate and to the true impact of a paper to become evident (W.-C. Lin & Chang, 2022). As noted before in Figure 4.3a, China started the race for research in this area after the US.

4.2.4 Affiliations - publications

As with the country analysis, the institution corresponds to the affiliation provided in the author's information. Among the 22 135 publications on EV batteries with author

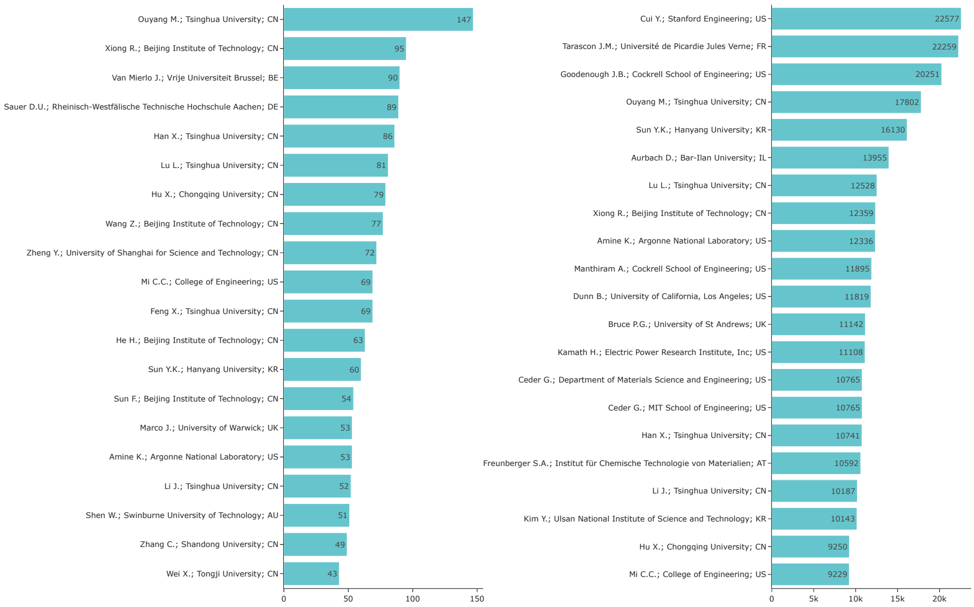


Figure 4.9: Most productive authors and their dominant affiliation, in the number of publications (left) and citations (right), from 2000 to 2022.

addresses, a total of 7 776 institutions have contributed to the field. These affiliations can be further categorised into academic and non-academic institutions.

Figure 4.10 illustrates the contribution of the top 20 most productive academic institutions from 2000 to 2022. Particularly, the majority of these top institutions are based in China, with only two universities from the US, and one each from Canada, Denmark, Germany, and Bangladesh. However, when considering the impact of academic institutions, a different trend emerges. The top positions are less occupied by Chinese universities, and these are substituted by key players, such as influential universities (MIT and Stanford) from the US, along with the Korea Advanced Institute of Science and Technology.

The contribution of the top 20 most productive non-academic institutions between 2000 and 2022 can be found in Figure 4.11, revealing a diverse set of institutional actors. The analysis identifies prominent players such as car manufacturers including General Motors, Ford, Jaguar, BMW, and Mercedes, alongside electric utility corporations like the State Grid Corporation of China or Hydro Quebec from Canada. Research centres such as Flanders Make, Deutsches Zentrum fur Luft und Raumfahrt DLR emerge as significant contributors, showcasing a substantial volume of published articles. Additionally, energy and building technology companies like Bosch and Samsung are contributing substantially to the research domain. Government entities like the Ministry of Education of the People's Republic of China also play an active role in shaping the research agenda.

Turning to the evaluation of publication impact in the right plot of Figure 4.11, additional influential actors come to light. These include several energy and technology

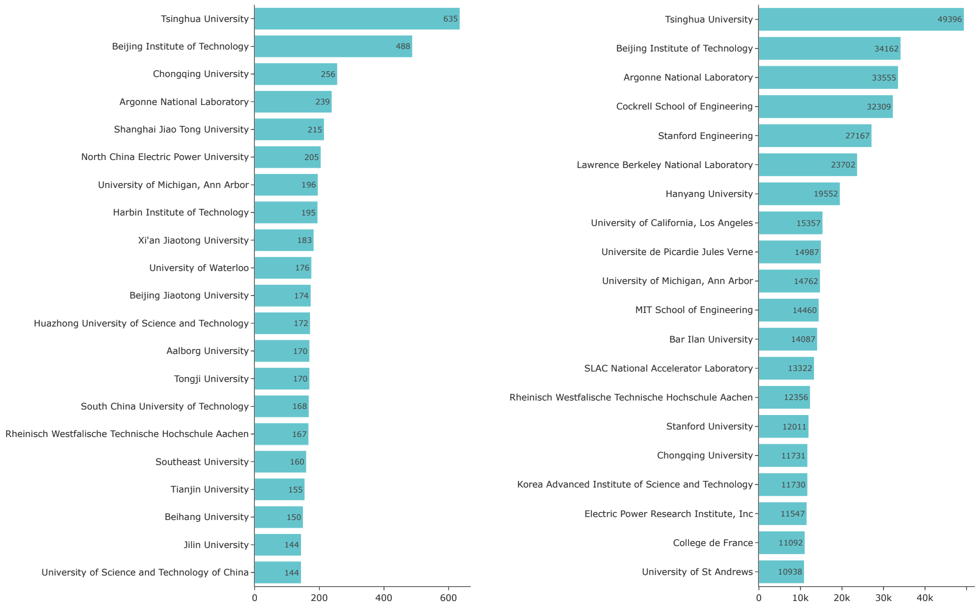


Figure 4.10: Most productive academic affiliations by number of articles (left) and total citations (right) (Top 20) from 2000 to 2022.

Figure 4.11: Most productive non-academic affiliations by number of articles (left) and total citations (right) (Top 20) from 2000 to 2022.

companies, such as Hitachi High Technologies, IBM, and EC Power, as well as battery companies, like Compact Power Inc. and Key Power Technology Corporation Ltd. Chemical companies, like BASF SE, a German company, also demonstrate significant influence. Furthermore, research centres like Stanford Synchrotron Radiation Lightsource emerge as key players, with 2 237 citations in their articles.

4.3 Most cited research

To answer the question ”Which studies and patents are considered to be key in the scientific and technical literature on EV batteries?” the most cited publications and IPFs were analysed, and the results are presented in Tables 4.1 and 4.2, respectively.

Table 4.1: Most cited articles (Top 20) on EV batteries between 2000 and 2022.

Article	Total Citations	Citations per Year	Year	Authors	Lead Country	Countries	Affiliations	Affiliation type
Electrical Energy Storage For The Grid: A Battery Of Choices	10 966	913.833333	2011	Dunn B.; Kamath H.; Tarascon J.M.	US	United States; France	University of California, Los Angeles; Electric Power Research Institute, Inc; Universite de Picardie Jules Verne; College de France	Academic
Challenges For Rechargeable Li Batteries	8 471	651.615385	2010	Goodenough J.B.; Kim Y.	US	United States	Cockrell School of Engineering	Academic
Li-O_2 And *Li*-*S* Batteries With High Energy Storage	7 691	699.181818	2012	Bruce P.G.; Freunberger S.A.; Hardwick L.J.; Tarascon J.M.	UK	United Kingdom; France	University of St Andrews; University of Liverpool; Laboratoire de Reactivite et Chimie des Solides LRCS	Academic
The Li-Ion Rechargeable Battery: A Perspective	6 977	697.7	2013	Goodenough J.B.; Park K.S.	US	United States	Cockrell School of Engineering	Academic
High-Performance Lithium Battery Anodes Using Silicon Nanowires	5 596	373.066667	2008	Chan C.K.; Peng H.; Liu G.; McIlwrath K.; Zhang X.F.; Huggins R.A.; Cui Y.	US	United States	Stanford University; Stanford Engineering; Lawrence Berkeley National Laboratory; Hitachi High Technologies America	Academic; Non Academic
Challenges In The Development Of Advanced Li-Ion Batteries: A Review	5 320	443.333333	2011	Etacheri V.; Marom R.; Elazari R.; Salitra G.; Aurbach D.	Israel	Israel; United States	Bar Ilan University; Lawrence Berkeley National Laboratory	Academic
Reviving The Lithium Metal Anode For High-Energy Batteries	4 435	739.166667	2017	Lin D.; Liu Y.; Cui Y.	US	United States	Stanford Engineering; SLAC National Accelerator Laboratory	Academic
Advanced Materials For Energy Storage	4 054	311.846154	2010	Liu C.; Li F.; Lai-Peng M.; Cheng H.M.	China	China	Institute of Metal Research Chinese Academy of Sciences	Academic
Lithium Batteries: Status, Prospects And Future	4 001	307.769231	2010	Scrosati B.; Garche J.	Italy	Italy	Sapienza Universita di Roma	Academic
Promise And Reality Of Post-Lithium-Ion Batteries With High Energy Densities	3 367	481	2016	Choi J.W.; Aurbach D.	South Korea	South Korea; Israel	Korea Advanced Institute of Science and Technology; Bar Ilan University	Academic

Table 4.1: (continuation)

Article	Total Citations	Citations per Year	Year	Authors	Lead Country	Countries	Affiliations	Affiliation type
A Lithium Superionic Conductor	3 351	279.25	2011	Kamaya N.; Homma K.; Yamakawa Y.; Hirayama M.; Kanno R.; Yonemura M.; Kamiyama T.; Kato Y.; Hama S.; Kawamoto K.; Mitsui A.	Japan	Japan	Tokyo Institute of Technology; High Energy Accelerator Research Organization, Institute of Materials Structure Science; Toyota Motor Corporation	Academic; Non Academic
A Review On The Key Issues For Lithium-Ion Battery Management In Electric Vehicles	3 301	330.1	2013	Lu L.; Han X.; Li J.; Hua J.; Ouyang M.	China	China	Tsinghua University; Key Power Technology Corporation, Ltd	Academic; Non Academic
Battery Materials For Ultrafast Charging And Discharging	3 040	217.142857	2009	Kang B.; Ceder G.	US	United States	MIT School of Engineering	Academic
Electrode Materials For Rechargeable Sodium-Ion Batteries: Potential Alternatives To Current Lithium-Ion Batteries	2 845	258.636364	2012	Kim S.W.; Seo D.H.; Ma X.; Ceder G.; Kang K.	US	South Korea; United States	Seoul National University; MIT School of Engineering	Academic
Ageing Mechanisms In Lithium-Ion Batteries	2 731	151.722222	2005	Vetter J.; Novák P.; Wagner M.; Veit C.; Möller K.; Besenhard J.; Winter M.; Wohlfahrt-Mehrens M.; Vogler C.; Hammouche A.	Switzerland	Switzerland; Austria; Germany	Paul Scherrer Institut; Technische Universitat Graz; Zentrum fur Sonnenenergie und Wasserstoff Forschung Baden Wurttemberg; Rheinisch Westfalische Technische Hochschule Aachen	Academic
Challenges Facing Lithium Batteries And Electrical Double-Layer Capacitors	2 328	211.636364	2012	Choi N.S.; Chen Z.; Freunberger S.A.; Ji X.; Sun Y.K.; Amine K.; Yushin G.; Nazar L.F.; Cho J.; Bruce P.G.	South Korea	South Korea; United States; United Kingdom; Austria; Canada	Ulsan National Institute of Science and Technology; Argonne National Laboratory; University of St Andrews; Institut fur Chemische Technologie von Materialien; University of Waterloo; Hanyang University; College of Engineering	Academic

Table 4.1: (continuation)

Article	Total Citations	Citations per Year	Year	Authors	Lead Country	Countries	Affiliations	Affiliation type
Ultrahigh-Power Micrometre-Sized Supercapacitors Based On Onion-Like Carbon	2 315	178.076923	2010	Pech D.; Brunet M.; Durou H.; Huang P.; Mochalin V.; Gogotsi Y.; Taberna P.L.; Simon P.	France	France; United States	Laboratoire d'Analyse et d'Architecture des Systemes; Universite Toulouse III Paul Sabatier; Drexel University College of Engineering	Academic
Electrodes With High Power And High Capacity For Rechargeable Lithium Batteries	2 308	135.764706	2006	Kang K.; Meng Y.S.; Bréger J.; Grey C.P.; Ceder G.	US	United States	MIT School of Engineering; Stony Brook University	Academic
Lithium-Ion Batteries. A Look Into The Future	2 175	181.25	2011	Scrosati B.; Hassoun J.; Sun Y.K.	Italy	Italy; South Korea	Sapienza Universita di Roma; Hanyang University	Academic
Lithium - Air Battery: Promise And Challenges	2 139	164.538462	2010	Girishkumar G.; McCloskey B.; Luntz A.; Swanson S.; Wilcke W.	US	United States	IBM Research Almaden	Non Academic

Table 4.2: Most cited IPFs (Top 20) between 2000 and 2022. *The titles presented are the last non-null English title for each patent family.*

Patent	Total Citations	Avg Time Between Citation and Publication	Earliest Publication Year	Countries	Is BMS	Is EV battery	Is Charging and Discharging
Multi-Dimensional Inductive Charger And Applications Thereof	822	-5.294118	2012	US	1	0	0
Hybrid Vehicle Configuration	786	1.426230	2001	US, unknown	1	1	1
Wireless Electromagnetic Energy Transfer Method And Device	710	5.872340	2007	Greece, Hungary, US, unknown	0	0	1
Self-Running Robot	491	2.800000	2008	US, unknown	1	0	1
Systems And Methods For Uav Docking	472	1.941176	2015	China, unknown	0	0	1

Table 4.2: (continuation)

Patent	Total Citations	Avg Time Between Citation and Publication	Earliest Publication Year	Countries	Is BMS	Is EV battery	Is Charging and Discharging
Apparatus, Method And Article For Authentication, Security And Control Of Power Storage Devices, Such As Batteries	435	-5.764706	2013	China, Hong Kong, Cayman Islands, US, unknown	1	1	0
Apparatus, Method And Article For Physical Security Of Power Storage Devices In Vehicles	432	0.138889	2013	China, Cayman Islands, Taiwan, US, unknown	1	1	0
Tunable Frangible Battery Pack System	430	-9.888889	2008	US	1	1	0
System And Method For Exchanging Batteries On Unmanned Aerial Vehicle	412	0.500000	2015	China, unknown	1	1	0
System And Method For Determining And Balancing State Of Charge Among Series Connected Electrical Energy Storage Units	390	-9.754902	2004	US, unknown	1	1	0
System For Electrically Connecting Battery To Electric Vehicle	380	-6.666667	2010	Switzerland , France, Israel, US, unknown	0	1	0
Lawnmower Robot	369	0.600000	2007	US, unknown	0	0	1
Water Drain Apparatus Of Mounting High Voltage Battery Pack In Vehicle	338	-4.500000	2012	South Korea, unknown	0	1	0
Multiport Vehicle Dc Charging System With Variable Power Distribution	334	-2.450000	2013	US, unknown	1	1	0
Battery Charging System And Method	333	-4.808511	2004	US, unknown	1	1	0

Table 4.2: (continuation)

Patent	Total Citations	Avg Time Between Citation and Publication	Earliest Publication Year	Countries	Is BMS	Is EV battery	Is Charging and Discharging
Application Of Localization, Positioning And Navigation Systems For Robotic Enabled Mobile Products	329	1.285714	2009	Italy, US, unknown	1	0	1
Stored Energy And Charging Appliance	321	-5.166667	2011	US, unknown	1	1	0
Power Storage Device	295	-1.857143	2003	JP, unknown	1	1	0
Electric Vehicle Station Equipment	291	3.605263	2011	US, unknown	0	1	0
Systems, Methods And Apparatus For Detection Of Metal Objects In Predetermined Space	281	1.352941	2014	Switzerland, US, unknown	1	0	0

On the publications side, the geography is dominated by the G7 countries, also combined with Israel, China, South Korea, Switzerland, and Austria. Most of the productions are connected to academic institutions, and we can find three partnerships between academic and non-academic institutions. Only one paper is fully non-academic, published by IBM Research Almaden. Nearly half of these publications (9) are a result of a collaboration between institutions from different countries and all publications are co-authorships, which sustains the premise that research collaboration is essential for tackling complicated topics and developing more advanced technologies ("Collaborations across the globe", 2022).

It is important to compute the average number of citations per year for each paper, by dividing the total number of citations by the number of years since publication. This metric enables a fair comparison of the impact of the different contributions, independently of the publication age (Brooks, 2000). While examining the most cited works, accounting for either the total or yearly amount of citations has minimal effect on the overall ranking. D. Lin et al. (2017) stands out as the second most prominent paper, despite being the most recent on the ranking. In their study, the authors discuss the limitations of Li-ion batteries and the need for alternative chemistries to meet the increasing demands. They review the potential of metallic lithium as an anode material for next-generation lithium batteries, particularly in Li-S and Li-air systems.

In the patent side, there are IPFs related to a variety of applications (robotic systems, and vehicle-specific innovations) that demonstrate the diverse applicability of EV battery technologies beyond conventional EVs.

The most cited patents are not recent, which aligns with a larger time frame for possible citations. Also, we can see that some patents have a negative average time between citation and publication. As mentioned before, the considered patents in the dataset are part of IPFs, so the citing patent might refer to a related document in a different jurisdiction that was published later sharing the same priority date. Delays in the publication of patents due to administrative or legal reasons can also cause negative citation lags.

4.4 Main thematic areas

We analysed the datasets to understand the main thematic axes that involve EV batteries, therefore to answer the question "Which themes come up most frequently in research about EV batteries?".

Table 4.3 presents a comprehensive analysis of the main thematic categories within the publications dataset. The aggregation of WoS disciplinary categories into broader fields follows the methodology outlined in Mendonça et al. (2022).

Table 4.3: Thematic categories from 2000 to 2022.

Category Group	Articles	Percentage	Average Citations	Average Citations per Year	Total Citations	Average Growth YoY
Electronics And Telecom Engineering	13 782	62.35%	51.94	11.33	715 835	27.8%
Energy	7 818	35.37%	55.05	12.92	430 385	28.37%
Materials And Chemistry	5 396	24.41%	85.69	15.7	462 407	18.83%
Information Technology And Processing	3 274	14.81%	33.03	7.78	108 139	42.22%
Transportation	2 450	11.08%	33.75	7.79	82 683	34.41%
Environment	1 568	7.09%	54.61	11.89	85 630	41.87%
Business And Economics	549	2.48%	48.3	9.8	26 517	48.25%
Health And Biosciences	61	0.28%	20.54	3.89	1 253	50.4%
Public Policy And International Governance	43	0.19%	26.74	6.47	1 150	28.03%
Education	28	0.13%	2.93	0.95	82	117.86%
Social Sciences And Humanities	12	0.05%	8.67	2.69	104	36.11%

Several significant observations can be made based on these results. The categories ”Electronics And Telecom Engineering” and ”Energy” prominently stand out as the main thematic areas, and combined they constitute a significant proportion of the publications (97.72%). Moreover, categories such as ”Materials And Chemistry”, ”Environment”, and ”Business And Economics” exhibit high average citation counts, indicating that research in these fields tends to attract more attention and recognition within the academic community. However, it is important to note that comparing fields solely based on citation counts is not completely accurate since the ”citation potential” varies across fields (Moed et al., 1985).

Furthermore, this analysis reveals a diverse range of thematic categories, that go further into the traditional engineering and energy domains, including for example ”Public Policy And International Governance” and ”Information Technology And Processing”. This diversity reflects the interdisciplinary nature of the research area and its intersection with various sectors. One unexpected result worth noting is the relatively modest representation of the ”Transportation” category group, only covering 11% of our dataset. This observation may be due to the fact that batteries are versatile and have applications beyond EVs. Therefore, findings from diverse areas may also hold relevance for electromobility, contributing to their inclusion in our dataset.

In Figure 4.12 we present the number of articles published for each category group between 2010 and 2022. Before 2010, roughly all category groups had a static trend, with minimal fluctuations in publication counts. By plotting these results after 2010 (when the number of publications started to increase significantly, as mentioned before), we can have a clearer understanding of the most recent trends and developments.

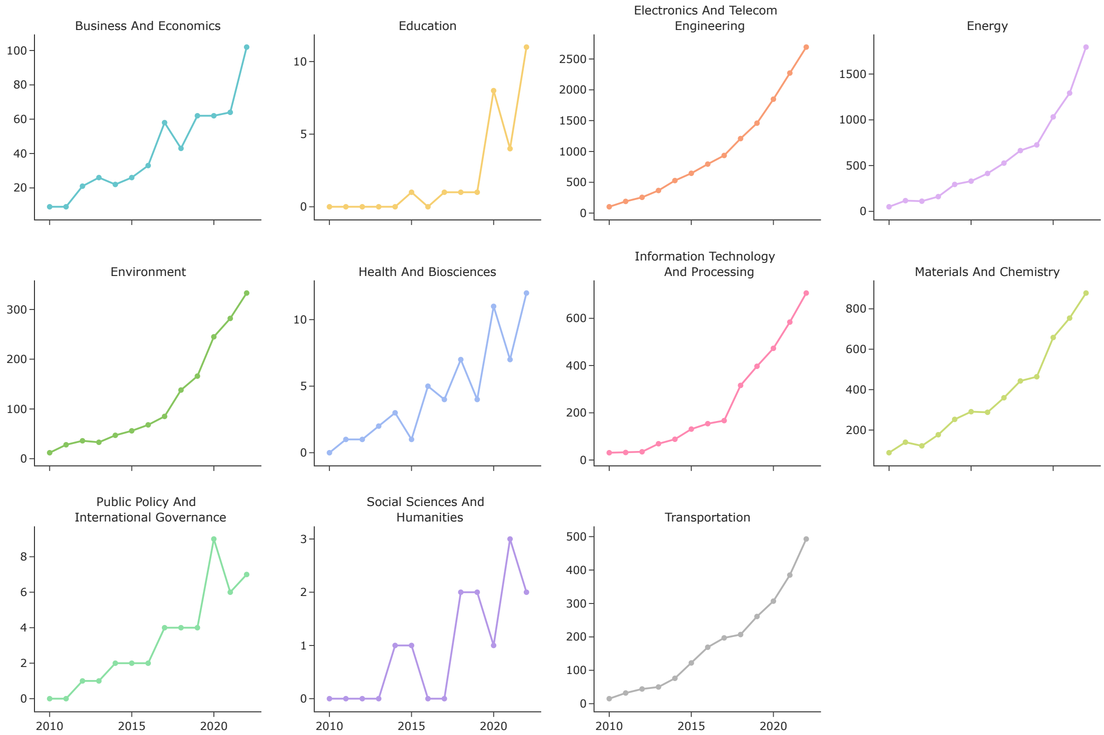


Figure 4.12: Evolution of disciplinary areas per year (absolute number of publications) from 2010 to 2022.

The main foundational areas of EV battery research are ”Electronics And Telecom Engineering”, ”Energy”, and ”Materials And Chemistry”, which are continuing to dominate in terms of the number of publications, sustaining the interest and investments. Category groups like ”Public Policy And International Governance” and ”Business And Economics” have become more noticeable in recent years, possibly due to the recognition of the broader societal and economic implications of these types of technologies.

As mentioned in Section 3.3.2, the patent data was divided into 3 main groups: charging technologies, BMS technologies, and EV batteries technologies. Therefore, this data can be analysed by focusing on these three different groups.

Figure 4.13 presents the evolution of the three groups in terms of absolute numbers. Overall, there has been an increase in patent activity across all three categories in the analysed time frame. The most significant growth is observed in the charging and discharging category.

Initially, the number of IPFs in the BMS category grew from 20.83 in 2000 to 191.33 in 2010, and then the patent count grew dramatically, reaching 1 387.17 in 2020. In battery technologies themselves, the numbers increased from 16.33 in 2000 to 231.33 in

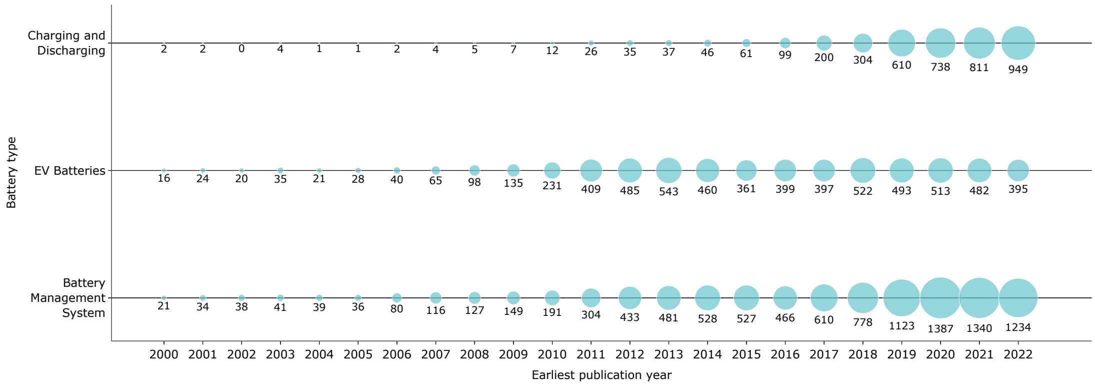


Figure 4.13: Global patenting activity for the three identified groups of technologies in EV batteries, from 2000 to 2022.

2010 showing a consistent innovation, essential for improving battery capacity and performance. However, the battery IPFs peaked at 543.17 in 2013, followed by a fluctuation but generally downward trend, with a notable drop to 395 IPFs in 2022. Finally, the charging and discharging category displays a very low count initially, with 1.83 IPFs in 2000. The minimal activity continues, showing a gradual increase, reaching 12.33 IPFs in 2010. But, particularly from 2016 onwards, the output count grew rapidly, peaking at 949 IPFs in 2022. This trend indicates a growing emphasis on improving charging efficiency and reducing charging times, critical for EV adoption (Tomaszewska et al., 2019).

4.5 Research networks - publications

Co-authorship in science can be used as a measure of collaboration between the different agents involved in research (OECD, 2009a). OECD emphasises the progressive embrace of open science practices, characterised by collaboration among researchers globally and across diverse institutional affiliations. In our dataset, the number of single-author publications is 658, which represents a small percentage of all EV batteries-related publications (around 2.98%). The average number of co-authors in the publications over the analysed time frame is 3.95, but we identify a growing trend (this value went from 3.52 in 2000 to 4.71 in 2022). Finally, the average number of countries involved in the publications has also been increasing, from 1.07 in 2002 to 1.42 in 2022. These statistics support the shift towards openness and more interdisciplinary scientific endeavours.

4.5.1 Countries

To further investigate the collaborative efforts between researchers, it is possible to visualise and analyse the connections between authors' countries. Figure 4.14 presents

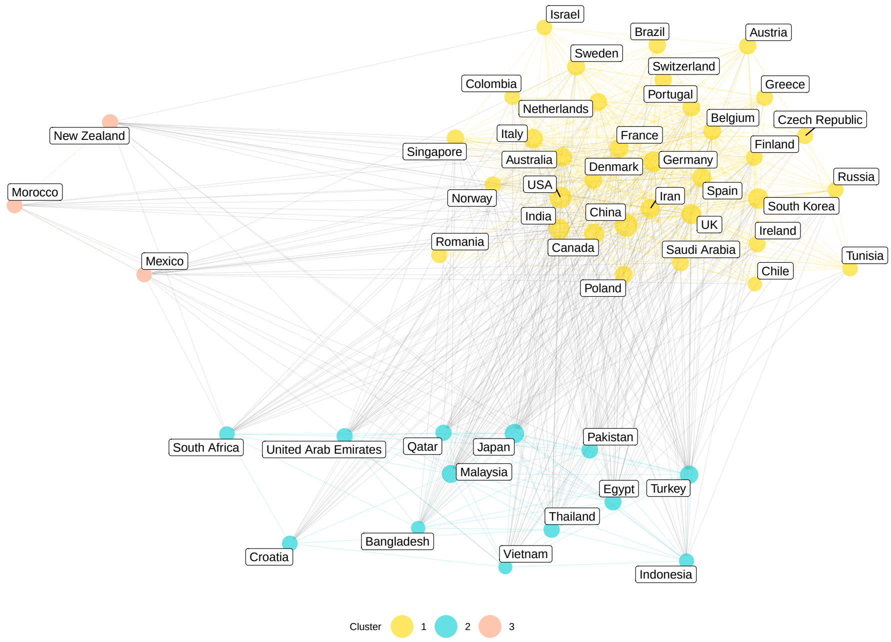


Figure 4.14: Country collaboration from 2010 to 2022. Only 50 countries are displayed. The size of the marker represents the number of publications.

our research network, containing nodes representing the countries and edges representing collaborative relationships between them. 50 countries are displayed in the network to clarify the network, otherwise, the nodes and the edges would become too complex, making it difficult to uncover the network relationships.

This network analysis reveals valuable insights into the structure and dynamics of the network and the metrics collectively provide a comprehensive understanding of the network's organisation. The network's density, representing the ratio of actual connections to potential connections, stands at 0.19, while the network's diameter, representing the longest shortest path between any two countries, is 4. Additionally, the average number of steps on the shortest path between any two potential country pairs is 5.12.

Regarding clusters, three distinct groups are formed: (1) the first cluster (blue) includes the major research powerhouses, such as China, the US, India, Germany, and the UK, alongside other countries from different regions, like South Korea, Canada; (2) the second cluster (yellow) with a lower level of collaboration compared to the first one; and (3) the third cluster (purple) with relatively lower contributions and collaboration levels.

Examining specific collaboration links, from Table 4.4, it is worth noting the partnership between the US and China, which stands out as the strongest, with 953 jointly developed publications. Furthermore, China emerges as a significant partner for several countries including the UK, Australia, Canada, Singapore, and Japan. Among the top 30 partnerships, China leads with collaborations involving 15 countries, followed closely by the US with 11 country collaborations.

Table 4.4: Country collaborations (Top 30 co-authorships) from 2000 to 2022.

Country	Country	Articles Together
China	US	953
China	UK	427
China	Australia	278
China	Canada	199
US	Canada	171
US	South Korea	162
China	Singapore	147
US	UK	120
China	Japan	117
US	Germany	95
China	Germany	88
US	India	83
India	Saudi Arabia	81
Australia	US	78
China	South Korea	73
China	Denmark	73
US	Iran	71
China	Saudi Arabia	70
Saudi Arabia	Egypt	69
US	Saudi Arabia	68
China	Sweden	67
China	Pakistan	62
China	India	61
Germany	UK	57
US	Italy	55
UK	India	54
US	Japan	54
China	France	52
China	Ireland	50
Canada	France	49
UK	Saudi Arabia	49

Table 4.5 shows measures of each country's importance and status inside the network. China is the country with the highest degree, meaning that is the country with more links to the other ones. The US is the country that serves more as an intermediary in this network, while the country that has the most indirect connections to the others is Poland. Unexpectedly, Poland serves as an important intermediary in the network and is well-connected maintaining close ties with its partners.

It is worth noting that while China leads in the number of publications, as previously observed, its centrality in the research network is not as high. This suggests that China's extensive research output has not translated into equally extensive international collaboration. Apart from the US and China, it is not clear the emergence of absolute leaders in this area.

Table 4.5: Country network statistics.

Country	Degree	Country	Betweenness	Country	Closeness
China	0.713	US	0.096	Poland	0.2614
US	0.6696	Poland	0.0925	Colombia	0.2452
India	0.6174	China	0.0912	Estonia	0.2416
UK	0.6087	India	0.0855	China	0.2411
Germany	0.5565	Canada	0.0576	Greece	0.2357
Canada	0.5391	Malaysia	0.0461	US	0.2328

Table 4.5: (continuation)

Country	Degree	Country	Betweenness	Country	Closeness
Saudi Arabia	0.4957	South Korea	0.0461	Malaysia	0.2323
France	0.487	Nigeria	0.0373	Germany	0.2305
Australia	0.4696	Colombia	0.0372	Bulgaria	0.2305
Spain	0.4609	Japan	0.0369	Nigeria	0.2305
Italy	0.4435	South Africa	0.0353	Mexico	0.23
Denmark	0.4348	Spain	0.0329	Finland	0.2268
Iran	0.4261	Germany	0.0312	India	0.225
South Korea	0.4087	UK	0.0297	Thailand	0.2237
Japan	0.4087	Estonia	0.0261	UK	0.2229
Pakistan	0.4087	France	0.0239	Norway	0.2229
Malaysia	0.4	Finland	0.0202	Tunisia	0.2229
Poland	0.4	Norway	0.0201	Algeria	0.2229
Egypt	0.3826	Serbia	0.0194	Hungary	0.2229
Turkey	0.3652	Australia	0.0182	Spain	0.222

4.5.2 Affiliations

Figure 4.15 contains the affiliation collaboration network, for the institutions with degree higher than 50. One characteristic that stands out in this network is the fact that the majority of its components are universities or other academic institutions. When calculating the centrality measures (displayed in Table 4.6), only 4 non-academic institutions appear in the Top 30.

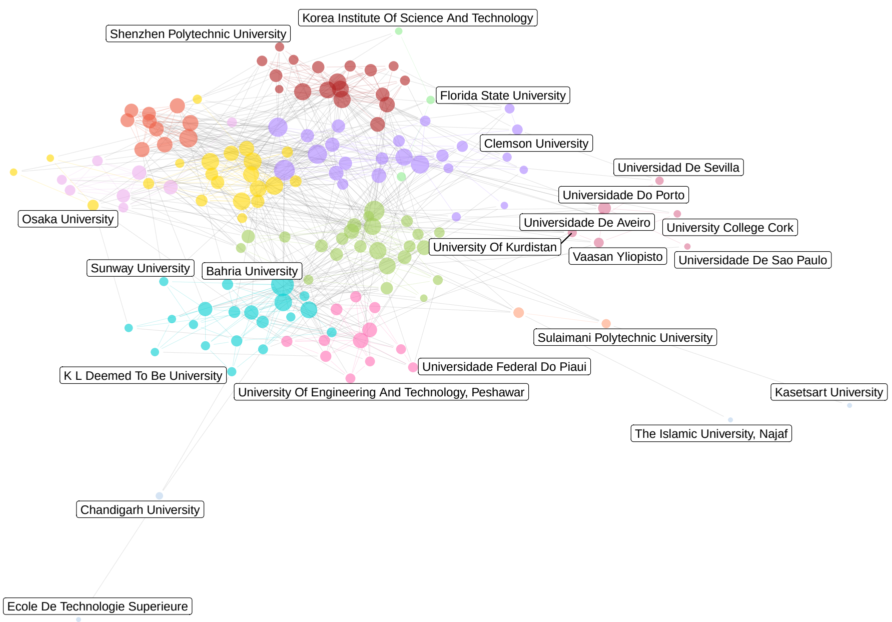


Figure 4.15: Affiliation collaboration from 2010 to 2022. Only affiliations with degree higher than 50 are displayed. The size of the nodes is given by the degree of each country.

From a perspective of the influence of the publications in this field, Wuhan University, from China, has the largest centrality degree, indicating its close cooperation with most affiliations in the cooperation network, followed by Aalborg University in Denmark, and Peking University also in China.

Table 4.6: Affiliation network statistics.

Affiliation	Degree	Affiliation	Betweenness	Affiliation	Close-ness
Wuhan University	0.2115	Wuhan University	0.1369	Wuhan University	0.0013
Aalborg University	0.1923	Aalborg University	0.0797	Aalborg University	0.0013
Peking University	0.1795	Peking University	0.0775	University Of Chinese Academy Of Sciences	0.0012
Sichuan University	0.1731	Prince Sattam Bin Abdulaziz University	0.061	Hong Kong University Of Science And Technology	0.0012
Prince Sattam Bin Abdulaziz University	0.1667	Hong Kong University Of Science And Technology	0.061	Peking University	0.0012
Imperial College London	0.1538	Massachusetts Institute Of Technology	0.0608	Massachusetts Institute Of Technology	0.0012
Hong Kong University Of Science And Technology	0.1538	Shanghai University	0.06	Duy Tan University	0.0012
University Of Chinese Academy Of Sciences	0.1474	Duy Tan University	0.0539	The University Of Manchester	0.0012
Shanghai University	0.1474	Imperial College London	0.0518	Sichuan University	0.0012
Shenzhen Institute Of Advanced Technology	0.141	Taif University	0.0494	King Abdulaziz University	0.0012
Lawrence Berkeley National Laboratory	0.1346	University Of Chinese Academy Of Sciences	0.0451	Imperial College London	0.0012
University Of California, Berkeley	0.1346	City University Of Hong Kong	0.0444	Stanford Engineering	0.0012
University Of Wollongong	0.1346	Unsw Sydney	0.0441	Shanghai University	0.0012
King Abdulaziz University	0.1346	National Institute For Materials Science	0.043	Zhejiang University	0.0011
University Of Oxford	0.1346	University Of California, Berkeley	0.0411	Prince Sattam Bin Abdulaziz University	0.0011
Brookhaven National Laboratory	0.1346	Universiti Malaya	0.0396	City University Of Hong Kong	0.0011
Taif University	0.1346	University Of Oxford	0.0393	Shenzhen Institute Of Advanced Technology	0.0011
City University Of Hong Kong	0.1282	Shanghai Maritime University	0.0357	University Of Wollongong	0.0011
Unsw Sydney	0.1282	Sichuan University	0.0354	Pacific Northwest National Laboratory	0.0011
Stanford Engineering	0.1282	National University Of Singapore	0.0351	Brunel University London	0.0011

4.6 Content analysis

To leverage the classical analysis of bibliometric methods and patent information, we conducted an analysis of the keywords present in articles' abstracts and patents' titles and abstracts. It is possible to plot the evolution of the different keywords since 2000, to uncover the trends or shifts in research focus within the area.

Table 4.7 illustrates the trajectory of the main unigrams present in the keywords of the collected publications. The keyword ”battery” consistently maintains a high ranking throughout the years, indicating a strong emphasis on studying individual battery components. This emphasis is further highlighted by the high ranking of ”cell” in the first year analysed. However, around the early 2010s and beyond, we observe a gradual increase in the ranking of the ”system” keyword, accompanied by a relative decline in the ranking of ”battery”. This shift is likely reflecting the recognition of the importance of integrating energy storage into larger systems and applications.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
anode	2	2	0	0	1	1	4	1	0	5	3	8	7	6	18	22	20	30	33	47	67	72	64
battery	3	4	4	6	6	5	8	13	11	20	24	25	26	52	64	79	92	108	142	159	347	448	492
behaviour	3	0	2	6	0	1	3	4	1	5	3	7	9	18	17	22	42	47	64	65	92	90	132
capacity	1	2	3	1	1	1	1	3	1	3	5	9	6	15	22	22	46	56	66	56	73	62	88
carbon	1	0	0	0	2	0	1	0	2	3	1	8	6	6	16	17	17	18	30	33	37	30	36
cathode	0	1	0	2	1	4	1	1	2	3	8	10	14	11	26	37	24	41	51	57	63	63	82
cell	5	1	4	4	3	1	2	2	6	10	10	14	18	21	36	34	71	90	106	74	125	117	160
challenge	0	0	0	0	0	0	0	0	0	0	0	5	6	11	17	19	13	30	27	34	57	60	97
charge	1	2	1	3	2	2	6	3	3	3	3	11	8	17	17	25	38	45	41	59	58	94	111
composite	0	1	0	1	1	1	1	0	0	1	3	6	9	11	17	25	28	30	50	37	64	44	70
design	0	1	1	4	3	4	4	10	9	10	10	16	18	38	54	90	97	137	176	196	239	251	331
discharge	1	0	2	1	0	1	2	5	0	2	3	4	5	12	11	10	14	18	19	27	31	45	43
electrode	0	1	4	7	0	7	3	7	2	7	12	5	12	28	24	42	39	41	49	51	72	61	87
electrolyte	0	1	3	1	1	0	3	2	2	2	8	3	11	16	17	20	20	19	38	38	38	56	90
emission	0	0	0	1	0	1	0	2	1	4	4	8	6	9	13	19	30	24	34	42	62	52	74
energy	0	0	1	1	1	0	1	0	1	2	4	6	9	17	26	36	45	61	102	102	138	144	171
hybrid	1	0	0	1	0	0	3	1	4	2	4	2	11	22	34	45	45	75	83	85	111	113	137
lithium	1	1	1	2	1	1	2	3	0	0	10	8	16	14	23	30	33	27	26	43	74	69	100
management	0	0	0	1	0	1	3	4	4	4	5	5	6	8	39	49	80	92	147	158	221	221	259
model	2	0	1	2	2	5	3	6	6	4	10	20	18	46	69	100	119	185	224	272	370	341	528
optimization	0	0	0	0	0	2	1	0	4	5	5	12	12	26	50	51	103	125	206	255	389	429	589
performance	0	4	3	0	2	7	8	8	8	12	16	23	27	39	85	78	85	148	159	202	282	291	377
power	1	0	0	2	0	0	2	0	1	0	3	7	16	16	34	37	42	44	61	67	82	111	112
simulation	0	0	2	2	3	6	3	7	3	3	5	9	10	14	31	33	38	45	71	71	82	94	111
soc	0	1	2	4	4	7	5	5	6	2	8	12	15	23	39	36	43	79	99	98	148	189	236
storage	0	1	0	0	0	0	0	0	2	1	5	9	12	11	21	22	35	43	58	73	92	81	99
supercapacitor	1	0	1	5	1	2	2	0	2	8	6	4	4	14	9	17	18	35	42	51	37	49	50
system	1	0	2	2	1	2	2	8	4	11	10	17	24	39	82	101	133	158	241	262	354	365	506
temperature	2	0	2	0	0	2	1	2	0	5	3	6	3	11	15	21	23	26	43	41	69	56	85
vehicle	1	1	0	2	0	3	1	0	1	3	4	5	7	11	8	20	21	37	54	55	72	76	106

Table 4.7: Top 30 unigram occurrence in publication abstracts. *The colour gradients represent intra-row relationships.*

Moreover, the prevalence of the use of the ”design” keyword indicates ongoing efforts among researchers to explore new design concepts, configurations, geometries, and materials to improve batteries' performance, efficiency, safety, and versatility.

In recent years, the ”optimisation” keyword has been the most used in publications, underscoring one of the biggest concerns related to EVs, which is their efficiency, effectiveness, and overall performance of their energy storage systems. Researchers continually seek to optimise various aspects, including battery chemistry, materials, configuration, operating conditions, and control strategies, to enhance batteries' cost-effectiveness. The same conclusion can be made regarding the ”performance” keyword, which has been consistently in the Top 5 of the most used unigrams.

Lastly, the consistent presence of the keyword ”model” suggests the use of modelling tools for optimising the design and control of energy storage systems. These modelling techniques play a crucial role in simulating and analysing the dynamic electrochemical, thermal, mechanical, and electrical processes occurring within batteries, which is important to surpass the challenges posed by the increasing demand for energy.

We can extend our analysis to include trigrams, which are keywords consisting of three or more words. The results are presented in Table 4.8. ”Lithium-ion battery” emerges as one of the most frequently used keywords in papers, reflecting their role as the predominant technology in EVs (Saw et al., 2016).

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
artificial neural network	1	1	0	1	0	0	2	1	0	1	0	0	2	0	1	1	1	1	6	13	15	20	22
battery electric vehicle	0	0	0	0	0	0	0	0	0	3	1	1	7	6	8	13	15	19	30	31	38	43	64
battery management system	0	0	1	0	3	0	2	1	0	1	0	6	1	11	17	12	31	18	40	38	46	57	72
double layer capacitor	0	0	1	0	0	0	1	0	0	0	2	0	1	4	1	3	1	1	2	3	2	3	2
electric vehicle battery	1	2	0	2	0	0	0	0	0	1	0	1	1	0	0	3	6	9	9	17	15	23	31
electrochemical impedance spectroscopy	0	0	2	0	0	0	0	0	0	1	0	4	1	5	1	6	6	5	10	8	11	25	18
energy management strategy	0	0	1	0	0	0	0	0	1	2	1	1	5	1	7	6	6	18	14	18	27	31	52
energy management system	0	0	0	1	1	0	0	0	0	0	1	0	1	5	7	14	14	14	25	34	30	39	54
energy storage system	0	0	0	0	0	0	0	0	0	1	1	1	4	4	5	10	14	28	29	27	45	43	69
extended kalman filter	0	0	0	0	4	0	2	2	1	0	1	0	4	5	7	8	11	22	26	15	13	21	27
fuel cell vehicle	0	0	0	0	0	0	0	3	1	3	0	3	5	1	1	2	0	2	4	6	7	11	12
greenhouse gas emissions	0	0	0	0	0	0	0	0	0	0	1	1	2	3	3	13	8	7	9	11	16	25	22
hybrid electric vehicle	3	4	8	9	6	7	12	13	16	19	14	12	24	24	40	33	42	49	55	52	64	71	79
hybrid energy storage system	0	0	0	0	0	0	0	0	0	1	1	2	1	1	5	11	11	20	17	17	14	20	25
inductive power transfer	0	0	0	0	1	1	0	0	0	1	0	0	2	3	3	12	9	14	15	22	17	25	28
lead acid battery	3	4	1	7	5	7	7	9	4	10	5	10	6	12	8	8	7	13	22	13	6	12	16
life cycle analysis	0	1	1	1	0	0	0	0	0	1	1	0	2	2	1	2	2	1	2	3	3	3	3
life cycle assessment	0	0	1	1	0	1	0	1	0	0	2	0	2	5	3	9	10	20	18	27	33	43	54
lithium ion battery	3	4	4	6	4	3	3	7	7	17	24	43	46	72	114	143	166	240	283	278	427	585	796
lithium ion cell	0	0	1	2	1	2	0	1	0	1	2	0	2	0	5	2	6	5	7	6	14	19	14
lithium iron phosphate	0	0	0	0	0	0	0	0	2	0	1	4	3	1	5	4	2	3	4	6	2	9	7
model predictive control	0	0	0	0	0	0	1	0	0	1	1	2	1	0	4	4	8	14	15	25	23	45	49
nickel metal hydride	0	0	2	0	2	0	1	1	0	0	1	1	1	3	1	0	1	2	3	1	3	2	5
open circuit voltage	0	0	0	0	0	0	0	0	0	0	1	2	3	2	6	9	15	16	24	13	21	23	23
pem fuel cell	2	0	0	0	1	2	0	0	0	1	1	2	1	0	2	2	2	2	3	2	2	5	6
phase change material	0	0	0	0	1	0	0	0	1	0	0	2	0	1	10	5	17	14	37	27	37	40	60
plug in hybrid electric vehicle	0	0	0	0	0	0	0	0	3	3	14	26	35	30	35	30	37	46	41	33	38	38	41
positive electrode material	0	0	0	0	0	0	1	0	0	2	1	5	2	3	3	4	3	10	5	6	15	11	9
vehicle to grid	0	0	0	0	0	0	0	0	0	0	3	8	15	19	24	30	33	35	59	67	101	114	132
x ray diffraction	0	0	0	0	0	1	0	1	1	1	2	2	4	4	5	8	2	12	8	9	11	7	7

Table 4.8: Top 30 trigram occurrence in publication abstracts. *The colour gradients represent intra-row relationships.*

A contrasting trend is observed with the keyword ”lead acid battery”, which has experienced a decline in rank in recent years, from being 1^{st} in the rank in 2000, 2001 and 2005, to 105^{th} in 2020. This decline aligns with the fact that lead acid batteries were historically significant, but are being gradually replaced with more advanced and efficient alternatives, such as the previously mentioned Li-ion batteries. Similarly, the Ni-MH batteries, which dominated the market in the early 2010s, with Toyota Prius (Rajashekara, 2013), are experiencing a downward trend after this period. The shift in research likely reflects the higher efficiency and energy density offered by the Li-ion batteries.

The keywords ”battery management system” and ”energy management system” witness relatively high ranks with minor fluctuations over time. This emphasises the importance of research and innovation in this area, aiming to optimise performance, longevity, and safety of EV systems.

Similarly, on the patent side, we did the same analysis. As mentioned before, patents contain information that can be grouped into three categories: technical description of the invention, development and ownership of the invention, and history of the application (OECD, 2009b). Abstracts and titles are unstructured items in patent documents, meaning they are free texts, containing different information (Tseng et al., 2007). Table 4.9 presents the absolute number of occurrences of bigrams in patent abstracts for each year, while Table 4.10 contains the scaled counts of occurrences of bigrams in patent abstracts for each year, per 1 000 abstracts. The keywords are displayed in descending order of total increase.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
electric vehicle	15	11	6	11	4	5	14	13	36	50	118	216	334	421	283	294	230	411	383	742	939	1128	1253
battery pack	11	19	6	14	24	19	35	61	91	86	84	217	246	376	352	295	335	409	479	768	786	1161	790
power supply	11	19	7	19	22	18	57	64	103	91	177	243	318	367	358	235	220	281	354	681	703	611	752
battery cell	1	11	1	4	10	19	9	20	27	71	120	288	396	414	417	372	457	351	446	599	769	701	666
battery module	7	6	8	6	8	10	28	47	30	59	114	220	304	352	378	242	261	286	442	510	516	596	503
control unit	7	5	3	6	1	15	6	31	53	41	54	109	118	179	148	158	117	176	218	309	457	422	484
vehicle charge	1	2	0	0	4	0	1	4	4	21	34	56	121	120	91	51	59	84	136	257	234	294	409
charge station	0	0	0	0	0	1	0	0	8	11	17	51	56	91	71	63	60	80	119	297	241	290	361
control device	1	1	6	16	4	1	6	24	32	24	37	72	158	124	153	138	95	134	231	264	356	337	359
vehicle battery	3	7	2	0	3	4	10	16	18	43	47	102	101	120	163	120	110	120	200	329	346	398	358
energy storage	0	3	3	24	7	23	20	46	104	43	105	124	254	281	284	178	218	282	286	462	400	348	354
battery swapping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	16	30	21	43	131	330
storage device	4	2	3	20	13	16	12	49	108	63	201	171	287	324	299	202	140	272	266	385	378	370	312
electric power	17	10	11	5	14	12	26	50	84	72	90	188	238	240	153	166	140	147	191	260	455	283	304
motor vehicle	1	3	1	5	7	4	9	16	8	15	37	73	99	97	109	74	90	144	185	358	288	265	270
plurality battery	4	12	1	7	4	7	6	19	13	23	40	104	107	108	106	101	137	132	192	151	245	281	273
management system	0	0	3	2	0	1	5	27	30	14	29	47	63	59	62	89	90	91	100	174	255	312	260
power storage	4	2	0	4	1	0	0	45	68	67	165	103	236	178	257	161	101	209	201	271	296	274	263
electric motor	3	13	12	6	9	7	13	23	10	29	32	31	52	59	71	66	70	70	145	173	190	211	248
traction battery	0	0	0	1	0	0	1	0	0	3	5	32	16	30	56	102	102	90	98	118	135	205	228
power battery	0	3	16	7	8	2	3	3	12	23	7	31	31	46	57	42	52	99	152	194	162	223	224
charge battery	17	22	17	14	10	6	6	19	17	35	57	78	144	120	104	96	86	109	139	217	256	263	233
voltage battery	11	24	6	15	9	5	22	39	17	45	51	69	146	146	142	109	110	163	225	287	363	221	222
state charge	3	31	24	18	14	8	20	31	27	38	55	61	127	86	128	156	145	149	128	168	239	293	208
charge system	6	2	6	0	2	3	7	3	11	10	31	46	61	63	38	41	54	50	97	116	134	150	204
battery system	3	3	1	3	0	4	9	9	1	19	48	81	87	80	138	119	134	147	171	160	222	199	198
charge device	2	0	4	1	1	0	0	1	16	15	19	53	113	69	106	40	39	51	86	165	184	234	193
battery charge	13	27	8	5	9	5	14	13	19	25	75	89	120	147	126	74	98	197	152	180	224	190	182
fuel cell	0	3	27	8	30	25	28	14	9	42	27	17	53	39	50	35	63	97	132	167	181	161	169
electrical energy	0	0	6	5	6	5	2	17	11	14	41	27	87	82	74	59	79	89	137	170	229	212	166

Table 4.9: Top 30 bigram occurrence in patent abstracts. *The colour gradients represent intra-row relationships.*

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
battery cell	26	186	17	51	161	288	73	108	117	244	276	390	416	391	404	396	476	293	282	272	295	271	266
charge station	0	0	0	0	0	15	0	0	35	38	39	69	59	86	69	67	62	67	75	135	92	112	144
energy storage	0	51	51	304	113	348	163	247	452	148	242	168	267	266	275	190	227	236	181	210	153	135	141
vehicle charge	26	34	0	0	65	0	8	22	17	72	78	76	127	113	88	54	61	70	86	117	90	114	163
battery swapping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	13	19	10	16	51	132
control device	26	17	102	203	65	15	49	129	139	82	85	98	166	117	148	147	99	112	146	120	137	130	143
electric vehicle	385	186	102	139	65	76	114	70	157	172	272	293	350	398	274	313	240	344	242	337	360	436	500
management system	0	0	51	25	0	15	41	145	130	48	67	64	66	56	60	95	94	76	63	79	98	121	104
traction battery	0	0	0	13	0	0	8	0	0	10	12	43	17	28	54	109	106	75	62	54	52	79	91
power battery	0	51	271	89	129	30	24	16	52	79	16	42	33	43	55	45	54	83	96	88	62	86	89
motor vehicle	26	51	17	63	113	61	73	86	35	52	85	99	104	92	106	79	94	120	117	163	110	102	108
fuel cell	0	51	458	101	484	379	228	75	39	144	62	23	56	37	48	37	66	81	83	76	69	62	67
electrical energy	0	0	102	63	97	76	16	91	48	48	94	37	91	78	72	63	82	74	86	77	88	82	66
vehicle battery	77	119	34	0	48	61	81	86	78	148	108	138	106	113	158	128	115	100	126	149	133	154	143
vehicle control	0	51	68	13	0	0	8	5	22	21	21	24	25	30	28	35	23	29	35	45	48	59	64
storage system	0	0	0	0	0	76	16	54	78	55	71	38	54	66	69	63	50	43	34	30	39	47	54
thermal management	0	0	0	0	0	0	0	0	22	17	9	16	6	8	22	10	28	19	13	22	48	63	53
energy store	0	17	0	38	0	0	0	43	17	7	14	53	63	34	31	64	66	36	57	58	55	48	52
supply power	0	68	17	38	48	30	89	27	30	34	32	35	35	52	64	48	26	33	37	44	48	39	46
supply device	0	0	0	25	48	0	41	43	61	41	53	41	55	55	84	34	35	23	25	62	38	36	45
battery housing	0	17	0	0	16	0	16	0	17	21	18	16	12	15	45	19	28	21	33	36	35	32	43
unit configured	0	0	0	0	0	0	0	5	0	0	2	20	35	29	19	37	34	41	33	47	52	50	43
battery vehicle	0	51	0	51	32	76	41	38	17	27	32	47	41	41	48	39	46	49	52	47	35	34	43
threshold value	0	51	68	89	0	45	0	27	30	3	41	23	29	47	33	32	32	34	22	22	22	43	42
electric machine	0	17	0	51	81	0	41	38	22	31	9	24	44	19	46	29	15	24	49	48	40	37	42
device battery	0	0	0	101	0	15	16	38	30	24	35	43	33	61	44	35	30	43	32	32	37	42	41
battery management	26	0	102	13	0	0	33	156	104	38	55	58	59	60	56	118	95	64	54	74	68	68	67
charge port	0	34	0	0	32	0	0	0	0	0	12	11	24	28	3	13	19	13	23	38	31	34	41
heat exchange	0	0	0	0	0	106	0	0	30	17	2	16	5	29	10	12	4	15	13	32	31	51	40
temperature control	0	0	17	25	0	61	0	11	17	14	21	33	35	28	11	24	12	7	28	32	37	43	39

Table 4.10: Top 30 bigram occurrence intensities (occurrences per 1000 abstracts) in patent abstracts. *The colour gradients represent intra-row relationships.*

We can see generic terms like "electric vehicle", "battery cell", or "energy storage" showing a significant rise in occurrences over the years, suggesting an increasing number of innovations related to generic core components of EVs and their energy systems. Some terms such as "fuel cell", show fluctuating occurrences (although growing in absolute number), which indicates changing interest or advancements in alternative energy storage technologies. This behaviour is acceptable since we only focus on EV batteries, even though we do not completely exclude the interaction between batteries and fuel cells.

Different areas of interest are emerging as well, such as ”battery swapping” that have appeared more frequently in recent years, with 51 and 132 normalised occurrences respectively in 2021 and 2022. Battery swapping is a method for recharging EVs by exchanging a depleted battery pack with a fully charged one at specialised stations, rather than plugging the vehicle into a charging point (Luo et al., 2024). The advantages include a rapid changeover, significantly reducing the time associated with conventional charging methods, and higher flexibility and efficiency since swapping stations can ensure that batteries are charged under optimal conditions, potentially extending battery life (Nayak & Misra, 2024).

The data also suggest shifts in market and technological focus, as evidenced by the rising and falling frequencies of different keywords. For example, notable bigrams in the sub-field of charging and EVs are ”charge station” and ”vehicle charge”, aligning with the fact that, according to various studies charging problems is one of the main barriers to consumers’ EV adoption (Pamidimukkala et al., 2024).

5 | Conclusions

The objective of this study is to present a systematic analysis of the development of EV batteries. Using bibliometric methods and patent analysis, we constructed a dataset of the key innovations. The data was retrieved from WoS and PATSTAT, complemented with information from Scopus, SJR, and the United Nations.

First, the preliminary conclusion drawn from the data is that, particularly since 2010, there has been a significant increase in scientific and technical output on this topic, with no signs of slowing down. This phenomenon, which involves more countries, authors/ inventors, journals and published papers and applied patents, highlights the critical role that EVs play in sustainability, as well as that batteries play in the development and uptake of this technology.

Second, the findings yield significant insights into the key contributors shaping the output related to the subject. China emerges as the front-runner in terms of publication volume, followed by the US and India. However, the research output is dominated by the first two countries, which account for nearly 44% of all publications. The impact of each country was also measured using citation counts and we conclude that China, in 22^{nd} place with 45.6 citations per publication, has room to enhance its impact and overall contribution to the field. G7 and BRICS countries show different behaviours in publishing scientific output and patenting inventions. BRICS currently dominate the scientific landscape, driven mainly by China, and as for IPFs, the G7 output largely outnumbers the BRICS contributions.

Third, the scientific research is dominated by academic institutions. We can see that the most productive (in terms of article output) non-academic affiliation, General Motors, is ranked in 55^{th} place. Although non-academic institutions such as car manufacturers, electric utility corporations, or energy and building technology companies publish less, they underscore the dynamic nature of this field, where research translates into innovation.

Fourth, the main areas of study for EV batteries are ”Electronics and Telecom Engineering” and ”Energy”, reflecting the interdisciplinary nature of this area. The main keywords found in the abstracts of publications are ”system”, ”optimisation”, ”performance”, ”lithium-ion battery”, and ”vehicle to grid”, encapsulating the main issues and the current trend in the area. Additionally, keyword analysis uncovers both the evolutionary shift in battery chemistries, with lead-acid batteries dominating in the early 2000s and gradually transitioning to lithium-ion batteries and the emergence of new technologies, namely battery swapping.

Finally, it is critical to discuss the limitations of this research. While comprehensive in scope, it remains non-exhaustive. In the quantitative science analysis, only one database (WoS) was considered for document retrieval, and only articles or review articles from academic journals were included. Books, conference papers, theses, and dissertations were not included, meaning that there may be relevant findings from sources that were unexplored. The propensity to publish and citation dynamics also vary along disciplinary lines (Leydesdorff et al., 2014). Even by complementing this analysis with patent data, these are just two methods of disclosing an innovation, alongside strategies such as preserving industrial secrecy or deliberately crafting intricate specifications. Therefore, many inventions never result in patent filings or publications (Cohen et al., 2000).

The study heavily relies on the availability and quality of the data. In the case of the bibliometric analysis, limitations may arise due to incomplete coverage of relevant literature (Romanelli et al., 2021). Identifying relevant sources of publications and selecting appropriate search terms is crucial. This process requires deep technical knowledge and involves structuring the context of interest into building blocks and combining selected terms to form an effective search string. In the case of the patent analysis, the main limitation is related to the discrepancies in how names are recorded across the dataset. There are variations in spelling and the harmonisation process was not complete, therefore the lack of standardisation complicates the counts and the analysis of institutional contributions to innovation.

Another limitation of the analysis relates to keyword analysis, which may lack context. Keywords alone cannot provide a comprehensive understanding of the content of a study or of an invention. Lastly, the citation analysis also brings challenges. Authors may excessively cite their own work or their closed peers' work to artificially inflate the citation count (D'Ippoliti, 2020), and citations might not completely capture quality aspects of the work (Aksnes et al., 2019; Velayos-Ortega & López-Carreño, 2023).

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("electric car$" OR "electromobility" OR "electric vehicle$" OR
"electric automobile*" OR "automotive") AND ("battery management system"
OR "management system" OR "battery system" OR "BMS" OR "SOH estimat*" OR
"SOC estimat*" OR "SOC" OR "SOH" OR "energy storage devices" OR "charg*" OR
"discharg*" OR (("batter*" OR "cell") AND ("lead acid" OR
"valve regulated lead acid" OR "VRLA" OR "SLA" OR "sealed lead acid" OR
"absorbent glass mat" OR "AGM" OR "lithium air" OR "li air" OR
"lithium oxygen" OR "li O2" OR "li ion" OR "lithium ion" OR "LIB$" OR
"Li Po" OR "Li poly*" OR "lithium poly*" OR "lithium cobalt" OR "LCO" OR
"lithium manganese" OR "LMO" OR "lithium nickel manganese cobalt*" OR "NMC"
OR "LNMC" OR "NCM" OR "lithium iron phosphate" OR "lithium phosphate" OR
"Li Fe PO" OR "LiFePO*" OR "LFP" OR "lithium nickel cobalt aluminium" OR
"NCA" OR "lithium titanate" OR "LTO" OR "lithium silicon" OR "li S" OR
"li sulphur" OR "li sulfur" OR "lithium sulphur" OR "lithium sulfur" OR
"lithium secondary" OR "magnesium ion" OR "Mg ion" OR "nickel cadmium"
OR "Ni cd" OR "nickel iron" OR "Ni Fe" OR "nickel zinc" OR "Ni Zn" OR
"nickel metal hydride" OR "NiMH" OR "rechargeable alkali*" OR
"alkali* rechargeable" OR "alkali* secondary" OR "secondary alkali*" OR
"sodium sulfur" OR "Na S" OR "sodium ion" OR "Na ion" OR "solid state" OR
"SSB$" OR "aluminium ion" OR "calcium ion" OR "ca ion" OR
"organic radical" OR "redox flow" OR "rfb" OR "vanadium redox" OR "vrb"
OR "zinc bromine" OR "uranium redox")))
```

B | PATSTAT Queries

These queries were used to retrieve the data from PATSTAT ONLINE, Autumn Edition 2023. They were adapted from GitHub/battery patents/01 PATSTAT/PATSTAT Online query.txt and from GitHub/battery patents/03 Extra data/PATSTAT citations (to and from H01M% + Charging)/the two queries.rtf.

The data should be downloaded separately for each desired year and attribute `appln_nr_epodoc` was not used in the queries, since it was deprecated. When writing the IPC codes, we must be careful with the formatting. The slash sign should be on position 9, therefore it might be necessary to include some spaces between positions 5-7.

B.1 First Query

The first query collects all family IDs of patent families that fulfil the following two conditions: (1) the family contains applications with at least one of the IPC codes of interest; (2) the family's smallest (i.e. earliest) value of the attributes `earliest_publn_date` / `earliest_publn_year` is inside the defined time frame. The query will retrieve the patent families in their entirety.

```
SELECT
a.docdb_family_id,
a.appln_id, a.granted,
a.earliest_filing_date, a.earliest_filing_year,
a.earliest_publn_date, a.earliest_publn_year,
string_agg(cast(c.ipc_class_symbol as NVARCHAR(MAX)), ',') as ipc_class_symbols,
pa.applt_seq_nr, pa.invt_seq_nr,
a.appln_auth, p.person_ctry_code,
p.psn_name, p.han_name,
t.appln_title, t.appln_title_lg,
ab.appln_abstract, ab.appln_abstract_lg,
-- the rest of the fields from TLS201_APPLN
a.appln_nr,
a.appln_kind,
```

```
a.appln_filing_date,
a.appln_filing_year,
a.appln_nr_original,
a.ipr_type,
a.receiving_office,
a.internat_appln_id,
a.int_phase,
a.reg_phase,
a.nat_phase,
a.earliest_filing_id,
a.earliest_pat_publn_id,
a.inpadoc_family_id,
a.docdb_family_size,
a.nb_citing_docdb_fam,
a.nb_applicants,
a.nb_inventors,
-- the rest of the fields from TLS206_PERSON
p.person_id,
p.person_name,
p.person_name_orig_lg,
p.person_address,
p.nuts,
p.nuts_level,
p.doc_std_name_id,
p.doc_std_name,
p.psn_id,
p.psn_level,
p.psn_sector,
p.han_id,
p.han_harmonized,
-- the rest of the fields from TLS209_APPLN_IPC in aggregated form
string_agg(cast(c.ipc_class_level as NVARCHAR(MAX)), ',') as ipc_class_levels,
string_agg(cast(c.ipc_version as NVARCHAR(MAX)), ',') as ipc_versions,
string_agg(cast(c.ipc_value as NVARCHAR(MAX)), ',') as ipc_values,
string_agg(cast(c.ipc_position as NVARCHAR(MAX)), ',') as ipc_positions,
string_agg(cast(c.ipc_gener_auth as NVARCHAR(MAX)), ',') as ipc_gener_auths

FROM
(((((tls201_appln a
LEFT OUTER JOIN tls207_pers_appln pa ON a.appln_id = pa.appln_id)
LEFT OUTER JOIN tls206_person p ON pa.person_id = p.person_id)
```

```
LEFT OUTER JOIN tls202_appln_title t ON a.appln_id = t.appln_id)
LEFT OUTER JOIN tls203_appln_abstr ab ON a.appln_id = ab.appln_id)
LEFT OUTER JOIN tls209_appln_ipc c ON a.appln_id = c.appln_id)

-- Time restriction
WHERE a.docdb_family_id IN
(
SELECT t2.docdb_family_id
FROM
(
SELECT a2.docdb_family_id,
MIN(a2.earliest_publn_year) as earliest_publn_year_family
FROM tls201_appln a2
GROUP BY a2.docdb_family_id
) AS t2

-- Marker --
-- This is where the year/timeframe is defined

WHERE t2.earliest_publn_year_family = 2022
)

-- IPC class restriction
AND a.docdb_family_id IN
(
SELECT DISTINCT docdb_family_id
FROM (tls201_appln a3 LEFT OUTER JOIN tls209_appln_ipc c3 ON
a3.appln_id = c3.appln_id)
WHERE
(
-- Processes or means, e.g. batteries, for the direct conversion of
chemical energy into electrical energy
c3.ipc_class_symbol LIKE 'H01M%'
-- Circuit arrangements for AC mains or AC distribution networks using
batteries with converting means
OR c3.ipc_class_symbol = 'H02J   3/32'
-- Circuit arrangements for charging or depolarising batteries or for
supplying loads from batteries
OR c3.ipc_class_symbol LIKE 'H02J   7%'
-- Methods of charging batteries, specially adapted for electric vehicles;
Charging stations or on-board charging equipment therefor; Exchange of
```

```
energy storage elements in electric vehicles
OR c3.ipc_class_symbol LIKE 'B60L  53%'
-- ALL CLASSES FOR B60L  50/50
-- Electric propulsion with power supplied within the vehicle. Using
propulsion power supplied by batteries or fuel cells
OR c3.ipc_class_symbol LIKE 'B60L  50/5%'
OR c3.ipc_class_symbol LIKE 'B60L  50/6%'
OR c3.ipc_class_symbol = 'B60L  50/75'
-- B60L  11/18 transferred to B60L  50/50
OR c3.ipc_class_symbol = 'B60L  11/18'
-- ALL CLASSES FOR B60L  58/00 except B60L 58/30
(For monitoring or controlling fuel cells).
-- Methods or circuit arrangements for monitoring or controlling batteries
or fuel cells, specially adapted for electric vehicles. For monitoring or
controlling batteries
OR c3.ipc_class_symbol LIKE 'B60L  58/1%'
OR c3.ipc_class_symbol LIKE 'B60L  58/2%'
-- Methods or circuit arrangements for monitoring or controlling batteries
or fuel cells, specially adapted for electric vehicles. For controlling
a combination of batteries and fuel cells
OR c3.ipc_class_symbol = 'B60L  58/40'
)
)

GROUP BY a.docdb_family_id, a.appln_id, a.granted, a.earliest_filing_date,
a.earliest_filing_year, a.earliest_publn_date, a.earliest_publn_year,
pa.applt_seq_nr, pa.invt_seq_nr, a.appln_auth, p.person_ctry_code,
p.psn_name, p.han_name, t.appln_title, t.appln_title_lg, ab.appln_abstract,
ab.appln_abstract_lg,
-- the rest of the fields from TLS201_APPLN
a.appln_nr,
a.appln_kind,
a.appln_filing_date,
a.appln_filing_year,
a.appln_nr_original,
a.ipr_type,
a.receiving_office,
a.internat_appln_id,
a.int_phase,
a.reg_phase,
a.nat_phase,
```

```
a.earliest_filing_id,
a.earliest_pat_publn_id,
a.inpadoc_family_id,
a.docdb_family_size,
a.nb_citing_docdb_fam,
a.nb_applicants,
a.nb_inventors,
-- the rest of the fields from TLS206_PERSON
p.person_id,
p.person_name,
p.person_name_orig_lg,
p.person_address,
p.nuts,
p.nuts_level,
p.doc_std_name_id,
p.doc_std_name,
p.psn_id,
p.psn_level,
p.psn_sector,
p.han_id,
p.han_harmonized
ORDER BY a.docdb_family_id, pa.invt_seq_nr, pa.applt_seq_nr,
a.earliest_publn_date ASC
```

B.2 Second Query

The second query collects the "cited by" information regarding the patents retrieved before, with the first query. Each entry in table `tls228_docdb_fam_citn` contains a citation between two patent families, where one member in one family cites at least one member of another family. It is important to consider that if multiple publications within one family cite one or multiple publications/applications of another family, it is considered as a single citation between these two families.

```
SELECT
t1.docdb_family_id,
string_agg(cast(t1.cited_by_docdb_family_id AS NVARCHAR(MAX)), ',') AS
cited_by_docdb_family_ids

FROM
(
SELECT DISTINCT
```

```
a.docdb_family_id,
cit.docdb_family_id AS cited_by_docdb_family_id

FROM
(
(
tls201_appln a
JOIN tls209_appln_ipc c ON a.appln_id = c.appln_id
)
JOIN tls228_docdb_fam_citn cit ON a.docdb_family_id = cit.cited_docdb_family_id
)

WHERE
(
-- Processes or means, e.g. batteries, for the direct conversion of
chemical energy into electrical energy
c3.ipc_class_symbol LIKE 'H01M%'
-- Circuit arrangements for AC mains or AC distribution networks using
batteries with converting means
OR c3.ipc_class_symbol = 'H02J   3/32'
-- Circuit arrangements for charging or depolarising batteries or for
supplying loads from batteries
OR c3.ipc_class_symbol LIKE 'H02J   7%'
-- Methods of charging batteries, specially adapted for electric vehicles;
Charging stations or on-board charging equipment therefor; Exchange of
energy storage elements in electric vehicles
OR c3.ipc_class_symbol LIKE 'B60L  53%'
-- ALL CLASSES FOR B60L  50/50
-- Electric propulsion with power supplied within the vehicle. Using
propulsion power supplied by batteries or fuel cells
OR c3.ipc_class_symbol LIKE 'B60L  50/5%'
OR c3.ipc_class_symbol LIKE 'B60L  50/6%'
OR c3.ipc_class_symbol = 'B60L  50/75'
-- B60L  11/18 transferred to B60L  50/50
OR c3.ipc_class_symbol = 'B60L  11/18'
-- ALL CLASSES FOR B60L  58/00 except B60L 58/30
(For monitoring or controlling fuel cells).
-- Methods or circuit arrangements for monitoring or controlling batteries
or fuel cells, specially adapted for electric vehicles. For monitoring or
controlling batteries
OR c3.ipc_class_symbol LIKE 'B60L  58/1%'
```

```
OR c3.ipc_class_symbol LIKE 'B60L  58/2%'
-- Methods or circuit arrangements for monitoring or controlling batteries
or fuel cells, specially adapted for electric vehicles. For controlling
a combination of batteries and fuel cells
OR c3.ipc_class_symbol = 'B60L  58/40'
)
) AS t1

GROUP BY t1.docdb_family_id

ORDER BY t1.docdb_family_id ASC
```

B.3 Third Query

Finally, the third query collects the "cited" information regarding the patents retrieved before, with the first query.

```
SELECT
t1.docdb_family_id,
string_agg(cast(t1.cited_docdb_family_id AS NVARCHAR(MAX)), ',') AS
cited_docdb_family_ids

FROM
(
SELECT DISTINCT
a.docdb_family_id,
cit.cited_docdb_family_id

FROM
(
(
tls201_appln a
JOIN tls209_appln_ipc c ON a.appln_id = c.appln_id
)
JOIN tls228_docdb_fam_citn cit ON a.docdb_family_id = cit.docdb_family_id
)

WHERE
(
-- Processes or means, e.g. batteries, for the direct conversion of
chemical energy into electrical energy
```

```
c3.ipc_class_symbol LIKE 'H01M%'
-- Circuit arrangements for AC mains or AC distribution networks using
batteries with converting means
OR c3.ipc_class_symbol = 'H02J   3/32'
-- Circuit arrangements for charging or depolarising batteries or for
supplying loads from batteries
OR c3.ipc_class_symbol LIKE 'H02J   7%'
-- Methods of charging batteries, specially adapted for electric vehicles;
Charging stations or on-board charging equipment therefor; Exchange of
energy storage elements in electric vehicles
OR c3.ipc_class_symbol LIKE 'B60L  53%'
-- ALL CLASSES FOR B60L  50/50
-- Electric propulsion with power supplied within the vehicle. Using
propulsion power supplied by batteries or fuel cells
OR c3.ipc_class_symbol LIKE 'B60L  50/5%'
OR c3.ipc_class_symbol LIKE 'B60L  50/6%'
OR c3.ipc_class_symbol = 'B60L  50/75'
-- B60L  11/18 transferred to B60L  50/50
OR c3.ipc_class_symbol = 'B60L  11/18'
-- ALL CLASSES FOR B60L  58/00 except B60L 58/30
(For monitoring or controlling fuel cells).
-- Methods or circuit arrangements for monitoring or controlling batteries
or fuel cells, specially adapted for electric vehicles. For monitoring or
controlling batteries
OR c3.ipc_class_symbol LIKE 'B60L  58/1%'
OR c3.ipc_class_symbol LIKE 'B60L  58/2%'
-- Methods or circuit arrangements for monitoring or controlling batteries
or fuel cells, specially adapted for electric vehicles. For controlling
a combination of batteries and fuel cells
OR c3.ipc_class_symbol = 'B60L  58/40'
)
) AS t1

GROUP BY t1.docdb_family_id

ORDER BY t1.docdb_family_id ASC
```

C | Included IPC codes

Table C.1: The IPC codes applied for data collection.

IPC code	Title
B60L 50/50	Subclass *B60L* contains applications related to the driving force of electrically-propelled vehicles. The group *B60L 50/00* includes electric propulsion with power supplied within the vehicle. Subgroup *B60L 50/50* relates specifically to using propulsion power supplied by batteries or fuel cells. **EXCLUDING** *B60L 50/70* (using power supplied by fuel cells)
B60L 53/00	Subclass *B60L* contains applications related to the driving force of electrically-propelled vehicles. The group *B60L 53/00* includes methods of charging batteries, specially adapted for electric vehicles; Charging stations or on-board charging equipment therefor; Exchange of energy storage elements in electric vehicles. **EXCLUDING** charging stations characterised by energy-storage or power-generation means: *B60L 53/54* (Fuel cells), *B60L 53/55* (Capacitors), and *B60L 53/56* (Mechanical storage means, e.g. fly wheels)
B60L 58/00	Subclass *B60L* contains applications related to the driving force of electrically-propelled vehicles. The group *B60L 58/00* includes methods or circuit arrangements for monitoring or controlling batteries or fuel cells, specially adapted for electric vehicles. **EXCLUDING** *B60L 58/30* (for monitoring or controlling fuel cells)

Table C.1: (continuation)

IPC code	Title
H02J 3/32	Subclass *H02J* contains circuit arrangements or systems for supplying or distributing electric power; systems for storing electric energy. The group *H02J 3/00* includes circuit arrangements for AC mains or AC distribution networks. Subgroup *H02J 3/28* refers to arrangements for balancing the load in a network by storage of energy, and drilling down one more level, subgroup *H02J 3/32* includes only uses of batteries with converting means
H02J 7/00	Subclass *H02J* contains circuit arrangements or systems for supplying or distributing electric power; systems for storing electric energy. The group *H02J 7/00* includes circuit arrangements for charging or depolarising batteries or for supplying loads from batteries
H01M 4/00	Subclass *H01M* contains processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy. The group *H01M 4/00* includes electrodes
H01M 10/00	Subclass *H01M* contains processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy. The group *H01M 10/00* includes secondary cells; manufacture thereof
H01M 10/44	Subclass *H01M* contains processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy. The group *H01M 10/00* includes secondary cells; manufacture thereof. Subgroup *H01M 10/42* refers to methods or arrangements for servicing or maintenance of secondary cells or secondary half-cells, while subgroup *H01M 10/44* includes only methods for charging or discharging

Table C.1: (continuation)

IPC code	Title
H01M 50/00	Subclass *H01M* contains processes or means, e.g. batteries, for the direct conversion of chemical energy into electrical energy. The group *H01M 50/00* includes constructional details or processes of manufacture of the non-active parts of electrochemical cells other than fuel cells, e.g. hybrid cells

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