electronics

MDPI

Article

AI on Wheels: Bibliometric Approach to Mapping of Research on Machine Learning and Deep Learning in Electric Vehicles

Adrian Domenteanu [1], Liviu-Adrian Cotfas [1,*], Paul Diaconu [2], George-Aurelian Tudor [2] and Camelia Delcea [1]

[1] Department of Economic Informatics and Cybernetics, Bucharest University of Economic Studies, 010552 Bucharest, Romania
[2] Department of Accounting and Audit, Bucharest University of Economic Studies, 010552 Bucharest, Romania
* Correspondence: liviu.cotfas@ase.ro; Tel.: +40-771269599

Abstract: The global transition to sustainable energy systems has placed the use of electric vehicles (EVs) among the areas that might contribute to reducing carbon emissions and optimizing energy usage. This paper presents a bibliometric analysis of the interconnected domains of EVs, artificial intelligence (AI), machine learning (ML), and deep learning (DL), revealing a significant annual growth rate of 56.4% in research activity. Key findings include the identification of influential journals, authors, countries, and collaborative networks that have driven advancements in this domain. This study highlights emerging trends, such as the integration of renewable energy sources, vehicle-to-grid (V2G) schemes, and the application of AI in EV battery optimization, charging infrastructure, and energy consumption prediction. The analysis also uncovers challenges in addressing information security concerns. By reviewing the top-cited papers, this research underlines the transformative potential of AI-driven solutions in enhancing EV performance and scalability. The results of this study can be useful for practitioners, academics, and policymakers.

Keywords: artificial intelligence; machine learning; deep learning; electric vehicles; bibliometrics

check for updates

Academic Editors: Zhiquan Liu, Zuobin Ying and Jingjing Guo

Received: 17 November 2024
Revised: 3 January 2025
Accepted: 9 January 2025
Published: 19 January 2025

Citation: Domenteanu, A.; Cotfas, L.-A.; Diaconu, P.; Tudor, G.-A.; Delcea, C. AI on Wheels: Bibliometric Approach to Mapping of Research on Machine Learning and Deep Learning in Electric Vehicles. *Electronics* **2025**, *14*, 378. https://doi.org/10.3390/electronics14020378

1. Introduction

Actual global energy production is strongly dependent on fossil fuels, including petroleum, natural gas, and coal, and their use causes numerous problems, such as health effects and environmental changes [1]. Given the progress in the power electronics domain, combined with technological evolution, engineers are focusing on various methods of making power electronics more reliable [2].

The adoption of EVs is seen as one of the best solutions for reducing CO_2 emissions while also providing a smarter means of transport [3]. According to the Department of Energy, USA, an EV is defined as a "vehicle that can be powered by an electric motor that draws electricity from a battery and is capable of being charged from an external source" [4]. This category of vehicles includes not only fully electric vehicles but also plug-in hybrid ones that also include a combustion engine in addition to an electric one [4].

Due to the high costs and limited range offered by the batteries in EVs, it is important to define algorithms, particularly those using AI, which will reduce costs. As stated by the International Organization for Standardization (ISO), AI is defined as "a technical and scientific field devoted to the engineered system that generates outputs such as content, forecasts, recommendations, or decisions for a given set of human-defined objectives" [5]. One of the main components of AI is ML, which involves "a broad range of techniques that enable computers to learn from and make inferences based on data without being explicitly programmed for specific tasks" [6]. Some of the most popular ML techniques include linear regression, logistic regression, decision trees, random forest, support vector machines (SVMs), K-nearest neighbor (KNN), and clustering [6]. Furthermore, a subset of ML that uses "multilayered neural networks, called deep neural networks, that more closely simulate the complex decision-making power of the human brain" is gathered under the DL umbrella [6].

In the transportation arena, ML algorithms are very useful, providing solutions to various problems, such as the prediction of consumer charging behavior and offering suggestions regarding routes in order to extend the range of EVs as much as possible [7,8]. ML is also capable of predicting battery performance and optimizing the fast-charging process, which could have a notable influence on increasing the number of EVs in service worldwide [9,10]. Furthermore, bio-inspired optimization algorithms, such as the artificial bee colony (ABC) method, which is used for autonomous underwater vehicles, have shown the potential of these techniques to provide solutions to complex problems in the transportation arena [11].

AI is used in many processes involved in car manufacturing, such as physical design, verification, and monitoring. Companies have also started to implement AI to accelerate the chip design's life cycle [2].

Considering works in the field of EV, some of the research presented in the following have arisen as prominent works, highlighting new trends and methodologies. Xing et al. [12] defined a real-time platform for electric vehicles' charging navigation in order to offer opportunities for efficient filling behavior by taking into consideration the connection of cars with charging stations and traffic networks. The scope of the model aims to reduce the charging fee and traveling time by using a deep reinforcement learning (DRL) model and a Markov decision process. The case studies that were conducted are from a practical zone within Nanjing, China. Zhong et al. [13] created a Stackelberg game where they included EVs and an energy hub (EH) as two followers, together with a distributionally robust optimization model that took into account the renewable generation uncertainty level. Multiple numerical case studies were conducted, obtaining numerous simulation results that confirmed the effectiveness of the model in defining a new low-carbon model for energy hubs and electric vehicles. Furthermore, Shang et al. [14] considered that EVs and renewable energy methods could lower air pollution. The authors detailed the vehicle-to-grid scheme, combined with renewable energy sources, edge community, photovoltaics, and an internet of smart charging points, obtaining a higher efficiency compared with existing methods. Additionally, Shang et al. [15] contributed to an innovative vehicle-to-grid (V2G) scheduling framework that leverages federated DL and distributed edge computing, offering enhanced efficiency, privacy preservation for EV users, and reduced computational and communication costs while providing a data-collecting approach and uncertainty barrier for traditional optimization methods.

Also, Xie et al. [16] investigated a new material liquid used for cooling battery thermal management systems and also examined the impacts of liquid flow direction, mass flow rate, and material melting point. Using ML and regression algorithms, multiple models were tested, and the prediction of temperature and energy consumption showed an error smaller than 5% using a random forest model. Zhang et al. [17] proposed an EV engine with a new sliding mode, which also has a speed controller that increases the efficiency of the constant-magnet synchronous engine traction. Wang et al. [18] explored the EV charging infrastructure and renewables in power grids, creating a framework that was able to choose the charging volume required in a recharging zone and conducting numerous simulations that demonstrate the various ratios for charging loads.

El-Azab et al. [19] used ML and DL methods in order to forecast the charging load profile for EVs, using data from Spain's electrical grid, with the purpose of increasing EV usage while facing existing threats that are stopping the penetration of EVs into the market. Using multiple ML and DL techniques, such as artificial neural networks, long short-term memory, and adaptive neuro-fuzzy interference systems, provided good results, especially the long short-term memory algorithm, which was capable of identifying patterns in the hourly historical charging data of EVs. Mohamed et al. [20] considered that ML and AI have gained significant popularity in the EV domain. However, due to the limited research in this area, the scope of their analysis was to provide a brief summary of the current states of AI and ML in the information security of EVs. The authors reviewed the existing academic literature, with their research revealing that AI and ML are used in numerous methods, aiming to improve information security in EVs, such as intrusion detection, attack prevention, or authentication. Numerous DL and neural network methods are becoming increasingly popular, with over 70% of the papers being based on DL. Kaplan et al. [21] considered diagnosis faults in EVs as one of the main challenges, so the objective of the research was to demonstrate detection through the use of an electromechanical conversion chain, collecting data such as voltages, currents, and speeds from various sensors. A long short-term memory algorithm was used for the fault diagnosis, which was also tested in practical applications, and the results confirmed that the accuracy is higher by using a ML algorithm.

Venkitaraman and Kosuru [22] presented EVs as an alternative to traditional gasoline cars. During their research, the forecasting of EV charging patterns was investigated using a recursive neural network and a gated recurrent unit (GRU) framework. The experimental results confirmed the capability of GRU to track the mileage of EVs. Zhu et al. [23] described load prediction as one of the main obstacles to power systems, so the authors proposed a DL method that predicts the super-short-term charging load for plug-in EVs. The outcomes showed a 30% reduction in forecasting error by using a DL algorithm compared to conventional artificial neural network algorithms. Sundaram et al. [24] considered that DL provides a significant improvement in numerous domains, such as science, government sectors, and business. The goal of their paper was to understand the usage of DL in various areas, presenting the architectures, techniques, and frameworks that are currently used in real-time applications, such as photovoltaic panels or EVs. Ma et al. [25] explored the role of EVs in reducing carbon emissions, regarding the optimal schedule of EVs as one of the main topics nowadays, thanks to a rise in blockchain and AI. The authors described the importance of AI, ML, and blockchain in EVs, providing suggestions regarding future research.

At the same time, ML can be used to optimize EV charging costs by analyzing the charging patterns and enabling real-time decision-making, as Mohammed et al. [26] explained in their research. Deep neural networks were used, with their results providing a cost reduction ranging from 28% to 74%, along with high median gains depending on the season.

The purpose of this study was to investigate the academical evolution of the analyzed areas in order to understand how the domains changed in the last years. In order to observe this evolution and to understand the main contributors to the field and how the domain evolved in terms of the published papers, international collaborations, key contributing journals and universities, key authors, and themes addressed in the most cited papers, a bibliometric analysis was conducted, as it provides a comprehensive method for identifying all the mentioned factors [27–29]. As highlighted by Block and Fisch [27], unlike a review analysis, which primarily aims to summarize the content and key findings of a specific research field, bibliometric analysis places greater emphasis on examining the structural aspects of the field, shedding light on its evolution and development over time. Through the bibliometric analysis, numerous key factors that contributed to the evolution of EVs, AI, ML, and DL were discovered, and the analysis focuses on answering the following analytical questions:

- SQ1: Which journals have published the highest number of articles on EVs, ML, and DL?
- SQ2: Is there any collaboration network between authors?
- SQ3: Which are the most relevant countries based on the number of citations and publications?
- SQ4: Which are the main keywords used in the papers?
- SQ5: Who are the most important authors in the analyzed areas?
- SQ6: What are the main terms included in the thematic maps?

Additionally, to provide a multi-dimensional analysis of the field, we have chosen to enhance our study by reviewing the top 10 most cited papers in the domain.

The decision to adopt a bibliometric approach to study the field related to the use of ML and DL in EVs is further supported by the fact that the bibliometric analysis enables the examination of large-scale publication data to identify trends, patterns, and key contributors in the field, compared to a qualitative approach, which often relies on subjective interpretation [30–33]. Furthermore, a bibliometric analysis provides both objective and reproducible results when following similar steps. Also, well-known indicators, such as the H-index and G-index (further explained in the paper), quantitatively assess the impact of a researcher or source over a specific field. Lastly, the decision to conduct a quantitative analysis is further emphasized by the nature of the research questions. Moreover, as mentioned above, we complemented the quantitative analysis conducted using bibliometric methods by incorporating a qualitative analysis through a review of the top 10 most cited papers.

In terms of the novelty of this study, it shall be stated that despite other bibliometric studies being conducted in the field of EVs, to the best of our knowledge, the use of ML and DL in EVs has not yet been specifically addressed in a dedicated paper with this particular focus. Considering the scientific literature, a series of bibliometric papers in the field of EVs has been identified, as seen in the results in Table 1, which are listed in alphabetical order by the first author's last name. Thus, in the area of AI in EVs, this paper presents key findings, including the identification of influential journals, authors, countries, and collaborative networks that have driven advancements in this domain, along with emerging trends. Furthermore, through the review provided in this paper, the research underscores the transformative potential of AI-driven solutions in enhancing EV performance and scalability and discusses the implications of various aspects related to AI in EVs in diagnostics and manufacturing processes, as well as in integration with renewable energy, in consumer behavior and market trends, and in information security.

This paper is divided into multiple parts as follows: The first section focuses on the introductory elements of the research, explaining the aim of the analysis, while the second section describes the major techniques used in the bibliometric approach, together with the data extraction steps. The third section presents the results obtained based on the extracted dataset, highlighting the major affiliations, countries, authors, keywords, and most cited papers. The fourth section includes the discussions and limitations of this study, while the fifth section incorporates the concluding remarks.

Table 1. Summary of previous bibliometric research papers on EVs.

Reference	Focus
Ayodele and Mustapa [34]	Life cycle cost assessment of EVs
Barbosa et al. [35]	EVs in general
Bhat and Verma [36]	Adoption behavior of EVs
Miah et al. [37]	Optimized energy management schemes for EV applications
Murugan et al. [38]	Thermal management system of lithium-ion battery packs for EVs
Nurdini et al. [39]	Waste from EV
Purwanto and Irawan [40]	EV adoption research
Raboaca et al. [41]	Optimal energy management strategies for EVs
Secinaro et al. [42]	Suitable business models for EVs
Singh et al. [43]	EV adoption and sustainability
Soares et al. [44]	EV supply chain management
Tambunan [45]	EV integration into electrical power system
Veza et al. [33]	EV trends, policy, lithium-ion batteries, battery management, charging infrastructure, smart charging, electric, and vehicle-to-everything (V2X)
Yao et al. [46]	EV energy efficiency and emission effects research

2. Materials and Methods

Based on the existing research, Clarivate Analytics' Web of Science Core Collection [47], also known as the ISI Web of Science or WoS, has been chosen in order to perform a bibliometric analysis. Bakir et al. [48] described why the ISI Web of Science is the better database to elaborate a bibliometric analysis, highlighting its extensive coverage of domains and indexed journals, making it one of the most well-known sources in the academical community. Even if the inclusivity level is narrower compared to other databases, WoS is still one of the most used sources for scientific literature [49–53].

After researching the scientific literature, it was observed that a crucial step in working with Clarivate Analytics' Web of Science Core Collection database is to mention the indexes that have been used in the extraction process, as Liu [54,55] presented. Access to the WoS database is subscription-based, and the search results can vary depending on the type of subscription held by the user. Consequently, some users may have limited access to certain indexes based on their subscription plan, while others may have full access due to a different subscription type. As Liu [55] emphasized, it is essential for authors conducting bibliometric analyses to clearly state their level of access to the WoS database. The range of available indexes can influence the number of papers included in the analysis, as WoS offers multiple subscription tiers. In our case, it is important to specify that we had access to all indexes provided by Clarivate Analytics' Web of Science Core Collection, as detailed below:

- Book Citation Index—Science (BKCI-S)—2010—present;
- Index Chemicus (IC)—2010—present;
- Social Sciences Citation Index (SSCI)—1975—present;
- Book Citation Index—Social Sciences and Humanities (BKCI-SSH)—2010—present;
- Arts and Humanities Citation Index (A&HCI)—1975—present;
- Current Chemical Reactions (CCR-Expanded)—2010-present; Emerging Sources Citations Index (ESCI)—2005—present;
- Science Citation Index Expanded (SCIE)—1900—present;
- Conference Proceedings Citation Index—Social Sciences and Humanities (CPCI-SSH)—1990—present;
- Conference Proceedings Citation Index—Science (CPCI-S)—1990—present.

The main steps required for a bibliometric analysis are described in Figure 1 and are consistent with the works conducted by Cobo et al. [56] and Zupic and Cater [57]. The initial step is dedicated to the extraction of the dataset using specific keywords, and then the subsequent step deals with the bibliometric research analysis. Based on the results, a discussion is provided, accompanied by a list of the limitations, followed by concluding remarks.

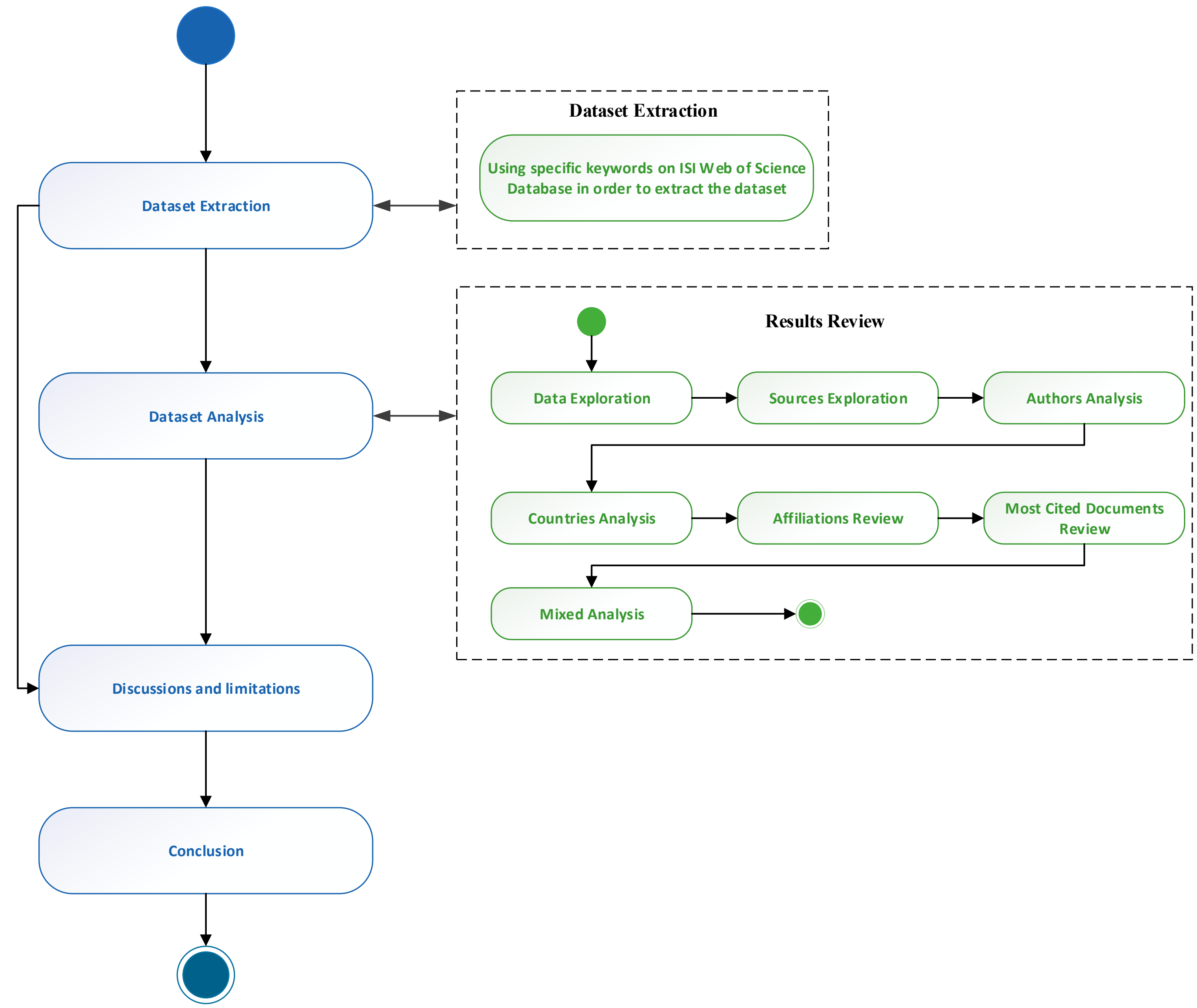

Figure 1. Steps in analysis.

Considering the scope of the research, a dataset was obtained from the Clarivate Analytics Web of Science Core Collection database website, and the main steps are described in Table 2.

The initial step filtered the titles, keywords, and abstracts by searching for “electric vehicle”, resulting in 73,887 documents. The use of the keywords listed in Table 2 aligns with similar bibliometric works in the field of EVs, which have examined current state-of-the-art EVs [35], analyzed EVs’ specific elements, such as lithium-ion batteries, charging infrastructure, and electric vehicle-to-everything [33], analyzed the optimized energy management schemes for EVs [37], and identified the EV supply chain management [44].

The second step was applied to keywords, titles, and abstracts, looking for “machine learning” and resulting in a total of 406,316 documents. The use of this keyword to search for papers within the database aligns with other bibliometric papers that have studied the use of ML in various fields, such as ML in energy efficiency [58], ML in disinformation detection [59], ML in fake news research [60], and ML field in general [61].

Table 2. Data selection steps.

Exploration Steps	Filters on Web of Science	Description	Query	Query Number	Count
1	Title/Abstract/Author's Keywords	Contains specific keywords related to EVs in title/abstract/authors' keywords	((TI = ("electric_vehicle*")) OR AB = ("electric_vehicle*")) OR AK = ("electric_vehicle*")	#1	73,887
2	Title/Abstract/Author's Keywords	Contains specific keywords related to ML in title/abstract/authors' keywords	((TI = ("machine_learning")) OR AB = ("machine_learning")) OR AK = ("machine_learning")	#2	406,316
3	Title/Abstract/Author's Keywords	Contains specific keywords related to DL in title/abstract/authors keywords	((TI = ("deep_learning")) OR AB = ("deep_learning")) OR AK = ("deep_learning")	#3	266,031
4	Title/Abstract/Author's Keywords	Contains one of the ML- or DL-specific keywords	#2 OR #3	#4	620,594
5	Title/Abstract/Author's Keywords	Contains one of the ML- or DL-specific keywords and EVs keywords	#1 AND #4	#5	1669
6	Language	Limit to English	(#1) AND LA = (English)	#6	1668
7	Document Type	Limit to Article	(#2) AND DT = (Article)	#7	1174
8	Year Published	Exclude 2024	(#3) NOT PY = (2024)	#8	932

The third filter searched the titles, abstracts, and keywords by using the words "deep learning", resulting in 266,031 publications. Similar bibliometric studies that utilized the mentioned searched keywords related to DL are the DL field in general [61], DL in disinformation detection [59], DL for precision agriculture [62], and DL in power systems [63].

The fourth step combines the second and third filters, looking for documents that contain either "machine learning" or "deep learning", resulting in a total of 620,594 papers.

The fifth step deals with searching after the papers and incorporates the fourth and first steps, looking for "electric vehicles" and "machine learning or deep learning", resulting in a total of 1669 papers.

The sixth filter focuses on the language of the published papers, restricting it to only English documents, reducing the dimensionality by 1 paper, leading to 1668 publications. English was chosen as a filtering step, as it is the language with the highest use by the research community [51,59]. Thangavel and Chandra [64] pointed out that using only English-written papers in bibliometric analyses is seen as an important criterion for maintaining both consistency and accessibility in the conducted analysis. Having more than one language in the dataset would have led to erroneous results when analyzing the words, themes, and n-grams in the selected dataset. As for other papers that have used this exclusion criterion, one can name the following: optimized energy management schemes for EVs [37], life cycle cost assessment in EVs [34], and EV supply chain management [44].

The seventh step keeps in the analysis only documents that are marked as "Article" in the WoS database. The category "Article", associated with a scientific paper by the WoS database, refers to new and original ideas [65]. Therefore, a conference publication could be included in this section, as well as other types of documents that were published in journals, if they are considered new and original by the database [65]. Based on the guidelines provided by Donner [66], we limited the type of documents to "Article", as each type of document receives a different number of citations (e.g., reviews, conference papers, book chapters, etc.), and this could affect the results of the bibliometric research indicators. It shall be stated that this decision was made with respect to other bibliometric papers from the field, analyzing various research areas, such as examining current state-of-the-art in EVs [35], analyzing the life cycle cost assessment in EVs [34], and identifying suitable business models for electric cars [42].

The last step excludes the 2024 year from the analysis, as this year was still ongoing at the time of the analysis, and the inclusion of only a part of the papers published and indexed in 2024 would affect various indicators, such as the annual scientific production or the number of citations, possibly conducting to erroneous conclusions related to the evolution of the field. Therefore, the final database contains 932 documents for analysis from a bibliometric perspective in the remainder of the present paper.

In terms of the used metrics, the results are presented by considering as much as possible of the classical metrics related to the number of documents in the dataset, the average years from publication, the average citations per document, the number of references, the number of authors, the number of co-authors per document, the number of author's keywords, the annual scientific production, the most relevant sources based on the number of publications, the authors' productivity, the number of papers according to the corresponding author's country, the most relevant affiliations based on the number of published papers, the number of citations per document, the number of total citations per document per year, etc. [49,64,67,68]. It shall be stated that we have included as much as possible of the available variables and indicators, in accordance with other studies from the field [49,64,67,68].

Besides the classical indicators mentioned above, a series of indicators are provided in the paper, which should be further explained due to their special nature—being either indicators specific to the database from which the dataset has been selected (e.g., Keywords Plus) or indicators whose name does not necessarily reflect the modality in which they have been determined (e.g., normalized total citations). These indicators are discussed in the following.

Keywords Plus [69] considers specific types of words that are automatically extracted by the ISI Web of Science platform based on the most frequently encountered words in the titles of the cited references of the papers included in the dataset.

Normalized total citations (NTC) describe the article's performance in terms of citations and are calculated as a division between the total citations for a paper and the average citations received by all papers in the dataset published in the same year as the analyzed document [60,70]. Basically, a NTC value of 5 shows that the current paper has exceeded 5 times the average number of citations obtained by all the papers in the dataset published in the same year as the analyzed paper.

The Hirsch index, also known as the H-index, is an important metric that measures the total number of documents for which the source has been cited at least the same number of times [71].

The G-index is an improvement of the H-index by taking the unique greatest numbers where the top g articles received together minimum g^2 citations [72].

In terms of laws, the following two analyses have been performed: Bradford's Law on sources and Lotka's law on author productivity:

- Bradford's Law—explores the most cited journals, isolating the less significant journals and maintaining only the most important ones. Bradford's law method includes a separation of journals into three categories based on the total number of papers. Each category must have the same amount of papers. In the final step, Bradford's law is clustering proportionally with $1{:}n{:}n^2$, as Yang et al. [73] presented.
- Lotka's Law—describes the productivity level of the authors, having the purpose of predicting the aggregate behavior of the researchers [74].
- Furthermore, a summary of the above-mentioned elements is presented in Table 3.

Table 3. Summary of key indexes/laws/variables.

Index/Law/Variable	Definition	Calculation	Purpose
Keywords Plus	An automated indexing feature that identifies additional terms derived from the titles of the references cited in a paper.	Extracted from reference titles of articles indexed in Web of Science.	Expands the scope of keyword analysis by including terms beyond the author's chosen keywords.
Normalized total citations (NTC)	Adjusts citation counts by considering the publication year and field-specific trends.	Total citations are divided by the average citations for all papers published in the same year in the dataset.	Ensures fair comparison of citations across time, emphasizing recent and influential contributions.
H-index	Measures the productivity and impact of an author, source, or journal.	With "h", the number of publications (h) that have at least h citations each is noted.	Balances productivity with citation impact, helping to identify influential authors and journals.
G-index	Extends the H-index by offering more weight to highly cited papers.	With "g" it has been noted as the highest number, such that the top g articles received collectively at least g^2 citations.	Highlights the overall impact of a researcher or source by emphasizing the influence of highly cited works.
Bradford's Law	Segments journals into "core" sources with high contributions and "peripheral" sources with fewer contributions.	According to the law, the journals are grouped into thirds, with a $1 : n : n^2$ distribution.	Identifies the most influential journals, allowing researchers to focus on core sources for high-impact research.
Lotka's Law	Describes the productivity distribution of authors, predicting that a small number of authors contribute to most publications.	The law considers a proportional rule of $1/n^2$ where n is the number of articles an author produces.	Identifies patterns in research productivity and recognizes the contributions of high-performing researchers.

Also, it shall be stated that there is a difference between the global citations and local citations extracted in the dataset. The global citations include the citations from "all over the world", while the local citations count the references received from papers included in the collection according to the Bibliometrix webpage [75].

3. Results Review

The third part of the research focuses on the results obtained using the R programming language library, called Biblioshiny [76], from different perspectives as follows: sources, authors, countries, affiliations, most cited papers, and mixed analysis.

3.1. Data Exploration

The first step of the third part is to have an overview of the data, extracting the timespan, total number of sources, documents, references, and authors.

Table 4 illustrates the preliminary analysis of the papers, offering a perspective over the timespan, number of sources, documents, and the average years or citations per paper. The first articles included in the analysis were published in 2006, while the latest ones were in 2023 and included 274 existing sources, 932 documents, and 30,422 references, with an average of 2.42 years from publication, which is a relatively small value for this indicator, showing that the majority of the papers in the dataset have been written in the last years, highlighting once more the novelty of the theme under investigation. The average number of citations per document is 22.79. Furthermore, the value recorded for the annual growth rate of 56.4% highlights increasing interest from the research community on the subject.

Table 4. Main information.

Indicator	Value
Timespan	2006:2023
Sources	274
Documents	932
Average years from publication	2.42
Average citations per document	22.79
References	30,422

Based on the information extracted related to the authors, it has been observed that there are 3314 authors included in the analysis, and only 22 performed a single-authored publication, while the remainder of the 3292 published were multiple-authored papers. The average number of co-authors per document is 4.53, and the international co-authorship is approximately 36.16%, which demonstrates the difficulty of the domain and the necessity of collaboration with international authors. Over 2754 authors' keywords and 1030 Keywords Plus have been used.

Table 5 describes the annual scientific production and the number of citations per year, together with the total number of citable years. The first year with a published paper is 2006, having 5.53 average citations per year, a total of 105 citations per article during the 19 citable years. Until 2011, no other article was published, and in 2011 and 2012, only one article was published each year. Starting with 2017, the trend started to grow significantly, from 3 papers in 2017 to 14 in 2018, 51 in 2019, 94 in 2020, 164 in 2021, 251 in 2022, and 335 in 2023. The highest total citations per article was obtained in 2012, with 133 citations. The highest average citations per article was in 2018, with a value of 15.34 citations.

Table 5. Annual scientific production and citations.

Year	Annual Scientific Production	Average Total Citations per Year	Average Total Citations per Article	Citable Years
2006	1	5.53	105.00	19
2007	0	0	0	0
2008	0	0	0	0
2009	0	0	0	0
2010	0	0	0	0
2011	1	5.21	73.00	14
2012	1	10.23	133.00	13
2013	2	6.04	72.50	12
2014	2	1.23	13.50	11
2015	6	11.52	115.17	10
2016	7	11.56	104.00	9
2017	3	9.83	78.67	8
2018	14	15.34	107.36	7
2019	51	9.30	55.82	6
2020	94	9.84	49.22	5
2021	164	7.76	31.06	4
2022	251	4.51	13.53	3
2023	335	2.44	4.87	2

Regarding the first paper written in 2006 and included in the dataset, Murphey et al. [77] aimed to demonstrate the applicability of machine learning (ML) methods by developing a diagnostic system trained on an electric drive model, enabling the accurate classification of various potential faults. The second paper, published in 2011 by Huang et al. [78], introduced a multifaceted statistical approach to automatically differentiate driving conditions in hybrid electric vehicles, employing support vector machines and other ML algorithms. In 2012, Murphey et al. [79] published their third paper, in which the authors proposed a machine learning framework, ML_EMO_HEV, designed to optimize energy management in hybrid electric vehicles using neural networks trained within this framework.

3.2. Sources Exploration

Sources represent a crucial part of the bibliometric analysis, offering the possibility of extracting relevant information regarding the best journals that published papers related to the EV, AI, ML, and DL domains.

Figure 2 includes the most important sources based on the number of published documents. In first place is *Energies* with 82 papers, followed by *IEEE Access* with 74 articles, and *Journal of Energy Storage* with 44 documents. *Applied Energy* has 43 publications, *Energy* has 33 articles, while *Sustainability* and *Electronics* has 23 and 20 papers. The last three journals are the *Journal of Power Sources*, *Applied Sciences-Basel,* and *IEEE Transactions on Industrial Informatics,* with 20, 19, and 19 publications.

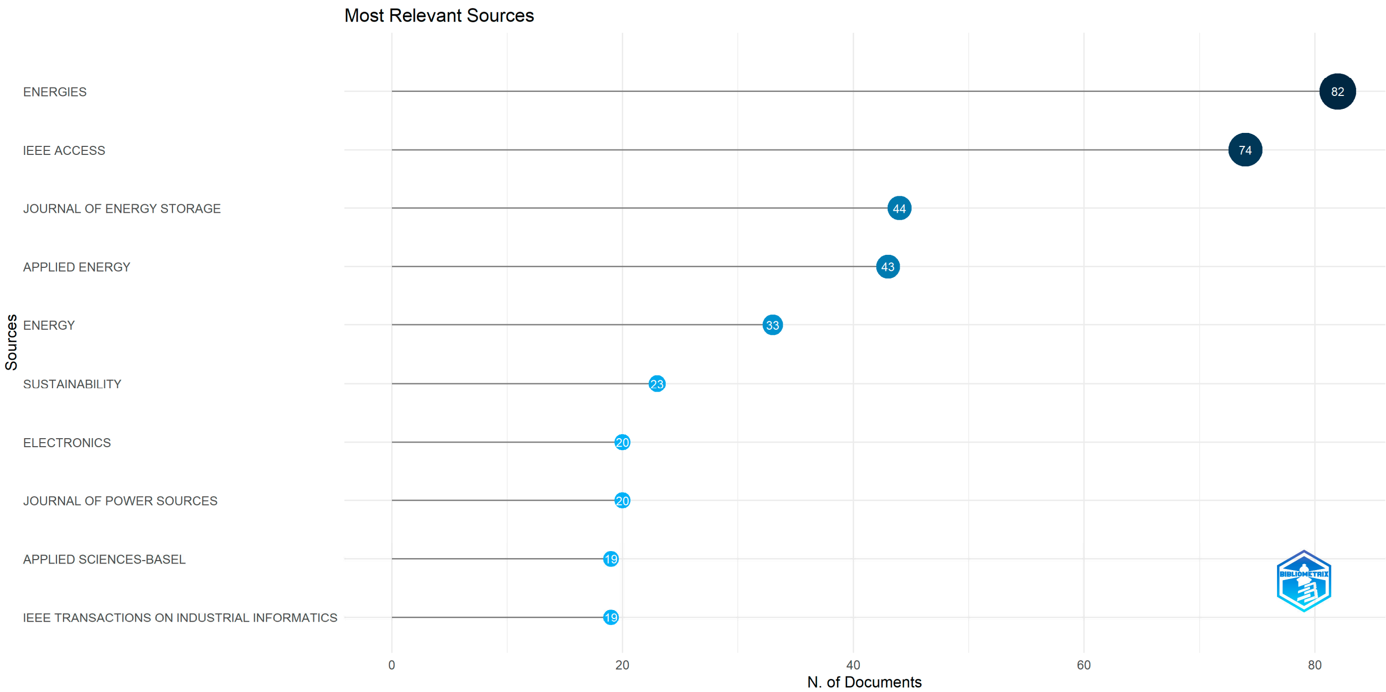

Figure 2. Top 10 most relevant sources.

Figure 3 incorporates the main journals related to the AI, ML, DL, and EV domains. The most representative is *Energies*, followed by *IEEE Access*, *Journal of Energy Storage*, *Applied Energy*, *Energy*, *Sustainability,* and *Electronics.*

Figure 4 explores the top 10 most important local sources based on the H-index.

According to the information in Figure 4, the most important local source based on the H-index and G-index is *Applied Energy*, with an H-index value of 23 and a G-index value of 43. The second most important source is *Energy*, with 18 and 33 values for the H-index and G-index.

Furthermore, *IEEE Access* has an H-index value of 18 and a G-index value of 31, while *Energies* has 17 H-index and 29 G-index values. The rest of the journals with a relevant contribution in terms of the mentioned indexes are as follows: *Journal of Energy Storage* (13 H-index, 23 G-index), *Journal of Power Sources* (13 H-index, 20 G-index), *IEEE Transactions on Industrial Informatics* (10 H-index and 19 G-index), *IEEE Transactions on Transportation*

Electrification (10 H-index and 16 G-index), *Electronics* (9 H-index and 13 G-index), and *IEEE Transactions on Vehicular Technology* (9 H-index and 11 G-index).

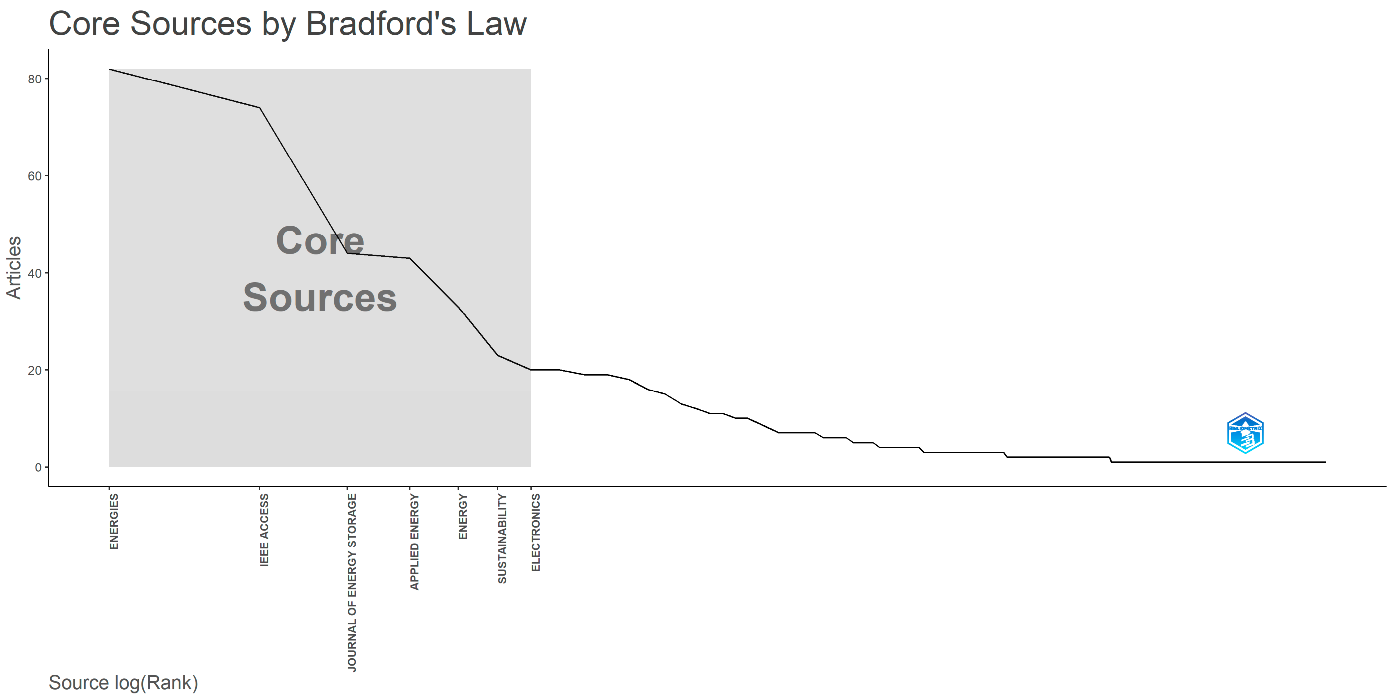

Figure 3. Core sources by Bradford's law.

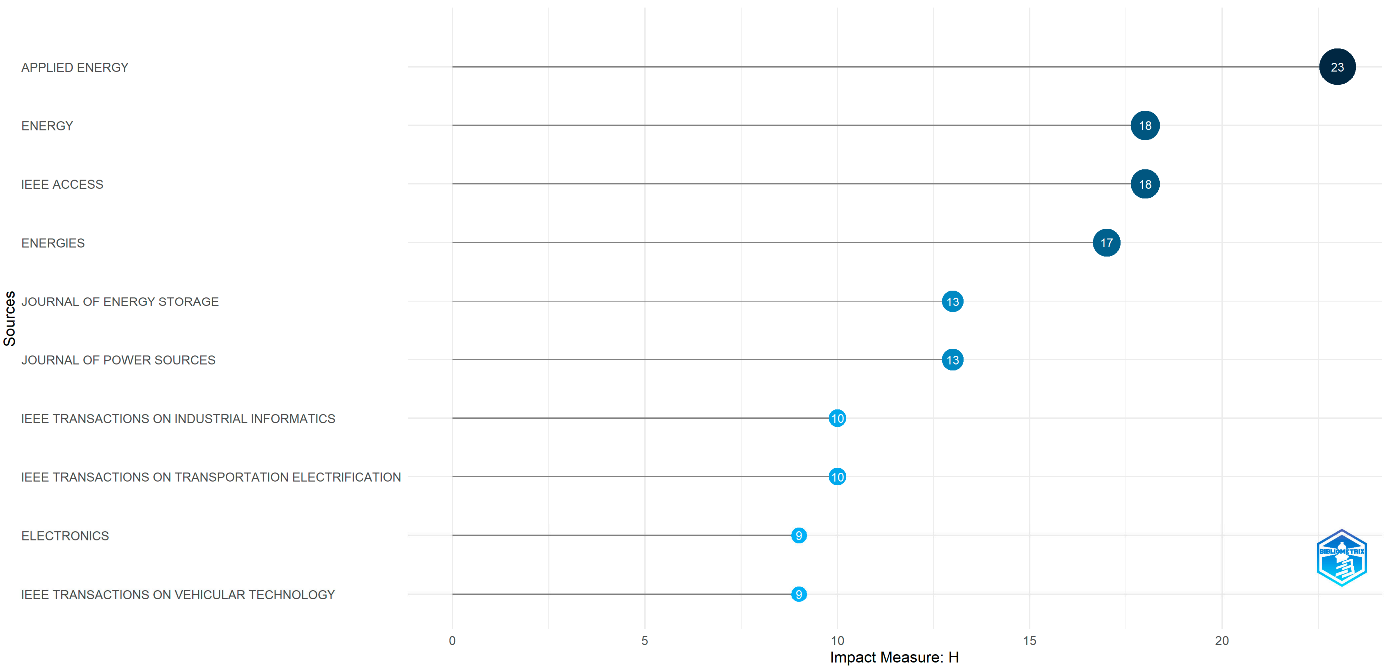

Figure 4. Top 10 sources of local impact by H-index.

Table 6 encloses the 10 most important local sources based on the number of citations. The most important journal according to the number of local citations is the *Journal of Powder Sources*, which has 2003 local citations, followed by *Applied Energy* with 1800 citations, *Energy* with 1215 citations, *Energies* with 1107 citations, and *IEEE Access*, which has 1079 citations. The rest of the journals have less than 1000 citations but are still relevant for our analysis: *IEEE Transactions on Smart Grid* with 821 citations, *Journal of Energy Storage* with 665 citations, *IEEE Transactions on Vehicular Technology* with 637 citations, *IEEE Transactions on Industrial Electronics*, which has 616 citations, and *Renewable and Sustainable Energy Reviews* with 596 citations.

Table 6. Top 10 most locally cited sources.

Sources	Number of Local Citations
Journal of Powder Sources	2003
Applied Energy	1800
Energy	1215
Energies	1107
IEEE Access	1079
IEEE Transactions on Smart Grid	821
Journal of Energy Storage	665
IEEE Transactions on Vehicular Technology	637
IEEE Transactions on Industrial Electronics	616
Renewable and Sustainable Energy Reviews	596

Figure 5 shows the most important 10 journals based on the number of publications. According to this criterion, the most relevant journal is *Energies*, with 200 publications. The first published article in this journal was in 2018, and the trend was ascending, having, in 2023, a total of 82 papers released. The second journal, according to the number of publications criterion, is *IEEE Access*, with 178 articles. Compared with *Energies*, *IEEE Access* published the first paper in 2015, and it continued to be released yearly until 2023, when it registered the highest number of papers, 74. *Applied Energy* has a total of 122 articles, the first one being published in 2015, and continued to be published yearly until 2023, when 43 articles were published. The remaining journals are still important, with a total number of publications below 100 papers as follows: *Energy* (80 papers), *Journal of Energy Storage* (71 papers), *Journal of Power Sources* (57 papers), *IEEE Transactions on Industrial Informatics* (52 papers), *Applied Sciences-Basel* (47 papers), *Sustainability* (44 papers), and *Electronics* (42 papers).

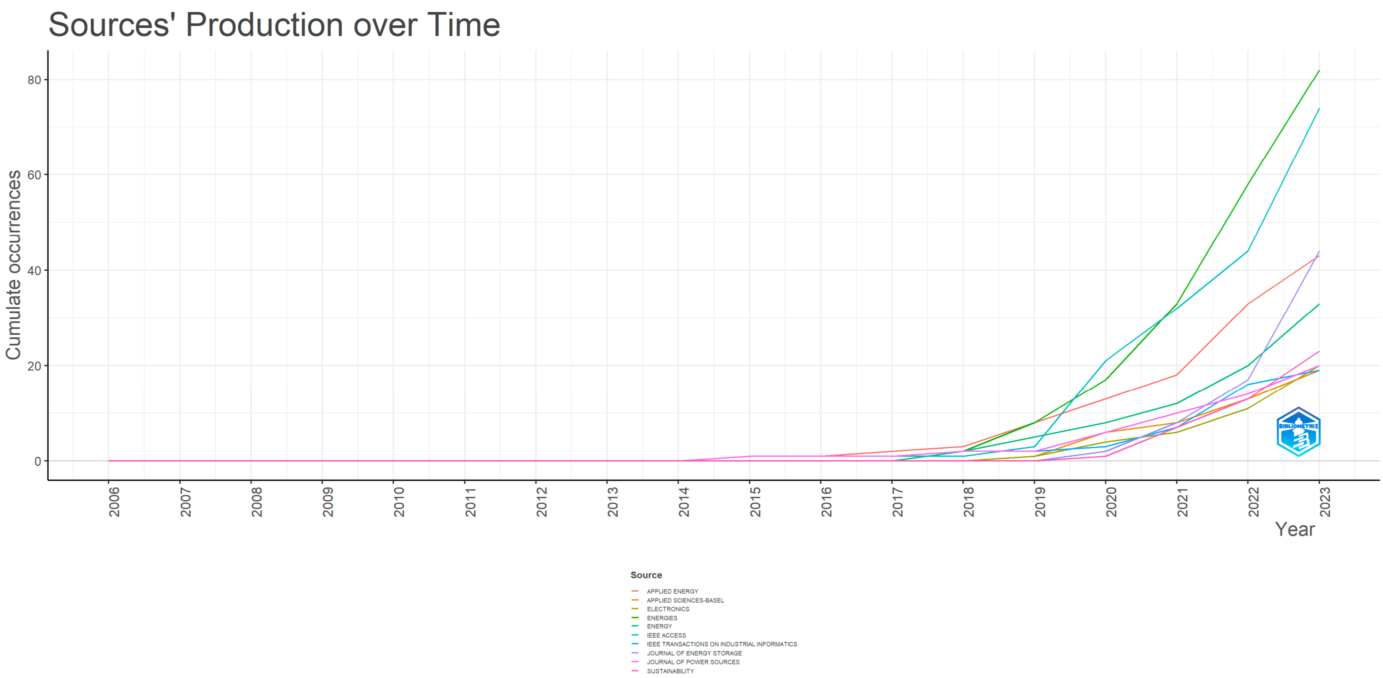

Figure 5. Top 10 sources of production over time.

Furthermore, the sources analysis is complemented by an analysis of the quartiles in which the journals have been categorized according to the *2023 ISI Web of Science Journal Citations Report* [80]. In order to conduct this analysis, each of the 274 journals in which the papers in the dataset have been published have been manually added to the ISI Web of Science website, and the information presented in Figure 6 has been obtained.

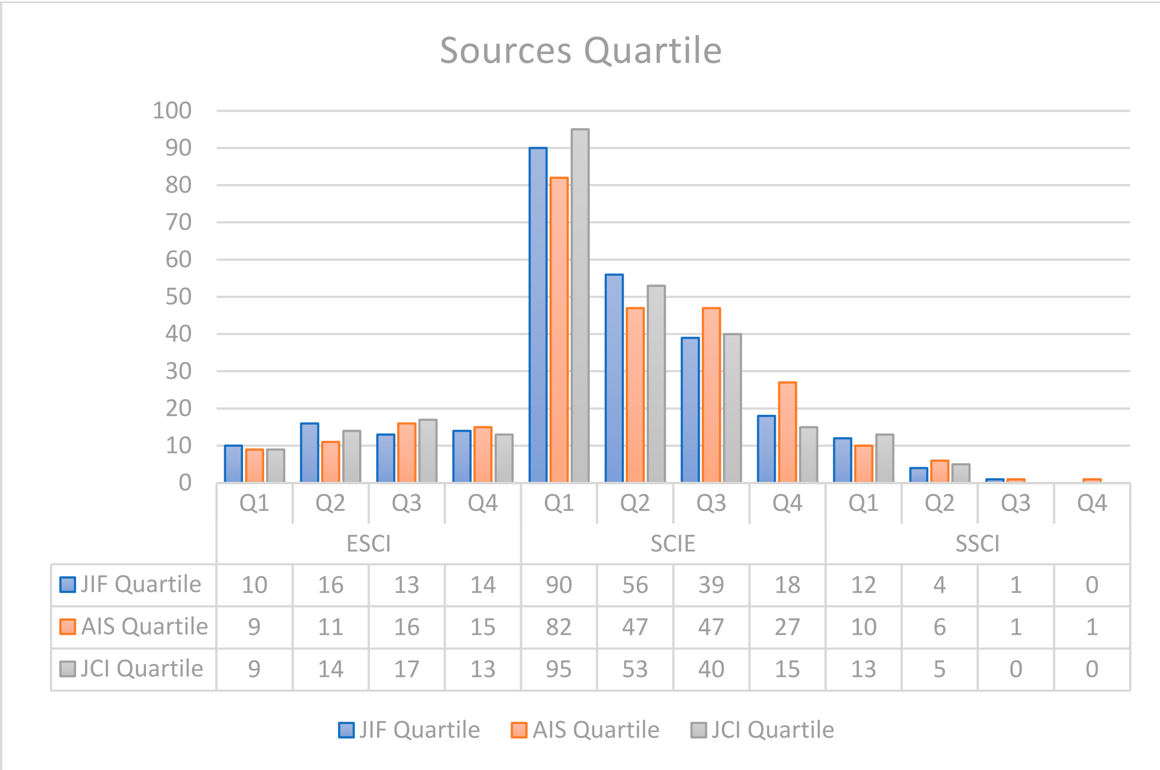

Figure 6. Sources quartiles.

In Figure 6, one can observe the distribution of the sources across the three indexes provided by ISI Web of Science, namely the Emerging Sources Citation Index (ESCI), Science Citation Index Expanded (SCIE), and Social Sciences Citation Index (SSCI), and on the quartile they belong as a result of the latest report offered by the database.

Based on the data in Figure 6, it can be noted that most of the journals are indexed in SCIE, namely 203 sources, representing 74.09% of the sources. A number of 53 sources are indexed in ESCI, representing 19.34% of the sources, while only 18 sources are indexed in SSCI, representing 6.57% of the sources.

In terms of quartiles, it can be observed that most of the journals in the SCIE category are included in the Q1 quartile, regardless of the indicator one is considering, namely the journal impact factor (JIF), article influence score (AIS), or journal citation indicator (JCI). The differences among the indicators can further be read in [81]. Also, it can be noted that the rest of the sources in SCIE are listed in the second and third quartiles, with only a small proportion of the journals in SCIE being in the fourth quartile, showcasing the fact that the papers related to AI in EVs have been published in high-ranking journals indexed in ISI Web of Science. The ESCI category has a more even distribution across quartiles, which might happen due to the role of this index, namely, to support emerging sources. As for the SSCI, as in the case of the SCIE, but at a reduced scale, it can be observed that most of the journals belong to the first quartile, underlying the importance of the theme and the advancements made through the papers published in the dataset.

3.3. Authors Analysis

A key aspect of bibliometric analysis involves examining authors to identify the most influential ones based on their number of citations and publications.

Figure 7 incorporates the most relevant 10 authors for the domains of ML, DL, and EVs.

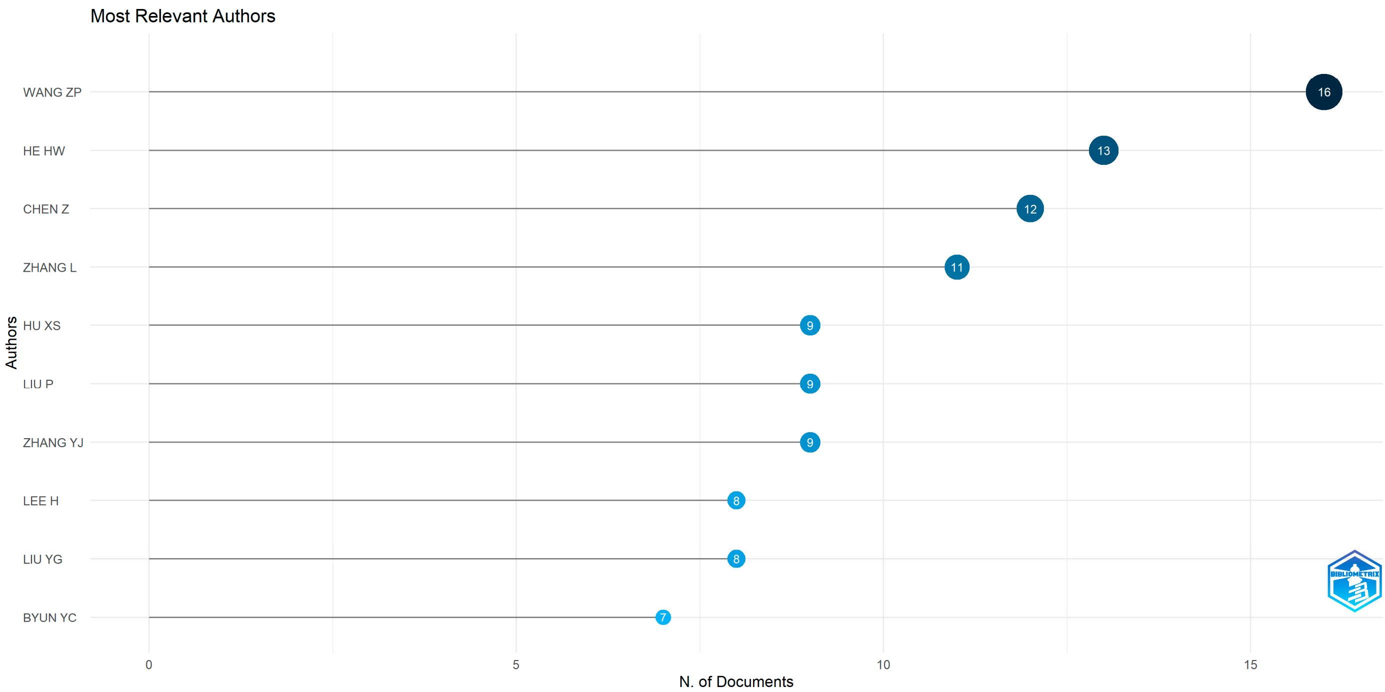

Figure 7. Top 10 most relevant authors.

Based on the fractionalized number of articles and articles—which express the individual author's contribution to a certain number of published papers [75]—it has been observed that Wang Z.P. has the highest number of articles published, namely 16 papers and, in the same time, has the highest articles fractionalized value of 3.13. He HW. is the second most relevant author based on the number of published papers, with 13 papers published and an article fractionalized value of 2.77, followed by Chen Z. with 12 articles and 2.22 documents fractionalized, while Zhang L. has 11 publications and 1.92 articles fractionalized. The rest of the authors included in the top 10 have less than 10 documents as follows: Hu XS. (9 articles, 2.00 articles fractionalized), Liu P. (9 papers, 1.56 articles fractionalized), Zhang YJ. (9 publications, 1.51 articles fractionalized), Lee H. (8 documents, 1.46 articles fractionalized), Liu YG. (8 articles, 1.38 articles fractionalized), Byun YC. (7 documents, 3.08 articles fractionalized).

According to Figure 8, the most important local author based on the number of local citations is Emadi A. with 85 local citations, followed by Wang ZP. with 67 local citations, and Kollmeyer PJ. with 66 local citations. Chemali E. and Preindl M. have 65 local citations each, while Hu XS. has 62 local citations. Hong JC. has only 46 local citations, Widanage WD. has 45, while Guo YJ. and Yang ZL. are the last two in the top 10, with 43 local citations each.

Figure 9 presents the yearly production of the most relevant 10 authors. Wang ZP. is the most important author based on the production over time, reaching a research peak in 2022, with four articles published and a total citation per year of 61.67. He HW. released his first article in 2019, achieving a peak in 2023 with four articles and a total citation per year of 31.5. Chen Z.'s first articles were published in 2020 and have 35.5 citations per year. Zhang L. published, for the first time, in 2017, an article that achieved 26.25 citations per year, and in 2022, published four papers, which have 54.67 citations per year. Among the top 10 authors, Hu XS. is the author who published the earliest articles compared to the other authors included in the analysis. Furthermore, in 2016, the author published two papers, which have a total citation per year of 71.56. The production over time of the remaining authors, namely Liu P., Zhang YJ., Lee H., Liu YG., and Byun YC, is further depicted in Figure 9.

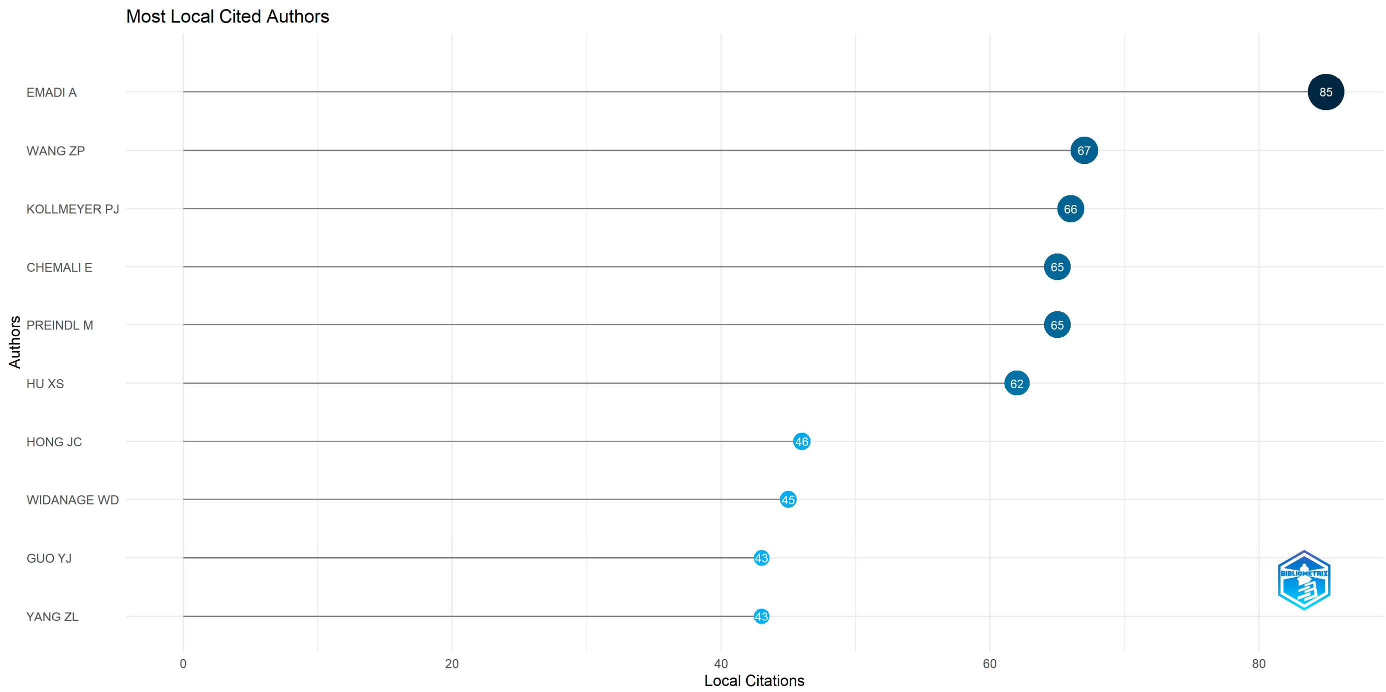

Figure 8. Top 10 most cited local authors.

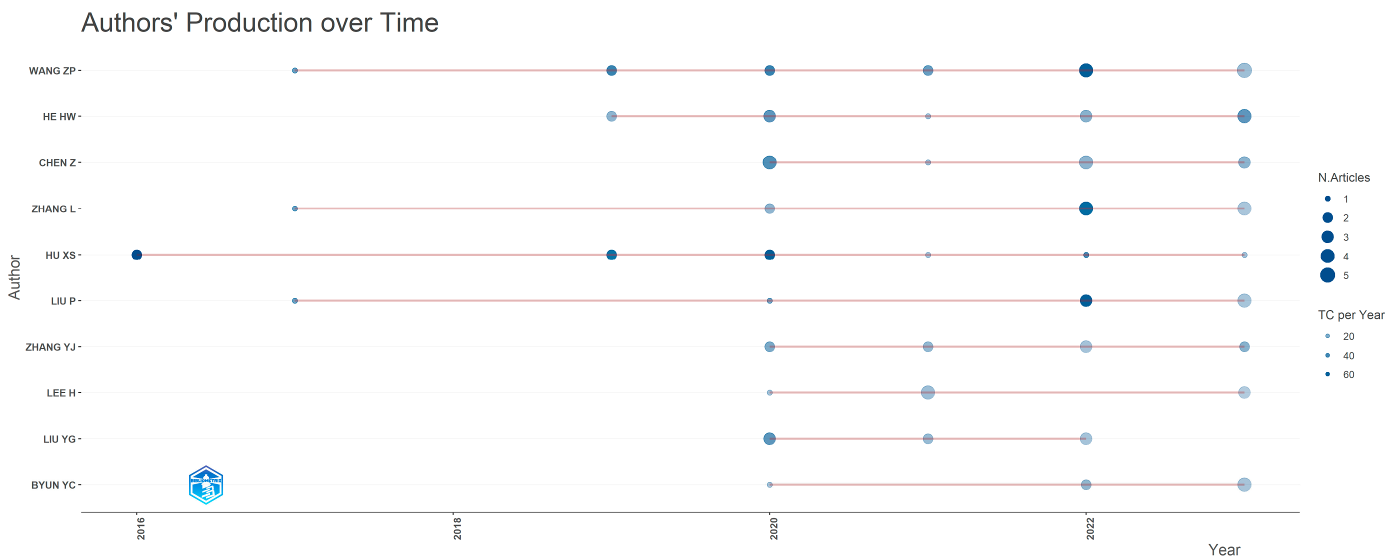

Figure 9. Top 10 authors' production over time.

Figure 10 incorporates the results of author productivity—the solid line represents the actual observed data that are based on the extracted dataset, while the dashed line represents the expected theoretical curve determined based on Lotka's law. In our case, Lotka's law shows a negative correlation between the number of papers and the percentage of authors, explaining the difficulty and challenges that researchers face during the process of publishing papers when investigating complex areas such as EVs, ML, AI, or DL.

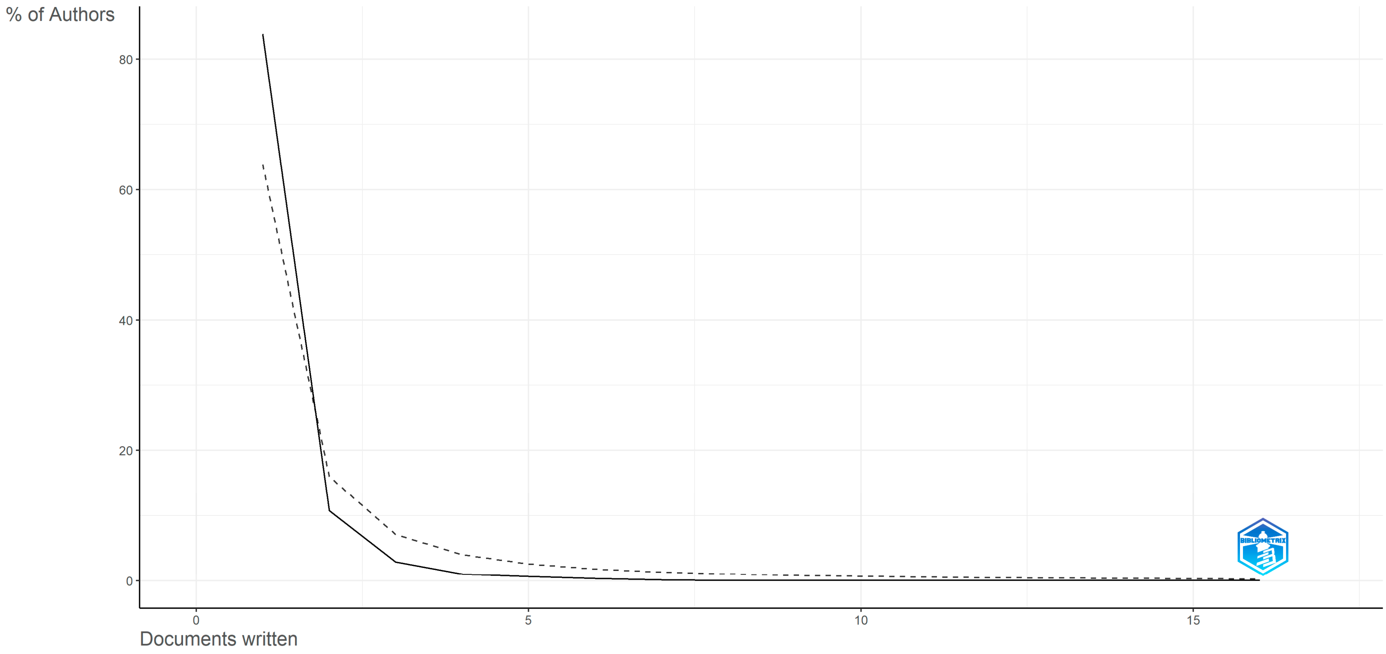

Figure 10. Author productivity based on Lotka's law.

Figure 11 explores the most cited authors based on the H-index (the H-index has been previously mentioned and discussed in connection with the data in Figure 4). He HW. has the highest impact based on the H-index and G-index, with a value of 11 for the H-index and 13 for the G-index, having in total of 391 citations. Wang ZP. is the second most relevant author, with a value for the H-index of 10 and G-index of 16, having 992 citations. Hu XS. has the highest number of citations, 1420, but the H-index value is only 9, smaller than the first two, while the G-index is 9.

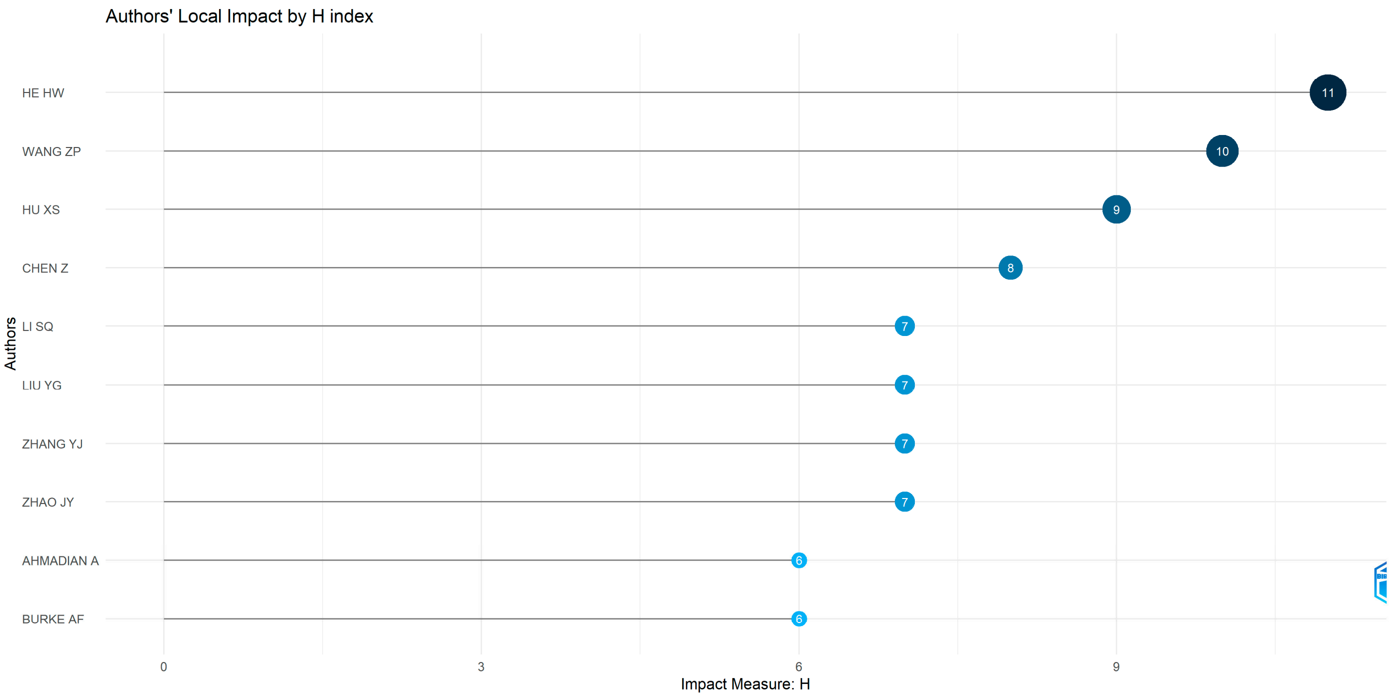

Figure 11. Top 10 authors' local impact by H-index.

The remainder of the authors have obtained less than 300 citations, as follows: Chen Z. has 287 citations, with a H-index value of 8 and G-index value of 12, while Li SQ. has a H-index of 7, a G-index of 8, and a number of citations of 290.

Furthermore, Liu YG. has a H-index of 7, a G-index of 8, and a total citation of 223, while Zhang YJ. has a H-index of 7, a G-index of 7, with 192 citations, Zhao JY. has a H-index of 7, a G-index of 7, and 192 citations. The last two authors, Ahmadian A. and Burke AF. have both a H-index and a G-index equal to 6, with 205 and, respectively, 146 citations.

Figure 12 depicts the most important countries for the AI, ML, DL, and EV domains based on the number of articles publicized.

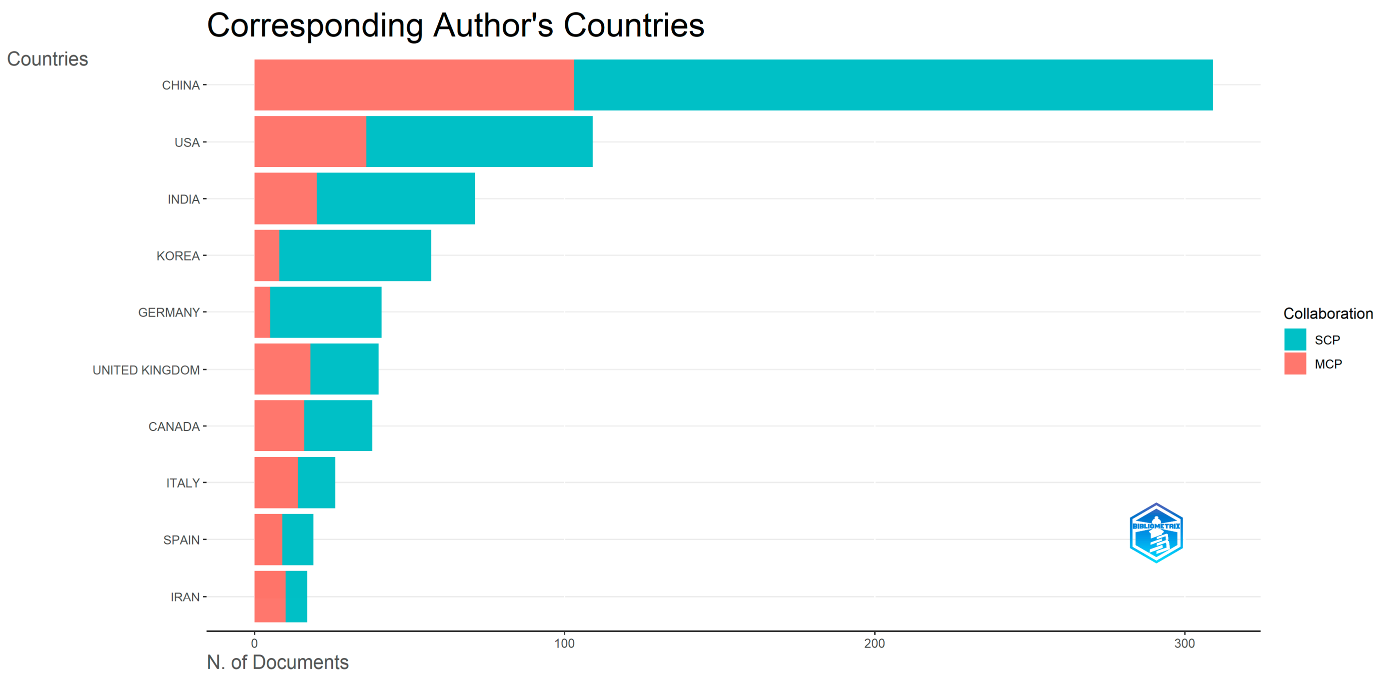

Figure 12. Top 10 most important corresponding author's country (SCP: Single-country publication; MCP: Multiple-country publication).

The most relevant country from the perspective of the corresponding author's country indicator is China, with 309 papers, which represents 33.2% of the total number of papers included in the dataset. It can be observed that there are 206 documents marked as single-country publications (SCPs) or 66.67%, and 103 as multiple-country publications or 33.33%.

The difference between the number of papers published by China and second place, which is the USA, is over 21.5%, namely 200 papers, which indicates the apport brought by the Chinese authors in the analyzed field. The USA is the second most important country from the perspective of the corresponding author's country of the papers included in the dataset, with 200 articles behind China, summing up a total of 109 articles, representing 11.7% of the total papers, with 73 of them being SCPs (66.97%) and 36 MCPs (33.03%).

The third place is occupied by India, with 71 documents, indicating 7.6% of the total papers published. There are 51 SCP documents (71.83%), while the MCP documents are only 20 (28.17%). South Korea is the fourth country in the above-mentioned top, which published 57 articles; 49 (85.96%) of them are SCPs, and only 8 (14.04%) are MCPs, representing 6.1% of total articles.

Germany has 41 publications to which the corresponding author belongs, with 36 of them being SCPs (87.80%) and 5 MCPs (12.20%), with a total contribution of 4.4%. The UK and Canada are the next two countries in terms of published papers based on the country of the corresponding author, with 40 and 38 documents published; both of them have published 22 SCPs (55% for the UK, 57.89% for Canada, while regarding MCPs, the UK has 18 (45%) and Canada 16 (42.11%), which represents 4.3% and, respectively, 4.1% of the total articles published.

Italy occupies eight positions, with 26 articles released; 12 of them are SCPs (46.15%) and 14 of them are MCPs (53.85%), having a contribution of just 2.8%. The last two countries listed in the above-mentioned top are Spain and Iran, having 19 and 17 publications; Spain has 10 SCPs (52.64%) and 9 MCPs (47.36%), while Iran has 7 (47.17%) SCPs and 10 MCPs (58.23%). Their contribution is around 2% for Spain and 1.8% for Iran.

3.4. Countries Analysis

In order to understand how relevant the domain is for countries, a detailed investigation was carried out, observing also the yearly production of the most relevant states.

Based on the total citations and average article citations, Figure 13 shows the top 10 most cited countries. The most important country from the point of view of the number of citations obtained for the papers included in the dataset is China, with 8187 citations and an average article citation of 26.50, having the highest influence in the domains of AI, ML, DL, and EVs, also taking into consideration the authors' contribution presented above in Figure 12.

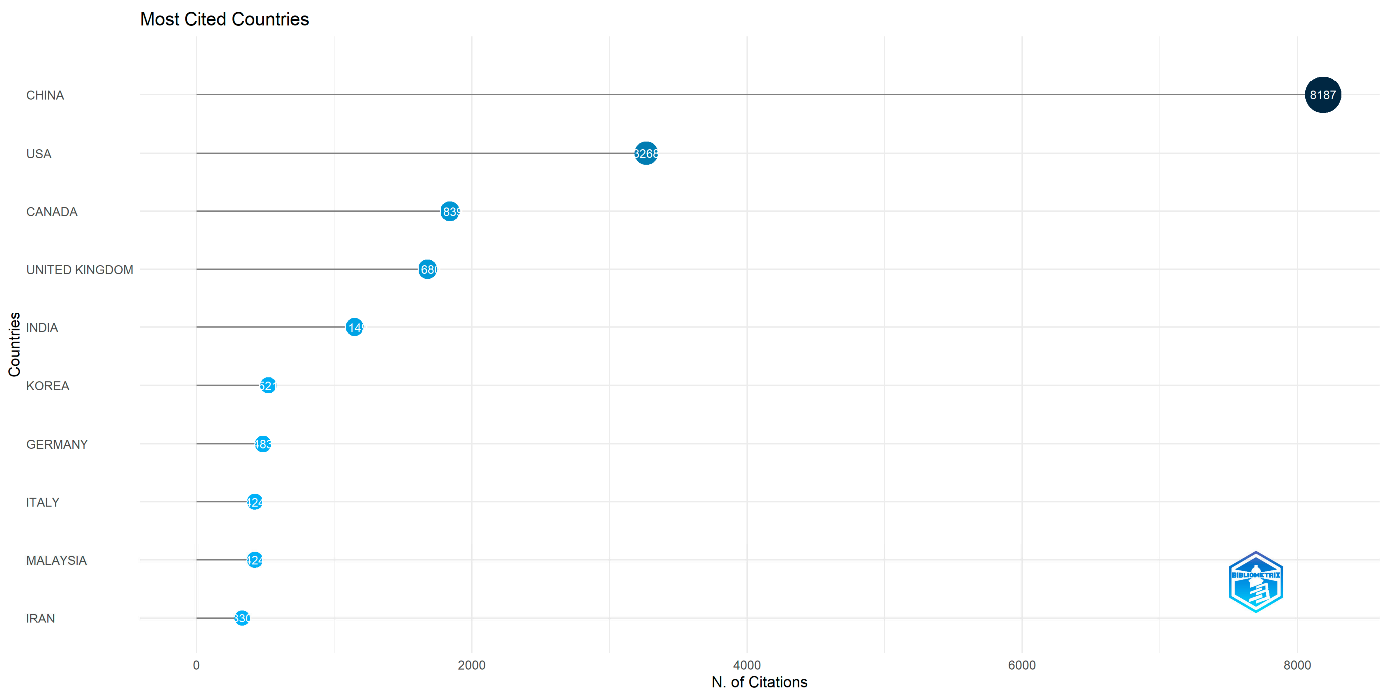

Figure 13. Top 10 most cited countries.

The second most important country from the point of view of the number of citations obtained for the papers included in the dataset, with almost 5000 citations less than China is the USA, with 3268 citations, having an average article citation of 30.00.

Canada is third, with 1839 citations, having the highest average article citations of 48.40, which is the highest value among the top 10, showing the utility of Canadian publications, which are frequently cited by the academic community.

In fourth place is the UK with 1680 citations and an average article citation of 42.00, followed by India with 1149 citations and an average article citation of 16.20. The rest of the countries have a reduced impact compared to the first five countries but are worthy of mentioning: Korea (521 citations, 9.10 average article citations), Germany (483 citations, 11.80 average article citations), Italy (424 citations, 16.30 average article citations), Malaysia (424 citations, 38.50 average article citations), and Iran (330 citations, 19.40 average article citations).

Figure 14 explores the production of the countries with the highest number of papers.

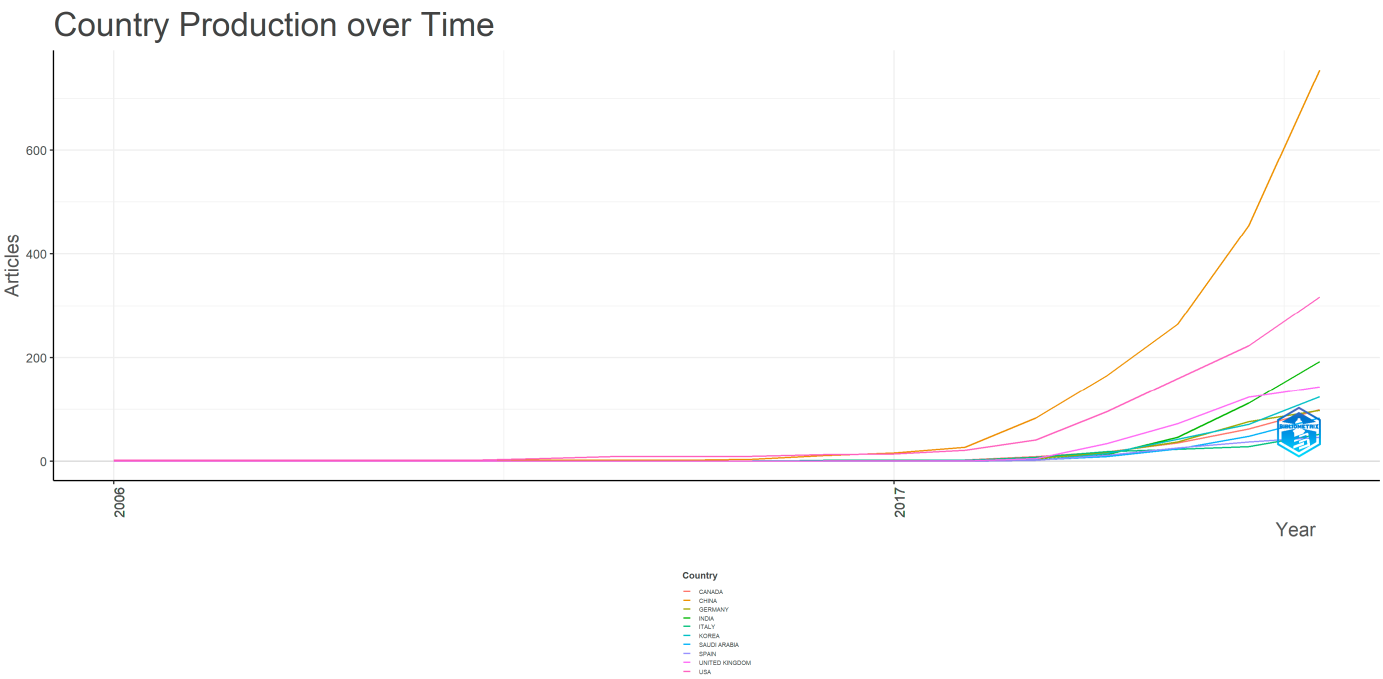

Figure 14. Top 10 countries' production over time.

According to the data in Figure 14, the USA released the first two articles in 2006, while the next papers were published 5 years later, in 2011, two by the USA and two by China.

Starting with 2015, more and more countries started to publish articles in the selected domain, such as Canada, India, and Korea, and in 2019, all the countries that are in the top 10 had papers released. The highest impact based on the number of publications is attributed to China, which has published during the analyzed period over 1788 papers, having a positive trend in the last years, starting with 27 papers in 2018, 83 in 2019, 165 in 2020, 264 in 2021, 455 in 2022, and achieving the peak of 755 papers in 2023.

In second place is the USA, with a difference of 1185 papers, totaling 603, having a similar trend to China, achieving its highest number of publications in 2023, with 317 documents. In third place is the UK with 380 papers, followed by India with 372 documents, and Korea with 259. All three countries respect the trend that has been presented for China and the USA, but with a considerably smaller yearly increase, having their peak of publications in 2023. The same applies to the rest of the countries, with Germany having 234 articles, Canada 229, Saudi Arabia 167, Italy 136, and Spain 123.

3.5. Affiliations Review

This section focuses on investigating the most important universities based on the number of publications and citations while also evaluating their yearly productivity.

Figure 15 shows the 10 most important universities by the number of published papers included in the dataset. In first place, one can find the Beijing Institute of Technology, China, with a total of 56 papers, followed by the University of California System, USA, with 35 documents. Third place is occupied by Chongqing University, China, with 33 publications, while the Egyptian Knowledge Bank (EKB), Egypt, has 32 documents, and the United States Department of Energy (DOE), USA, has 30 documents. Tsinghua

University, China, published 27 articles; the Chinese Academy of Sciences, China, has 26 papers; the University of Waterloo, Canada, has 23 papers; the University System of Georgia, USA, has 23 publications; while the Georgia Institute of Technology, USA, is the last university listed in top 10, with 20 documents.

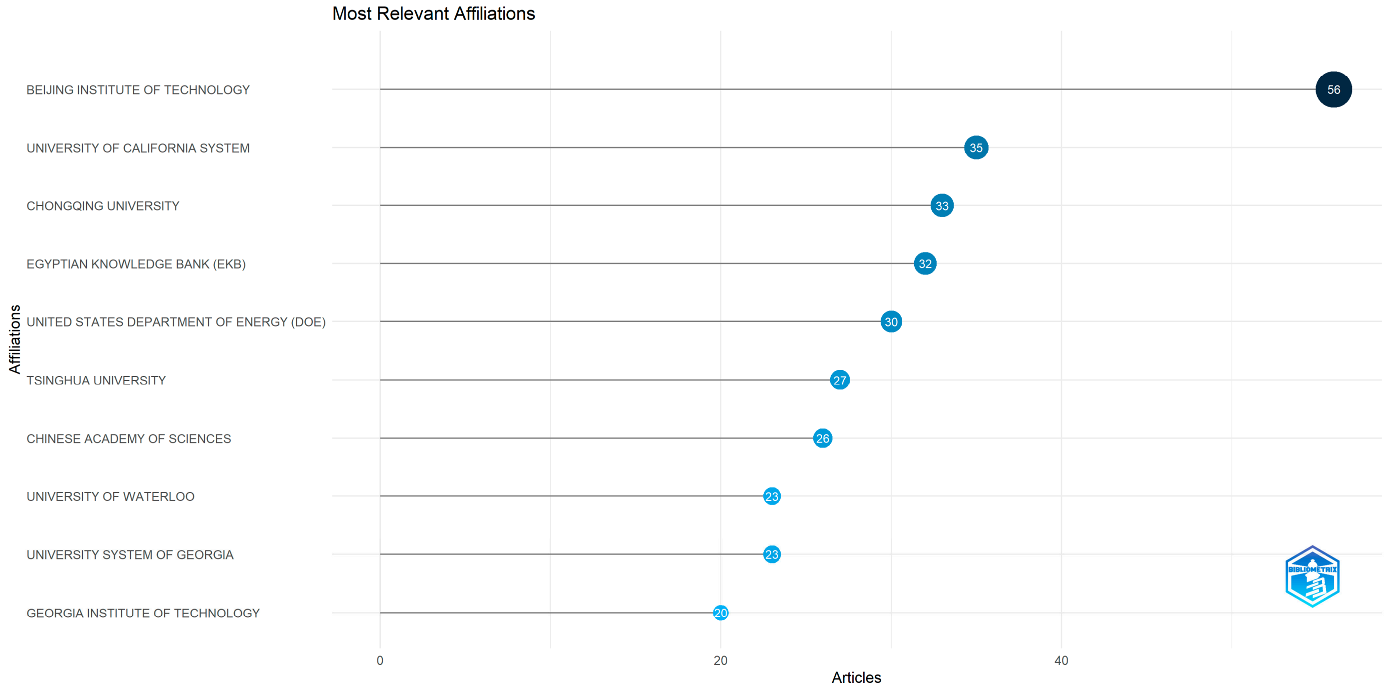

Figure 15. Top 10 most relevant affiliations.

Figure 16 describes the yearly production of the top 10 most important affiliations.

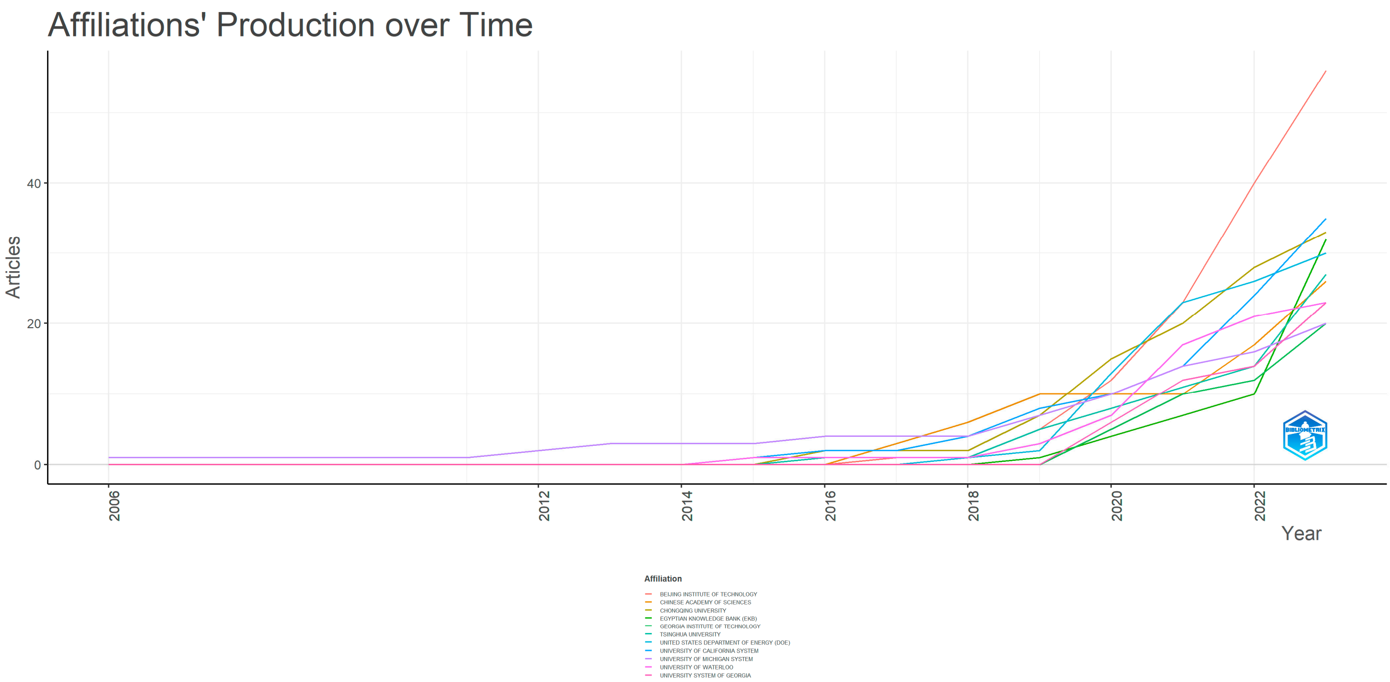

Figure 16. Top 10 affiliations production over time.

In first place is the Beijing Institute of Technology, which published for the first time in 2017 a paper related to EVs, AI, ML, and DL, and, starting with 2019, the number of articles published grew exponentially, having released 5 papers in 2019, 12 in 2020, 23 in 2021, 40 in 2022 and, in 2023, the peak, with 56 papers, having a total of 138 publications.

In second place is Chongqing University, which published for the first time in 2016 2 documents, 9 in 2019, 15 in 2020, 20 in 2021, 28 in 2022, and 33 in 2023, having a total of 109 documents.

Very close to second place is the University of California System, which published earlier than the Beijing Institute of Technology, having 2 papers in 2016, but the yearly growth rate was much smaller, with 10 papers in 2020, 14 in 2021, 24 in 2022, and 35 in 2023, resulting in a total of 100 papers.

In fourth place is the United States Department of Energy, which published the first article in 2018, followed by 2 other papers in 2019, 13 in 2020, 23 in 2021, 26 in 2022, and 30 in 2023, having a total of 82 documents.

In fifth place is the Egyptian Knowledge Bank, which released its first publication in 2019 and had a positive trend until 2023, with 4 papers in 2020, 7 in 2021, 10 in 2022, and 32 in 2023, having a total of 54 documents.

The reminder of the affiliations included in the top 10 based on production over time is as follows: Tsinghua University (27 articles), the Chinese Academy of Sciences (26 articles), the University System of Georgia (23 papers), the University of Waterloo (23 papers), and the University of Michigan System (20 publications).

3.6. Most Cited Documents

This section focuses on analyzing the top 10 most cited documents in the examined area, with the aim of understanding the primary research themes within the dataset and identifying the key topics that have garnered significant attention from the research community in the selected domain.

Table 7 combines the details from the most cited 10 documents on the analyzed domain globally, containing the number of authors, region, total citations (TC), total citations per year (TCY), and normalized total citations (NTC).

Table 7. Top 10 most cited documents.

No.	Paper (First Author, Year, Journal, Reference)	Number of Authors	Region/ Country	Total Citations (TC)	Total Citations per Year (TCY)	Normalized TC (NTC)
1	Chemali E., 2017, *IEEE Transactions on Industrial Electronics* [82]	5	Canada, USA	437	62.43	4.07
2	Attia P., 2020, *Nature* [10]	16	USA	435	87.00	8.84
3	Chemali E., 2018, *Journal of Power Sources* [83]	4	Canada, USA	420	60.00	3.91
4	Hu X., 2016, *IEEE Transactions on Industrial Electronics* [84]	4	USA, China, UK, Sweden	397	44.11	3.82
5	Liu K., 2021, *IEEE Transactions on Industrial Electronics* [85]	4	UK, China	394	98.50	12.68
6	Patil MA., 2015, *Applied Energy* [86]	7	India, South Korea	376	37.60	3.26
7	Zhang Y., 2020, *Nature Communication* [87]	6	UK	349	69.80	7.09
8	Feng X., 2019, *IEEE Transactions on Vehicular Technology* [88]	7	China, USA	262	43.67	4.69
9	Hu X., 2016 *IEEE Transactions on Industrial Electronics* [89]	3	China	247	27.44	2.38
10	Roman D., 2021, *Nature Machine Intelligence* [90]	5	UK, USA, Netherlands	233	58.25	7.50

The most referenced document was published by Chemali et al. [82], and the authors presented the state-of-charge (SOC), which became vital to the reliability and safety of Li-ion batteries that are applied in EVs, smart grid systems, and unmanned aerial vehicles. The authors created a new method using a neural network (RNN) with long short-term memory (LSTM), which approximates more accurately the SOC for Li-ion batteries. Thanks to the huge amount of data produced nowadays by the energy sector, ML algorithms are suited for parameter estimation, being able to learn on their own and provide relevant outputs. The advantage of using the ML algorithm is the possibility of generalizing the process and learning abstractions during training. The results of the LSTM-RNN model showed a mean absolute error (MAE) value of 0.573% for a constant environmental temperature, while the MAE value was 1.606% for an ambient value, which increases from 10 to 25 degrees. During the research, five different authors worked from Canada and the USA, and the document has 437 citations, with a mean value for citations per year of 62.43, while the normalized total citation value is 4.07.

Attia et al. [10] demonstrated that simultaneous optimization for multiple parameters in order to extend the battery lifetime as much as possible is time-consuming and, in the end, it is not worth enough, and the best example is the fine-tuning of the control parameters for lithium-ion batteries at different stages, such as cell manufacturing, operating, and materials selection. The authors developed and explained a ML method that optimizes a parameter for voltage profiles in an efficient manner based on six steps. One of the main concerns that causes anxiety among electric vehicle users is the battery's cycle life of the EV, which is optimized thanks to the presented model, combining an early prediction model that reduces the period for each experiment by forecasting the end lifespan, and a Bayesian optimization model by reducing the number of studies. The authors found 224 candidates in 16 days among high-cycle-life charging protocols, and based on the data, which compares over 500 days, the accuracy and efficiency were calculated. In total, there are 16 authors from the USA that participated in the research, having a total of 435 citations, with a TCY value of 87 and a NTC of 8.84.

Chemali et al. [83] pointed out the importance of an accurate estimation for SOC, which ensures a safe and reliable operation for Li-ion batteries, which are more and more used in EVs, manned and unmanned flying vehicles, and grid-tied load-leveling. The article presents an innovative method of using deep feedforward neural networks (DNN), which have been utilized to predict SOC for battery measurements. The data included in the research contain temperatures between −20 degrees and 25 degrees, and after the training, the process estimated the SOC for various conditions. The model has a MAE of 1.10% for temperatures over 25 degrees, while the MAE for the dataset with values over −20 degrees is 2.17%. Four authors worked on this paper from Canada and the USA, obtaining 420 quotations, with an average citation per year of 60 and a NTC value of 3.91.

Hu et al. [84] explained that the monitoring and management of battery health represent crucial elements for the costs and performance of EVs. Advanced sparse Bayesian predictive modeling (SBPM) has the potential to capture the correspondence between energy loss and sample entropy. The authors proposed a SBPM-based SOH model, which was compared with a polynomial model developed in prior research. The model offers the possibility of temperature effects, and the performance and complexity are explained by the support vector machine (SVM) scheme. The dataset was built based on multiple lithium-ion battery cells used at different temperatures. This is the first solution that combines SBPM and sample entropy to forecast the battery's health. Four authors from the USA, China, the UK, and Sweden contributed to the creation of the article. The paper reached up, to the moment of our research, a total of 397 references, with an average value of yearly citations of 44.11, while the NTC value was 3.82.

Liu et al. [85] presented the key role of battery health diagnosis and management, which is the prediction of remaining useful life (RUL) and future capacities. The authors used a ML algorithm in order to obtain more efficient capacities and to predict the RUL for Li-ion batteries using reliable uncertainty management. Initially, an empirical manner decomposition method (EMD) was used, dividing the battery capacity data into intrinsic mode functions (IMFs), and then a LSTM model was applied in order to estimate the residual. A Gaussian process regression (GPR) was utilized to fit the IMFs, and the results showed great adaptability and reliability for battery health diagnosis. There are four authors from the UK and China that contributed to the creation of the paper, achieving a total of 394 references, with a mean of 98.5 citations per year, which is the highest value in the top 10, showing the high quality of research, while the NTC value is 12.68.

Patil et al. [86] considered that the ability to predict live remaining useful life (RUL) for Li-ion batteries is a crucial feature of a robust battery management system (BMS). The authors defined a method that combines classification and regression attributes of the support vector algorithm that estimates a Li-ion battery's RUL. The ML models were developed based on critical attributes from the SVM, providing a gross estimation, and the support vector regression model predicts the accuracy of RUL and checks if the batteries are close to their lifespan's end. The multistage approach that has been included in research offers the possibility of faster computations that could be run simultaneously and could potentially provide real-time RUL estimations for EV batteries. In total, seven authors from India and South Korea worked on the analyzed research, obtaining 349 citations, with a total references per year of 37.60 and a NTC value of 3.26.

Zhang et al. [87] evaluated the relevance of forecasting the remaining life and health of Li-ion batteries, which is still a real challenge for EVs and consumer electronics. The model that has been created forecasts the battery by integrating the Gaussian process and electrochemical impendence spectroscopy (EIS), which is an information-rich measurement and non-invasive method part of battery diagnosis. The data were collected from Li-ion batteries from over 20,000 EIS spectra, with different health, temperatures, and state-of-charges. The Gaussian model can estimate the degradation level with high accuracy, demonstrating the importance of the EIS signal in battery management systems. Six authors from the UK are part of the research; the article has a total of 349 citations, with a mean yearly reference of 69.80 and a NTC value of 7.09.

Feng et al. [88] detailed the battery state-of-health (SOH) online projection as a crucial issue for smart energy control of autonomous EVs, but by using ML algorithms, the SOH estimation can be improved significantly. The purpose of the research was to build a ML diagnosis model using a support vector machine (SVM), where vectors are defined based on the charged data of fresh cells, which contains the intrinsic characteristics of the batteries. The algorithms compare the stored levels with partial charging curves, such as 15 min charging. The findings revealed great precision of the model, with less than a 2% error for the Li-ion SOH in 80% of all the scenarios. For 95% of all cases, the error was approximately 3%. In total, seven authors from China and the USA contributed to the article, having a total of 262 citations, a mean citation per year of 43.67, and a NTC value of 4.69.

Hu et al. [89] considered ML as the appropriate approach for ensuring reliable battery management in EVs and a performant state-of-charge (SOC) estimator. A clustering method based on fuzzy C-means (FCM) was developed, which learns the configuration and antecedent variables of the algorithm. The recursive least-squared method was applied in order to extract the consequent parameters, and the model was adapted to antecedent and consequent information, optimizing resilience and accuracy. The results show a higher accuracy for the developed model compared with fuzzy traditional methods. The research was conducted by three different authors from China; the paper has a total of 247 citations, 27.44 average annual citations, and a 2.38 NTC value.

Roman et al. [90] explained that lithium-ion batteries migrated from portable electronic devices to EVs, and the reliability of a battery's state-of-health (SOH) in real time is a critical step for the safe operation of batteries. The authors designed a ML algorithm that estimates the battery capacity by analyzing 179 cells cycled in diverse situations. The model calculates the battery SOH within a probability range by taking into account two non-parametric and two parametric algorithms, obtaining 30 features by using sections of input voltage and current curves and having an automated feature selection and calibration. The root mean squared error of the algorithm is just 0.45%, offering a powerful model that estimates with a high accuracy of battery SOH. The research was performed by five authors from the UK, USA, and the Netherlands, and the publication has 233 references, with an average of 58.25 citations per year and a NTC value of 7.50.

Reflecting on the reviewed documents, it can be noted that a part of the topics approached in the papers are interconnected to the management and optimization of lithium-ion batteries, particularly in applications such as electric vehicles (EVs), smart grids, and aerial vehicles. A primary research theme is state-of-charge (SOC) forecasting, while another major area of focus is state-of-health (SOH) monitoring and projection. Other topics refer to remaining useful life (RUL) forecasting and optimization of a battery's performance and lifetime.

Table 8 details the most globally cited papers, indicating the primary author, year of publication, journal, title, data, and scope of each paper.

Table 8. Brief summary of the content of the top 10 most globally cited documents.

No.	Paper (Primary Author, Year, Journal, Reference)	Title	Data	Purpose
1	Chemali E., 2017, *IEEE Transactions on Industrial Electronics* [82]	Long Short-Term Memory Networks for Accurate State-of-Charge Estimation of Li-ion Batteries	Dataset containing various ambient temperatures	To estimate the SOC in order to make for reliable and safe Li-ion batteries used in EVs by creating a LSTM-RNN model
2	Attia P., 2020, *Nature* [10]	Closed-loop optimization of fast-charging protocols for batteries with machine learning	Data from using cycles from 224 candidates in 16 days	To optimize the current and voltage for ten-minute fast charging and optimize battery's cycle life for EVs by using a Bayesian algorithm
3	Chemali E., 2018, *Journal of Power Sources* [83]	State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach	Data generated by using the drive cycle at different ambient temperatures	To define a ML model using deep feedforward neural network (DNN) to estimate the battery state-of-charge (SOC)
4	Hu X., 2016, *IEEE Transactions on Industrial Electronics* [84]	Battery Health Prognosis for Electric Vehicles Using Sample Entropy and Sparse Bayesian Predictive Modeling	Experimental data from various lithium-ion battery cells at different temperatures	To create a model that combines SBPM and sample entropy, which estimates the battery health
5	Liu K., 2021, *IEEE Transactions on Industrial Electronics* [85]	A Data-Driven Approach With Uncertainty Quantification for Predicting Future Capacities and Remaining Useful Life of Lithium-ion Battery	Experimental data from various batteries	To predict the battery health using an empirical mode for decomposition, a LSTM, and Gaussian process regression
6	Patil MA., 2015, *Applied Energy* [86]	A novel multistage Support Vector Machine based approach for Li-ion battery remaining useful life estimation	Experimental data from various batteries	To define a model that estimates in real time the remaining useful life of the batteries using SVM and SVR models

Table 8. *Cont.*

No.	Paper (Primary Author, Year, Journal, Reference)	Title	Data	Purpose
7	Zhang Y., 2020, *Nature Communication* [87]	Identifying degradation patterns of lithium-ion batteries from impedance spectroscopy using machine learning	20,000 EIS spectra from commercial Li-ion batteries	To forecast the health and useful life of Li-ion batteries using a combination of a Gaussian process and electrochemical impedance spectroscopy
8	Feng X., 2019, *IEEE Transactions on Vehicular Technology* [88]	Online State-of-Health Estimation for Li-Ion Battery Using Partial Charging Segment Based on Support Vector Machine	Charging data from fresh cells	To build a ML model that estimates the lithium-ion batteries' state-of-health (SOH) using a support vector machine (SVM)
9	Hu X., 2016, *IEEE Transactions on Industrial Electronics* [89]	Advanced Machine Learning Approach for Lithium-ion Battery State Estimation in Electric Vehicles	Data sampled from lithium-ion batteries driving cycle-based	To design a fuzzy C-means cluster method (FCM) that estimates the state-of-charge for lithium-ion batteries
10	Chemali E., 2017, *IEEE Transactions on Industrial Electronics* [82]	Machine learning pipeline for battery state-of-health estimation	179 cells cycled under diverse conditions	To create a model that estimates the battery's SOH, using parametric and non-parametric algorithms, by analyzing 179 cells cycled

As observed above in the examination of the top 10 most cited papers, it can be highlighted that, overall, the research highlights the pivotal role of machine learning in advancing battery governance systems, addressing critical challenges in SOC and SOH estimations, RUL predictions, and battery performance optimization.

Figure 17 includes the collaboration network among 50 authors grouped into 10 different clusters. Cluster 1, colored in red, contains two authors, Hannah MA. and Lipu MSH., who have limited impact on the analyzed domain, focusing their research on estimating the SOC for Li-ion batteries using ML algorithms such as the deep neural network, random forest regression, tree parzen estimator, or self-supervised transformer model.

The second cluster contains five authors, He HW., Li SQ., Han XB., Li JW., and Zhang Y., who are represented by the blue color in the graph. Their focus was on improving the longevity of Li-ion batteries using DL and ML algorithms.

The third cluster, colored in green, contains the most influential authors in the field of EVs, ML, DL, and AI. Wang ZP. is the most relevant author, as his text size is larger compared to the other authors, who are also noteworthy, such as Zhang I., Liu P., Hong JC., Li WH., Zhang J., Zhao Y., Jiang J., Li Y., Sauer DU., Zhang ZS., and Chen W. Due to the high number of researchers that are part of the cluster, the number of papers and the researched areas are more varied and include using ML algorithms, and the accuracy of SOH for EV batteries, which represented some of the main topics discussed, or predicting the age of the batteries using statistical features and ML [91,92]. The energy consumption of EVs, the battery thermal runaway fault, the prediction of battery SOC using multiple ML algorithms, fault and defect diagnosis for EVs, and battery charging capacity abnormality evaluations represent other solutions for the estimation of battery health [91,93–98].

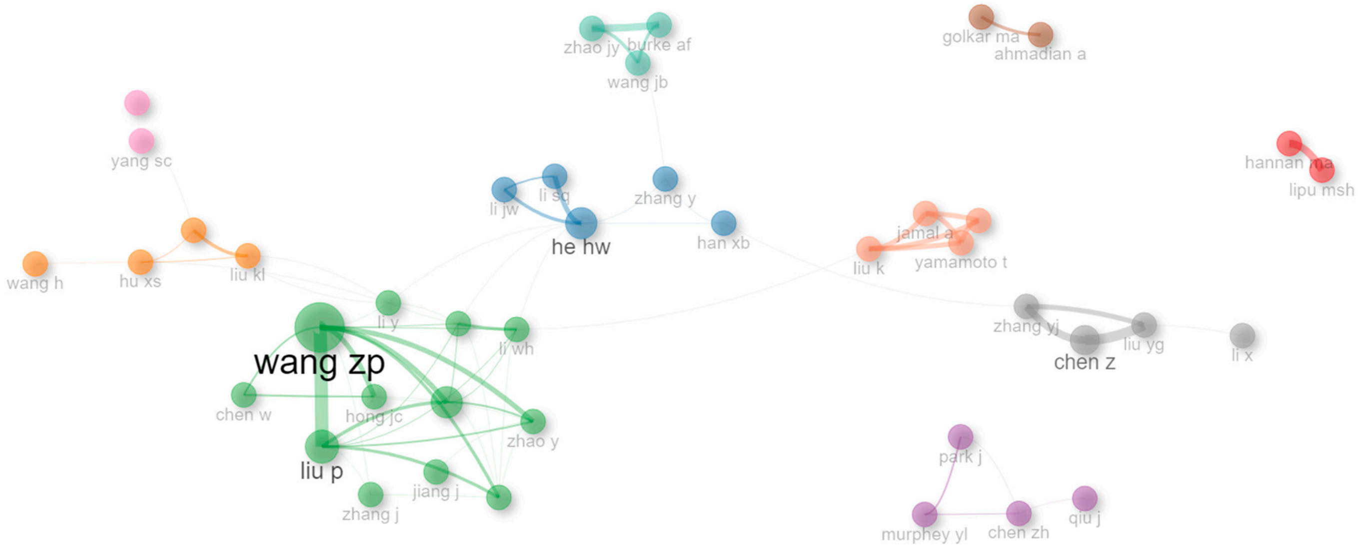

Figure 17. Collaboration network.

The fourth cluster, represented in purple, contains four authors: Murphey YL., Park J., Qiu J., and Chen ZH. The authors focused on identifying an intelligent method for hybrid vehicles that optimizes power management or predicts fault diagnosis for EVs [77,79].

The fifth cluster, represented in yellow, consists of four authors: Wang H., Hu XS., Liu KL., and Widanage WD. The authors focused on evaluating various modeling techniques for forecasting the lifespan of lithium-ion batteries, recovering large-scale batteries, and forecasting charging for EVs using DL models [99–101].

The sixth cluster, colored brown, consists of only two authors, Ahmadian A. and Golkar MA. The authors worked on understanding the performance of plug-in electric vehicles in the energy market, using DL, analyzing electric vehicle demand that is based on convolutional generative adversarial networks, and managing the governance of virtual power plants that integrate renewable energy resources and EVs [102–104].

Cluster number seven, colored in pink, is formed by two authors, Li W. and Yang SC. The authors have only one paper published together, where the focus was on intelligent hybrid EVs using cyber-hierarchy multiscale integrated energy management [105].

The eighth cluster, colored in gray, contains four authors, Chen Z., Zhang YJ., Liu YG., and Li X., who focused on ML algorithms that predict the construction and validation of plug-in hybrid electric vehicles, optimizing control strategies and applying ML-based prediction in a case of study on energy management for these vehicles [106,107].

The ninth cluster, represented in turquoise, is formed by three authors, Zhao JY., Burke AF., and Wang JB. The authors collaborated on multiple publications, where the aim was to predict battery SOC and SOH using cloud-based DL, spatial-temporal self-attention for battery SOC forecasting, ML prognosis for battery capacity, and forecasting the battery failure in EVs [108–111].

The last cluster, colored in orange, contains four authors, Liu K., Jamal A., Ullah I., Yamamoto T. The focus of the authors was to forecast the charging time of EVs using ML algorithms, Shapley additive explanations, and gray wolf optimizer, or to evaluate the effectiveness of the algorithms in estimating the EV's energy consumption [112–114].

Figure 18 highlights the world map of the countries' collaboration. In this figure, the countries have been colored either in gray or in various nuances of blue. The countries colored in gray have not contributed to any papers in the selected domain, while the countries colored in blue have made contributions (darker blue signifies a higher number of papers, while lighter blue signifies a lower number of papers). The width of the red lines indicates the intensity of the collaborations among the two countries placed at the end of the line.

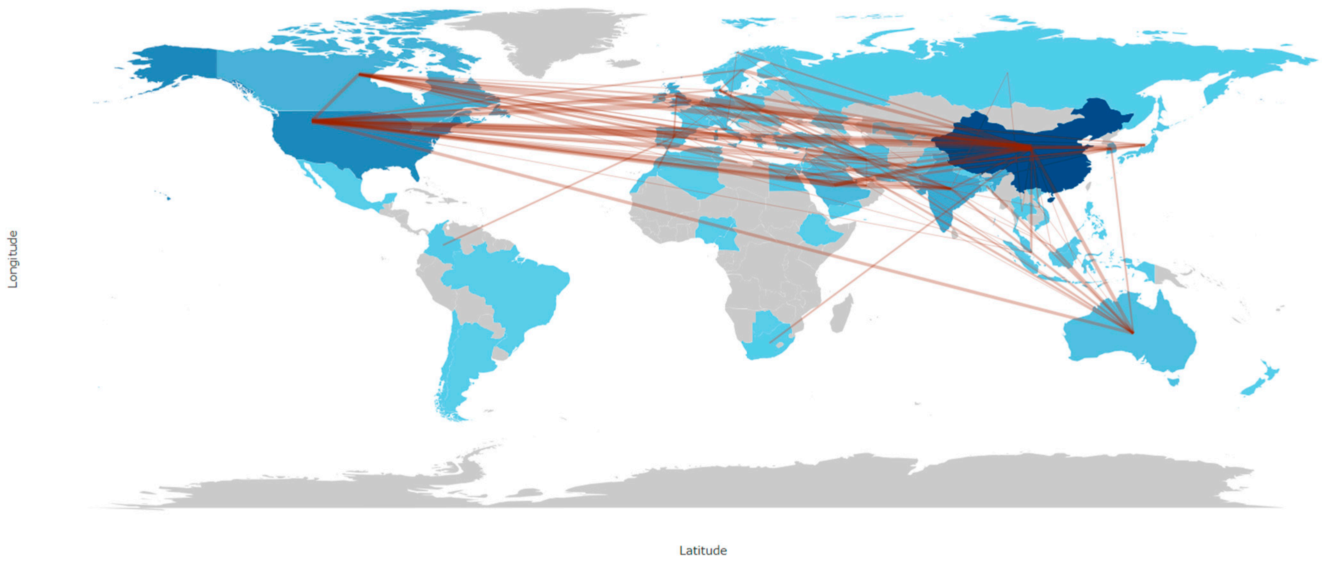

Figure 18. Countries collaboration world map.

According to the data in Figure 18, the most fruitful collaboration was between China and the UK, achieving a total of 41 papers together, followed by China and the USA with 39 papers. The difference between second and third place is significant, with China and Canada having only 18 papers together. The rest of the collaborations that are worthy of mentioning are between the following countries: Saudi Arabia–Egypt (14 articles), China–Saudi Arabia (12 articles), the USA–Saudi Arabia (12 articles), Saudi Arabia–Pakistan (10 articles), China–Australia (9 articles), India–Saudi Arabia (9 articles), and China–Sweden (8 articles).

3.7. Mixed Analysis

This section will describe the main topics discussed in the analyzed papers, together with the most used words, bigrams (group of two words), trigrams (group of three words), and the collaboration between countries, authors, keywords, affiliations, and Keywords Plus.

Figure 19 explores the factorial analysis of the 50 most used authors' keywords, grouped in three clusters.

The most important cluster, which contains the majority of the keywords, is the red one. The keywords describe the algorithms and ML models used in the EV domain, their impact, the prediction of the fault, how to optimize state-of-charge, and the state of EV batteries.

The second cluster, the blue one, expresses the estimation of the battery's degradation using predictive models and feature extraction, while the third cluster, the green one, presents the uncertainty among electric vehicles.

Figure 20 presents the 50 most used Keywords Plus using the factorial analysis method by grouping the keywords into three clusters. The first cluster, the red one, focuses on the impact of lithium-ion batteries, how to optimize energy consumption using algorithms and models, and how to forecast energy demand. The second cluster, the green one, explores the capacity of EV batteries, forecasting the performance health level of lithium-ion batteries and their degradation. The last cluster, the blue one, shows the simulations on charge estimation, the life of batteries, and the frameworks used in the domain.

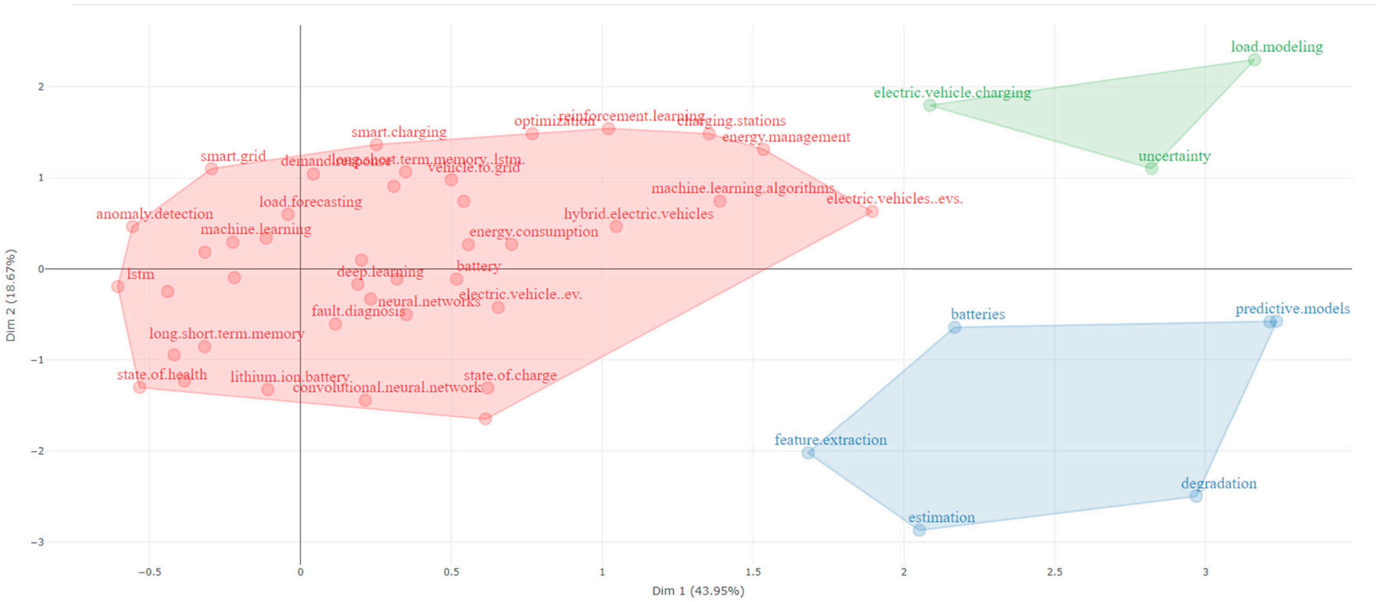

Figure 19. Factorial analysis for authors' keywords.

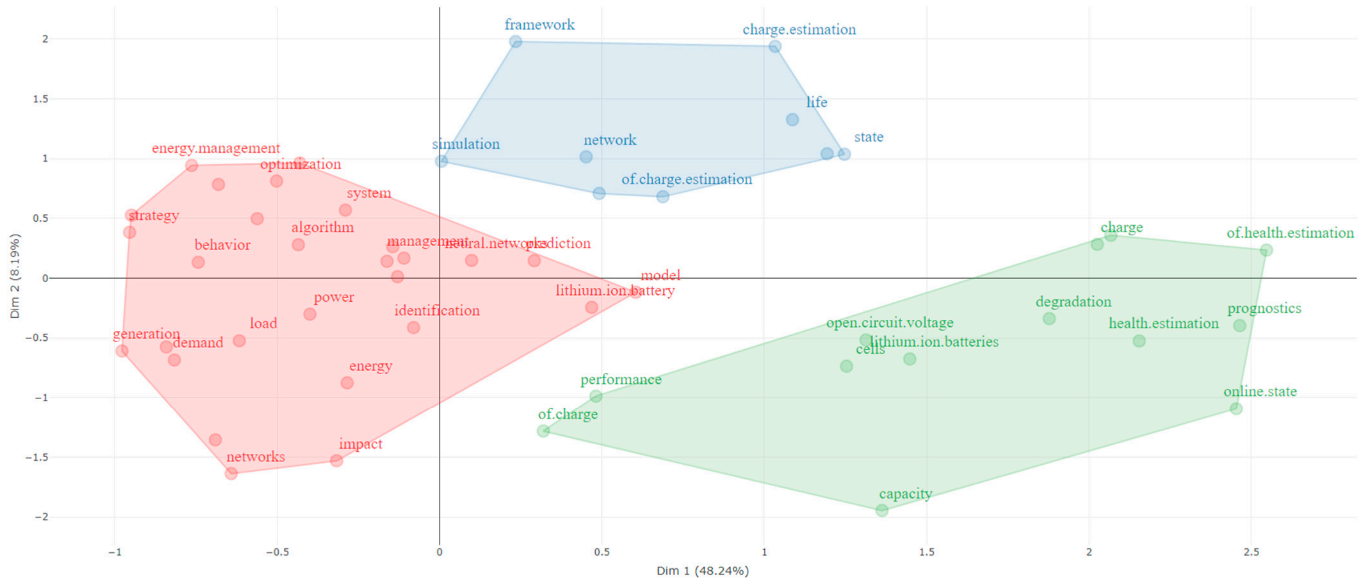

Figure 20. Factorial analysis for Keywords Plus.

Figure 21 includes the 250 most used Keywords Plus, presented as a thematic map, organized into three clusters. The density represents the degree of development by taking into account the internal association between the keywords of the themes, while the centrality presents the relevance of the keywords used in the themes by analyzing the external associations [115].

The densest cluster, the red one, is on the bottom right part of the graph, on the basic themes quadrant, which expresses a low value for the density and a high centrality. The cluster contains the following keywords: "management" (76 occurrences), "optimization" (74 occurrences), "system" (73 occurrences), "algorithm" (45 occurrences), "design" (40 occurrences), "strategy" (37 occurrences), "electric vehicles" (36 occurrences), "energy" (34), "network" (31 occurrences), and "energy management" (29 occurrences). Considering the keywords included in this quadrant, it is expected that the papers included here will approach foundational or broadly applicable research topics that are essential for the development of AI and DL applications in electric vehicles, such as the following: energy management in electric vehicles, optimization of vehicle systems, algorithmic design for EV systems, networked energy systems and infrastructure, and strategy development in EVs. Furthermore, the high centrality of this cluster suggests that these topics are crucial for advancing the field, while their lower density might indicate they are still emerging or evolving themes.

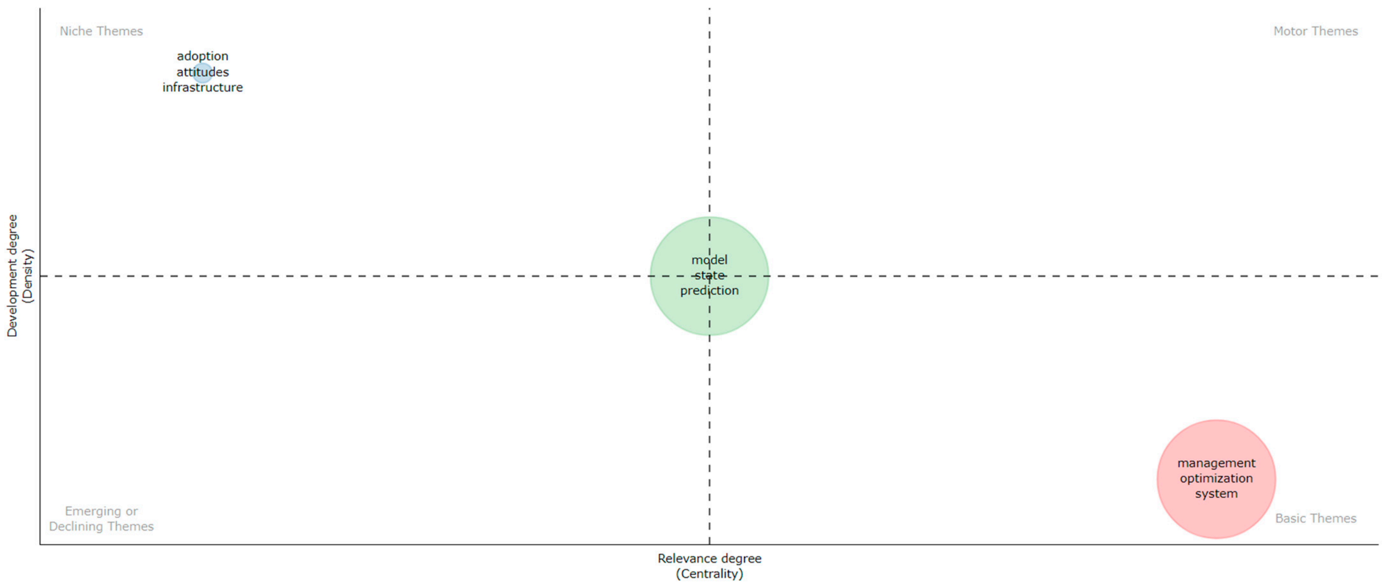

Figure 21. Thematic map Keywords Plus.

The second cluster, colored in green, is at the border between all four quadrants, with a medium density and a medium centrality value. The most frequent keywords that are in the green cluster are as follows: "model" (153 appearances), "state" (77 appearances), "prediction" (66 appearances), "lithium-ion batteries" (53 appearances), "neural networks" (31 appearances), "charge" (28 appearances), "regression" (26 appearances), and "prognostics" (25 appearances). Based on the extracted keywords, the papers included in this cluster comprise research areas likely focusing on themes related to battery modeling and prediction, state estimation, and prognostics, such as battery modeling and performance prediction, state estimation for lithium-ion batteries, lithium-ion battery prognostics, neural networks for battery charge and energy management, and models for battery and vehicle data.

The third cluster, presented in the top left part, has a high-density value and a small centrality. The most used keywords are as follows: "adoption" (11 appearances), "attitudes" (8 appearances), "infrastructure" (6 appearances), and "policy" (6 appearances). The papers included in this cluster focus on social, behavioral, and policy aspects of EV adoption, discussing themes related to the following: EV adoption and consumer behavior, public attitudes toward electric vehicles, EV infrastructure and its role in adoption, and policy and regulation impacts on EV adoption.

Figure 22 illustrates the 250 most used authors' keywords as a thematic map, grouped into two clusters. The red cluster, which is more relevant for the analysis, has a high centrality and a small density, containing a series of the following keywords: "machine learning" (287 appearances), "deep learning" (182 appearances), "electric vehicles" (166 appearances), "electric vehicle" (124 appearances), "lithium-ion battery" (64 appearances), "state of charge" (54 appearances), "lithium-ion batteries" (36 appearances), "state of health" (31 appearances), "artificial intelligence" (29 appearances), and "neural networks" (25 appearances). The second cluster, much smaller than the first one, depicted in green in Figure 22, has a high density and a small centrality, containing the following terms: "batteries" (48 occurrences), "optimization" (44 occurrences), "predictive models" (33 occurrences), "energy management" (29 occurrences), "energy consumption" (26 occurrences), "reinforcement learning" (24 occurrences), "electric vehicle (ev)" (24 occurrences), "electric vehicle charging" (22 occurrences), "data models" (19 occurrences), and "demand response" (19 occurrences).

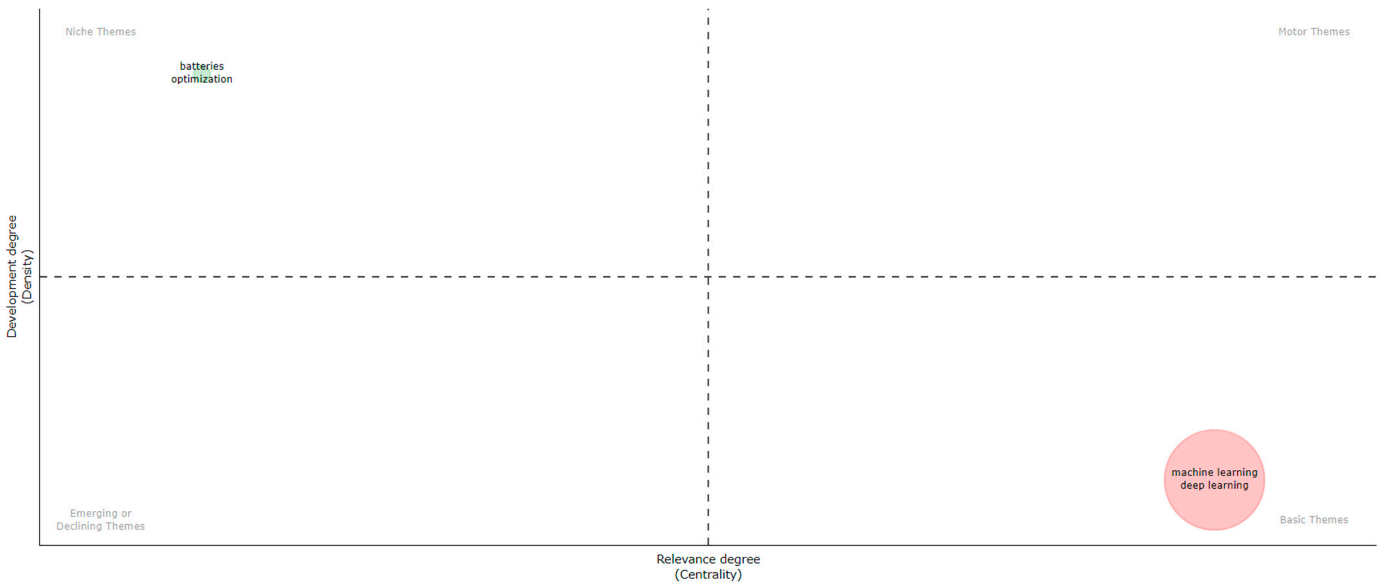

Figure 22. Thematic map Authors' Keywords.

Using the Biblioshiny library, which is part of the R programming language, Figure 23 contains word clouds, presenting the most frequently used words.

Figure 23. Top 50 words based on authors' keywords (**A**), and Keywords Plus (**B**).

The size of the text reflects the frequency of the words. The top 50 most used authors' keywords are described on the left part. The most used keyword is "machine learning", with 291 appearances, followed by "deep learning" and "electric vehicles", with 187 and 172 occurrences. The right part contains the most used 50 Keywords Plus. The highest frequency is for "model", which appeared 153 times, while "state" and "management" are the next two keywords, with 77 and 76 occurrences.

Table 9 contains the most used group of the words (bigrams) in the titles and abstracts. Since there are numerous similarities between terms, a list of synonyms was created to cluster the keywords.

Table 9. Top 10 most used bigrams in titles and abstracts.

Bigrams in Titles	Frequency of the Bigrams in Titles	Bigrams in Abstracts	Frequency of the Bigrams in Abstracts
electric vehicles	414	electric vehicles	1588
machine learning	239	machine learning	1088
lithium-ion batteries	108	energy storage	449
deep learning	103	deep learning	257
energy storage	94	charging stations	225
hybrid electric	53	lithium-ion batteries	203
vehicle charging	52	soc estimation	128
learning approach	39	management system	109
charging stations	35	hybrid electric	97
charging estimation	29	soh estimation	88

On the left part of the table are presented the bigrams in titles and their frequency. Synonyms for "electric vehicles" include "electric vehicles", "electric vehicle", "vehicles evs", and "ev charging", and they appeared 414 times.

The second list, which is called "machine learning", contains the words "neural network", "neural networks", "machine learning", "machine-learning based", and "short-term memory" and has a frequency of 239.

The third list, "lithium-ion batteries", includes "lithium-ion batteries" and "lithium-ion battery", and appeared 108 times. The fourth list, "energy storage", includes "energy consumption", and "energy management" with a total of 94 occurrences, while "hybrid electric" appeared 53 times, "vehicle charging" (52 times), "learning approach" (39 times), and the last list created is "charging stations", with 35 appearances, which includes "charging stations" and "charging station", while the last bigram in titles is "charging estimation", with 29 occurrences.

On the right side of Table 9, the bigrams in the abstracts are provided, along with their number of appearances. It shall be mentioned that we have used the same list of synonyms.

The bigram with the highest frequency is "electric vehicles", with 1588 appearances, followed by "machine learning", with 1088 occurrences. In third place is "energy storage", with 449 appearances, while "deep learning" appeared 257 times, "charging stations" appeared 225 times, "lithium-ion batteries" appeared 203 times, and "soc estimation" appeared 128 times. The last three bigrams are "management system", with 109 occurrences, "hybrid electric", which has a total frequency of 97, and "soh estimation", which appeared 88 times. It shall be stated that the identified bigrams appear in the selected papers included in the dataset, highlighting the main issues that have been discussed in these papers but without offering further details on how these bigrams are connected within the paper. For example, some papers may relate the "vehicle charging" theme to the use of AI in the development of the EV charging infrastructure [116], while in other papers, the identified bigram "vehicle charging" might refer to the challenges faced by the use of AI in the context of EVs [1]. As presented in this example, the bigrams only offer a facet of the theme classification but do not guarantee that the general theme of the paper focuses on the potential solutions regarding the theme rather than on the challenges associated with this topic.

Table 10 presents the most frequently used group of three words (trigrams) in the titles and abstracts. On the left part, the trigrams in titles are described, while in the right part, the trigrams in abstracts are explored. Similar to the bigrams, a list of synonyms was defined since there are multiple similarities between terms. "Electric vehicles charging" include "electric vehicle charging", "electric vehicles charging", "electric vehicles based", "vehicle charging station", "electric vehicle battery", "electric vehicle fleet", "electric vehicles fleet", and "vehicle charging demand", having a total of 121 appearances.

Table 10. Top 10 most used trigrams in titles and abstracts.

Trigrams in Titles	Frequency of the Trigrams in Titles	Trigrams in Abstracts	Frequency of the Trigrams in Abstracts
electric vehicles charging	121	electric vehicles evs	322
hybrid electric vehicles	71	machine learning ml	304
machine learning approach	45	electric vehicle charging	70
energy management strategy	17	hybrid electric vehicles	64
deep learning approach	14	support vector machine	57
lithium-ion batteries based	14	short-term memory lstm	54
model predictive control	7	battery management system	45
vehicle charging stations	7	convolutional neural network	42
convolutional neural networks	6	renewable energy sources	35
energy consumption prediction	5	energy management strategy	34

The second list of trigrams is represented by “hybrid electric vehicles” and combines the following keywords: “hybrid electric vehicles”, “plug-in hybrid electric”, and “hybrid electric vehicle”, having a total frequency of 71. The last list is defined as “machine learning approach” and contains “machine learning approach”, “machine learning based”, “machine learning techniques”, and “machine learning algorithm”, with a total of 45 appearances. “Energy management strategy” appeared 17 times, while “deep learning approach” and “lithium-ion batteries based” have a frequency of 14 each. “Model predictive control” and “vehicle charging stations” appeared seven times each. The last two trigrams are “convolutional neural networks”, with six occurrences, and “energy consumption prediction”, with five appearances.

For the trigrams in abstracts, a different list of synonyms was defined. “Electric vehicles evs” include “electric vehicles evs”, “electric vehicles ev”, and “electric vehicles ev” with a total frequency of 322, while “machine learning ml” contains “machine learning ml”, “machine learning approach”, “machine learning techniques”, “machine learning models”, “machine learning algorithms”, “machine learning models”, and “machine learning algorithm”, appearing for 304 times. “Electric vehicle charging” occurred 70 times, “hybrid electric vehicles” appeared 64 times, “support vector machine” had a frequency of 57 times, while “short-term memory lstm” appeared 54 times. “Battery management system” has a total frequency of 45, while “convolutional neural network” appeared 42 times. The last two trigrams are “renewable energy sources” and “energy management strategy”, which occurred 35 and 34 times.

Figure 24 explores the relationship between the countries, authors, and keywords in the analyzed domain, which further confirms the elements discussed above.

The diagram highlights the collaborative nature of the research across geographic regions, as connections from countries (AU_CO) to authors (AU) demonstrate the diversity of authorship by nationality. For example, China, the United States, and the United Kingdom appear as major contributors, with multiple authors linked to these countries. The middle column, listing individual authors, serves as a bridge, linking their respective countries to specific research disciplines.

The rightmost column (DE) refers to the used keywords in the selected papers. Here, one can identify keywords such as “deep learning”, “machine learning”, “electric vehicles”, and “battery management systems”. Furthermore, dense linkages suggest areas where significant collaboration and contributions converge, such as in machine learning applications for battery optimization.

The diagram highlights once more the contribution of international collaboration to advancements in the research domain analyzed in the present paper, reflecting the interdisciplinary and global nature of the research. The flow from countries to topics via individual authors also underscores the pivotal role of certain nations and researchers in advancing these fields, as presented in the analysis conducted on authors and countries above.

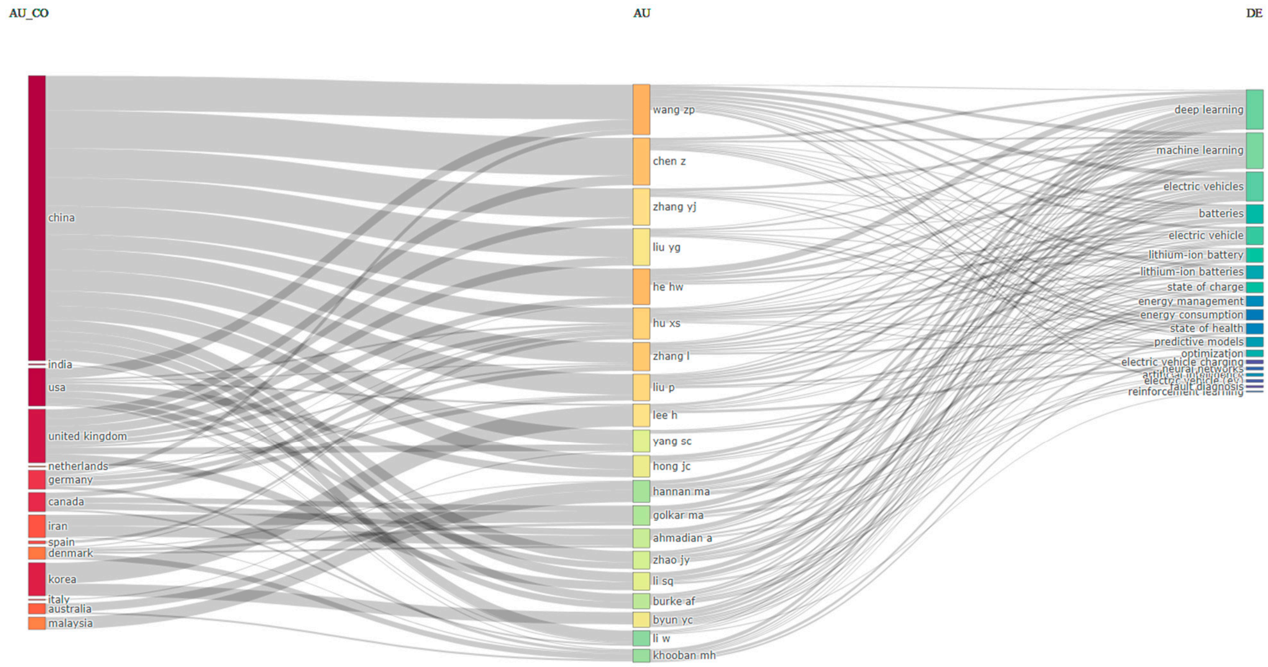

Figure 24. Three-field plot: countries (**left**), authors (**middle**), and keywords (**right**).

Figure 25 presents the collaboration between affiliations, authors, and Keywords Plus between ML, AI, DL, and EVs. The diagram aims to show how research institutions contribute to specific research domains through their affiliated authors.

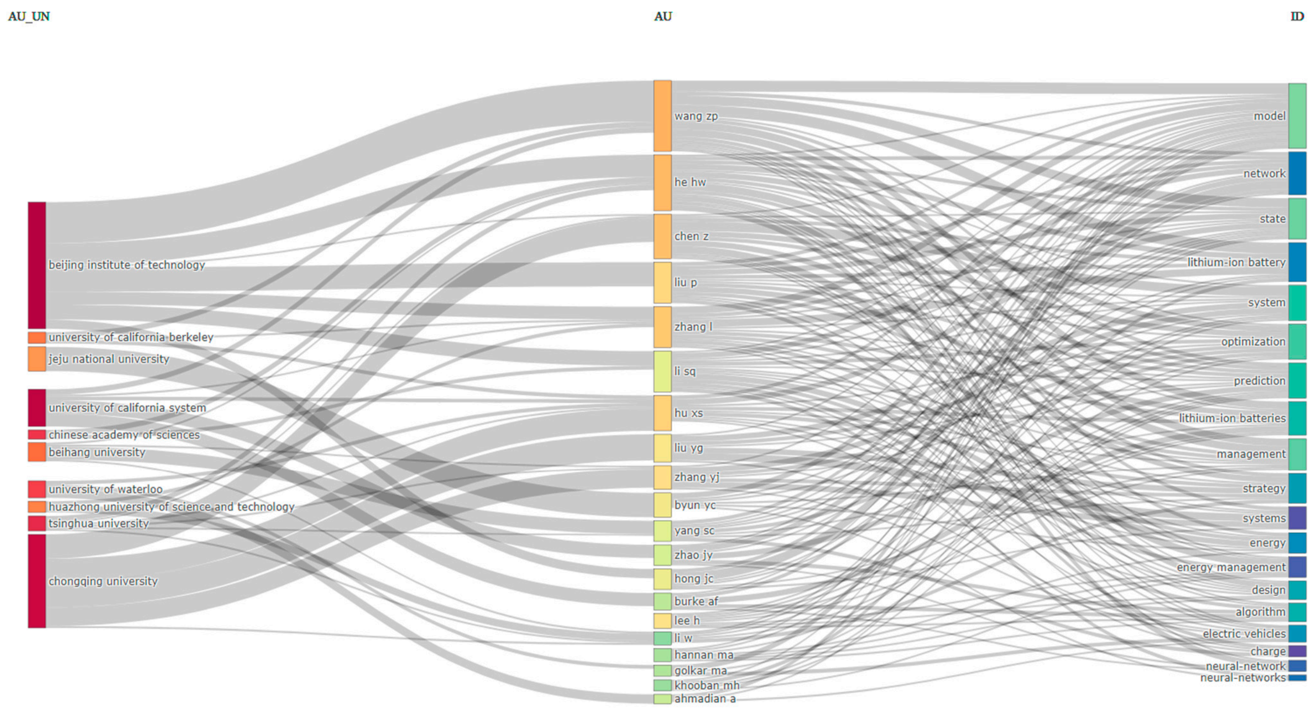

Figure 25. Three-field plot: affiliations (**left**), authors (**middle**), and Keywords Plus (**right**).

Based on the diagram, it can be observed that institutions such as the Beijing Institute of Technology, University of California Berkeley, and Stanford University are shown as significant contributors, with connections to numerous authors listed in the middle column.

Furthermore, by following the flow between the left and middle columns in Figure 25, one can better observe the global distribution of expertise across various universities and research centers.

The rightmost column (ID) showcases the main research Keywords Plus. It shall be mentioned once more that the Keywords Plus are words or phrases that appear in the titles of the papers referenced by the papers included in the database. In this case, key elements such as "machine learning", "prediction", "battery management", "electric vehicles", "optimization", and "neural networks" have been extracted. Thus, Figure 25 reveals that the extracted Keywords Plus are strongly linked to multiple authors, emphasizing their centrality in recent research. Moreover, dense interconnections between authors and the extracted Keywords Plus suggest collaborative efforts and multidisciplinary approaches, particularly in areas such as prediction models and battery optimization.

4. Discussions and Limitations

In this section, discussions are provided based on the obtained results, as well as introducing limitations.

4.1. Bibliometric Analysis Results and Comparison with Other Studies

The bibliometric research explored, from a comprehensive perspective, the evolution of EVs together with ML and DL, starting in 2006, when the first paper was published in the analyzed domain; however, the impact of the publication was minimal. Due to technological advancements, the domain has grown exponentially in the last years, having a positive trend during the timespan, achieving a peak in 2023, with a total of 335 papers.

In recent years, the domain attracted researchers' interest due to the evolution of EVs, in order to estimate battery health and how fast the batteries can charge. China is the leading country, having a total of 309 papers and 8187 citations. In second place is the USA, with 109 papers and a total citation of 3268. The influence of Chinese papers is observed also by the presence of four universities among the top ten most relevant universities based on the number of publications as follows: Beijing Institute of Technology, Chongqing University, Tsinghua University, and the Chinese Academy of Sciences. The results obtained are correlated with other authors' outcomes. For example, Ullah et al. [117] found China as the most important country based on the number of citations and number of publications, with 5933 papers and 70,685 citations, having a contribution of 42.72%, followed by the USA with 1891 papers and 59,679 citations. Among the top 15 most cited universities are Tsinghua University, Beijing Institute of Technology, and Chongqing University. Barbosa et al. [35] explored electric vehicles using bibliometric analysis and found that China has the most number of publications, over 9138 documents, followed by the USA with 4843 papers.

There are numerous journals that, in recent years, published papers related to EVs, AI, ML, and DL. The most prominent journals are *Energies*, *IEEE Access*, *Journal of Energy Storage*, *Applied Energy*, *Energy*, *Sustainability*, *Electronics*, *Journal of Power Sources*, *Applied Sciences-Basel*, and *IEEE Transactions on Industrial Informatics.* Based on Ullah et al. [117] and Barbosa et al. [35], similar journals were reported as being the most relevant for EVs and ML domains, such as *Energies*, *Applied Energy*, *IEEE Access*, and *Energy.*

Thanks to the rapid growth of the domain, numerous papers were published, with remarkable efforts from authors. The most relevant authors on the EV, ML, AI, and DL domains are Wang ZP., He HW., Chen Z., Zhang L., Hu XS., Liu P., Zhang YJ., Lee H., Liu YG., and Byun YC. Ullah et al. [117] found similar authors as being most important in the EV domain.

4.2. Discussions of Specific Themes

In this sub-section, various themes addressed in the papers included in the dataset have been selected to provide a clearer understanding of various aspects of ML and DL applications in EVs.

4.2.1. Implications of AI Advancements in EV Diagnostics and Manufacturing Processes

Regarding the implications of AI advancements in EV diagnostics and manufacturing processes it shall be noted that, based on the papers included in the dataset, it has been observed that AI has contributed to both diagnostics and manufacturing in EVs.

In terms of diagnostic applications, the work conducted by Murphey et al. [77] on fault diagnosis in the case of electric drives has demonstrated that the proposed machine learning-based fault diagnostics system is able to accurately detect and classify the electric drives across a wide operational domain, being able to enhance operational safety and reliability [77].

Also, the work conducted by Li et al. [118] in the area of battery health diagnostics enhanced the advancements made in the field by introducing a new method that combines pulse-injection-aided machine learning for lithium-ion battery diagnostics. As a result, the proposed solution can be used in practice to ensure a precise determination in the case of a battery's health and power states [118].

Furthermore, the research performed by Wongchai et al. [119] underscores the use of DL in fault diagnostics in the case of sustainable EVs. According to the authors, the proposed model has achieved high accuracy in diagnosing complex faults, such as fuel cell flooding under variable load conditions [119].

As for the manufacturing implications, it has been observed that AI can be successfully used in EV manufacturing processes, as it provides a series of advantages such as improved efficiency, quality, and sustainability.

In this regard, the research conducted by Rohkohl et al. [120] contributes to the optimization of the production processes by proposing a real-time DL model for the optimization of continuous battery cell production. Based on the results, it has been observed that the proposed approach has the potential to reduce costs and environmental impact while maintaining high-quality output [120].

Another issue discussed, in the context of the manufacturing implications of AI in EVs, is related to the fault tolerance of the manufacturing systems. Regarding this issue, Liu et al. [121] provide a fault diagnosis algorithm (called a reduced depth kernel extreme learning machine, RDK-ELM) for fault-tolerant systems in hybrid electric vehicle manufacturing. According to the authors, based on the simulations, it has been observed that the algorithm offers a high classification accuracy (namely 97.12%) while needing a lower time for training the model [121].

Extending the range beyond diagnostics and manufacturing, it has been observed that there is a series of papers included in the dataset that deal with issues related to lifecycle management, emphasizing sustainability and efficient recycling. For example, Li et al. [122] proposed an augmented reality-assisted system that enhances efficiency and accuracy in disassembling end-of-life EV batteries. Additionally, Meng et al. [123] provided a systematic review of AI-driven methods for the intelligent disassembly of lithium-ion batteries. Among other topics, the authors also address the critical challenges in recycling in relation to the EVs batteries.

Based on the papers discussed above, it can be observed that the implications of AI advancements in EV diagnostics and manufacturing processes mostly refer to the transformative impact AI has had in the area of EVs in terms of operational safety, reliability, and efficiency in diagnostics [77,118,119], optimizing production processes for cost reduction and sustainability [120,121], and fostering innovative solutions for lifecycle management and recycling [122,123]. As a result, the general contribution of AI in EVs refers to creating a more sustainable and efficient ecosystem.

4.2.2. Implications of AI in Integrating Renewable Energy with EV Infrastructure

Focusing on the implications of AI in integrating renewable energy with EV infrastructure, a series of research has been identified.

First of all, the work conducted by Frendo et al. [124] on smart charging can be mentioned. The authors propose a smart charging algorithm that has the ability to optimize infrastructure use and enable the efficient allocation of renewable energy to EVs. According to the simulations conducted by the authors, the proposed model, which accounts for the charge profiles, is capable of leading to a more effective infrastructure while offering 21% more energy charge when compared to smart charging in the absence of charge profiles [124].

Also, Yoon et al. [125] discuss the situation in which the EV charging platforms are integrated within buildings that have a photovoltaic (PV) system. The authors propose a long short-term memory (LSTM) prediction model for PV energy supply. The proposed solution has the potential to increase renewable energy adoption and reduce carbon emissions [125].

In terms of creating a better charging infrastructure, Golsefidi et al. [126] propose a predictive optimization approach. Contrary to the classical methods for demand-based expansion, which are based on surveys and simple rules of thumb, the approach offered by the authors ensures flexibility and responsiveness to changing demands [126].

Li et al. [127] explore the integration of distributed energy systems with an EV charging supply in neighborhood business centers through the use of an approach based on ML. The results obtained by the authors show that the integration case with a moderate limitation can provide a reduction of 67.8% in economic costs and a 31.6% reduction in carbon emissions [127].

As for green renewable energy integration, Hong et al. [128] proposed a 6G-based intelligent system that integrates state grids, EVs, and renewable energy sources. The systems proposed by the authors use big data and the Internet of Things (IoT) to optimize the EV charging schedule. As a result, energy efficiency is improved as a result of both real and simulated data [128].

Thus, based on the works discussed above, it can be observed that the integration of AI into EVs has been made through a multitude of applications, which refer, but are not limited to, enabling smarter energy allocation through predictive optimization and smart charging algorithms [124,125], enhancing infrastructure flexibility and responsiveness to evolving demands [126], reducing economic costs and carbon emissions through distributed energy systems [127], and optimizing energy efficiency via big data and IoT-based intelligent systems [128].

4.2.3. Implications of AI in EVs on Consumer Behavior and Market Trends

In terms of consumer behavior, it has been observed that the use of AI in EVs has contributed to transformations in consumer behavior. Jia et al. [129] have analyzed the regional adoption of EVs and have provided a map regarding how the adoption of EVs has been predicted. According to the authors, EV owners represent only 1.29% of vehicle owners, and targeted marketing strategies are needed to promote the adoption in various regions [129].

Also, in the area of consumer perceptions of EVs, Jena [130] has addressed the issue of consumer sentiment over EV adoption in the case of Indian consumers. The author has observed that price, safety, and maintenance are the most commonly mentioned features related to EV adoption [130].

Furthermore, Zarazua de Rubens [131] has tried to answer in his research the question related to who will buy EVs after early adopters. To address this research question, the author has used a 5067-respondent dataset and has observed that price is the main determinant—at least for a short time—for EV mass adoption [131].

As for the market dynamics and consumer clustering, the work of Bas et al. [132] has focused on classifying potential buyers in the context of EVs. The authors have observed that some of the most important variables that can be used for classifying the potential adopters of EVs are the socio-economic, attitudinal, and vehicle-related factors [132]. In further research, Bas et al. [133] have enhanced the list of possible factors in EV adoption, adding also information related to ride-sourcing factors, such as the frequency of Uber or Lyft rides [133].

Regarding the market trends, the work conducted by Yeh and Wang [134] can be mentioned. The authors focus on predicting EV sales in 31 countries and noticed that elements such as CO_2 emissions, renewable energy, life expectancy, PM2.5, and consumer price index (CPI) are significantly and positively related to the level of sales for EVs [134].

As a result, it can be observed that, at a micro level, the consumer's behavior in the case of EV adoption has been analyzed through various studies oriented to extracting opinions related to EV adoption, while, at a macro level, EV adoption has been predicted based on a series of specific indicators.

4.2.4. Implications of AI Application in Enhancing Information Security for EVs

In the area of ensuring data integrity and preserving false data injection attacks, Shafee et al. [135] began with the premise that there are cases where EVs may send false information in order to receive higher charging priorities and analyzed the impact of this situation for both "honest" and "lying" EVs. The authors introduced an anomaly based detector using a deep neural network to identify EVs that report false data during charging coordination. Based on the data, the authors state that their proposed detector is able to detect lying EVs with high accuracy [135].

Also, Alomrani et al. [136] refer, in their work, to the cyberattack cases in which malicious owners can mislead EV charging networks by submitting false information in order to obtain various advantages such as higher charging priorities, more power, or better charging schedules. The authors propose a learning-based detection model that can identify such "deceptive" EVs [136].

Acharya et al. [137] used real-life EV charging data from Manhattan, New York, to analyze the feasibility of false data injection attacks on the data market for EV charging stations. Furthermore, the authors proposed a defense mechanism to improve the accuracy of EV charging demand forecasts while ensuring cybersecurity in data exchange systems [137].

False data injection attacks in peer-to-peer energy transactions between connected EVs using machine learning techniques, including support vector machines (SVM), are addressed by Said et al. [138] in their paper. The simulation results support the use of the proposed model [138].

Cui et al. [139] provide a model that includes smart plug-in electric vehicles. The authors apply DL to improve cybersecurity measures in EV systems [139].

ElKashlan et al. [140] propose a classification algorithm for detecting malicious traffic in IoT-based EV charging systems. Through the implementation of the proposed solution, the stability in charging ecosystems can be enhanced while cyberattacks can be reduced [140].

Considering the research presented above, it can be observed that in the case of AI advancements in cybersecurity for EV systems, a critical role played by AI can be observed, highlighted by a multitude of practical applications, such as, but not limited to, ensuring data integrity and mitigating false data injection attacks through anomaly based detectors using deep neural networks [135], learning-based detection models [136], and defense mechanisms for improving demand forecasts and secure data exchange [137]. Furthermore, in order to reduce vulnerabilities in EV charging networks, various AI techniques can be employed, as shown by Said et al. [138], Cui et al. [139], and ElKashlan et al. [140].

4.3. Key Limitations to Applicability of ML and DL to EVs

Besides the elements uncovered in the current paper related to the use and applicability of AI, ML, or DL approaches in the EV field, which have been highlighted through the thematic maps, n-gram analysis, factorial analysis, and the review of the most cited 10 papers, one should also mention that there is also a series of key limitations in the applicability of AI, ML, or DL to EVs, which warrant attention, such as the challenges related to the data, such as data scarcity, data privacy, or imbalanced data. As many studies rely on the availability of high-quality and real-world data for training AI models, the lack of such data might affect the performance of the created models. As Naresh et al. [141] pointed out in the case of the batteries used in EVs, the challenges that AI methods face in this area are highly related to the dynamicity and analysis of large-scale data. As the authors pointed out, while ML models have the ability to select optimum strategies in real time based on a series of variables, such as traffic/driving/weather conditions, traffic patterns, terrain, or user preferences, the reliability of the proposed solution is highly dependent on a large amount of high-quality data [141]. Thus, for example, in the case of the batteries used for EVs, in order to ensure the optimization of battery performance, the data preprocessing step (which might include removing erroneous data or outliers) becomes essential for obtaining proper data to feed the AI models being used. Furthermore, in terms of data privacy, it should be mentioned that particular attention should be given to data privacy and security, as the AI models work with real-life data that can be both sensitive vehicle and user data [141]. Nevertheless, in the case of research dealing with fault detection or rare event prediction, data imbalance might be an issue, as it limits the dataset as a result of the fact that the number of fault situations is significantly lower than the normal-functioning cases.

From another point of view, limitations in the integration of AI, ML, or Dl to EVs might also be observed in terms of model complexity and interpretability. As Arevallo et al. [142] observed, although significant progress has been made in integrating AI into EVs, there are still issues related to real-time optimization and adapting the algorithms to various conditions, such as driving conditions. As Chougule et al. [143] pointed out, in the case of electric autonomous vehicles, the use of AI faces an additional challenge: making real-time decisions that are not only secure but also justifiable in order to comply with legal requirements across various jurisdictions. Also, the use of advanced AI algorithms requires both a considerable storage capacity and processing power, which can be a challenge due to its associated costs and sometimes the difficulties faced in implementation [142,144,145] and interoperability [146]. Additionally, cybersecurity can be seen as a limitation in the use of AI, ML, or DL in the case of EVs [147], which needs to be considered when using such models by fortifying the created systems against cyberattacks [148,149].

4.4. Biases in Publication Trends

Furthermore, the biases in publication trends should be highlighted. For example, one can refer to the geographical and institutional biases that are related to the fact that some of the countries and/or institutions might be overrepresented in the dataset due to either the dimensions (expressed, for example, in the number of researchers) or the level of financing offered by the government/university/research centers to a particular area of research. In this context, there might be significant contributions regarding the value of research and the advancement made in the field, but lower when considering the number of contributions from underrepresented regions. Also, it is possible that some developing economies contribute less to this area due to other factors, such as a socio-economic context that has not allowed underdeveloped countries to adopt a particular technology and, in our case, to adopt the use of EVs.

On another note, it should be noted that the increase in research interest in a particular area might be driven by a growing interest in the field itself, but it may also result from a general upward trend in research activity at the global or national level, influenced by various socio-economic factors that favor research across all domains. As Ofer et al. [150] pointed out, it has been observed that the number of scientific papers has increased at an accelerating rate over the last four decades. The authors pointed out that this trend might be driven by the continuous growth in the number of research institutes and researchers as well as by academic careers [150]. Furthermore, the authors consider that increasing trends might also be driven by the better-automated data indexing observed through the use of various databases, as well as the use of the keyword annotation scheme by research subjects [150]. Nevertheless, Ofer et al. [150] nominalize the occurrence of open access policies and the increased expectancy of research productivity output in many fields as a trigger for the increase in the number of publications globally. Also, the occurrence of advancements in computer science has impacted technological breakthroughs, which have impacted many other research fields and have contributed to the increase in the number of outputs [150]. These observations are further supported by the early work of Vincent-Lacrin [151], which observed that the number of books published in US universities between 1993–2007 increased by 32%, while the number of researchers between 1981 and 1999 increased by 127%, representing an average of 7% per year [151]. The author observed that even research output increased by 52% between 1988 and 2005. According to the author, this increase can be correlated to the growth in research and development expenditure and the overall number of researchers in the field [151].

4.5. Limitations Related to Dataset Extraction and Used Database

The analysis led to a number of limitations, mostly related to the process of dataset retrieval.

The first limitation is that the selection of the publications included only a single database, known as ISI Web of Science. The decision to use the ISI Web of Science database was based on its reputation for providing high-quality sources, as acknowledged in the scientific literature, and its inclusion of various citation indexes, such as the Science Citation Index Expanded (SCIE) and Social Sciences Citation Index (SSCI), which enable robust citation analyses. Additionally, the ISI Web of Science offers Keywords Plus, a unique feature that enhances the analysis by identifying additional terms derived from the references in the papers, thereby broadening the scope of the study.

However, it is important to consider the potential biases associated with this database, including its emphasis on English-language papers and limited temporal coverage for older publications. Given that the focus of the present study is a contemporary topic—namely, the use of ML and DL in the context of EVs—the issue of limited inclusion of older publications does not apply. Regarding the focus on English-language papers, while we acknowledge this limitation, we intentionally restricted our analysis to English-written papers to ensure the accurate extraction of n-grams and the generation of thematic maps.

Including papers in multiple languages could have compromised the accuracy of word extraction and, consequently, the reliability of n-gram analysis, factorial analysis, thematic mapping, and even the review process, as the authors of this study have limited proficiency in languages other than English and a few common ones. Nevertheless, as in our case, only one paper has been excluded due to not being written in English, representing 0.11% of the remaining dataset; we think that this limitation does not affect the accuracy of the results. Although the database is well recognized in the academical community, including wide-ranging domains, excluding other databases and other papers on the same topic could lead to a database with a higher variety, which might influence different datasets and provide slightly different results. Even though the option to include and merge information from various databases exists, it should be stated that this decision comes with numerous drawbacks. First, as mentioned above, all the analyses, including Keywords Plus (a special feature offered by ISI Web of Science)—e.g., thematic map based on Keywords Plus, factorial analysis conducted on Keywords Plus, WordClouds based on Keywords Plus, and the three-field plots that include Keywords Plus—would not have been possible. Secondly, when combining information from multiple databases, it is possible for some papers to appear in more than one database. Consequently, the citation counts for these papers can vary across databases. For instance, Table 11 illustrates this issue with the most cited paper in our dataset, authored by Chamali et al. [82]. According to ISI Web of Science, the paper has 437 citations, while Scopus reports 595 citations, and the IEEE database lists 541 citations. This discrepancy raises an important question when integrating data from these three databases: which citation count should be assigned to the paper?

Table 11. Example of various numbers of citations based on the selected database.

Paper	Number of Citations in Various Databases		
	ISI Web of Science (Database Used in This Study)	**Scopus**	**IEEE**
Chemali et al. [82]	437	595	541

It is worth noting that files exported from the WoS database can be seamlessly imported into the bibliometric analysis software used in this study, namely Biblioshiny [76,152]. It is also important to emphasize that popular bibliometric platforms such as Biblioshiny and VOSviewer can only process data from specific databases [152]. For instance, Biblioshiny supports files from WoS, Lens, PubMed, Scopus, Dimensions, and Cochrane Library [76], whereas VOSviewer is compatible with WoS, Lens, Scopus, Dimensions, and PubMed [153].

The second limitation is caused by the keywords used in the extraction of the dataset, which affect the number of total papers included in the dataset.

Another limitation is related to the type of documents that were included in the dataset. As mentioned above, we have excluded the papers that were not marked as "articles" in ISI Web of Science. We have to mention that this step was necessary in order to have a relevant comparison between papers from the content and the number of citation points of view.

In addition to these limitations, which are inherent to this type of analysis, it shall be stated that there might be cases of ambiguity in theme classification, which derive from the nature of the extracted n-grams, which only offer a part of the information related to the topic of the paper but do not uncover the entire context. As shown above, the identified terms can be used in papers in the context in which the authors provide solutions to the selected topic, but at the same time, there might be research in which the authors are discussing the potential challenges implied by the use of the selected terms, which are not necessarily offering a solution to the issue but rather increasing the awareness on the occurrence of various challenges related to the topic.

5. Conclusions

This research presents a comprehensive evaluation of the domains of EVs, ML, and DL, with a particular emphasis on their evolution and interrelation. The technological advancements within these fields have played a pivotal role in shaping their development. Through the use of a bibliometric approach, this study successfully identified the most influential journals, authors, documents, topics, and collaborative networks. To articulate the findings, this study addresses several research questions outlined in the initial section of the paper.

It shall be stated that through the research conducted in the present paper, we have answered the research questions, finding that:

- The most important journals, in terms of the number of publications that had a significant contribution to the EV, AI, ML and DL domains are as follows: *Energies* (82 publications), *IEEE Access* (74 publications), *Journal of Energy Storage* (44 publications), *Applied Sciences* (43 publications), *Energy* (33 publications), *Sustainability* (23 publications), *Electronics* (20 publications), *Journal of Power Sources* (20 publications), *Applied Sciences-Basel* (19 publications), and *IEEE Transactions on Industrial Informatics* (19 publications).
- The collaboration among authors is observed based on the number of SCPs and MCPs. The most important country in terms of publications is China, with 309 papers published (206 SCPs and 103 MCPs), with a total contribution of 33.2%. The USA authors published 109 articles (73 SCPs and 36 MCPs), with a total contribution of 11.7%. India has 71 articles (51 SCPs and 20 MCPs), with a contribution of 7.6.%. The rest of the countries have a smaller impact but are still important and are as follows: South Korea (49 SCPs, 8 MCPs), Germany (36 SCPs, 5 MCPs), UK (22 SCPs, 18 MCPs), Canada (22 SCPs, 16 MCPs), Italy (12 SCPs and 14 MCPs), Spain (10 SCPs, 9 MCPs), and Iran (7 SCPs, 9 MCPs).
- Taking into consideration the number of citations, China is the most influential country, with 8187 citations. In second place is the USA with 3268, third is Canada with 1839 citations, while the UK is fourth with 1680 citations. In fifth place is India with 1149 citations, Korea with 521 citations, and Germany with 483 citations, while the last three countries are Italy with 424 citations, Malaysia with 424 citations, and Iran with 330 citations.
- Analyzing the authors' keywords, the most important terms are "machine learning", "deep learning", and "electric vehicles", while for Keywords Plus, the most common terms are "model", "state", and "management". Investigating the abstracts, the most used keywords are "electric vehicles", "machine learning", and "energy storage", and for titles, they are "electric vehicles", "machine learning", and "lithium-ion batteries".
- The most influential authors, based on the number of articles that were included in the dataset, are: Wang ZP. (16 papers), He HW. (13 papers), Chen Z. (12 papers), Zhang L. (11 papers), Hu XS. (9 papers), Liu P. (9 papers), Zhang YJ. (9 papers), Lee H. (8 papers), Liu YG. (8 papers), and Byun YC. (7 papers).
- The EV, ML, AI, and DL domains were analyzed using thematic maps, which extracted the main topics from Keywords Plus and authors' keywords, obtaining information related to energy management, optimization, infrastructure, policy, lithium-ion batteries, design, strategy, regression, and neural networks.

In terms of the implications of the findings for industry stakeholders, it should be stated that multiple avenues are available, as supported by the research included in the dataset, such as, but not limited to the use of AI methods in the disassembly and/or recycling on the lithium-ion batteries, which can contribute to the mitigation of the environmental challenges and to creating a more sustainable environment [122,123,154–156];

the use of AI in the optimization of the charging infrastructure, with effects in efficient resources allocation [126,157]; the creation of AI-powered frameworks, which facilitate the integration of renewable energy with EV charging infrastructure, having a key role in a reduction in carbon emissions [125,127,158–160]; the use of AI in traffic prediction, in the context of autonomous EV technologies [161], or regarding the alleviation traffic congestion [162], or to mitigate traffic oscillations [163]; or even the use of AI in user behavior prediction in the context of EVs, such as predicting the popularity of EV charging infrastructure [164], or quantifying the uncertainty of EV charging demands [165].

Also, in terms of the practical outcomes of using AI in the EV industry, several directions can be mentioned, resulting from the works included in the dataset, such as, but not limited to, the deployment challenges that derive from the complexity of the integration, such as in the case of lithium-ion batteries [123] or from the quality and availability of data (being well-known that, in some cases, there is limited access to high-quality datasets and that further efforts should be made to address these limitations [126]), as well as from cyberattacks (as in where false data are injected into the system and should be mitigated using appropriate anomaly detection models [166]). Nevertheless, as previously mentioned, the use of AI has provided effective solutions to real-world problems, such as reducing costs and improving the scalability of EV charging infrastructure, as well as increasing the material recovery rates in the case of lithium-ion batteries while maintaining a proper safety standard [123]. As a result, the economic implications of AI use in EVs have become more and more evident, primarily related to a reduction in costs in manufacturing [123] and increasing the revenues in the case of EV service providers by maximizing the utilization of the infrastructure [167].

Considering the results, it should be mentioned that there are few papers included in the dataset related to federated learning and edge AI, which represent transformative opportunities in managing EVs. Among the key implications that result from the papers included in the dataset, one can name the use of federated learning in the area of battery management and aging prediction. As a result, the work conducted by Kroger et al. [168] proposed a federated learning-based framework for predicting battery aging, which is able to provide accurate results without sharing sensitive data. Another area of applicability for federated learning is related to EV fleet coordination. For example, Chu et al. [169] proposed a multi-agent federated reinforcement learning model for fleet charging coordination in residential areas. The authors demonstrate that the proposed approach enhances system stability in a significant manner while offering proper user privacy [169]. Nevertheless, cybersecurity issues are addressed through the use of federated learning, especially in cases related to intrusion detection. To this extent, Xu et al. [170] provide a robust intrusion system that takes advantage of a federated learning approach combined with techniques related to privacy preservation. The proposed solution can be successfully used in cases of secure intrusion detection in inter-vehicle networks [170]. Lastly, the work conducted by Saputra et al. [11] in the area of smart charging optimization takes advantage of a federated learning approach. The authors developed a federated learning framework integrated with contract theory to optimize EV charging station networks. The proposed solution improved the demand prediction accuracy and economic outcomes for charging station operators [11].

Future research in the area of AI in EVs might consider continuing the efforts made in scientific research in areas of automation of lithium-ion batteries' disassembly, as suggested by Meng et al. [123] and Li et al. [122], enhancing cybersecurity for preventing cyberattacks and ensuring data integrity, as suggested by Said et al. [138] and Algarni and Thayananthan [171], or grid integration optimization, as highlighted by Dong et al [172].

Author Contributions: Conceptualization, A.D., G.-A.T. and C.D.; Data curation, A.D., L.-A.C., P.D., G.-A.T. and C.D.; Formal analysis, A.D., L.-A.C. and P.D.; Investigation, A.D., L.-A.C., P.D., G.-A.T. and C.D.; Methodology, A.D. and C.D.; Project administration, L.-A.C.; Resources, A.D., L.-A.C., P.D. and C.D.; Software, A.D., L.-A.C. and G.-A.T.; Supervision, L.-A.C. and C.D.; Validation, A.D., L.-A.C., P.D., G.-A.T. and C.D.; Visualization, A.D., P.D. and G.-A.T.; Writing—original draft, A.D. and C.D.; Writing—review & editing, L.-A.C., P.D. and G.-A.T. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by a grant from the Romanian Ministry of Research, Innovation, and Digitalization, project CF 178/31.07.2023—'JobKG—A Knowledge Graph of the Romanian Job Market based on Natural Language Processing'.

Data Availability Statement: Data are contained within the paper.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ahmed, M.; Zheng, Y.; Amine, A.; Fathiannasab, H.; Chen, Z. The Role of Artificial Intelligence in the Mass Adoption of Electric Vehicles. *Joule* **2021**, *5*, 2296–2322. [CrossRef]
2. Paret, P.; Finegan, D.; Narumanchi, S. Artificial Intelligence for Power Electronics in Electric Vehicles: Challenges and Opportunities. *J. Electron. Packag.* **2022**, *145*, 034501. [CrossRef]
3. Rigas, E.S.; Ramchurn, S.D.; Bassiliades, N. Managing Electric Vehicles in the Smart Grid Using Artificial Intelligence: A Survey. *IEEE Trans. Intell. Transp. Syst.* **2015**, *16*, 1619–1635. [CrossRef]
4. U.S. Department of Energy Alternative Fuels Data Center: Electric Vehicle (EV) Definition. Available online: https://afdc.energy.gov/laws/12660 (accessed on 2 January 2025).
5. ISO. *Information Technology—Artificial Intelligence—Artificial Intelligence Concepts and Terminology*; ISO: Geneva, Switzerland, 2022.
6. Stryker, C.; Kavlakoglu, E. What Is Artificial Intelligence (AI)? | IBM. Available online: https://www.ibm.com/think/topics/artificial-intelligence (accessed on 2 January 2025).
7. Dorokhova, M.; Ballif, C.; Wyrsch, N. Routing of Electric Vehicles With Intermediary Charging Stations: A Reinforcement Learning Approach. *Front. Big Data* **2021**, *4*, 586481. [CrossRef] [PubMed]
8. Shahriar, S.; Al-Ali, A.R.; Osman, A.H.; Dhou, S.; Nijim, M. Machine Learning Approaches for EV Charging Behavior: A Review. *IEEE Access* **2020**, *8*, 168980–168993. [CrossRef]
9. Severson, K.A.; Attia, P.M.; Jin, N.; Perkins, N.; Jiang, B.; Yang, Z.; Chen, M.H.; Aykol, M.; Herring, P.K.; Fraggedakis, D.; et al. Data-Driven Prediction of Battery Cycle Life before Capacity Degradation. *Nat. Energy* **2019**, *4*, 383–391. [CrossRef]
10. Attia, P.M.; Grover, A.; Jin, N.; Severson, K.A.; Markov, T.M.; Liao, Y.-H.; Chen, M.H.; Cheong, B.; Perkins, N.; Yang, Z.; et al. Closed-Loop Optimization of Fast-Charging Protocols for Batteries with Machine Learning. *Nature* **2020**, *578*, 397–402. [CrossRef]
11. Saputra, Y.M.; Nguyen, D.; Dinh, H.T.; Vu, T.X.; Dutkiewicz, E.; Chatzinotas, S. Federated Learning Meets Contract Theory: Economic-Efficiency Framework for Electric Vehicle Networks. *IEEE Trans. Mob. Comput.* **2020**, *21*, 2803–2817. [CrossRef]
12. Xing, Q.; Xu, Y.; Chen, Z.; Zhang, Z.; Shi, Z. A Graph Reinforcement Learning-Based Decision-Making Platform for Real-Time Charging Navigation of Urban Electric Vehicles. *IEEE Trans. Ind. Inform.* **2023**, *19*, 3284–3295. [CrossRef]
13. Zhong, J.; Li, Y.; Wu, Y.; Cao, Y.; Li, Z.; Peng, Y.; Qiao, X.; Xu, Y.; Yu, Q.; Yang, X.; et al. Optimal Operation of Energy Hub: An Integrated Model Combined Distributionally Robust Optimization Method With Stackelberg Game. *IEEE Trans. Sustain. Energy* **2023**, *14*, 1835–1848. [CrossRef]
14. Shang, Y.; Liu, M.; Shao, Z.; Jian, L. Internet of Smart Charging Points with Photovoltaic Integration: A High-Efficiency Scheme Enabling Optimal Dispatching between Electric Vehicles and Power Grids. *Appl. Energy* **2020**, *278*, 115640. [CrossRef]
15. Shang, Y.; Li, Z.; Li, S.; Shao, Z.; Jian, L. An Information Security Solution for Vehicle-to-Grid Scheduling by Distributed Edge Computing and Federated Deep Learning. *IEEE Trans. Ind. Appl.* **2024**, *60*, 4381–4395. [CrossRef]
16. Xie, S.; Xu, C.; Li, W.; Kang, Y.; Feng, X.; Wu, W. Machine Learning Accelerated the Performance Analysis on PCM-Liquid Coupled Battery Thermal Management System. *J. Energy Storage* **2024**, *100*, 113479. [CrossRef]
17. Zhang, D.; Zhang, H.; Li, X.; Zhao, H.; Zhang, Y.; Wang, S.; Ahmad, T.; Liu, T.; Shuang, F.; Wu, T. A PMSM Control System for Electric Vehicle Using Improved Exponential Reaching Law and Proportional Resonance Theory. *IEEE Trans. Veh. Technol.* **2023**, *72*, 8566–8578. [CrossRef]
18. Wang, B.; Dehghanian, P.; Zhao, D. Coordinated Planning of Electric Vehicle Charging Infrastructure and Renewables in Power Grids. *IEEE Open Access J. Power Energy* **2023**, *10*, 233–244. [CrossRef]
19. El-Azab, H.-A.I.; Swief, R.A.; El-Amary, N.H.; Temraz, H.K. Seasonal Electric Vehicle Forecasting Model Based on Machine Learning and Deep Learning Techniques. *Energy AI* **2023**, *14*, 100285. [CrossRef]

20. Mohamed, N.; Almazrouei, S.K.; Oubelaid, A.; Bajaj, M.; Jurado, F.; Kamel, S. Artificial Intelligence (AI) and Machine Learning (ML)-Based Information Security in Electric Vehicles: A Review. In Proceedings of the 2023 5th Global Power, Energy and Communication Conference (GPECOM), Nevsehir, Turkiye, 14–16 June 2023; pp. 108–113.
21. Kaplan, H.; Tehrani, K.; Jamshidi, M. A Fault Diagnosis Design Based on Deep Learning Approach for Electric Vehicle Applications. *Energies* **2021**, *14*, 6599. [CrossRef]
22. Venkitaraman, A.K.; Kosuru, V.S.R. Hybrid Deep Learning Mechanism for Charging Control and Management of Electric Vehicles. *Eur. J. Electr. Eng. Comput. Sci.* **2023**, *7*, 38–46. [CrossRef]
23. Zhu, J.; Yang, Z.; Mourshed, M.; Guo, Y.; Zhou, Y.; Chang, Y.; Wei, Y.; Feng, S. Electric Vehicle Charging Load Forecasting: A Comparative Study of Deep Learning Approaches. *Energies* **2019**, *12*, 2692. [CrossRef]
24. Sundaram, K.M.; Hussain, A.; Sanjeevikumar, P.; Holm-Nielsen, J.B.; Kaliappan, V.K.; Santhoshi, B.K. Deep Learning for Fault Diagnostics in Bearings, Insulators, PV Panels, Power Lines, and Electric Vehicle Applications—The State-of-the-Art Approaches. *IEEE Access* **2021**, *9*, 41246–41260. [CrossRef]
25. Ma, W.; Hu, J.; Yao, L.; Fu, Z.; Morais, H.; Marinelli, M. New Technologies for Optimal Scheduling of Electric Vehicles in Renewable Energy-Oriented Power Systems: A Review of Deep Learning, Deep Reinforcement Learning and Blockchain Technology. *Energy Convers. Econ.* **2022**, *3*, 345–359. [CrossRef]
26. Mohammed, Y.; Manoharan, A.; Kappagantula, S.; Manoharan, H. Optimizing Electric Vehicle Charging Costs Using Machine Learning. | Ingénierie Des Systèmes d'Information | EBSCOhost. Available online: https://openurl.ebsco.com/contentitem/doi:10.18280/isi.290326?sid=ebsco:plink:crawler&id=ebsco:doi:10.18280/isi.290326 (accessed on 5 September 2024).
27. Block, J.H.; Fisch, C. Eight Tips and Questions for Your Bibliographic Study in Business and Management Research. *Manag. Rev. Q.* **2020**, *70*, 307–312. [CrossRef]
28. Cibu, B.; Delcea, C.; Domenteanu, A.; Dumitrescu, G. Mapping the Evolution of Cybernetics: A Bibliometric Perspective. *Computers* **2023**, *12*, 237. [CrossRef]
29. Delcea, C.; Javed, S.A.; Florescu, M.-S.; Ioanas, C.; Cotfas, L.-A. 35 Years of Grey System Theory in Economics and Education. *Kybernetes* **2023**, *54*, 649–683. [CrossRef]
30. Domenteanu, A.; Delcea, C.; Chiriță, N.; Ioanăș, C. From Data to Insights: A Bibliometric Assessment of Agent-Based Modeling Applications in Transportation. *Appl. Sci.* **2023**, *13*, 12693. [CrossRef]
31. Jigani, A.-I.; Delcea, C.; Florescu, M.-S.; Cotfas, L.-A. Tracking Happiness in Times of COVID-19: A Bibliometric Exploration. *Sustainability* **2024**, *16*, 4918. [CrossRef]
32. Profiroiu, C.M.; Cibu, B.; Delcea, C.; Cotfas, L.-A. Charting the Course of School Dropout Research: A Bibliometric Exploration. *IEEE Access* **2024**, *12*, 71453–71478. [CrossRef]
33. Veza, I.; Syaifuddin, M.; Idris, M.; Herawan, S.G.; Yusuf, A.A.; Fattah, I.M.R. Electric Vehicle (EV) Review: Bibliometric Analysis of Electric Vehicle Trend, Policy, Lithium-Ion Battery, Battery Management, Charging Infrastructure, Smart Charging, and Electric Vehicle-to-Everything (V2X). *Energies* **2024**, *17*, 3786. [CrossRef]
34. Ayodele, B.V.; Mustapa, S.I. Life Cycle Cost Assessment of Electric Vehicles: A Review and Bibliometric Analysis. *Sustainability* **2020**, *12*, 2387. [CrossRef]
35. Barbosa, W.; Prado, T.; Batista, C.; Câmara, J.C.; Cerqueira, R.; Coelho, R.; Guarieiro, L. Electric Vehicles: Bibliometric Analysis of the Current State of the Art and Perspectives. *Energies* **2022**, *15*, 395. [CrossRef]
36. Bhat, F.A.; Verma, A. A Bibliometric Analysis and Review of Adoption Behaviour of Electric Vehicles. *Transp. Dev. Econ.* **2023**, *9*, 5. [CrossRef]
37. Miah, M.S.; Hossain Lipu, M.S.; Meraj, S.T.; Hasan, K.; Ansari, S.; Jamal, T.; Masrur, H.; Elavarasan, R.M.; Hussain, A. Optimized Energy Management Schemes for Electric Vehicle Applications: A Bibliometric Analysis towards Future Trends. *Sustainability* **2021**, *13*, 12800. [CrossRef]
38. Murugan, M.; Saravanan, A.; Elumalai, P.V.; Murali, G.; Dhineshbabu, N.R.; Kumar, P.; Afzal, A. Thermal Management System of Lithium-Ion Battery Packs for Electric Vehicles: An Insight Based on Bibliometric Study. *J. Energy Storage* **2022**, *52*, 104723. [CrossRef]
39. Nurdini, A.; Nurcahyo, R.; Prabuwono, A.S. Waste from Electric Vehicle: A Bibliometric Analysis from 1995 to 2023. *World Electr. Veh. J.* **2023**, *14*, 300. [CrossRef]
40. Purwanto, E.; Irawan, A.P. Bibliometric Analysis of Electric Vehicle Adoption Research: Trends, Implications, and Future Directions. *Int. J. Saf. Secur. Eng.* **2023**, *13*, 789–800. [CrossRef]
41. Raboaca, M.S.; Bizon, N.; Grosu, O.V. Optimal Energy Management Strategies for the Electric Vehicles Compiling Bibliometric Maps. *Int. J. Energy Res.* **2021**, *45*, 10129–10172. [CrossRef]
42. Secinaro, S.; Brescia, V.; Calandra, D.; Biancone, P. Employing Bibliometric Analysis to Identify Suitable Business Models for Electric Cars. *J. Clean. Prod.* **2020**, *264*, 121503. [CrossRef]
43. Singh, G.; Misra, S.C.; Daultani, Y.; Singh, S. Electric Vehicle Adoption and Sustainability: Insights from the Bibliometric Analysis, Cluster Analysis, and Morphology Analysis. *Oper. Manag. Res.* **2024**, *17*, 635–659. [CrossRef]

44. Soares, L.O.; Reis, A.D.C.; Vieira, P.S.; Hernández-Callejo, L.; Boloy, R.A.M. Electric Vehicle Supply Chain Management: A Bibliometric and Systematic Review. *Energies* **2023**, *16*, 1563. [CrossRef]
45. Tambunan, H.B. Electric Vehicle Integration Into Electrical Power System: A Bibliometric Review. In Proceedings of the 2022 International Conference on Technology and Policy in Energy and Electric Power (ICT-PEP), Jakarta, Indonesia, 18 October 2022; pp. 65–70.
46. Yao, S.; Bian, Z.; Hasan, M.K.; Ding, R.; Li, S.; Wang, Y.; Song, S. A Bibliometric Review on Electric Vehicle (EV) Energy Efficiency and Emission Effect Research. *Environ. Sci. Pollut. Res.* **2023**, *30*, 95172–95196. [CrossRef] [PubMed]
47. WoS Web of Science. Available online: https://webofscience.clarivate.cn/wos/woscc/basic-search (accessed on 9 September 2023).
48. Bakır, M.; Özdemir, E.; Akan, Ş.; Atalık, Ö. A Bibliometric Analysis of Airport Service Quality. *J. Air Transp. Manag.* **2022**, *104*, 102273. [CrossRef]
49. Crețu, R.F.; Țuțui, D.; Banța, V.C.; Șerban, E.C.; Barna, L.E.L.; Crețu, R.C. The Effects of the Implementation of Artificial Intelligence-Based Technologies on the Skills Needed in the Automotive Industry—A Bibliometric Analysis. *Amfiteatru Economic* **2024**, *3*, 658–673. [CrossRef]
50. Domenteanu, A.; Delcea, C.; Florescu, M.-S.; Gherai, D.S.; Bugnar, N.; Cotfas, L.-A. United in Green: A Bibliometric Exploration of Renewable Energy Communities. *Electronics* **2024**, *13*, 3312. [CrossRef]
51. Sandu, A.; Cotfas, L.-A.; Stănescu, A.; Delcea, C. Guiding Urban Decision-Making: A Study on Recommender Systems in Smart Cities. *Electronics* **2024**, *13*, 2151. [CrossRef]
52. Delcea, C.; Oprea, S.-V.; Dima, A.M.; Domenteanu, A.; Bara, A.; Cotfas, L.-A. Energy Communities: Insights from Scientific Publications. *Oeconomia Copernic.* **2024**, *15*, 1101–1155. [CrossRef]
53. Tătaru, G.-C.; Domenteanu, A.; Delcea, C.; Florescu, M.S.; Orzan, M.; Cotfas, L.-A. Navigating the Disinformation Maze: A Bibliometric Analysis of Scholarly Efforts. *Information* **2024**, *15*, 742. [CrossRef]
54. Liu, F. Retrieval Strategy and Possible Explanations for the Abnormal Growth of Research Publications: Re-Evaluating a Bibliometric Analysis of Climate Change. *Scientometrics* **2023**, *128*, 853–859. [CrossRef] [PubMed]
55. Liu, W. The Data Source of This Study Is Web of Science Core Collection? Not Enough. *Scientometrics* **2019**, *121*, 1815–1824. [CrossRef]
56. Cobo, M.J.; López-Herrera, A.G.; Herrera-Viedma, E.; Herrera, F. Science Mapping Software Tools: Review, Analysis, and Cooperative Study among Tools. *J. Am. Soc. Inf. Sci. Technol.* **2011**, *62*, 1382–1402. [CrossRef]
57. Zupic, I.; Čater, T. Bibliometric Methods in Management and Organization. *Organ. Res. Methods* **2015**, *18*, 429–472. [CrossRef]
58. Valencia-Arias, A.; García-Pineda, V.; González-Ruiz, J.D.; Medina-Valderrama, C.J.; Bao García, R. Machine-Learning Applications in Energy Efficiency: A Bibliometric Approach and Research Agenda. *Designs* **2023**, *7*, 71. [CrossRef]
59. Sandu, A.; Cotfas, L.-A.; Delcea, C.; Ioanăș, C.; Florescu, M.-S.; Orzan, M. Machine Learning and Deep Learning Applications in Disinformation Detection: A Bibliometric Assessment. *Electronics* **2024**, *13*, 4352. [CrossRef]
60. Sandu, A.; Ioanăș, I.; Delcea, C.; Florescu, M.-S.; Cotfas, L.-A. Numbers Do Not Lie: A Bibliometric Examination of Machine Learning Techniques in Fake News Research. *Algorithms* **2024**, *17*, 70. [CrossRef]
61. Li, Y.; Xu, Z.; Wang, X.; Wang, X. A Bibliometric Analysis on Deep Learning during 2007–2019. *Int. J. Mach. Learn. Cybern.* **2020**, *11*, 2807–2826. [CrossRef]
62. Coulibaly, S.; Kamsu-Foguem, B.; Kamissoko, D.; Traore, D. Deep Learning for Precision Agriculture: A Bibliometric Analysis. *Intell. Syst. Appl.* **2022**, *16*, 200102. [CrossRef]
63. Miraftabzadeh, S.M.; Martino, A.D.; Longo, M.; Zaninelli, D. Deep Learning in Power Systems: A Bibliometric Analysis and Future Trends. *IEEE Access* **2024**, *12*, 163172–163196. [CrossRef]
64. Thangavel, P.; Chandra, B. Two Decades of M-Commerce Consumer Research: A Bibliometric Analysis Using R Biblioshiny. *Sustainability* **2023**, *15*, 11835. [CrossRef]
65. Document Types. Available online: https://webofscience.help.clarivate.com/en-us/Content/document-types.html (accessed on 7 September 2024).
66. Donner, P. Document Type Assignment Accuracy in the Journal Citation Index Data of Web of Science. *Scientometrics* **2017**, *113*, 219–236. [CrossRef]
67. Abafe, E.A.; Bahta, Y.T.; Jordaan, H. Exploring Biblioshiny for Historical Assessment of Global Research on Sustainable Use of Water in Agriculture. *Sustainability* **2022**, *14*, 10651. [CrossRef]
68. Thakuria, A.; Chakraborty, I.; Deka, D. A Bibliometric Review on Serendipity Literature Available in Web of Science Database Using HistCite and Biblioshiny. *Inf. Discov. Deliv.* **2024**, *52*, 227–242. [CrossRef]
69. ISI WOS KeyWords Plus Generation, Creation, and Changes. Available online: https://support.clarivate.com/ScientificandAcademicResearch/s/article/KeyWords-Plus-generation-creation-and-changes?language=en_US (accessed on 17 November 2024).

70. Sandu, A.; Cotfas, L.-A.; Delcea, C.; Crăciun, L.; Molănescu, A.G. Sentiment Analysis in the Age of COVID-19: A Bibliometric Perspective. *Information* **2023**, *14*, 659. [CrossRef]
71. Hirsch, J.E. An Index to Quantify an Individual's Scientific Research Output. *Proc. Natl. Acad. Sci. USA* **2005**, *102*, 16569–16572. [CrossRef] [PubMed]
72. Egghe, L. Theory and Practise of the G-Index. *Scientometrics* **2006**, *69*, 131–152. [CrossRef]
73. Yang, J.-M.; Tseng, S.-F.; Won, Y.-L. A Bibliometric Analysis on Data Mining Using Bradford's Law. In Proceedings of the 3rd International Conference on Intelligent Technologies and Engineering Systems (ICITES2014); Juang, J., Ed.; Springer International Publishing: Cham, Switzerland, 2016; pp. 613–620.
74. Newby, G.B.; Greenberg, J.; Jones, P. Open Source Software Development and Lotka's Law: Bibliometric Patterns in Programming. *J. Am. Soc. Inf. Sci. Technol.* **2003**, *54*, 169–178. [CrossRef]
75. Bibliometrix—Home. Available online: https://www.bibliometrix.org/home/ (accessed on 3 July 2024).
76. Aria, M.; Cuccurullo, C. Bibliometrix: An R-Tool for Comprehensive Science Mapping Analysis. *J. Informetr.* **2017**, *11*, 959–975. [CrossRef]
77. Murphey, Y.L.; Masrur, M.A.; Chen, Z.; Zhang, B. Model-Based Fault Diagnosis in Electric Drives Using Machine Learning. *IEEEASME Trans. Mechatron.* **2006**, *11*, 290–303. [CrossRef]
78. Huang, X.; Tan, Y.; He, X. An Intelligent Multifeature Statistical Approach for the Discrimination of Driving Conditions of a Hybrid Electric Vehicle. *IEEE Trans. Intell. Transp. Syst.* **2011**, *12*, 453–465. [CrossRef]
79. Murphey, Y.L.; Park, J.; Chen, Z.; Kuang, M.L.; Masrur, M.A.; Phillips, A.M. Intelligent Hybrid Vehicle Power Control—Part I: Machine Learning of Optimal Vehicle Power. *IEEE Trans. Veh. Technol.* **2012**, *61*, 3519–3530. [CrossRef]
80. ISI WOS Journal Citation Reports for Researchers | Clarivate. Available online: https://clarivate.com/academia-government/scientific-and-academic-research/research-funding-analytics/journal-citation-reports/researchers/ (accessed on 2 January 2025).
81. WoS Research Team. Difference between JIF and JCI?—WoS Journals—All Information You Need to Know. Available online: https://wos-journal.info/blog/difference-between-jif-and-jci/ (accessed on 8 January 2025).
82. Chemali, E.; Kollmeyer, P.J.; Preindl, M.; Ahmed, R.; Emadi, A. Long Short-Term Memory Networks for Accurate State-of-Charge Estimation of Li-Ion Batteries. *IEEE Trans. Ind. Electron.* **2018**, *65*, 6730–6739. [CrossRef]
83. Chemali, E.; Kollmeyer, P.J.; Preindl, M.; Emadi, A. State-of-Charge Estimation of Li-Ion Batteries Using Deep Neural Networks: A Machine Learning Approach. *J. Power Sources* **2018**, *400*, 242–255. [CrossRef]
84. Hu, X.; Jiang, J.; Cao, D.; Egardt, B. Battery Health Prognosis for Electric Vehicles Using Sample Entropy and Sparse Bayesian Predictive Modeling. *IEEE Trans. Ind. Electron.* **2016**, *63*, 2645–2656. [CrossRef]
85. Liu, K.; Shang, Y.; Ouyang, Q.; Widanage, W.D. A Data-Driven Approach With Uncertainty Quantification for Predicting Future Capacities and Remaining Useful Life of Lithium-Ion Battery. *IEEE Trans. Ind. Electron.* **2021**, *68*, 3170–3180. [CrossRef]
86. Patil, M.A.; Tagade, P.; Hariharan, K.S.; Kolake, S.M.; Song, T.; Yeo, T.; Doo, S. A Novel Multistage Support Vector Machine Based Approach for Li Ion Battery Remaining Useful Life Estimation. *Appl. Energy* **2015**, *159*, 285–297. [CrossRef]
87. Zhang, Y.; Tang, Q.; Zhang, Y.; Wang, J.; Stimming, U.; Lee, A.A. Identifying Degradation Patterns of Lithium Ion Batteries from Impedance Spectroscopy Using Machine Learning. *Nat. Commun.* **2020**, *11*, 1706. [CrossRef] [PubMed]
88. Feng, X.; Weng, C.; He, X.; Han, X.; Lu, L.; Ren, D.; Ouyang, M. Online State-of-Health Estimation for Li-Ion Battery Using Partial Charging Segment Based on Support Vector Machine. *IEEE Trans. Veh. Technol.* **2019**, *68*, 8583–8592. [CrossRef]
89. Hu, X.; Li, S.E.; Yang, Y. Advanced Machine Learning Approach for Lithium-Ion Battery State Estimation in Electric Vehicles. *IEEE Trans. Transp. Electrif.* **2016**, *2*, 140–149. [CrossRef]
90. Roman, D.; Saxena, S.; Robu, V.; Pecht, M.; Flynn, D. Machine Learning Pipeline for Battery State-of-Health Estimation. *Nat. Mach. Intell.* **2021**, *3*, 447–456. [CrossRef]
91. Hong, J.; Wang, Z.; Chen, W.; Wang, L.; Lin, P.; Qu, C. Online Accurate State of Health Estimation for Battery Systems on Real-World Electric Vehicles with Variable Driving Conditions Considered. *J. Clean. Prod.* **2021**, *294*, 125814. [CrossRef]
92. Wang, Q.; Wang, Z.; Liu, P.; Zhang, L.; Sauer, D.U.; Li, W. Large-Scale Field Data-Based Battery Aging Prediction Driven by Statistical Features and Machine Learning. *Cell Rep. Phys. Sci.* **2023**, *4*, 101720. [CrossRef]
93. Zhao, Y.; Liu, P.; Wang, Z.; Zhang, L.; Hong, J. Fault and Defect Diagnosis of Battery for Electric Vehicles Based on Big Data Analysis Methods. *Appl. Energy* **2017**, *207*, 354–362. [CrossRef]
94. Wang, Z.; Song, C.; Zhang, L.; Zhao, Y.; Liu, P.; Dorrell, D.G. A Data-Driven Method for Battery Charging Capacity Abnormality Diagnosis in Electric Vehicle Applications. *IEEE Trans. Transp. Electrif.* **2022**, *8*, 990–999. [CrossRef]
95. Hong, J.; Wang, Z.; Chen, W.; Wang, L.-Y.; Qu, C. Online Joint-Prediction of Multi-Forward-Step Battery SOC Using LSTM Neural Networks and Multiple Linear Regression for Real-World Electric Vehicles. *J. Energy Storage* **2020**, *30*, 101459. [CrossRef]
96. Li, D.; Liu, P.; Zhang, Z.; Zhang, L.; Deng, J.; Wang, Z.; Dorrell, D.G.; Li, W.; Sauer, D.U. Battery Thermal Runaway Fault Prognosis in Electric Vehicles Based on Abnormal Heat Generation and Deep Learning Algorithms. *IEEE Trans. Power Electron.* **2022**, *37*, 8513–8525. [CrossRef]

97. Zhang, J.; Wang, Z.; Liu, P.; Zhang, Z. Energy Consumption Analysis and Prediction of Electric Vehicles Based on Real-World Driving Data. *Appl. Energy* **2020**, *275*, 115408. [CrossRef]
98. She, C.; Li, Y.; Zou, C.; Wik, T.; Wang, Z.; Sun, F. Offline and Online Blended Machine Learning for Lithium-Ion Battery Health State Estimation. *IEEE Trans. Transp. Electrif.* **2022**, *8*, 1604–1618. [CrossRef]
99. Zhao, D.; Wang, H.; Liu, Z. Charging-Related State Prediction for Electric Vehicles Using the Deep Learning Model. *J. Adv. Transp.* **2022**, *2022*, 4372168. [CrossRef]
100. Liu, K.; Ashwin, T.R.; Hu, X.; Lucu, M.; Widanage, W.D. An Evaluation Study of Different Modelling Techniques for Calendar Ageing Prediction of Lithium-Ion Batteries. *Renew. Sustain. Energy Rev.* **2020**, *131*, 110017. [CrossRef]
101. Tang, X.; Liu, K.; Li, K.; Widanage, W.D.; Kendrick, E.; Gao, F. Recovering Large-Scale Battery Aging Dataset with Machine Learning. *Patterns* **2021**, *2*, 100302. [CrossRef]
102. Ahmadian, A.; Ponnambalam, K.; Almansoori, A.; Elkamel, A. Optimal Management of a Virtual Power Plant Consisting of Renewable Energy Resources and Electric Vehicles Using Mixed-Integer Linear Programming and Deep Learning. *Energies* **2023**, *16*, 1000. [CrossRef]
103. Jahangir, H.; Gougheri, S.S.; Vatandoust, B.; Golkar, M.A.; Ahmadian, A.; Hajizadeh, A. Plug-in Electric Vehicle Behavior Modeling in Energy Market: A Novel Deep Learning-Based Approach With Clustering Technique. *IEEE Trans. Smart Grid* **2020**, *11*, 4738–4748. [CrossRef]
104. Jahangir, H.; Gougheri, S.S.; Vatandoust, B.; Golkar, M.A.; Golkar, M.A.; Ahmadian, A.; Hajizadeh, A. A Novel Cross-Case Electric Vehicle Demand Modeling Based on 3D Convolutional Generative Adversarial Networks. *IEEE Trans. Power Syst.* **2022**, *37*, 1173–1183. [CrossRef]
105. Gao, Y.; Yang, S.; Wang, X.; Li, W.; Hou, Q.; Cheng, Q. Cyber Hierarchy Multiscale Integrated Energy Management of Intelligent Hybrid Electric Vehicles. *Automot. Innov.* **2022**, *5*, 438–452. [CrossRef]
106. Zhang, Y.; Chen, Z.; Li, G.; Liu, Y.; Chen, H.; Cunningham, G.; Early, J. Machine Learning-Based Vehicle Model Construction and Validation—Toward Optimal Control Strategy Development for Plug-In Hybrid Electric Vehicles. *IEEE Trans. Transp. Electrif.* **2022**, *8*, 1590–1603. [CrossRef]
107. Liu, Y.; Li, J.; Gao, J.; Lei, Z.; Zhang, Y.; Chen, Z. Prediction of Vehicle Driving Conditions with Incorporation of Stochastic Forecasting and Machine Learning and a Case Study in Energy Management of Plug-in Hybrid Electric Vehicles. *Mech. Syst. Signal Process.* **2021**, *158*, 107765. [CrossRef]
108. Zhao, J.; Ling, H.; Wang, J.; Burke, A.F.; Lian, Y. Data-Driven Prediction of Battery Failure for Electric Vehicles. *iScience* **2022**, *25*, 104172. [CrossRef] [PubMed]
109. Zhao, J.; Ling, H.; Liu, J.; Wang, J.; Burke, A.F.; Lian, Y. Machine Learning for Predicting Battery Capacity for Electric Vehicles. *eTransportation* **2023**, *15*, 100214. [CrossRef]
110. Shi, D.; Zhao, J.; Wang, Z.; Zhao, H.; Wang, J.; Lian, Y.; Burke, A.F. Spatial-Temporal Self-Attention Transformer Networks for Battery State of Charge Estimation. *Electronics* **2023**, *12*, 2598. [CrossRef]
111. Shi, D.; Zhao, J.; Wang, Z.; Zhao, H.; Eze, C.; Wang, J.; Lian, Y.; Burke, A.F. Cloud-Based Deep Learning for Co-Estimation of Battery State of Charge and State of Health. *Energies* **2023**, *16*, 3855. [CrossRef]
112. Ullah, I.; Liu, K.; Yamamoto, T.; Al Mamlook, R.E.; Jamal, A. A Comparative Performance of Machine Learning Algorithm to Predict Electric Vehicles Energy Consumption: A Path towards Sustainability. *Energy Environ.* **2022**, *33*, 1583–1612. [CrossRef]
113. Ullah, I.; Liu, K.; Yamamoto, T.; Shafiullah, M.; Jamal, A. Grey Wolf Optimizer-Based Machine Learning Algorithm to Predict Electric Vehicle Charging Duration Time. *Transp. Lett.* **2023**, *15*, 889–906. [CrossRef]
114. Ullah, I.; Liu, K.; Yamamoto, T.; Zahid, M.; Jamal, A. Prediction of Electric Vehicle Charging Duration Time Using Ensemble Machine Learning Algorithm and Shapley Additive Explanations. *Int. J. Energy Res.* **2022**, *46*, 15211–15230. [CrossRef]
115. Wilczewski, M.; Alon, I. Language and Communication in International Students' Adaptation: A Bibliometric and Content Analysis Review. *High. Educ.* **2023**, *85*, 1235–1256. [CrossRef] [PubMed]
116. Shern, S.J.; Sarker, M.T.; Ramasamy, G.; Thiagarajah, S.P.; Al Farid, F.; Suganthi, S.T. Artificial Intelligence-Based Electric Vehicle Smart Charging System in Malaysia. *World Electr. Veh. J.* **2024**, *15*, 440. [CrossRef]
117. Ullah, I.; Safdar, M.; Zheng, J.; Severino, A.; Jamal, A. Employing Bibliometric Analysis to Identify the Current State of the Art and Future Prospects of Electric Vehicles. *Energies* **2023**, *16*, 2344. [CrossRef]
118. Li, A.G.; Wang, W.; West, A.C.; Preindl, M. Health and Performance Diagnostics in Li-Ion Batteries with Pulse-Injection-Aided Machine Learning. *Appl. Energy* **2022**, *315*, 119005. [CrossRef]
119. Wongchai, A.; Aoudni, Y.; Yesubabu, M.; Ahmad Reegu, F.; Vasantha Gowri, N.; Vijayakumar, P. Sustainable Electric Vehicles Fault Detection Based on Monitoring by Deep Learning Architectures in Feature Extraction and Classification. *Sustain. Energy Technol. Assess.* **2023**, *57*, 103178. [CrossRef]
120. Rohkohl, E.; Schönemann, M.; Bodrov, Y.; Herrmann, C. Multi-Criteria and Real-Time Control of Continuous Battery Cell Production Steps Using Deep Learning. *Adv. Ind. Manuf. Eng.* **2023**, *6*, 100108. [CrossRef]

121. Liu, H.; Ke, F.; Zhang, Z.; Gao, Y.; Zhang, Q. Fault Tolerance in Electric Vehicles Using Deep Learning for Intelligent Transportation Systems. *Mob. Netw. Appl.* **2023**, *28*, 2109–2117. [CrossRef]
122. Li, J.; Liu, B.; Duan, L.; Bao, J. An Augmented Reality-Assisted Disassembly Approach for End-of-Life Vehicle Power Batteries. *Machines* **2023**, *11*, 1041. [CrossRef]
123. Meng, K.; Xu, G.; Peng, X.; Youcef-Toumi, K.; Li, J. Intelligent Disassembly of Electric-Vehicle Batteries: A Forward-Looking Overview. *Resour. Conserv. Recycl.* **2022**, *182*, 106207. [CrossRef]
124. Frendo, O.; Graf, J.; Gaertner, N.; Stuckenschmidt, H. Data-Driven Smart Charging for Heterogeneous Electric Vehicle Fleets. *Energy AI* **2020**, *1*, 100007. [CrossRef]
125. Yoon, G.; Kim, S.; Shin, H.; Cho, K.; Jang, H.; Lee, T.; Choi, M.; Kang, B.; Park, S.; Lee, S.; et al. Carbon-Neutral ESG Method Based on PV Energy Generation Prediction Model in Buildings for EV Charging Platform. *Buildings* **2023**, *13*, 2098. [CrossRef]
126. Golsefidi, A.H.; Hüttel, F.B.; Peled, I.; Samaranayake, S.; Pereira, F.C. A Joint Machine Learning and Optimization Approach for Incremental Expansion of Electric Vehicle Charging Infrastructure. *Transp. Res. Part Policy Pract.* **2023**, *178*, 103863. [CrossRef]
127. Li, X.; He, Y.; Guo, L.; Yang, G. Multi-Year Planning for the Integration Combining Distributed Energy System and Electric Vehicle in Neighborhood Based on Data-Driven Model. *Int. J. Electr. Power Energy Syst.* **2022**, *140*, 108079. [CrossRef]
128. Hong, T.; Cao, J.; Fang, C.; Li, D. 6G Based Intelligent Charging Management for Autonomous Electric Vehicles. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 7574–7585. [CrossRef]
129. Jia, J.; Shi, B.; Che, F.; Zhang, H. Predicting the Regional Adoption of Electric Vehicle (EV) With Comprehensive Models. *IEEE Access* **2020**, *8*, 147275–147285. [CrossRef]
130. Jena, R. An Empirical Case Study on Indian Consumers' Sentiment towards Electric Vehicles: A Big Data Analytics Approach. *Ind. Mark. Manag.* **2020**, *90*, 605–616. [CrossRef]
131. Zarazua de Rubens, G. Who Will Buy Electric Vehicles after Early Adopters? Using Machine Learning to Identify the Electric Vehicle Mainstream Market. *Energy* **2019**, *172*, 243–254. [CrossRef]
132. Bas, J.; Cirillo, C.; Cherchi, E. Classification of Potential Electric Vehicle Purchasers: A Machine Learning Approach. *Technol. Forecast. Soc. Change* **2021**, *168*, 120759. [CrossRef]
133. Bas Vicente, J.; Zou, Z.; Cirillo, C. An Interpretable Machine Learning Approach to Understanding the Impacts of Attitudinal and Ridesourcing Factors on Electric Vehicle Adoption. *Transp. Lett.* **2021**, *15*, 30–41. [CrossRef]
134. Yeh, J.-Y.; Wang, Y.-T. A Prediction Model for Electric Vehicle Sales Using Machine Learning Approaches. *J. Glob. Inf. Manag.* **2023**, *31*, 1–21. [CrossRef]
135. Shafee, A.A.; Fouda, M.M.; Mahmoud, M.M.E.A.; Aljohani, A.J.; Alasmary, W.; Amsaad, F. Detection of Lying Electrical Vehicles in Charging Coordination Using Deep Learning. *IEEE Access* **2020**, *8*, 179400–179414. [CrossRef]
136. Alomrani, M.A.; Tushar, M.H.K.; Kundur, D. Detecting State of Charge False Reporting Attacks via Reinforcement Learning Approach. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 10467–10476. [CrossRef]
137. Acharya, S.; Mieth, R.; Karri, R.; Dvorkin, Y. False Data Injection Attacks on Data Markets for Electric Vehicle Charging Stations. *Adv. Appl. Energy* **2022**, *7*, 100098. [CrossRef]
138. Said, D.; Elloumi, M.; Khoukhi, L. Cyber-Attack on P2P Energy Transaction Between Connected Electric Vehicles: A False Data Injection Detection Based Machine Learning Model. *IEEE Access* **2022**, *10*, 63640–63647. [CrossRef]
139. Cui, H.; Dong, X.; Deng, H.; Dehghani, M.; Alsubhi, K.; Aljahdali, H.M.A. Cyber Attack Detection Process in Sensor of DC Micro-Grids Under Electric Vehicle Based on Hilbert–Huang Transform and Deep Learning. *IEEE Sens. J.* **2021**, *21*, 15885–15894. [CrossRef]
140. ElKashlan, M.; Elsayed, M.S.; Jurcut, A.D.; Azer, M. A Machine Learning-Based Intrusion Detection System for IoT Electric Vehicle Charging Stations (EVCSs). *Electronics* **2023**, *12*, 1044. [CrossRef]
141. Naresh, V.S.; Ratnakara Rao, G.V.N.S.R.; Prabhakar, D.V.N. Predictive Machine Learning in Optimizing the Performance of Electric Vehicle Batteries: Techniques, Challenges, and Solutions. *WIREs Data Min. Knowl. Discov.* **2024**, *14*, e1539. [CrossRef]
142. Arévalo, P.; Ochoa-Correa, D.; Villa-Ávila, E. A Systematic Review on the Integration of Artificial Intelligence into Energy Management Systems for Electric Vehicles: Recent Advances and Future Perspectives. *World Electr. Veh. J.* **2024**, *15*, 364. [CrossRef]
143. Chougule, S.B.; Chaudhari, B.S.; Ghorpade, S.N.; Zennaro, M. Exploring Computing Paradigms for Electric Vehicles: From Cloud to Edge Intelligence, Challenges and Future Directions. *World Electr. Veh. J.* **2024**, *15*, 39. [CrossRef]
144. Huang, R.; He, H. A Novel Data-Driven Energy Management Strategy for Fuel Cell Hybrid Electric Bus Based on Improved Twin Delayed Deep Deterministic Policy Gradient Algorithm. *Int. J. Hydrogen Energy* **2024**, *52*, 782–798. [CrossRef]
145. Teimoori, Z.; Yassine, A.; Lu, C. Deep Transfer Learning for Detecting Electric Vehicles Highly Correlated Energy Consumption Parameters. *IEEE Trans. Artif. Intell.* **2024**, *5*, 4087–4100. [CrossRef]
146. Macharia, V.M.; Garg, V.K.; Kumar, D. A Review of Electric Vehicle Technology: Architectures, Battery Technology and Its Management System, Relevant Standards, Application of Artificial Intelligence, Cyber Security, and Interoperability Challenges. *IET Electr. Syst. Transp.* **2023**, *13*, e12083. [CrossRef]

147. Kanz Abdillah, H.; Wildan Rizkia, N.A.H.; Sidharta, S. Exploring the Role of Artificial Intelligence in Enhancing Battery Performance and Mitigating Cybersecurity Threats in Electric Vehicles: A Systematic Literature Review. *Procedia Comput. Sci.* **2024**, *245*, 155–165. [CrossRef]
148. Rehan, H. The Future of Electric Vehicles: Navigating the Intersection of AI, Cloud Technology, and Cybersecurity. *Val. Int. J. Digit. Libr.* **2024**, *12*, 1127–1143. [CrossRef]
149. Ojha, N.K.; Pandita, A.; Vaish, A. Chapter 12—Cyber-Security Challenges for Artificial Intelligence-Empowered Electric Vehicles—Analysis and Current Status. In *Artificial Intelligence-Empowered Modern Electric Vehicles in Smart Grid Systems*; Kumari, A., Tanwar, S., Eds.; Elsevier: Amsterdam, The Netherlands, 2024; pp. 317–346. ISBN 978-0-443-23814-7.
150. Ofer, D.; Kaufman, H.; Linial, M. What's next? Forecasting Scientific Research Trends. *Heliyon* **2024**, *10*, e23781. [CrossRef] [PubMed]
151. Vincent-Lancrin, S. What Is Changing in Academic Research? Trends and Futures Scenarios. *Eur. J. Educ.* **2006**, *41*, 169–202. [CrossRef]
152. Delcea, C.; Domenteanu, A.; Ioanăș, C.; Vargas, V.M.; Ciucu-Durnoi, A.N. Quantifying Neutrosophic Research: A Bibliometric Study. *Axioms* **2023**, *12*, 1083. [CrossRef]
153. Tay, A. Using VOSviewer as a Bibliometric Mapping or Analysis Tool in Business, Management & Accounting. Available online: https://library.smu.edu.sg/topics-insights/using-vosviewer-bibliometric-mapping-or-analysis-tool-business-management (accessed on 22 November 2023).
154. Li, H.; Cong, L.; Ma, H.; Liu, W.; Deng, Y.; Kong, S. Screening of Retired Lithium-Ion Batteries Using Incremental Capacity Charging Curve-Based Residual Capacity Estimation Method for Facilitating Sustainable Circular Lithium-Ion Battery System. *J. Manuf. Sci. Eng.* **2021**, *144*, 021003. [CrossRef]
155. Ghosh, N.; Garg, A.; Li, W.; Gao, L.; Nguyen-Thoi, T. Engineering Design of Battery Module for Electric Vehicles: Comprehensive Framework Development Based on Density Functional Theory, Topology Optimization, Machine Learning, Multidisciplinary Design Optimization, and Digital Twins. *J. Electrochem. Energy Convers. Storage* **2021**, *19*, 030902. [CrossRef]
156. Fei, Z.; Zhang, Z.; Yang, F.; Tsui, K.-L. Deep Learning Powered Rapid Lifetime Classification of Lithium-Ion Batteries. *eTransportation* **2023**, *18*, 100286. [CrossRef]
157. Shahriar, S.; Al-Ali, A.R.; Osman, A.H.; Dhou, S.; Nijim, M. Prediction of EV Charging Behavior Using Machine Learning. *IEEE Access* **2021**, *9*, 111576–111586. [CrossRef]
158. Ghafoori, M.; Abdallah, M.; Kim, S. Electricity Peak Shaving for Commercial Buildings Using Machine Learning and Vehicle to Building (V2B) System. *Appl. Energy* **2023**, *340*, 121052. [CrossRef]
159. Zhou, H.; Zhou, Y.; Hu, J.; Yang, G.; Xie, D.; Xue, Y.; Nordstrom, L. LSTM-Based Energy Management for Electric Vehicle Charging in Commercial-Building Prosumers. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 1205–1216. [CrossRef]
160. Steens, T.; Telle, J.-S.; Hanke, B.; von Maydell, K.; Agert, C.; Di Modica, G.-L.; Engel, B.; Grottke, M. A Forecast-Based Load Management Approach for Commercial Buildings Demonstrated on an Integration of BEV. *Energies* **2021**, *14*, 3576. [CrossRef]
161. Thamizhazhagan, P.; Sujatha, M.; Umadevi, S.; Priyadarshini, K.; Subbiah Parvathy, V.; Pustokhina, I.V.; Pustokhin, D.A. AI Based Traffic Flow Prediction Model for Connected and Autonomous Electric Vehicles. *Comput. Mater. Contin.* **2022**, *70*, 3333–3347. [CrossRef]
162. Huang, C.-J.; Hu, K.-W.; Ho, H.-Y.; Chuang, H.-W. Congestion-Preventing Routing and Charging Scheduling Mechanism for Electric Vehicles in Dense Urban Areas. *Inf. Technol. Control* **2021**, *50*, 284–307. [CrossRef]
163. Qu, X.; Yu, Y.; Zhou, M.; Lin, C.-T.; Wang, X. Jointly Dampening Traffic Oscillations and Improving Energy Consumption with Electric, Connected and Automated Vehicles: A Reinforcement Learning Based Approach. *Appl. Energy* **2020**, *257*, 114030. [CrossRef]
164. Straka, M.; De Falco, P.; Ferruzzi, G.; Proto, D.; Van Der Poel, G.; Khormali, S.; Buzna, L. Predicting Popularity of Electric Vehicle Charging Infrastructure in Urban Context. *IEEE Access* **2020**, *8*, 11315–11327. [CrossRef]
165. Li, Y.; Chai, S.; Zhang, X.; Wang, G.; Zhu, R.; Chung, E. STPNet: Quantifying the Uncertainty of Electric Vehicle Charging Demand via Long-Term Spatiotemporal Traffic Flow Prediction Intervals. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 15018–15034. [CrossRef]
166. Dixit, P.; Bhattacharya, P.; Tanwar, S.; Gupta, R. Anomaly Detection in Autonomous Electric Vehicles Using AI Techniques: A Comprehensive Survey. *Expert Syst.* **2022**, *39*, e12754. [CrossRef]
167. Gharibi, M.A.; Nafisi, H.; Askarian-abyaneh, H.; Hajizadeh, A. Deep Learning Framework for Day-Ahead Optimal Charging Scheduling of Electric Vehicles in Parking Lot. *Appl. Energy* **2023**, *349*, 121614. [CrossRef]
168. Kröger, T.; Belnarsch, A.; Bilfinger, P.; Ratzke, W.; Lienkamp, M. Collaborative Training of Deep Neural Networks for the Lithium-Ion Battery Aging Prediction with Federated Learning. *eTransportation* **2023**, *18*, 100294. [CrossRef]
169. Chu, Y.; Wei, Z.; Fang, X.; Chen, S.; Zhou, Y. A Multiagent Federated Reinforcement Learning Approach for Plug-In Electric Vehicle Fleet Charging Coordination in a Residential Community. *IEEE Access* **2022**, *10*, 98535–98548. [CrossRef]
170. Xu, Q.; Zhang, L.; Ou, D.; Yu, W. Secure Intrusion Detection by Differentially Private Federated Learning for Inter-Vehicle Networks. *Transp. Res. Rec. J. Transp. Res. Board* **2023**, *2677*, 421–437. [CrossRef]

171. Algarni, A.M.; Thayananthan, V. Autonomous Vehicles With a 6G-Based Intelligent Cybersecurity Model. *IEEE Access* **2023**, *11*, 15284–15296. [CrossRef]
172. Dong, J.; Yassine, A.; Armitage, A.; Hossain, M.S. Multi-Agent Reinforcement Learning for Intelligent V2G Integration in Future Transportation Systems. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 15974–15983. [CrossRef]