batteries

Review

Electric Vehicle Battery Technologies and Capacity Prediction: A Comprehensive Literature Review of Trends and Influencing Factors

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Abstract: Electric vehicle (EV) battery technology is at the forefront of the shift towards sustainable transportation. However, maximising the environmental and economic benefits of electric vehicles depends on advances in battery life cycle management. This comprehensive review analyses trends, techniques, and challenges across EV battery development, capacity prediction, and recycling, drawing on a dataset of over 22,000 articles from four major databases. Using Dynamic Topic Modelling (DTM), this study identifies key innovations and evolving research themes in battery-related technologies, capacity degradation factors, and recycling methods. The literature is structured into two primary themes: (1) "Electric Vehicle Battery Technologies, Development & Trends" and (2) "Capacity Prediction and Influencing Factors". DTM revealed pivotal findings: advancements in lithium-ion and solid-state batteries for higher energy density, improvements in recycling technologies to reduce environmental impact, and the efficacy of machine learning-based models for real-time capacity prediction. Gaps persist in scaling sustainable recycling methods, developing cost-effective manufacturing processes, and creating standards for life cycle impact assessment. Future directions emphasise multidisciplinary research on new battery chemistries, efficient end-of-life management, and policy frameworks that support circular economy practices. This review serves as a resource for stakeholders to address the critical technological and regulatory challenges that will shape the sustainable future of electric vehicles.

Keywords: electric vehicle battery; dynamic topic modelling; literature review

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1. Introduction

Electric vehicles (EVs) present a critical pathway to reducing the environmental impacts associated with internal combustion engine (ICE) vehicles, which are substantial contributors to global greenhouse gas (GHG) emissions and urban air pollution. In 2020, transportation alone accounted for 36% of total CO_2 emissions in the United States according to the U.S. Energy Information Administration, highlighting the need for electric mobility to meet climate targets and improve urban air quality. While EVs offer solutions by eliminating tailpipe emissions, their long-term sustainability is closely tied to the life cycle management of lithium-ion batteries, which are resource-intensive to produce and require scarce materials like lithium, cobalt, and nickel. The extraction and processing of these materials bring significant environmental and social challenges, from water depletion and habitat destruction to labour issues, with projections indicating that lithium supply may only meet half of the anticipated demand by 2030. Governments worldwide have enacted regulations and incentives, and major automakers have pledged to phase out ICE vehicles, accelerating EV adoption at a 54% compound annual growth rate from 2015 to 2020; these data are from the U.S. Energy Information. Yet, scaling sustainable battery technology remains challenging as batteries degrade over time, losing capacity and efficiency due to factors like high charging rates and temperature extremes. High charging rates can accelerate the degradation of lithium-ion batteries by inducing stress on electrode materials, leading to increased internal resistance and capacity loss. Similarly, exposure to extreme temperatures affects electrochemical reactions within the battery; high temperatures can enhance side reactions and accelerate ageing, while low temperatures reduce ionic conductivity, impairing performance. This degradation not only diminishes EV performance, manifesting as reduced driving range and power output, but also complicates recycling due to the variable state of health (SOH) of spent batteries.

To address these challenges, advanced thermal management systems—such as liquid cooling, phase-change materials, and air cooling—have been developed to maintain optimal battery temperatures. Smart charging strategies, including controlled rates and adaptive algorithms, help reduce stress during charging cycles. Innovations in materials and chemistries, such as solid-state batteries and stable electrode designs, further enhance tolerance to high charging rates and temperature fluctuations. While these measures improve battery life and EV performance, persistent degradation highlights the need for efficient recycling and secondary-use applications to mitigate environmental impacts. Sustainable battery management is critical to realising the environmental benefits of EVs.

This literature review aims to map the evolution of EV battery-related technologies and provide valuable insights for a wide range of stakeholders. While previous studies have examined the technical and environmental aspects of EV battery technology, such as the comparative benefits over ICE vehicles, recycling challenges, and battery degradation methods, much of the existing literature remains fragmented. Ref. [1] indicates that EVs provide substantial emissions savings, yet these benefits are heavily dependent on factors like production emissions, energy grid composition, and recycling practices. However, critical gaps remain in understanding how advancements in battery health prediction, recycling techniques, and life cycle optimisation can be integrated into a comprehensive, sustainable framework. This review bridges these gaps by connecting technological developments with practical, scalable solutions, contributing to a more holistic sustainability strategy for EV batteries.

To structure the exploration of these complex issues, this review divides into two primary themes: (1) “Electric Vehicle Battery Technologies, Development & Trends” and (2) “Capacity Prediction and Influencing Factors”. The first theme focuses on advancements in battery materials, improvements in energy density, and the development of sustainable recycling technologies, all of which are pivotal for the continued progress and scaling of EV battery technology. The second theme addresses techniques for predicting battery capacity and degradation over time, with an emphasis on data-driven methods like machine learning models that improve real-time monitoring and optimise battery management. This structured thematic approach aligns with the evolving research landscape and facilitates a comprehensive understanding of battery technology and its role in EV sustainability.

This integrated approach naturally leads to the three primary research questions driving this study: (1) What is the trend of battery-related technologies? (2) In line with technology development, what are the techniques used in predicting the remaining capacity of spent batteries? (3) What are the important elements that affect the remaining capacity? By addressing these questions, this study seeks to deepen our understanding of EV battery technology’s role in sustainability, providing a foundation for innovative solutions that support the global transition to a low-carbon economy.

In the context of EV battery systems, individual battery cells are typically assembled into modules and then integrated into packs to meet the power and energy requirements of the vehicle. The design and management of these battery modules and packs are crucial for ensuring safety, reliability, and performance. Innovations in battery module and pack technology, such as thermal management, structural integrity, and intelligent control systems, play a significant role in advancing EV technology. Therefore, understanding developments in battery modules and packs is essential for comprehensively addressing the challenges and opportunities in EV battery technology.

The objectives of this study are threefold: First, to identify and analyse technological trends driving advancements in EV batteries, particularly focusing on new materials, design improvements, and manufacturing processes that enhance battery energy density, safety, and sustainability. Second, to evaluate the effectiveness of existing capacity prediction methodologies—such as machine learning models, Electrochemical Impedance Spectroscopy, and data-driven approaches—and propose refinements that could improve their accuracy and applicability in real-world scenarios. Third, to explore how technological innovations in battery recycling and secondary use applications can be effectively implemented to optimise battery life cycle management, thus contributing to a circular economy.

To achieve the research objectives, this study utilises Dynamic Topic Modelling to capture technological trends in battery development, drawing on data from scientific publications to identify key innovations and emerging research clusters. DTM enables both the analysis of methodologies for predicting battery capacity and the identification of factors influencing battery performance over time. This approach provides a comprehensive view of macro-level trends in battery technology and micro-level insights into technical aspects affecting battery health and sustainability. By integrating these analyses, the study seeks to bridge the gap between theoretical research and practical applications, offering a holistic perspective on EV battery life cycle management.

The remainder of this paper is organised as follows. Section 2 provides a descriptive analysis of the reviewed dataset, outlining the research design and detailing the proposed methodological framework and the implementation process of DTM analysis. In Section 3, we dive into the results and conduct an in-depth review of the research themes and topics from those results. Based on the findings in Section 3, we continue to expand those findings with discussion, gaps, and future direction in Section 4. Section 5 concludes the work.

2. Materials and Methods

2.1. Methodology Framework

This section presents a refined methodology framework for conducting a systematic literature review in Figure 1. The framework consists of seven key steps: (1) establishing the research background to provide context and direction for the study, (2) defining precise search terms and collecting relevant data using advanced search functions in Scopus, Science Direct, EBSCOhost, and Web of Science, ensuring comprehensive coverage of peer-reviewed literature, (3) data cleaning and data preparation, (4) a descriptive analysis is presented to offer key insights and an overview of the subject area, (5) the feature reduction for selecting the most relevant terms in the text data, aiding in clearer and more efficient data analysis, (6) a DTM analysis is used to analyse and track how topics evolve over time within a collection of documents, and (7) we synthesise findings in the discussion, identifying gaps, and providing future research directions. This structured framework ensures a thorough exploration of the research landscape, leading to meaningful insights and recommendations.

2.2. Material Collection and Data Cleaning

The aim of this research is to explore trends in EV battery technologies, capacity prediction methods, and influencing factors throughout the battery life cycle. Therefore, two groups of keywords representing different aspects of the research were developed to effectively capture the relevant literature:

- Battery technology keyword group: “electric vehicle”, “battery”, “EV”, “technology”, “development”, “innovation”, “trend”.
- Battery capacity and influencing factors keyword group: “second-Life”, “battery life cycle”, “remaining useful life”, “life cycle assessment”, “recycling”, “degradation”, “predict”, “reuse”, “impact factor”, “battery health”.

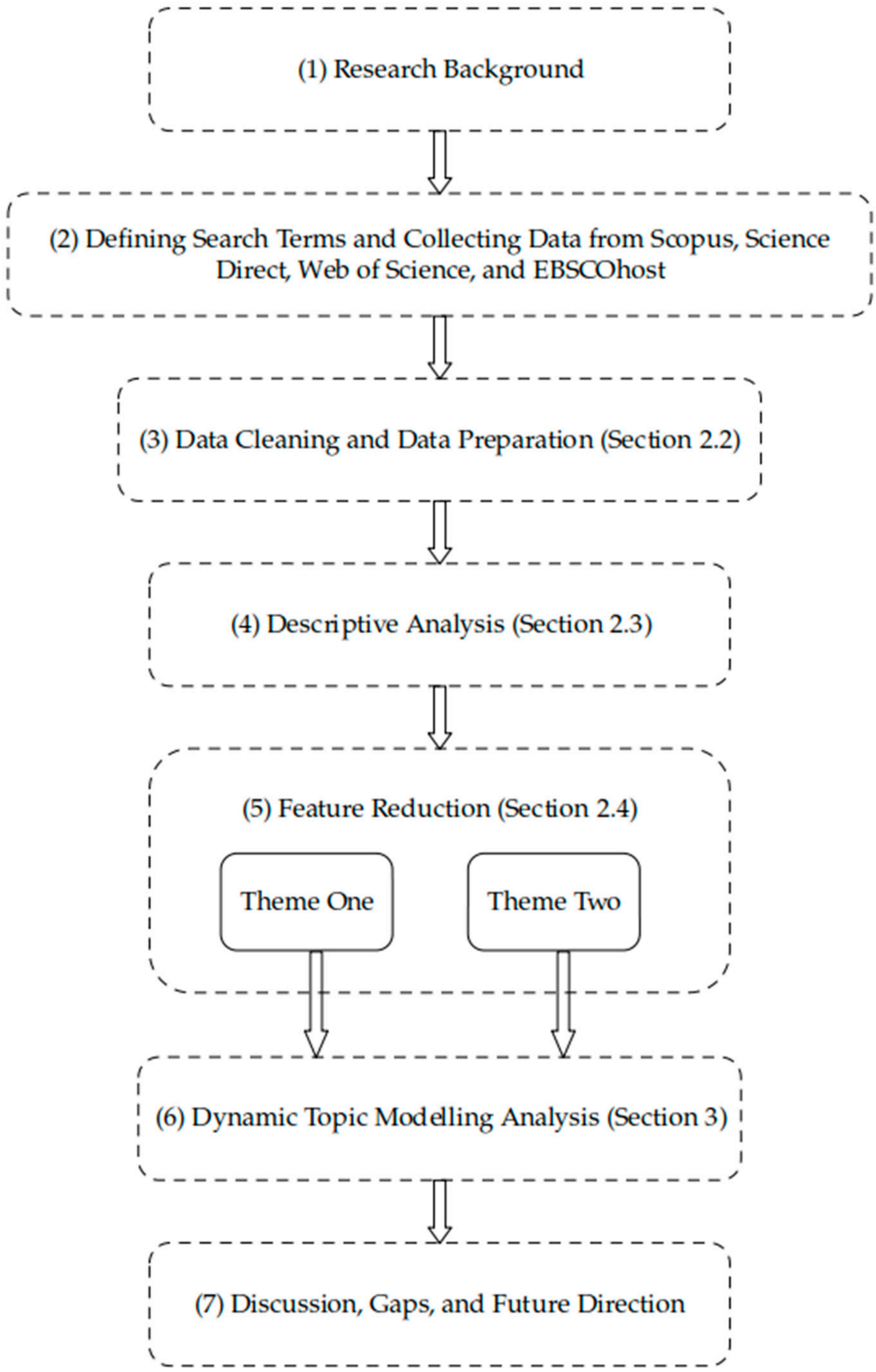

Figure 1. Methodology framework.

Search terms were formed by combining keywords from these two groups, ensuring a comprehensive search strategy. Data were gathered from four well-established academic databases, namely Scopus, Science Direct, Web of Science, and EBSCOhost, covering peer-reviewed journal articles published in English. No restrictions were placed on the publication year because we wanted to track down the development of EV or EV battery from the beginning until the present. The dataset structures are not completely standardised between the databases, so Python 3.12 was used for exacting relevant information among all the datasets for standardisation purposes and aggregated into one main dataset.

This process involved the following steps. The process began with data acquisition, where articles were sourced from four selected databases. Each database provided files in various formats, including Excel (.xlsx), RIS (.ris), and CSV (.csv). These files were then examined to assess their formats and content structures. This step was essential because each database presents information differently, necessitating customised parsing methods for each format.

To ensure consistency and relevance across the aggregated data, seven key variables common to all datasets were identified, shown as follows: Author, Title, Journal, Publication Year, Abstract, Keywords, and DOI. These variables formed the foundation of the master dataset, facilitating the integration of information from diverse sources.

Next, data processing was conducted using Python. Custom scripts were developed to efficiently load and parse datasets, leveraging libraries such as pandas to handle the varying file formats. These scripts extracted the identified key variables from each dataset, accommodating complexities such as nested fields in RIS files and varying column headers in CSV and Excel files. Extracted data were then standardised into a uniform format to ensure compatibility across datasets.

Following standardisation, the data from all the databases were aggregated into a single master dataset. Duplicate entries were identified and removed based on matching DOIs and titles to ensure each article was uniquely represented. Finally, the aggregated dataset underwent a thorough validation process. This included checking for completeness and accuracy, addressing any missing values, and resolving inconsistencies to produce a high-quality dataset ready for analysis.

The initial number of articles collected from the four databases was 1980 for Web of Science, 11,730 for Scopus, 14,824 for Science Direct, and 2755 for EBSCOhost. After being aggregated into one main dataset, we excluded duplicate results, missing, invalid or omitted values; the final dataset contained 22,982 articles.

2.3. Descriptive Analysis

The descriptive analysis of article distribution by year is shown in Figure 2, highlighting a steady rise in publications on battery technology, EVs, and sustainability, reflecting shifting research and industry priorities. Early studies (1970s–2000s) focused on foundational battery science. From the 2000s, growth accelerated with lithium-ion advancements and EV adoption, emphasising energy density and safety. A sharp increase (2010s–2020) was driven by renewable energy policies and reduced battery costs, peaking in 2020–2025 with a focus on zero-emission vehicles, battery lifespan, and recycling. Future trends point to solid-state batteries, fast charging, and second-life applications, with interdisciplinary research integrating AI and life cycle assessments. This evolution underscores the value of DTM in analysing emerging research themes.

Figure 3 shows the descriptive analysis of the top 20 journals in the dataset. Leading publications like *Renewable and Sustainable Energy Reviews* and *Journal of Energy Storage* feature over 1000 articles, emphasising sustainability in EV and battery research. Key journals such as *Journal of Power Sources and Energies* focus on energy systems, while *Energy Storage Materials* and *Journal of Cleaner Production* highlight material science and sustainable production. *World Electric Vehicle Journal* specialises in EV research, and interdisciplinary journals like *IEEE Access* and *International Journal of Hydrogen Energy* bridge engineering, hydrogen, and alternative fuels. Emerging journals like *Nano Energy* reflect a shift towards advanced battery technologies, guiding targeted reviews across sustainability and niche topics.

Figure 4 highlights publication trends across the top 20 journals, with *Renewable and Sustainable Energy Reviews* and *Journal of Energy Storage* leading in renewable and storage research. *Journal of Power Sources* maintains a steady presence with foundational contributions to battery and EV technology, while *Energy Storage Materials* and *World Electric Vehicle Journal* show recent growth, reflecting increased demand for specialised research. Broad-impact journals like *Applied Energy and Energies* align with the global shift to renewables, while interdisciplinary journals such as *IEEE Access*, *International Journal of Hydrogen Energy*, and *Journal of Cleaner Production* bridge engineering and environmental science. Emerging journals like *Nano Energy* focus on advanced materials, showcasing the field's dynamic evolution towards cutting-edge EV and battery solutions.

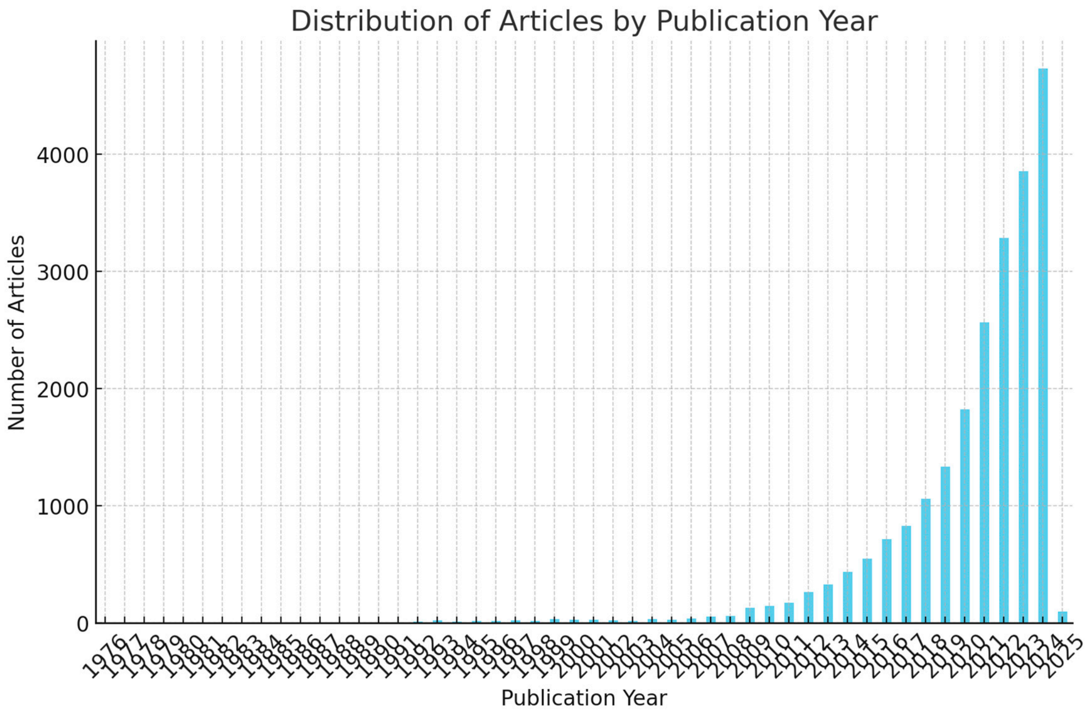

Figure 2. Distribution of articles by publication year.

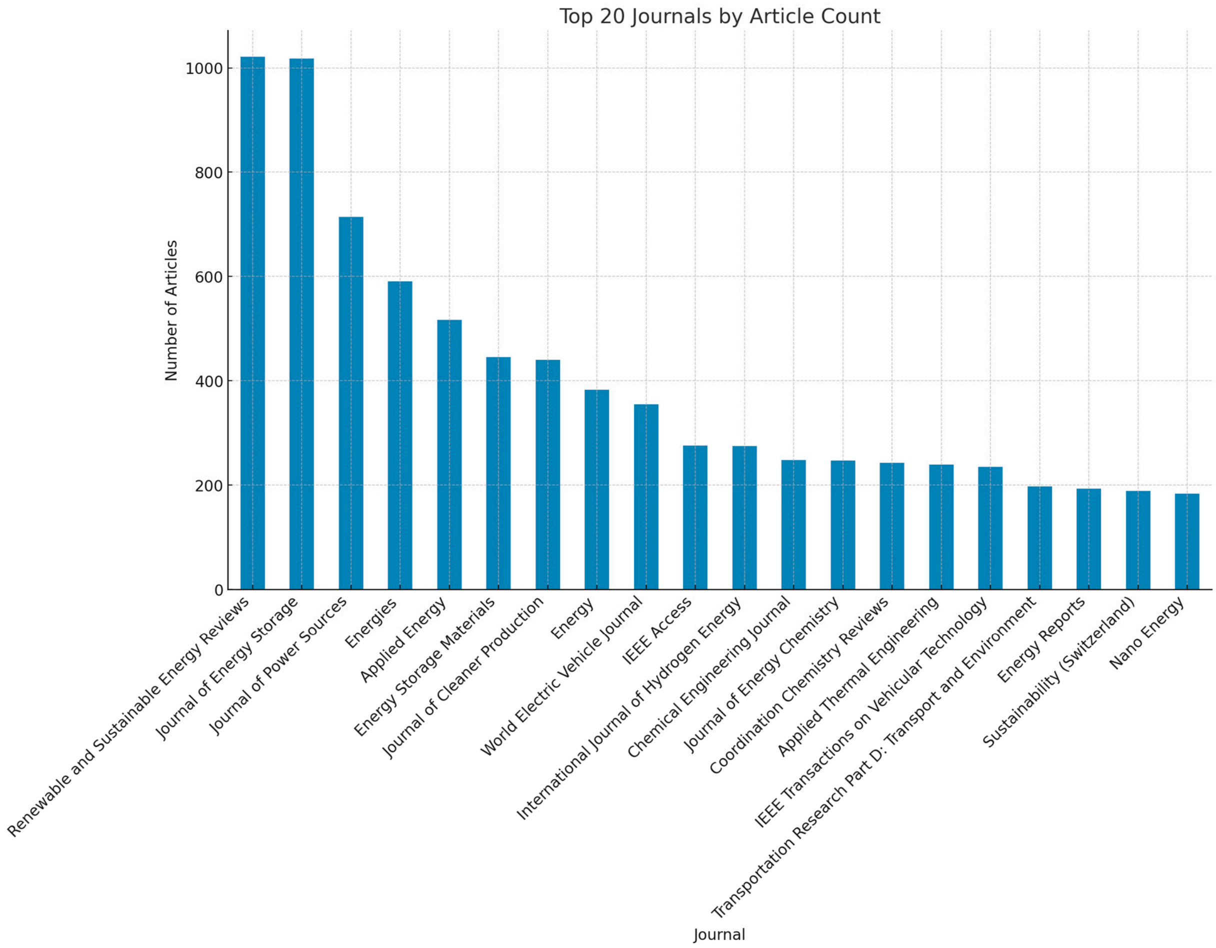

Figure 3. Top 20 journals by article count.

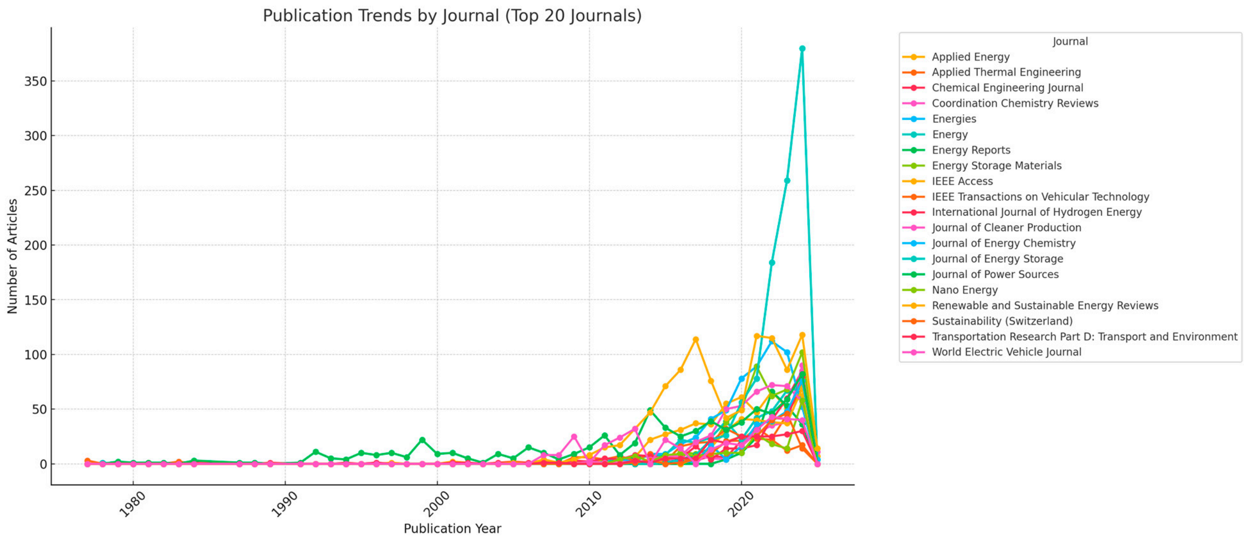

Figure 4. Publication trends by journal (top 20 journals).

2.4. Feature Reduction with TF-IDF

To manage the extensive dataset of 22,982 articles spanning from 1976 to 2025, we applied Term Frequency-Inverse Document Frequency (TF-IDF) to streamline the data for a more focused analysis. While a large dataset provides comprehensive insights, it also introduces high noise levels, increases processing time, and complicates interpretation. Initial analysis indicated the need for feature reduction to ensure clarity and focus.

TF-IDF is a numerical statistic used to reflect the importance of a word in a document relative to a corpus. It combines two components:

- Term Frequency (TF): Measures how frequently a term appears in a document, indicating its importance within that document.
- Inverse Document Frequency (IDF): Assesses how unique or rare a term is across the entire corpus, reducing the weight of common terms.

By multiplying TF and IDF, TF-IDF assigns higher scores to terms that are significant in a document but less frequent across other documents. This helps in identifying key terms that characterise the content, enabling us to assess the relevance of each article to specific research themes.

Alternative techniques for feature extraction and text representation include methods such as Count Vectorizer, Bag of Words (BoW), and word embedding techniques like Word2Vec and Continuous Bag of Words (CBOW). Count Vectoriser and BoW are simple approaches that represent documents as term frequency matrices without considering the importance or uniqueness of terms across the corpus. While these methods are straightforward and computationally efficient, they often produce sparse matrices and fail to capture semantic relationships between words.

In contrast, word embedding techniques like Word2Vec and CBOW generate dense vector representations of words by mapping them into a continuous vector space. These methods capture semantic similarity between words and are highly effective for advanced natural language processing tasks. However, they require significant computational resources and a well-defined corpus for training, making them less practical at this exploratory stage.

Compared to these techniques, TF-IDF [2] strikes a balance by assigning importance to terms that are both frequent within a document and distinctive across the corpus. This approach provides a more focused representation of key terms without the complexity and resource demands of word embeddings or the interpretability limitations of sparse vector techniques. Its simplicity and computational efficiency make TF-IDF particularly suitable for our initial feature reduction and dataset segmentation process.

We also want to utilise this step to divide our research into two themes: (1) "Electric Vehicle Battery Technologies, Development & Trend" to answer the first research question and (2) "Electric Vehicle Battery Capacity Prediction: Influencing Factors" for the remaining two questions. By setting a 0.9 threshold [3] and running TF-IDF for two themes, we selected the top 10% of articles most relevant to each theme. This yielded two focused datasets, each containing 2290 articles, enhancing the depth and clarity of our analysis.

2.5. Dynamic Topic Modelling (DTM)

DTM is a method that examines topic evolution within a body of literature over time, making it particularly valuable for analysing fields experiencing rapid development. Unlike static models, DTM captures shifts in word distributions across specified intervals, revealing changes in research focus and emerging themes. This approach is well suited for fields like EV battery technology, where trends evolve swiftly in response to advancements and innovations.

In the context of this literature review on EV battery technologies and capacity prediction, DTM effectively supports the research goals by uncovering temporal trends, analysing evolving methodologies, and identifying influential factors affecting battery performance. This aligns with the research questions, as it enables the tracking of technological shifts, examination of prominent capacity prediction techniques, and identification of emerging influences on battery longevity. By clustering the literature into topic–time groups, DTM aids in selecting key articles, facilitating a deeper understanding of the field's progress. We ran two separated DTM models, one for each theme.

DTM requires the user to pre-define the number of k, which represents the number of topics the model will try to identify and track over time. This is similar to traditional topic models like LDA, where specifying k is essential to define the scope and granularity of the topics.

To find the optimal number of k, ref. [4] proposed a coherence score, which becomes one of the most popular methods to identify k in topic modelling. We used the Python Gensim package. For each potential k value, the model calculates the coherence score, which measures how well the words in each topic are semantically related. The k value with the highest coherence score generally indicates the best model. The DTM model with the k having the highest coherence score will be selected as the optimal number of topics for the dataset. We trained DTM in a loop with k values from 2 to 52; according to [5], 50-loop is the most reasonable value for k. Figures 5 and 6 are the results for Theme 1 and Theme 2.

We can see that the optimal k value for Theme 1 is 3 and Theme 2 is 6.

The procedure for DTM method has the following steps: (1) Abstracts cleaning and preparation. (2) Identifying the optimal value of k using the coherence score. (3) Clustering 2290 abstracts using the DTM model and the optimal k for each time point (1976–2925) which is the publication year in our dataset. (4) Visualising the top 30 keywords in each topic in each time point using the pyLDAvis package in Python. (5) Labelling each topic for every time point using the top 30 keywords. (6) Examining each topic's label, identifying the evolution of each topic and creating a new label for each evolution. (7) Combining the evolution of each topic and creating one final evolution of the main theme.

This is the original DTM design for both Theme 1 and Theme 2. However, in step 5 of Theme 2's DTM analysis, we observed that all articles related to Theme 2 were classified under a single topic (Topic 5) and spanned a narrow publication period from 2022 to 2024. With such a short timeframe, we were unable to observe or identify any meaningful evolution. Therefore, we decided to reclassify these articles into distinct topics based on their titles. This approach allowed us to identify various methods and techniques for battery capacity prediction, as well as the influencing factors. Furthermore, our primary goals in Theme 2 were to identify current methods for battery capacity prediction and relevant influencing factors. So, this was justifiable for us to adapt to the situation and make necessary adjustments.

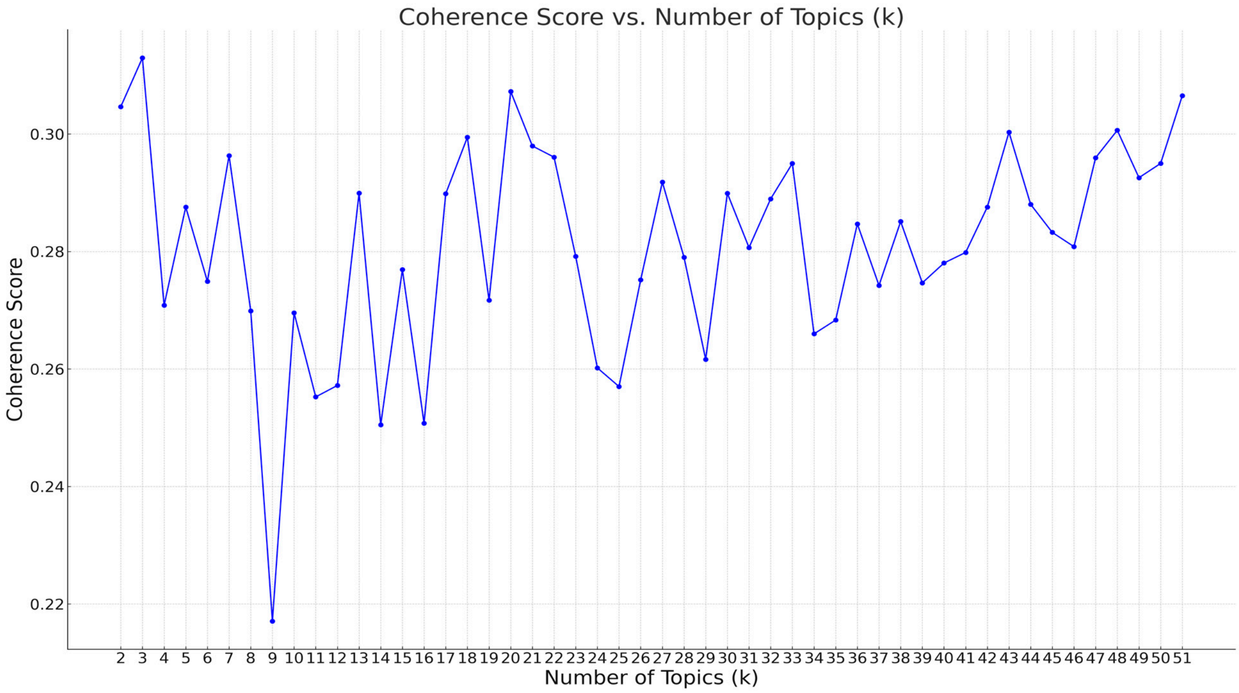

Figure 5. Coherence score vs. number of topics (k) for Dynamic Topic Modelling of Theme 1: "Electric Vehicle Battery Technologies, Development & Trend".

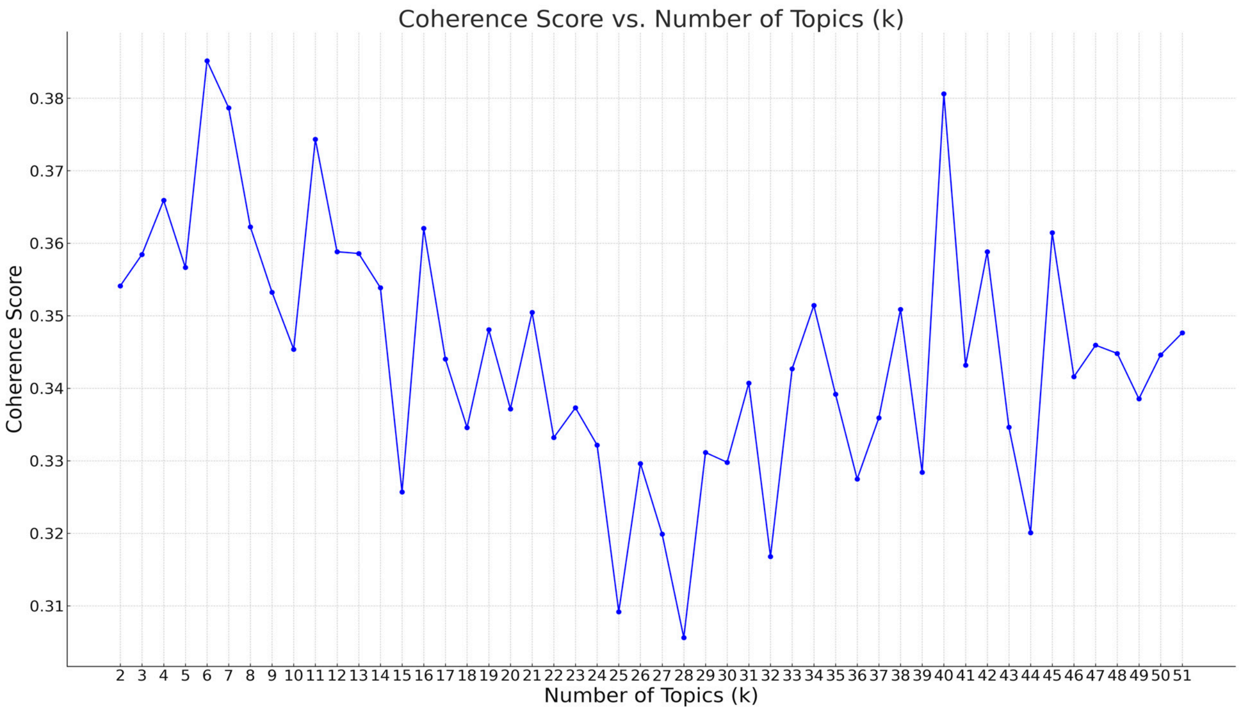

Figure 6. Coherence score vs. number of topics (k) for Dynamic Topic Modelling of Theme 2: "Electric Vehicle Battery Capacity Prediction: Influencing Factors".

Figures 7 and 8 and Table 1 show the visualisation of all the topics in Theme 1 for the years 1976 and 2024, respectively. Figures 9 and 10 and Table 2 present the visualisation for Theme 2. We selected these 2 years out of 50 to present the beginning and the end of Theme 1 so that we could see the difference.

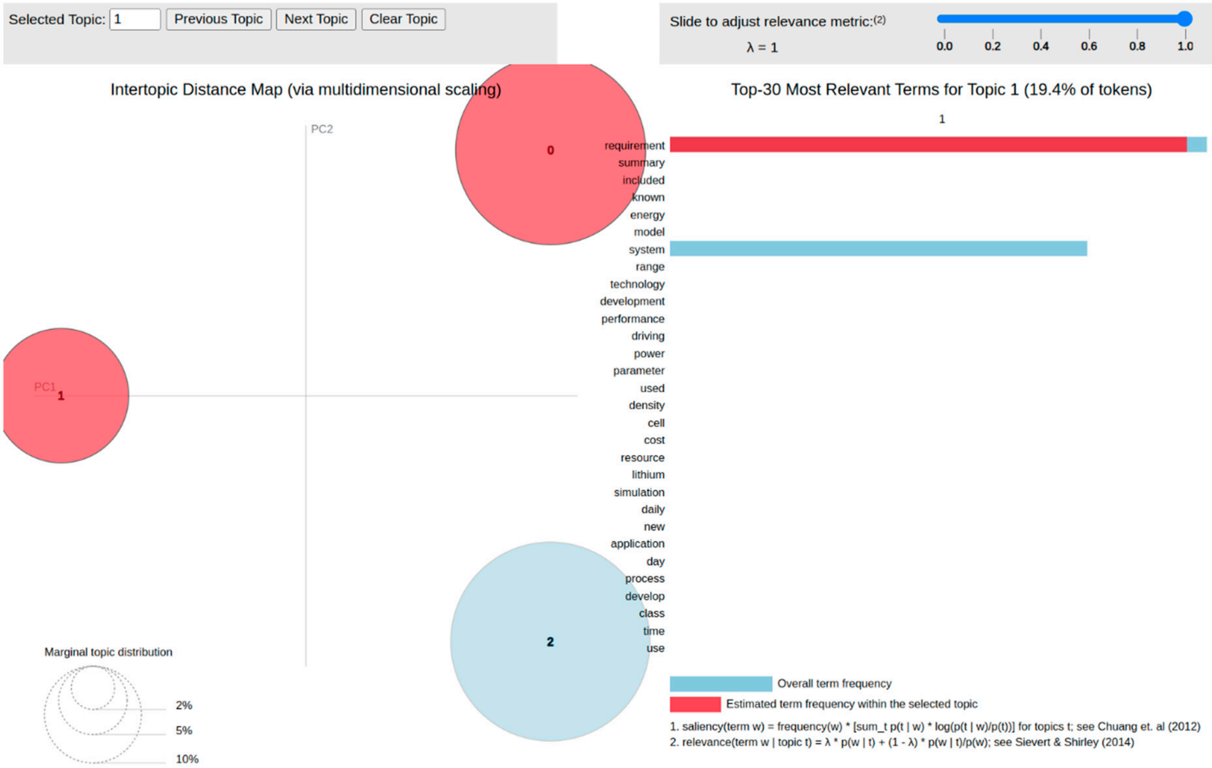

Figure 7. Sematic keyword visualisation in Theme 1 in 1976 [6,7].

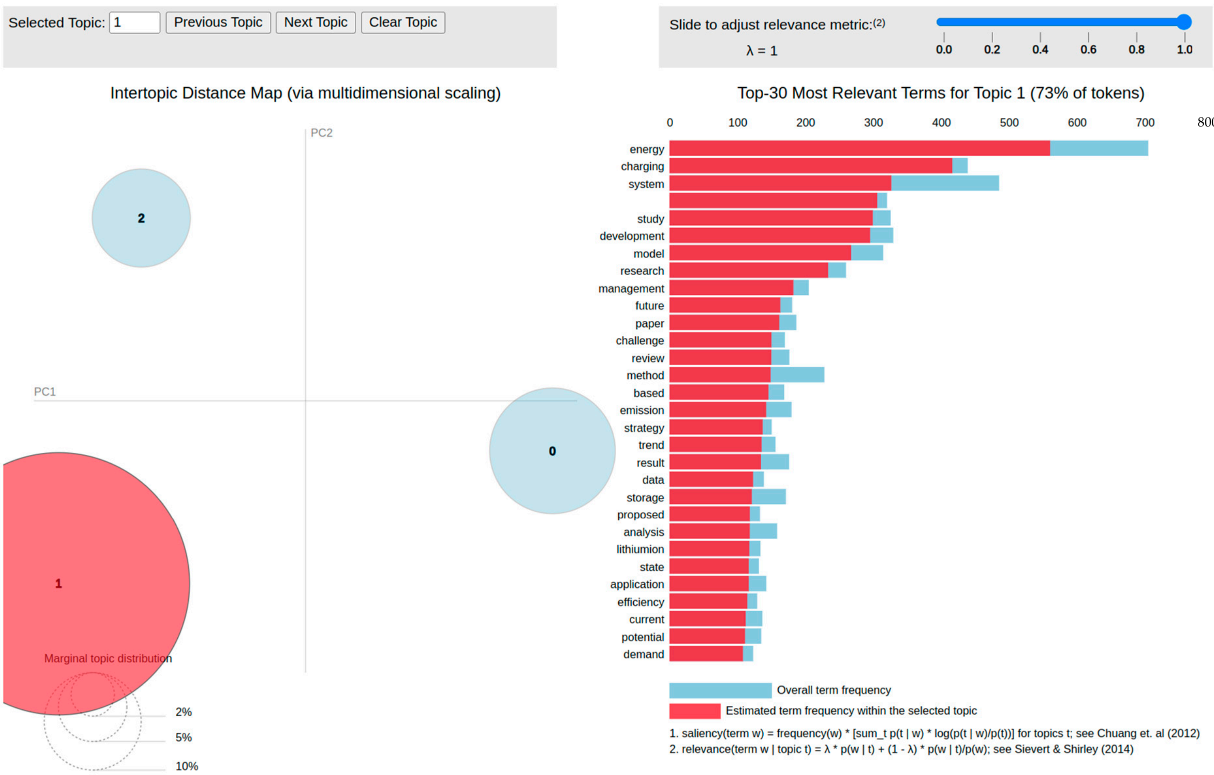

Figure 8. Sematic keywords visualisation in Theme 1 in 2024 [6,7].

Table 1. Theme 1 top 30 salient and relevant keywords and frequency in 1976 and 2024.

Year	Salient Words	Topic 0	Topic 1	Topic 2
1976	Requirement system summary included known short thus considering prospect presented worth background evaluated nearterm longterm many experimental considered based future candidate research little model energy range technology development driving simulation	Thus 0 short 0 considering 0 presented 0 worth 0 background 0 evaluated 0 nearterm 0 little 0 prospect 0 energy 0 system 0 range 0 model 0 technology 0 development 0 power 0 performance 0 parameter 0 driving 0 density 0 lithium 0 used 0 resource 0 requirement 0 cell 0 discussed 0 cost 0 time 0 new 0	Requirement 1.8 summary 0 included 0 known 0 energy 0 model 0 system 0 range 0 technology 0 development 0 performance 0 driving 0 power 0 parameter 0 used 0 density 0 cell 0 cost 0 resource 0 lithium 0 simulation 0 daily 0 new 0 application 0 day 0 process 0 develop 0 class 0 time 0 use 0	System 1.4 research 0 longterm 0 experimental 0 many 0 considered 0 based 0 future 0 candidate 0 little 0 energy 0 model 0 range 0 development 0 power 0 technology 0 performance 0 parameter 0 resources 0 driving 0 density 0 cost 0 used 0 daily 0 urban 0 cell 0 discussed 0 lithium 0 requirement 0 new 0
1976	Summary of Energy System Requirements: Evaluating Long-term and Near-term Prospects for Technology Development	Overview of Energy Resource Parameters: Evaluating Technology Requirements and Performance	Understanding Energy Resource Requirements: A Focus on Performance and Application	Systematic Approach to Resource Requirements in Energy Applications
2024	technology power energy system material performance cell method cost using different storage emission model analysis result fuel recycling environmental application impact development also stability use current research potential trend capacity	Technology 460 power 220 system 140 material 90 performance 86 cell 80 energy 80 method 65 cost 45 storage 40 result 30 analysis 29 model 27 recycling 22 environmental 20 different 18 also 18 fuel 15 review 15 management 15 emission 15 study 15 development 15 new 12 based 12 paper 12 current 11 potential 11 application 11 impact 11	Energy 560 charging 410 system 325 study 300 development 290 model 265 research 240 management 185 future 175 paper 170 challenge 150 review 150 method 150 based 145 emission 140 strategy 135 trend 130 result 130 data 120 storage 118 proposed 115 analysis 115 lithiumion 115 state 115 application 115 efficiency 110 current 108 potential 105 demand 100	Energy 70 using 25 different 25 system 25 model 24 cost 22 emission 20 cell 15 performance 15 development 15 method 15 storage 12 analysis 9 fuel 9 result 9 research 9 application 6 charging 6 technology 6 impact 5 trend 5 power 5 paper 5 recycling 5 current 4 study 4 environmental 4 potential 4 also 4 review 4
2024	Technological Advances in Power and Energy Systems: Material Use, Emission Reduction, and Recycling	Technological Developments in Power Systems: Material Performance, Recycling, and Environmental Impact	Energy Systems Development: Charging Challenges, Emission Strategies, and Future Trends	Energy Systems and Emission Reduction: Cost, Models, and Performance Analysis

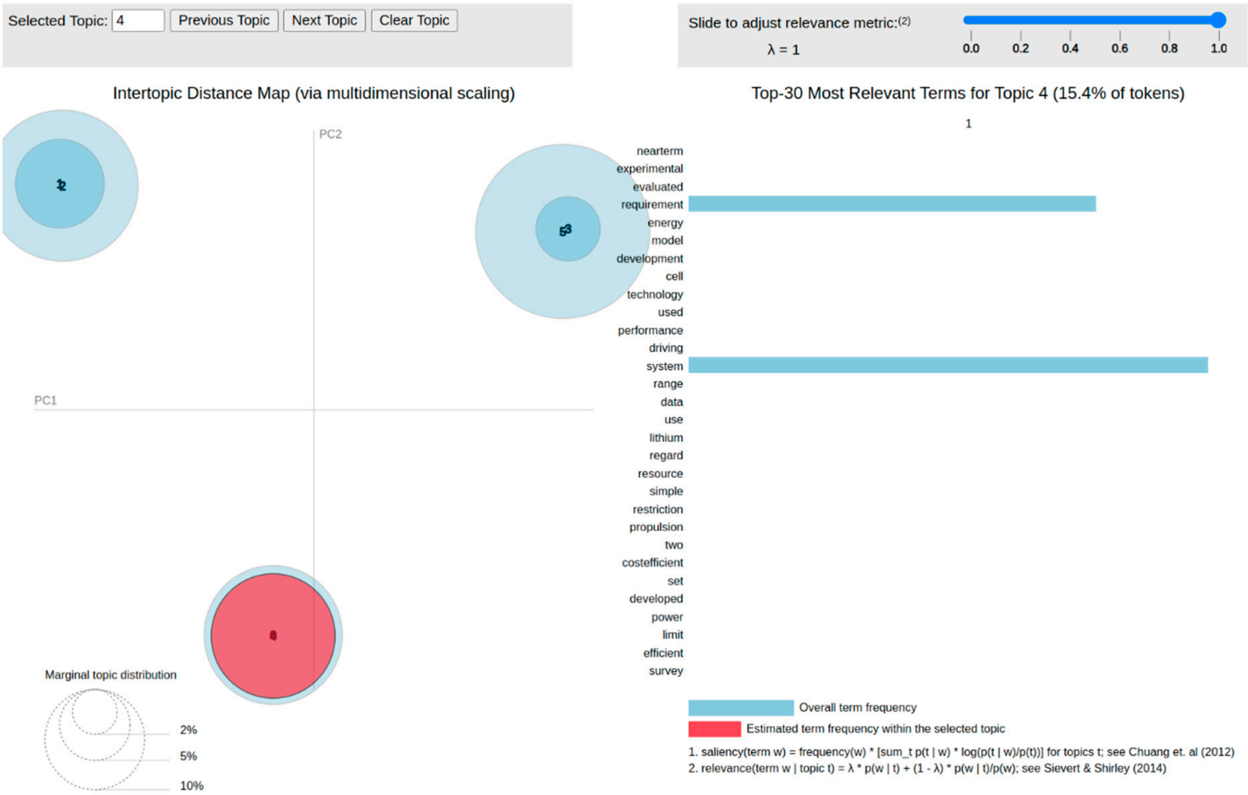

Figure 9. Sematic keywords visualisation in Theme 2 in 1976 [6,7].

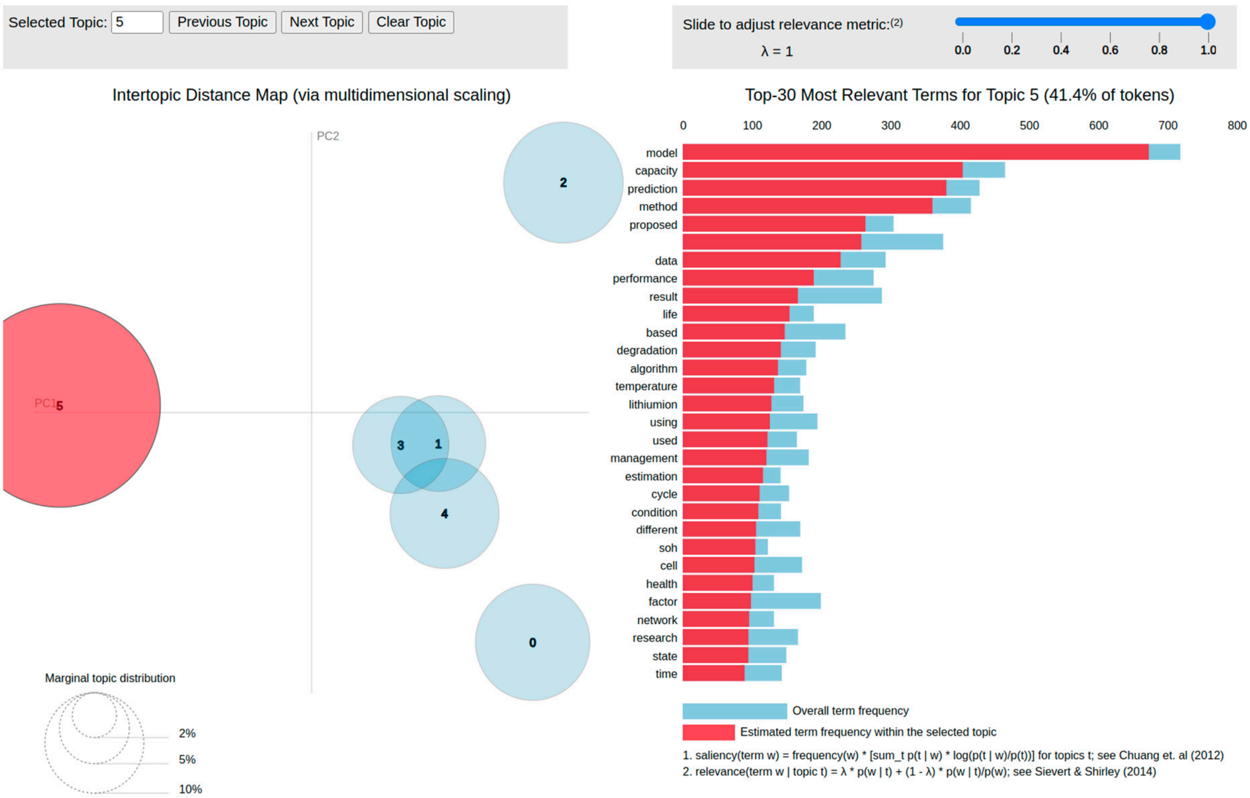

Figure 10. Sematic keywords visualisation in Theme 2 in 2024 [6,7].

Table 2. Theme 2 top 30 salient and relevant keywords and frequency in 1976 and 2024.

Year	Salient Words	Topic 0	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
1976	little system thus requirement nearterm experimental evaluated candidate summary prospect based longterm considering short presented research background many worth known future considered included model performance development energy driving range power	candidate summary prospect based requirement model energy development system cell resource power technology data range driving performance research lithium measurement various pattern simple restriction made discussed using new cost two	thus system model energy performance development power range technology cell assess resource lithium used restriction differential new measurement various simplified based driving city storage internal number two aim coupled progress	longterm research system considering presented short energy model development performance technology resource power range driving requirement data cell measurement made result used occurrence evaluated developed survey propulsion requires lithium granularity	little model performance development energy driving technology cell system range lithium requirement resource set measurement used power made restriction discussed storage behaviour application research data environment estimate result simple control	nearterm experimental evaluated requirement energy model development cell technology used performance driving system range data use lithium regard resource simple restriction propulsion two costefficient set developed power limit efficient survey	background many worth known future included considered little model energy cell technology resource performance range system requirement made driving data used survey lithium research development today internal application geological efficient
1976	Experimental Approaches for Short- and Long-Term Battery System Requirements	Requirement-Based Development and Performance Models for Lithium Battery Systems	Energy and Performance Models for Lithium Battery Systems in Various Driving Conditions	Long-Term System Development and Performance Evaluation in Lithium-Based Energy Models	Small-Scale Model Performance and Energy Resource Estimation for Lithium-Based Systems	Near-Term Experimental Evaluation of Cost-Efficient Lithium-Based Energy Models	Background and Future Considerations for Lithium-Based Energy Models and Performance Requirements
2024	energy charging system study model power prediction technology storage capacity paper method proposed result cost emission performance analysis recycling development adoption factor potential grid policy also review management thermal	Energy 660 storage 75 power 40 paper 35 technology 33 analysis 31 factor 25 cost 23 result 20 system 20 using 19 however 18 study 217.5 strategy 17 research 16 high 15.5 fuel 15 cell 14.5 state 14 performance 13.5 degradation 12 used 12 management 12 application 12 capacity 12 material 12 based 12 current 12 different 12	Paper 35 performance 20 system 19 power 18 technology 18 study 15 result 15 cost 12 management 12 energy 12 application 12 factor 10 research 9 analysis 9 prediction 9 development 9 also 9 method 9 recycling 8 state 8 data 8 strategy 8 based 8 carbon 8 cell 8 lithiumion 8 using 8 capacity 8 emission 8	Charging 560 study 320 power 80 cost 50 factor 40 development 36 based 34 technology 20 energy 20 emission 19 paper 17 using 15 result 15 data 15 demand 15 grid 15 also 15 capacity 15 storage 13 station 11 cell 11 performance 11 efficiency 11 material 9 research 9 current 9 time 9 system 9 fuel 9	Technology 20 power 19 performance 16 result 14 cell 12 model 12 cost 11 management 10 paper 10 system 10 based 10 capacity 10 research 9 different 9 factor 9 approach 9 lithiumion 9 data 8 challenge 8 prediction 8 analysis 8 range 8 also 7 potential 7 adoption 7 strategy 7 high 7 development 7 future 7	System 450 technology 70 result 50 power 50 paper 35 energy 25 emission 25 different 20 based 18 development 17 factor 16 method 16 research 16 analysis 16 cost 14 strategy 14 performance 14 data 12 time 12 thermal 12 using 11 also 10 study 9 review 9 grid 9 high 9 cell 9 management 9 cycle 9	Model 670 capacity 400 prediction 380 method 360 proposed 270 data 240 performance 200 result 180 life 165 based 155 degradation 150 algorithm 145 temperature 140 lithiumion 135 using 132 used 128 management 125 estimation 120 cycle 115 condition 110 different 105 soh 100 cell 95 health 90 factor 88 network 87 research 87 state 87 time 85

Table 2. *Cont.*

Year	Salient Words	Topic 0	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
2024	Energy System Analysis: Predictive Modelling and Performance Evaluation for Enhanced Charging and Storage Solutions	Energy Analysis: Evaluating Storage and Power Technologies for Enhanced System Performance and Cost-Effectiveness	Energy System Performance: A Comprehensive Study on Power Technology, Cost Management, and Carbon Emission Strategies	Charging Infrastructure Study: Evaluating Power, Cost Factors, and Emission Impacts in Energy Storage Development	Technology Assessment for Power and Performance in Lithium-Ion Cell Models: Cost Management and Future Challenges	Systematic Evaluation of Technology and Power Factors in Energy Research: Analysing Cost, Performance, and Emission Strategies	Modelling Capacity and Performance Prediction Methods: A Comprehensive Analysis of Lithium-Ion Systems and Their Degradation Factors

2.6. Paper Selection for Content Discussion

To determine which articles are ideal for a deep-dive discussion after DTM, we used the metric called "document topic distribution", which is one of the direct results from DTM. By focusing on High-Probability Documents per Topic, after DTM assigned topics over time, we could identify articles that had high relevance scores within specific topics. Articles with the highest probability for a given topic can offer rich details and unique insights into that theme, making them suitable for an in-depth analysis. This method allowed us to focus on core articles that best represent each evolving topic within the research timeframe, ensuring they covered the essence of the identified trends. Based on the DTM results, 150 articles were chosen for in-depth analysis in Theme 1 with $k = 3$, and 300 articles for Theme 2 with $k = 6$, which will be further explored in the upcoming section on results and thematic review.

3. DTM Analysis, Results, and In-Depth Review of Research Themes and Topics

3.1. Theme 1: Electric Vehicle Battery Technologies: Development and Trends

3.1.1. Topic 1: Foundations and Early Innovations (1976–1985)

- Energy Resource Evaluation and Performance Optimisation (1976–1978)

During the late 1970s, research focused on evaluating energy resources and understanding the technological requirements for enhancing transportation efficiency. Studies emphasised performance optimisation for internal combustion engines and explored systematic approaches to resource requirements in energy applications. The development of daily density models for transportation systems aimed to improve range and efficiency, laying the groundwork for future battery innovations. Ref. [8] presents short summaries of most of the battery systems that can be considered for EVs. Many little-known systems are included, some with little or no experimental background, and thus are worth considering for future research. Electric vehicle battery requirements are postulated, and based on these requirements the battery candidates are evaluated for their near-term and long-term prospects. Being the first article on EV battery systems, this work plays a foundational role in assessing various battery technologies for EVs. It explores early requirements and the potential of different systems, setting the stage for future innovations in the field. Ref. [9] introduces a model to estimate energy and power needs for EVs in different driving environments. It compares EVs to internal combustion vehicles, analysing energy use and range for various vehicle types using both lead–acid and high-performance batteries. Results show that EVs can be efficient in urban settings but are less effective for inter-city travel, where combustion engines perform better. The model also serves as a foundation for more advanced simulations in the future.

- Development of Lead–Acid and Early Lithium Technologies (1979–1983)

The period from 1979 to 1983 witnessed significant advancements in lead–acid battery development, particularly for telecommunications and component performance. Concurrently, initial explorations into lithium technologies began, aiming to improve energy systems' efficiency and performance. Efforts were made to enhance cell technology, reduce density in battery systems, and implement practical design improvements to extend system range. Ref. [10] discusses the future applications of battery energy storage in transport and stationary settings, focusing on environmental benefits and advancements in battery technologies. Motivated by the 1970s energy crisis, it examines existing battery chemistries (lead–acid, nickel–cadmium) and emerging systems like sodium–sulphur and lithium-based batteries. Findings suggest batteries are crucial for future energy storage, addressing energy density and cost challenges. The paper provides foundational knowledge for understanding the role of batteries in reducing fossil fuel reliance and integrating renewable energy. Ref. [11] examines improvements in lead–acid batteries for EVs through a systems design approach. The EV-3000 battery demonstrated effective advancements in energy density, power, and cycle life, highlighting that lead–acid batteries can still be viable for near-term EV use, especially in cost-sensitive markets.

3.1.2. Advancements and Market Influences (1986–1995)

- Chemical System Innovations and Environmental Considerations (1986)

In 1986, research delved into nonaqueous chemical systems, addressing challenges and fostering innovations in battery technology. Advancements in sodium-based energy systems focused on development and application perspectives, signalling a shift towards exploring alternative battery chemistries. Ref. [12] explores the challenges in developing advanced traction batteries for EVs. It highlights the demanding specifications needed, which slows progress in battery development. Many parameters are interdependent, requiring compromises. Advanced batteries, including nonaqueous lithium and sodium designs, are briefly described, with the author suggesting that these may ultimately be ideal for EVs, though further work is needed.

- Impact of Advanced Technologies and Market Dynamics (1988–1991)

Between 1988 and 1991, evaluations of advanced lithium technologies highlighted their impact on EV performance and cost. Studies assessed the performance and cost factors of advanced energy systems for urban EVs, considering market implications. The development of advanced nuclear power systems and a major utility programme in Europe emphasised clean energy initiatives and environmental sustainability. Ref. [13] discusses the impact of political events, like the Gulf Crisis and Clean Air Act amendments, on energy technologies and EV adoption. It highlights how socio-political pressures have driven innovation in EVs, providing historical context for the evolution of energy solutions, though lacking in detailed technological analysis.

- Emergence of Hybrid Power Systems and Material Advancements (1992–1995)

From 1992 to 1995, the introduction of hybrid lead–acid cell technology for urban safety marked a significant milestone. The automotive industry recognised the need for a new environmental programme, leading to advancements in motor technology. Innovations included synchronous systems and hybrid energy solutions, enhancing infrastructure efficiency and reducing environmental impact. Developments in platinum-based energy systems and advanced separator technologies improved efficiency and traction in hybrid technologies. Ref. [14] discusses MARVEL, which is an interactive microcomputer software developed to analyse battery, heat engine, and hybrid vehicle systems, focusing on least-life-cycle-cost analysis. It models interrelationships between battery parameters while avoiding premature specifications. MARVEL includes default data for various vehicles, driving profiles, and battery technologies, and can analyse electric, heat engine, or hybrid vehicles. The software is written in PL/I for IBM-compatible microcomputers. Ref. [15] explores the feasibility of lead–acid batteries for EVs and compares them to alternatives like PEM fuel cells and nickel–metal hydride batteries, in light of the California ZEV mandate. It finds that lead–acid batteries are cost-effective but limited by energy density, whereas fuel cells show promise for higher efficiency. The study provides insights into policy-driven development and highlights the early challenges in battery evolution for zero-emission vehicles.

3.1.3. Emergence of Hybrid and Fuel Cell Technologies (1996–2005)

- Addressing Performance Challenges in Lead–Acid Batteries (1996–1997)

Efforts to address performance challenges in lead–acid applications led to the development of additives that enhanced battery efficacy. The creation of lithium alloy technologies improved charge efficiency in automobiles, contributing to the advancement of zero-emission vehicles. Ref. [16] develops scalable lithium polymer batteries for EVs, with cell capacities up to 40 Ah. Using a cost-effective extrusion process, the batteries showed consistent performance and energy densities between 100 and 175 Wh/kg. While promising, the study lacks long-term data for larger cells and an economic analysis for mass production, contributing insights into scalable production and EV battery viability. These innovations were crucial in promoting sustainable transportation and reducing environmental pollutants. The main challenge is the lack of extensive real-world application data for the Zebra battery system. While the studies provide a thorough theoretical exploration of material synthesis and the electrochemical structure, the findings are largely limited to lab-scale production and simulations. This gap in real-world testing presents a significant barrier to validating the technology for broader commercial adoption and understanding its true performance under practical conditions. Ref. [17] reviews the advancements in the Zebra (sodium–nickel chloride) battery for EVs, focusing on the beta-alumina ceramic electrolyte critical for performance and safety. The Zebra battery, or sodium–nickel chloride battery, is a high-temperature energy storage system that uses a beta-alumina ceramic electrolyte to transport sodium ions between a liquid sodium negative electrode and a nickel chloride positive electrode. During charging, sodium ions move through the electrolyte, forming liquid sodium at the negative electrode while nickel chloride converts to nickel metal. This process is reversed during discharge, releasing energy. Operating at around 300 °C, the molten state of the electrodes enhances ionic conductivity and efficiency. The Zebra battery offers high energy and power densities, making it ideal for electric vehicles. Unlike lithium-ion batteries, it avoids handling hazardous metallic sodium during assembly, as sodium is formed electrochemically during initial charging. It features intrinsic safety mechanisms, including overcharge protection, and relies on abundant, recyclable materials like salt and nickel, simplifying recycling and reducing environmental impact. Its durability and efficiency at high temperatures make it a robust and environmentally friendly choice. Ref. [18] assesses the readiness of advanced batteries for EV commercialisation under the California ZEV mandate. It projects nickel–metal hydride and lithium-ion as leading technologies and outlines a seven-stage commercialisation process. Though based on 1996 data, it provides key insights into battery commercialisation and the impact of regulations on EV technology.

- Development of High-Performance Hybrid Systems (1998–2001)

Between 1998 and 2001, research focused on enhancing the energy system range through new technologies. The power and development of high-performance hybrid energy systems were explored, with advances in lithium and nickel–metal hydride (NiMH) technologies. Enhancements in power and charging performance in hybrid lithium polymer storage systems were achieved, emphasising cost-effective solutions for hybrid EVs (HEVs). Ref. [19] details advancements in NiMH batteries for EVs and HEVs, focusing on performance improvement and cost reduction. Three battery iterations (GM01, GM02, GM03) were developed, achieving specific energy up to 95 Wh/kg. The study emphasises enhanced manufacturability but lacks real-world performance data and discussion on large-scale production challenges. Ref. [20] reviews advancements in Ni-MH batteries, focusing on material improvements and their use in EVs like the Toyota RAV4 EV. It highlights increased energy density and better performance but mainly focuses on Japanese developments and lacks a cost comparison with lithium-ion batteries.

- Integration and Fuel Technology Advancements (2002–2005)

The importance of integration in hybrid automobile technology development was emphasised during this period. Cost-effective fuel technologies were developed to advance hybrid and fuel cell vehicle designs. Optimising fuel cell performance and autonomy in hydrogen packs enhanced electric vehicle technology, contributing to the broader adoption of sustainable energy solutions. Ref. [21] reviews advancements in EV batteries, focusing on improved energy management, durability, and cost reduction. Key developments include better integrated circuits, enhanced nickel–metal hydride and lithium-ion batteries, and advanced thermal management. These advancements aim to make EVs more competitive with gasoline vehicles by extending battery life and improving efficiency. Ref. [22] presents a BMS to optimise the NiMH battery performance, safety, and life cycle in EVs. Key features include real-time state-of-charge (SOC) calculation, thermal management, and diagnostics, improving battery durability and safety.

3.1.4. Focus on Efficiency and Environmental Impact (2006–2015)

- Advancements in Hydrogen Fuel Cells and Emission Reduction (2006–2007)

Significant advancements in hydrogen fuel cell technology occurred between 2006 and 2007, focusing on performance enhancements and economic implications. The development of hybrid power systems with applications in fuel and energy sectors contributed to efforts in reducing emissions and promoting environmental sustainability. Ref. [23] examines China's efforts to balance automotive growth with environmental goals by adopting cleaner technologies, such as hybrids and hydrogen vehicles. Government initiatives are highlighted as crucial, though challenges like high costs and infrastructure remain. The paper offers a policy-focused view on cleaner vehicle adoption, relevant for understanding regulatory impacts on EV technology advancement. Ref. [24] presents a hybrid electric airport vehicle powered by hydrogen fuel cells and batteries, extending operational time beyond 6 h. The fuel cells supply base power while batteries handle peak demands, improving efficiency and reducing emissions. The study highlights the potential of hydrogen-battery hybrids but lacks an analysis of economic feasibility and scalability. Ref. [25] reviews advancements in Li-ion batteries for EVs, focusing on improving energy density, safety, and thermal management. Key developments include new anode materials like silicon composites, improved cathode chemistries, and enhanced cooling systems. While the study provides insights into material and thermal advancements, it lacks cost analysis and experimental performance data. These findings are crucial for understanding Li-ion battery technology trends, predicting battery performance, and assessing secondary use in electric vehicle applications.

- Power and Performance Optimisation in Hybrid Technology (2008–2010)

From 2008 to 2010, key developments in hybrid technology aimed at enhancing fuel efficiency and power management. Innovations included advancements in energy systems and driving modes, improving the overall performance of hybrid vehicles. Ref. [26] explores system-level reliability in hybrid EVs (HEVs) and the trade-offs between fuel economy and reliability. It finds that HEVs, particularly parallel architectures, have lower reliability than ICE vehicles due to added complexity but can achieve partial functionality through graceful degradation. The study highlights the need to balance fuel efficiency with reliability in HEV design, encouraging manufacturers to consider partial reliability as a strategy to enhance vehicle performance under failure conditions. Ref. [27] explores key design aspects and technological hurdles in PHEV development. It emphasises optimising battery capacity, control strategies based on state-of-charge (SOC), and integrating efficient components like lithium-ion batteries. The study highlights the importance of scalable, efficient systems, and government incentives for advancing PHEV adoption. While the paper provides a comprehensive theoretical overview, it lacks empirical validation, suggesting future research should focus on real-world testing of these design considerations.

- Energy and Power Systems Evaluation (2011–2015)

Evaluations of energy and power systems in hybrid and EVs were conducted to assess the impacts on range, cost, and efficiency. Cost management and emission reduction strategies were implemented in high-efficiency hybrid energy systems. Studies explored alternative fuels in urban transportation and conducted cycle and emission analyses to advance hybrid technology. Ref. [28] explores the use of nanostructured anode and cathode materials to improve the power density in lithium-ion batteries while maintaining high energy density. Key findings include enhanced performance using nanostructured graphene, silicon, and $LiFePO_4$ materials. The study emphasises that nanostructuring can make lithium-ion batteries more suitable for EVs by bridging the gap between energy and power densities. However, it lacks discussion on scalability and cost, suggesting future research should address commercial production challenges. Ref. [29] assesses the economic viability of V2G and B2G applications for EV batteries. V2G has potential in high-value grid services but faces cost barriers, while B2G's appeal is limited by uncertainties around residual value. Profitability remains marginal without subsidies. The study provides insights into secondary battery use, emphasising the need for cost reductions or favourable policies for economic viability. Ref. [30] evaluates advanced rechargeable batteries (LIB, LIP, ZEBRA, Ni–Cd) based on energy, environmental, economic, and technical metrics. LIBs stand out for their energy density and cost-effectiveness, making them ideal for portable electronics and EVs. LIP batteries also show potential but require improvements, while ZEBRA batteries are limited by higher costs. The study emphasises life cycle efficiency and environmental impacts but lacks extensive recycling and end-of-life analysis. Ref. [31] evaluates different vehicle technologies (petrol, diesel, HEVs, BEVs, PHEVs) using life cycle assessment (LCA) and Total Cost of Ownership (TCO). BEVs and PHEVs have the lowest environmental impact, but high purchase cost leads to a higher TCO compared to conventional vehicles. The study highlights the trade-off between environmental performance and cost, suggesting incentives may be needed for BEV adoption. This integrated environmental and financial analysis informs policymaking and supports the transition to cleaner vehicle technologies.

3.1.5. Sustainability and Material Efficiency (2016–2025)

- Technological Advancements and Emission Challenges (2016–2019)

Advancements in energy technologies concentrated on fuel utilisation and power systems, addressing emission challenges through innovative solutions. Emphasis was placed on technological development and performance analysis for cost efficiency, paving the way for more sustainable battery technologies. Ref. [32] compares the costs of managing peak electricity demand using traditional technologies, such as gas turbines and hydroelectric storage, with newer solutions like battery storage and vehicle-to-grid (V2G) systems. It finds that battery storage is more cost-effective for managing short peak periods under an hour, while traditional power plants and hydro storage are more economical for longer durations. V2G technology proves more efficient in low-voltage power grids, particularly for short-duration peak loads of up to 1–2 h. Despite traditional power stations being generally cost-effective, battery storage and V2G can be advantageous in locations lacking natural gas infrastructure or where environmental regulations restrict fossil fuel use. The study recommends government support for R&D, reducing battery costs, and establishing favourable regulations to promote the adoption of battery storage and V2G technologies.

In the late 2010s to early 2020s, significant progress has been made in the design and optimisation of battery modules and packs for EVs. The focus has shifted towards improving energy density at the pack level, enhancing thermal management systems, and integrating advanced battery management systems (BMSs) to monitor and control individual cells within modules.

Researchers have developed new module designs that reduce the weight and volume of battery packs while increasing their energy density. This is achieved by optimising the arrangement of cells within modules and improving the structural components to provide better mechanical stability and safety. For instance, the development of cell-to-pack and cell-to-chassis technologies eliminates intermediate modules, directly integrating cells into the vehicle structure, thereby increasing volumetric efficiency.

Thermal management at the module and pack level has also seen advancements. Efficient cooling systems are critical to prevent overheating, which can lead to capacity loss and safety risks. Innovations include liquid cooling systems that circulate coolant through channels within the battery pack, phase-change materials that absorb excess heat, and advanced thermal interface materials that improve heat dissipation between cells and modules.

Moreover, the integration of intelligent BMSs at the module and pack level allows for real-time monitoring of cell voltages, temperatures, and states of charge. This ensures balanced charging and discharging among cells, prolonging battery life and improving performance. Machine learning algorithms are increasingly used within BMSs to predict potential failures and optimise energy use.

The development of modular battery packs also facilitates easier assembly, maintenance, and recycling. Standardized modules can be replaced or upgraded without needing to replace the entire pack, reducing costs and environmental impact. Modular designs also support second-life applications, where retired EV batteries can be repurposed for energy storage systems.

These advancements in battery module and pack technologies are crucial for enhancing the overall efficiency, safety, and sustainability of EVs, aligning with the industry's goals towards a more sustainable future.

- Lithium-Ion Technologies and Recycling Methods (2020–2023)

From 2020 to 2023, focus shifted to energy systems incorporating lithium-ion cell technologies. Emission reduction strategies and recycling methods were implemented to address environmental concerns and material scarcity. Evaluations of charging methods and performance trends in lithium-ion technologies were conducted to enhance efficiency. Ref. [33] presents an optimised liquid cooling thermal management system (BTM) for cylindrical lithium-ion batteries. Using COMSOL simulations, the study found that a staggered cooling channel configuration improves temperature control, reducing risks of thermal runaway. The model shows potential for enhancing battery safety in EVs, although real-world testing is recommended. Ref. [34] evaluates different machine learning models—linear regression, neural network, and modified support vector machine (M-SVM)—to predict the SOH of lithium-ion batteries in EVs. The M-SVM model showed superior performance in predicting battery SOH, indicating lower errors compared to the other methods. The study highlights the effectiveness of M-SVM in battery management systems for real-time health monitoring, though further research is needed to validate results across diverse datasets and conditions. Ref. [35] reviews battery thermal management (BTM) strategies for EVs, including active, passive, hybrid systems, and deep learning methods. It highlights hybrid cooling as the most efficient approach but notes its complexity and cost. Deep learning methods show promise for optimising BTM through real-time adjustments, enhancing battery longevity. The study suggests a shift towards smarter, adaptive BTM systems, though more experimental validation is needed to confirm the findings in real-world conditions.

Recycling batteries is vital for protecting the environment and conserving resources. Discarded batteries contain toxic substances like heavy metals and electrolytes, which, if mishandled, could lead to serious environmental harm. At the same time, these batteries are a rich source of valuable materials such as lithium, cobalt, nickel, and manganese—essential for manufacturing new batteries yet finite and subject to supply chain vulnerabilities. Recycling these materials not only reduces reliance on raw resource extraction but also promotes a sustainable circular economy for the EV industry.

Conventional recycling approaches primarily utilise pyrometallurgy and hydrometallurgy. Pyrometallurgy involves high-temperature processes to recover metals like cobalt, nickel, and copper, but lithium is often lost during processing. While this method is well established and robust, it is energy-intensive and generates significant emissions. In contrast, hydrometallurgy uses chemical solutions to extract a broader range of metals, including lithium, with lower energy demands. However, this approach involves intricate steps and generates chemical waste, raising concerns about economic feasibility and environmental impact.

To overcome the limitations of traditional methods, cutting-edge recycling technologies have been developed. Direct recycling focuses on reclaiming and restoring intact electrode materials, reducing energy use and costs but facing challenges related to standardisation and quality assurance. Mechanochemical methods activate materials mechanically for easier leaching, minimising energy consumption yet struggling with scalability. Bioleaching employs microorganisms to extract metals, offering an eco-friendly alternative, though the process is slower. Electrochemical recycling uses electric currents to recover high-purity metals but demands substantial energy and specialised equipment.

Innovations in the field continue to improve recycling processes. Automation and robotics enhance the safety and efficiency of battery disassembly, cutting labour costs and reducing exposure to hazardous materials. Advanced sorting technologies, such as infrared spectroscopy and X-ray fluorescence, refine material recovery. Additionally, second-life applications extend the utility of batteries before recycling, using them for less demanding purposes like energy storage systems.

- Emission Reduction and Optimisation (2024–2025)

The emphasis on emission reduction continued into 2024 and 2025, with cost, model, and performance analyses conducted to optimise lithium-ion energy systems. Enhancements in charging, heat management, and emission reduction techniques were implemented, preparing the industry for future challenges and promoting sustainability. Ref. [36] develops a physics-based model to evaluate energy losses and use-phase carbon emissions of EV batteries. It highlights how factors like regional GHG intensity and temperature impact emissions, with the thermal management system being a major contributor. The study underscores the significance of considering operational conditions for sustainable battery use, offering insights into improving battery efficiency and carbon management in diverse climates. The model provides a valuable tool for evaluating emissions but requires real-world validation.

- Digital Twins of Physical Batteries (2022–2025)

The concept of digital twins has gained traction as a transformative technology in the realm of electric vehicle battery systems. A digital twin is a virtual replica of a physical battery, designed to mirror its real-time performance, health, and operating conditions through continuous data exchange. This technology leverages advanced sensors, Internet of Things (IoT) frameworks, and machine learning algorithms to create a dynamic digital model that evolves alongside its physical counterpart.

In the context of batteries, digital twins offer unprecedented insights into performance optimisation and life cycle management. By continuously monitoring variables such as temperature, state of charge, voltage, and capacity fade, digital twins provide real-time diagnostics and predictive analytics. This enables early detection of potential failures, improved safety measures, and precise estimation of remaining useful life. Furthermore, digital twins facilitate the optimisation of charging and discharging cycles, contributing to enhanced efficiency and prolonged battery lifespan.

Another critical application of digital twins lies in accelerating the development of advanced battery technologies. Virtual simulations conducted through digital twins reduce the need for physical testing, thereby shortening development timelines and lowering costs. Additionally, the integration of digital twins with real-world operational data can inform the design of next-generation battery systems, ensuring they are tailored to specific use cases and environmental conditions.

The adoption of digital twins also aligns with the principles of sustainability and circular economy. By enabling accurate end-of-life predictions and optimising second-life applications, digital twins support effective resource utilisation and reduce waste. As the electric vehicle industry continues to evolve, the integration of digital twins into battery systems represents a forward-looking approach that combines technological innovation with environmental responsibility.

3.2. Theme 2: Electric Vehicle Battery Capacity Prediction: Influencing Factors

3.2.1. Topic 1: Machine Learning Model for Battery Capacity Prediction

This theme focuses on using machine learning techniques to predict battery capacity and state of health in EVs. Methods like neural networks and ensemble models help capture complex battery degradation patterns, improving prediction accuracy and enabling real-time monitoring to optimise battery performance and lifespan.

Ref. [37] presents a novel hybrid approach for improving the accuracy and efficiency of SOH estimation in lithium-ion batteries. The authors combine Empirical Mode Decomposition (EMD), Gated Recurrent Unit (GRU) neural networks, Random Forest (RF), and the Variance Contribution Ratio (VCR) to develop an effective model for battery health prediction. Using the NASA PCoE Li-ion battery dataset, the model outperforms traditional methods with prediction errors below 4%, making a notable contribution to advancing battery capacity prediction and health management for EVs. Ref. [38] introduces a hybrid deep neural network (HDNN) for battery capacity estimation in EVs, using real-world data from 40 electric buses. The HDNN, combining convolutional and fully connected networks, achieved a MAPE of 2.79%, outperforming traditional methods, and is suitable for real-time battery management. The study significantly improves accuracy and robustness in battery health estimation. Ref. [39] reviews deep learning methods for predicting the remaining useful life (RUL) of energy storage systems like lithium-ion batteries. It finds that models like LSTM, GRU, CNN, and autoencoders, particularly in hybrid forms, outperform traditional methods in accuracy and efficiency. These techniques can enhance battery management by adapting to degradation over time, but further validation under real-world conditions is needed, along with improvements in generalisability and computational efficiency. Ref. [40] presents a hybrid deep learning model for predicting the RUL of lithium-ion batteries. The model combines domain knowledge-based features with features learned by a neural network, using a one-dimensional convolutional neural network (1D-CNN) and a fully connected network enhanced by a snapshot ensemble strategy. Trained on data from 124 commercial lithium-ion battery cells, the model outperformed traditional methods like SVR, GRU-RNN, and CNN-LSTM, achieving better accuracy and generalizability. This approach improves early RUL prediction, contributing to efficient EV battery management. Ref. [41] proposes a hybrid neural network combining 1D CNN and BiLSTM to improve the prediction accuracy of lithium-ion battery RUL. Tested on NASA's battery datasets, the model outperformed traditional methods like RNN and LSTM by achieving lower prediction errors. The hybrid approach enhances feature extraction and time-series analysis, making it more accurate and reliable for battery management, though further testing on diverse datasets is needed. Ref. [42] presents an optimised hybrid neural network using CNN and Bi-LSTM, improved with the Sparrow Search Algorithm (SSA), to predict the SOH of lithium-ion batteries. Their model, tested on NASA battery data, showed high accuracy with prediction errors under 0.7%, outperforming traditional models. This approach enhances SOH prediction for EV batteries, making it suitable for battery management, though more testing on different battery types is needed.

3.2.2. Topic 2: Hybrid Models, Transfer Learning, and Data-Driven Method for Battery Capacity Prediction

This topic includes discussed hybrid models combining data-driven methods for battery capacity.

Ref. [43] develops a hybrid machine learning model called N-CatBoost to estimate the SOH of lithium-ion batteries using real-world data from the EVs. By combining CatBoost and NGBoost algorithms, their model provides accurate SOH predictions with uncertainty estimates. Tested on data from 15 EVs over a year, it achieved high accuracy with a MAPE of 0.817%, outperforming other machine learning methods. This approach improves battery health estimation in practical EV applications but requires further validation with more diverse data. Ref. [44] proposes a data-driven method for estimating $LiFePO_4$ battery capacity using cloud-based charging data from EVs. By combining linear regression for slow-charging data and a neural network for fast-charging data, their approach achieved high accuracy with data from 85 vehicles over one year. This method enhances battery management by improving capacity estimation in real-world conditions, supporting better battery life for EVs. Ref. [45] develops a model for estimating the health of lithium-ion batteries in EVs, using real-world data like driving mileage and seasonal temperature. They applied advanced algorithms (VFFRLS and EPF) to achieve accurate capacity estimation, keeping errors within $\pm 1.2\%$. This approach improves battery management under real-world conditions, although broader testing is needed for general use. Ref. [46] develops a voltage prediction method for lithium-ion batteries using sparse data. By using a self-attention network with transfer learning and a new SEE loss function, they achieved a mean error below 0.5%, outperforming traditional models. This approach improves battery monitoring in EVs, making battery management more accurate and efficient, but needs further testing in varied conditions.

Ref. [47] develops DLPformer, a hybrid model for predicting the state of charge in EVs, using linear trend analysis and transformer-based machine learning. By integrating battery and vehicle data, the model improves prediction accuracy compared to traditional methods. It shows promising results for better battery management, but further testing under different conditions is needed for broader use. Ref. [48] proposes a hybrid model that combines physics-based and data-driven methods to predict Li-ion battery degradation. Using a sequence-to-sequence deep learning approach, the model accurately predicts battery capacity using just 20% of early-cycle data, achieving a MAPE of less than 2.5%. This approach offers an efficient solution for early prediction, though more validation under varied conditions is needed. Ref. [49] proposes a battery capacity estimation method combining an equivalent circuit model with quantile regression (QR) to address low-quality, inconsistent real-world data from EVs. By using QR to manage outliers and refine capacity estimation, the model achieved errors within 3.2%, significantly outperforming ordinary least squares (OLS) regression. This approach is effective for improving battery capacity estimation in practical, large-scale applications, though further validation in varied temperature conditions is needed.

Ref. [50] develops a hybrid transfer learning method for predicting lithium-ion battery capacity. By combining EEMD, SVR, and BiLSTM-AM, the approach captures both local and long-term degradation features, achieving high accuracy with errors between 0.6% and 6.96%. The method outperformed traditional models and is suitable for battery management systems, though further validation on diverse batteries is recommended. Ref. [51] develops an LSTM-based model to estimate lithium-ion battery health using incremental capacity analysis and transfer learning. This approach achieved high prediction accuracy, with an error under 2%, and adapted well to different battery conditions, providing a reliable solution for improving battery management systems in EVs.

3.2.3. Topic 3: Advanced Signal Processing and Feature Extraction Techniques

This theme includes articles utilising advanced signal processing methods, such as incremental capacity analysis, differential voltage analysis, and wavelet transforms, to extract meaningful features for capacity prediction.

The evolution of battery capacity prediction models has been significantly influenced by advanced signal processing and feature extraction methods. These techniques allow researchers to distil meaningful information from raw battery data, enhancing the accuracy of capacity and state-of-health (SOH) predictions. A crucial aspect of this progression is rooted in foundational electrochemical methods developed over the past decades, such as Electrochemical Impedance Spectroscopy (EIS), Linear Sweep Voltammetry (LSV), Cyclic Voltammetry (CV), and controlled charging/discharging protocols. These methods have provided essential data for developing and validating battery behaviour models.

Electrochemical Impedance Spectroscopy (EIS), which gained prominence in the 1980s, has been instrumental in probing internal battery processes. By applying an alternating current over a range of frequencies and measuring the resulting impedance, EIS offers insights into charge transfer resistance, double-layer capacitance, and diffusion phenomena within electrode materials. This technique enables the modelling of complex electrochemical dynamics, contributing to more accurate simulations of battery behaviour.

Cyclic Voltammetry (CV) and Linear Sweep Voltammetry (LSV), fundamental since the mid-20th century but widely adopted in battery research during the 1970s and 1980s, involve sweeping the electrode potential and recording the current response. These methods reveal information about redox reactions, reaction kinetics, and material stability. Data from CV and LSV have been crucial for identifying suitable electrode materials and understanding their behaviour under different conditions, feeding directly into physics-based models.

Controlled charging and discharging experiments have long been central to battery testing. Standardized cycling protocols provide consistent datasets for evaluating performance metrics like energy density, power density, cycle life, and efficiency. These experiments have historically offered empirical data essential for both developing models and validating simulations.

Building upon these foundational methods, recent studies have employed advanced signal processing and feature extraction techniques to enhance capacity prediction models. Ref. [52] develops a hybrid model combining Discrete Wavelet Transform (DWT) and an improved semi-empirical (ISE) ageing model to predict the RUL of lithium-ion batteries. Their model outperformed others like Particle Filter and LSTM, offering high accuracy with minimal data. This approach provides reliable early RUL predictions to optimise maintenance. Ref. [53] presents a practical SoH estimation method for $LiFePO_4$ batteries using Gaussian mixture regression (GMR) combined with incremental capacity (IC) analysis. This approach, validated through ageing tests, outperformed traditional methods like linear regression and neural networks in accuracy, achieving MAE and RMSE below 1%. The GMR-based method is suitable for EV battery management, offering high adaptability and low computational complexity. Future research should explore its applicability under dynamic charging conditions and for different battery types. Ref. [54] proposes a SOH prediction method for lithium-ion batteries using wavelet-convolutional neural regression networks (CNRNs) with Electrochemical Impedance Spectroscopy (EIS) frequency profiles. This method, validated with Eunicell LR2032 cells under various temperatures, improved SOH prediction accuracy by using wavelet decomposition for feature extraction in both time and frequency domains. Hybrid models like CNRN-GPR further boosted prediction performance. The study suggests expanding the dataset for more battery types and real-world testing to confirm robustness, making it relevant for battery health monitoring in EVs and energy storage systems. Ref. [55] proposes a method for estimating lithium-ion battery state-of-health (SOH) using incremental energy analysis (IEA) and a Bayesian-transformer model. The model achieved high accuracy, outperforming traditional methods like LSTM and SVR. This approach effectively enhances SOH prediction, supporting improved battery management and extended life cycle.

These advanced techniques address challenges in capacity prediction by capturing complex degradation patterns and intrinsic electrochemical behaviours not apparent from raw data alone. By leveraging insights from EIS, CV, and ICA, models become more accurate and interpretable. Furthermore, these methods enhance the generalizability of models across different battery chemistries and operating conditions. Focusing on fundamental electrochemical features allows for adaptability without extensive retraining, which is crucial for practical applications in EVs with varying battery designs and usage patterns.

3.2.4. Topic 4: Impact of Temperature and Thermal Effects on Battery Capacity

This topic focuses on how temperature influences battery capacity and the methodologies developed to predict and manage thermal effects.

Temperature plays a pivotal role in the performance and longevity of lithium-ion batteries by significantly influencing their internal chemical reactions and, consequently, their capacity. At elevated temperatures, the kinetics of electrochemical reactions are enhanced, leading to increased ion mobility and reduced internal resistance. This can temporarily boost the battery's capacity and power output. However, prolonged exposure to high temperatures accelerates degradation processes such as electrolyte decomposition, growth of the solid electrolyte interphase (SEI) layer, and structural damage to electrode materials. These degradation mechanisms result in capacity fade, reduced cycle life, and can pose safety risks due to potential thermal runaway scenarios.

Conversely, at low temperatures, the electrochemical reaction rates decrease, causing increased internal resistance and reduced ionic conductivity. This leads to diminished battery capacity and poor power performance. Low temperatures can also induce lithium plating on the anode during charging, which not only decreases capacity but also increases the risk of internal short circuits due to dendrite formation. Understanding and managing these temperature effects are crucial for optimising battery performance and ensuring safety in EVs.

To address these challenges, various methodologies have been developed to predict and manage thermal effects in lithium-ion batteries. For instance, Ref. [56] proposed a model to estimate the internal temperature and state-of-charge (SOC) of lithium-ion batteries using a fractional-order thermoelectric approach. This method achieved high accuracy, with errors of 0.5% for SOC and 0.3 °C for temperature. It improves battery safety and management for electric vehicles, though further testing is needed for real-world use. Ref. [57] used ANN models to predict lithium-ion battery performance with direct oil cooling. The ANN_LM-Tan model showed high accuracy, predicting temperature within ±0.97% and voltage within ±4.81%. This method improves cooling system design for Evs. Ref. [58] developed ANN models (BP-NN, RBF-NN, Elman-NN) to predict lithium-ion battery temperatures under metal foam cooling. The Elman-NN model outperformed others in adaptability and speed, suggesting ANN as an efficient alternative to CFD for battery thermal management. Experimental validation is needed for real-world use. Ref. [59] used an ANN, specifically the Elman-NN model, to predict battery cell temperatures with a refrigerant direct cooling system (RDC-TMS). The Elman-NN showed high accuracy and RDC-TMS outperformed other cooling methods. This model improves battery cooling in electric vehicles, but future studies should test it under dynamic conditions and fast charging.

Temperature significantly affects lithium-ion battery capacity by influencing internal chemical reactions. High temperatures can temporarily enhance performance but accelerate degradation, while low temperatures reduce capacity and pose safety risks. Advanced modelling techniques, such as fractional-order thermoelectric models and ANN-based predictive models, offer promising solutions for managing thermal effects and optimising battery performance in EVs. Ongoing research and experimental validation are essential to translate these methodologies into practical, real-world applications.

3.2.5. Topic 5: State-of-Charge (SOC) Estimation Methods

This theme focuses on articles that develop and improve SOC estimation methods, essential for accurate capacity prediction. Ref. [60] introduced an Interacting Multiple Model (IMM) method to estimate SOC and SOH in lithium-ion batteries, effectively addressing temperature and ageing effects, with an SOC error margin around 2%. Future testing could apply this to various battery types. Ref. [61] utilises neural networks to predict the SOC-OCV relationship, achieving higher accuracy and lower complexity than traditional methods, which could enhance battery management system reliability under dynamic conditions. Ref. [62] introduces a passive equalisation strategy designed to improve efficiency and extend the battery life of lithium-ion battery packs. The strategy operates by using resistive components to dissipate excess energy from cells with a higher state of charge, thereby balancing the charge levels across all cells in the pack. This process reduces the disparities in cell voltages and capacities, preventing overcharging and deep discharging of individual cells. By maintaining balanced charge levels, the strategy enhances overall performance and prolongs the lifespan of the battery pack. Compared to traditional methods, this passive equalisation approach is simpler and more cost-effective, making it suitable for electric vehicle applications. While initial results are promising, further real-world testing is recommended to fully validate its effectiveness in practical scenarios.

3.2.6. Topic 6: Factors Influencing Battery Degradation and Capacity Loss

This topic explores factors significantly impacting lithium-ion battery (LIB) degradation in EVs, including operating conditions, SOC range, and charging patterns, all contributing to battery lifespan and performance. Key influences on degradation are temperature, depth of discharge (DoD), SOC, charging rates, chemical mechanisms, and also charging mode. Temperature plays a crucial role; high temperatures accelerate reactions like solid electrolyte interphase (SEI) growth and electrolyte oxidation, while low temperatures increase internal resistance, risking issues like lithium plating. DoD directly affects mechanical and thermal stress: deeper discharges lead to structural changes, while a moderate DoD around 50% is optimal to reduce wear. SOC levels also impact degradation, with high SOC accelerating wear through increased chemical reactivity and low SOC increasing internal resistance. Maintaining SOC in an optimal range during cycling and storage is beneficial for longevity. Charging rates, or C-rates, further influence battery health: high rates induce thermal and mechanical stress, causing SEI growth, lithium plating, and capacity loss, while lower rates are preferable to reduce wear. Chemical degradation mechanisms like SEI growth, loss of lithium inventory (LLI), loss of active materials (LAM), and electrolyte loss also contribute to gradual capacity fade. SEI layer growth reduces capacity by consuming lithium ions, while LAM results from structural damage that limits the available reaction mass. Additional factors affecting LIB health include cycling frequency, user behaviour, vehicle weight, infrastructure, and environmental conditions, such as climate and road types, which impact battery load and stress. For example, aggressive driving and heavy use of auxiliary systems may reduce battery life, and infrastructure aspects like charging station types and electricity mix can influence efficiency. Considering these varied factors is crucial for effective battery management, and strategies such as thermal management, optimised charging practices, moderate driving, and energy management systems collectively extend battery lifespan and enhance EV sustainability.

Ref. [63] developed a lithium-ion battery degradation model for EVs, incorporating time-varying temperatures and charge cycles, which outperformed traditional models with a prediction error of 2.34% compared to 11.18%. This model, optimised with Particle Swarm Optimisation, underscores the impact of temperature fluctuations on battery capacity and suggests incorporating these factors in degradation models for better battery management. Ref. [64] proposes a degradation model using MEEMD, MIV, and Bi-LSTM, achieving high accuracy (MAE of 0.0143) by using capacity, voltage, current, and temperature data. This study identifies key degradation factors, emphasising the roles of internal parameters and operating conditions, such as high and fluctuating temperatures and frequent charging cycles. Ref. [65] reviews life cycle impacts, noting that battery degradation is influenced by production impacts of materials like cobalt, lithium, and nickel, as well as temperature fluctuations and charging patterns during use. Efficient recycling and second-life applications were also found to reduce degradation and environmental impact. Additional studies like [66,67] advanced degradation prediction methods by using partial charging segments for multi-type batteries, deep reinforcement learning for multi-formulation Li-ion batteries, respectively. These diverse approaches reflect ongoing efforts to enhance degradation predictions and improve the sustainability and performance of lithium-ion batteries in Evs.

The charging modes of EVs significantly influence the performance and longevity of lithium-ion batteries, particularly affecting the state of charge and state of health. The two primary charging methods—direct current (DC) fast charging and alternating current

(AC) charging—impart distinct impacts on battery dynamics due to their operational characteristics.

DC Fast Charging and Its Impact on SOC and SOH: DC fast charging is characterised by high voltage and current levels, enabling rapid replenishment of the battery's SOC. This method is advantageous for reducing charging time; however, it introduces considerable thermal and electrochemical stresses on the battery cells. High charging currents accelerate side reactions, most notably lithium plating on the anode surface—a phenomenon where lithium ions deposit as metallic lithium rather than intercalating into the anode material [68,69]. Lithium plating is an irreversible process that diminishes the availability of active lithium ions, leading to capacity loss and degradation of the SOH. Moreover, lithium plating poses safety risks due to the potential formation of dendrites, which can penetrate the separator and cause internal short circuits, leading to thermal runaway [68].

Elevated temperatures during DC fast charging exacerbate the growth of the solid electrolyte interphase (SEI) layer and accelerate electrolyte decomposition. The thickening of the SEI layer increases internal resistance and contributes to further capacity fade and reduced cycle life [69,70]. Additionally, the uneven lithium-ion distribution and localised heating can cause mechanical stresses within the electrode materials, leading to structural degradation over time [69].

AC Charging and Its Effects on Battery Health: In contrast, AC charging operates at lower power levels and provides a more controlled and uniform charging process. This mode minimises thermal and electrochemical stresses, thereby preserving the structural integrity of electrode materials and maintaining the SOH over extended usage [68,70]. The slower charging rate associated with AC charging allows for uniform lithium-ion intercalation within the electrode materials, reducing the likelihood of lithium plating and other degradation mechanisms [70]. Consequently, batteries charged using AC methods tend to exhibit longer cycle life and more stable performance over time. However, the extended charging duration may impact practicality for users requiring rapid energy replenishment.

Mitigation Strategies and Advanced Charging Protocols: To harness the benefits of DC fast charging while mitigating its adverse effects on the SOH, advanced charging protocols and battery management strategies have been proposed. Tailored charging protocols such as multistage constant current charging (MSCC) and pulse charging techniques aim to reduce thermal and structural stresses by dynamically adjusting charging currents [69]. These methods promote uniform lithium-ion distribution and reduce heat generation, thus preserving the SOH without significantly compromising the charging speed.

The integration of adaptive algorithms and advanced battery management systems (BMS) enables real-time monitoring and control of charging conditions, optimising the balance between charging efficiency and battery longevity [70,71]. Deep learning methodologies and machine learning models have shown promise in enhancing SOC and SOH estimation accuracy, allowing for predictive adjustments to charging protocols based on operational data [71,72]. These data-driven approaches facilitate the development of adaptive charging strategies that respond to the battery's condition and external factors, such as temperature and usage patterns.

Moreover, preheating strategies at low ambient temperatures have been suggested to minimise lithium plating risks during fast charging by improving the kinetics of lithium intercalation [68]. Innovations in converter topologies, such as bidirectional and quasi-Z-source converters, further enhance charging system efficiency by optimising power flow and reducing voltage stress on battery cells [69].

4. Discussion, Gaps, and Future Direction

4.1. Theme 1: Electric Vehicle Battery Technologies: Development and Trends

4.1.1. Discussion

The initial stages of EV battery development centred on foundational innovations with lead–acid and early lithium technologies. Research during 1976–1985 laid the groundwork by evaluating energy resources and optimising performance for internal combustion engines and early EVs. The introduction of lead–acid batteries and explorations into lithium technologies marked significant milestones, setting the stage for future advancements.

Between 1986 and 1995, there was a shift towards chemical system innovations and addressing environmental considerations. The development of hybrid power systems and material advancements reflected a growing awareness of the need for cleaner energy solutions. The automotive industry's recognition of an environmental programme led to innovations that enhanced infrastructure efficiency and reduced environmental impact.

The period from 1996 to 2005 witnessed the emergence of hybrid and fuel cell technologies, focusing on addressing performance challenges and integrating new power systems. Advancements in lithium and nickel–metal hydride (NiMH) technologies improved power and charging performance, making hybrid EVs (HEVs) more viable and cost-effective.

From 2006 to 2015, the focus intensified on efficiency and environmental impact. Significant advancements in hydrogen fuel cells and efforts to reduce emissions highlighted the industry's commitment to sustainability. Evaluations of energy and power systems during this time contributed to optimising hybrid and EVs, enhancing their range, cost-efficiency, and overall performance.

The most recent phase, from 2016 to 2025, emphasises sustainability and material efficiency. Technological advancements aim at emission challenges, with a particular focus on lithium-ion technologies and recycling methods. Efforts to incorporate recycling address environmental concerns and material scarcity, ensuring the sustainable use of resources. Enhancements in charging methods, heat management, and emission reduction techniques prepare the industry for future challenges.

Advances in battery modules and packs have greatly improved EV performance and safety. Innovations in thermal management and battery management systems have increased energy density and reliability at the system level. Integrated designs like cell-to-pack configurations have simplified manufacturing and made better use of space. These developments tackle practical challenges in vehicle integration, highlighting the importance of viewing the battery system as a whole rather than just individual cells.

4.1.2. Gaps

Despite considerable progress, several critical gaps remain. Scaling advanced technologies like solid-state and lithium–sulphur batteries for mass production is challenging, with economic viability and quality maintenance requiring further research. Comprehensive life cycle environmental impact assessments of new battery materials are lacking, making it difficult to ensure true sustainability. The absence of standardised testing protocols hinders reliable comparisons of performance and safety across emerging technologies. High production costs for advanced batteries limit accessibility, highlighting the need for cost-reduction innovations. Recycling methods for new chemistries remain underdeveloped, emphasising the importance of sustainable end-of-life solutions as EV adoption grows. Integrating EVs into current energy grids, particularly with vehicle-to-grid (V2G) capabilities, presents infrastructure challenges, especially in managing peak loads. Extreme temperature conditions degrade battery performance, necessitating advanced thermal management systems. Additionally, reliance on scarce or ethically contentious materials, like cobalt, raises sustainability and social responsibility concerns. Although the advancements in battery modules and packs, optimising battery modules and packs still faces challenges. Significant hurdles include thermal runaway within packs, mechanical stresses during operation, and difficulties in scaling up production. The lack of standardisation in designs can hinder interoperability and raise manufacturing costs. Additionally, integrating advanced battery management systems brings up issues related to data processing and cybersecurity.

4.1.3. Future Directions

To address existing gaps, several future directions are recommended. Scalable manufacturing processes should be developed to enable economical mass production of advanced batteries without sacrificing quality. Comprehensive life cycle analyses are necessary to understand and mitigate environmental impacts throughout battery lifespans. Industry-wide standards for testing and evaluating batteries would ensure reliable assessments of performance and safety. Cost-reduction efforts should focus on alternative materials and production techniques to broaden accessibility. Advances in recycling technologies are essential to recover valuable materials and reduce environmental harm, while improved thermal management systems can optimise battery performance under varying conditions. Expanding infrastructure, including charging stations and smart grid technologies, is key to supporting the growing EV market and enabling vehicle-to-grid (V2G) capabilities. Research into abundant, ethically sourced materials can reduce dependence on scarce resources, and interdisciplinary collaboration among industry, academia, and government will further accelerate innovation, knowledge sharing, and policy development. Improving battery module and pack design is crucial for safer, better-performing, and more manufacturable EV batteries. Future research should focus on advanced thermal insulation materials, structural designs that reduce mechanical stress, and standardised architectures to streamline production and recycling. Using intelligent battery management systems with real-time data can optimise performance and extend battery life. Collaboration among researchers, manufacturers, and policymakers is essential to tackle these challenges and promote sustainable EV battery systems.

4.2. Theme 2: Electric Vehicle Battery Capacity Prediction: Influencing Factors

4.2.1. Discussion

The comprehensive review of the current literature on electric vehicle (EV) battery capacity prediction reveals significant advancements driven primarily by the integration of machine learning (ML) and data-driven methodologies. The predominant focus across studies is the development and refinement of ML models, including neural networks, ensemble methods, and hybrid approaches, to accurately predict battery capacity and SOH. For instance, Ref. [37] demonstrated that combining Empirical Mode Decomposition (EMD) with Gated Recurrent Unit (GRU) neural networks and Random Forest (RF) significantly enhances SOH estimation accuracy, achieving prediction errors below 4%. Similarly, Gao et al. (2023) [41] and Zhou et al. (2024) [42] showcased hybrid neural networks incorporating convolutional neural networks (CNNs) and bidirectional long short-term memory (BiLSTM) units, further reducing prediction errors and improving reliability.

Hybrid models that merge data-driven techniques with physics-based approaches have emerged as robust solutions for capacity prediction. Xu et al. (2023) [48] and Chou et al. (2023) [50] highlighted the efficacy of combining empirical models with deep learning frameworks, enabling accurate degradation trajectory predictions using limited early cycle data. These hybrid methodologies address data scarcity issues and enhance model generalizability across diverse battery types and operational conditions.

Advanced signal processing and feature extraction techniques have also played a pivotal role in improving prediction accuracy. Techniques such as Discrete Wavelet Transform (DWT), incremental capacity (IC) analysis, and Electrochemical Impedance Spectroscopy (EIS) have been effectively utilised to extract meaningful features from battery performance data. Ref. [52] and Al-Hiyali et al. (2024) [54] demonstrated that integrating these signal processing methods with machine learning models significantly enhances the fidelity of remaining useful life (RUL) predictions, achieving errors below 1%.

Temperature and thermal effects have been identified as critical factors influencing battery degradation. Studies [56,57] developed accurate models for estimating internal battery temperatures and predicting thermal performance under various cooling strategies. Effective thermal management is essential not only for preventing thermal runaway but also for prolonging battery lifespan by mitigating temperature-induced degradation mechanisms.

SOC estimation remains a cornerstone for accurate capacity prediction. Advanced SOC estimation methods, such as the Interacting Multiple Model (IMM) employed by Wu et al. (2022) [60], have shown high accuracy in decoupling temperature and ageing effects, maintaining SOC estimation errors around 2%. Precise SOC estimation is crucial for optimising battery management systems, ensuring optimal performance, and extending battery life.

Moreover, the identification and analysis of factors influencing battery degradation—such as operating conditions, SOC range, charging patterns, and mechanical stresses—underscore the multifaceted nature of battery capacity loss. Ref. [63] emphasised the substantial impact of temperature fluctuations, depth of discharge (DoD), and charging rates on battery health, advocating for comprehensive models that incorporate these variables to enhance prediction accuracy and battery life cycle sustainability.

The reliability and accuracy of battery behaviour models depend on data quality and advanced analytical techniques. Recent advancements in data acquisition and analytical methods have significantly improved model capabilities, enabling precise predictions of battery performance.

Modern EVs, equipped with advanced battery management systems (BMSs), collect high-resolution data on parameters like voltage, current, and temperature under diverse conditions. These detailed data enhance the understanding of battery behaviour, capturing transient events and subtle degradation patterns. The rise in connected devices and IoT has also expanded large-scale datasets, allowing manufacturers and fleet operators to aggregate data from thousands of vehicles. These comprehensive datasets improve model robustness and generalizability.

On the analytical side, machine learning, particularly deep learning architectures like CNNs, RNNs, and LSTMs, efficiently process large datasets and capture nonlinear relationships in battery systems. Hybrid models combining data-driven methods with physics-based principles further enhance predictions by balancing accuracy and interpretability. Advanced feature extraction techniques, such as incremental capacity analysis (ICA) and differential voltage analysis (DVA), provide key battery health indicators, improving model inputs and predictions.

These advancements have significantly increased the reliability of battery models, reducing uncertainty and supporting better decision-making. Accurate models optimise battery usage, maintenance, and failure prevention, enhancing EV safety, efficiency, and lifespan. They also build consumer and manufacturer confidence in EV battery performance and durability, promoting electric mobility adoption and enabling better energy management for sustainable systems.

4.2.2. Gaps

Despite notable progress in EV battery capacity prediction, several key research gaps remain. Limited real-world validation restricts model robustness, as many models rely on controlled datasets with minimal validation across diverse EV types and conditions. Most studies focus on specific lithium-ion chemistries, limiting generalisation across battery types and configurations. Models also often omit important operational factors such as user behaviour and environmental conditions, leading to incomplete degradation predictions. High computational demands of advanced models hinder real-time application, underscoring the need for optimisation. Current models struggle with long-term degradation forecasting across a battery's life cycle, especially under varying conditions. Privacy and security concerns in data-driven models require further exploration, with federated learning offering potential but underexplored solutions. Additionally, limited integration of materials science, chemistry, and engineering insights restricts a holistic understanding of degradation, suggesting a need for multidisciplinary approaches to improve model accuracy.

4.2.3. Future Suggestions

To address these gaps and advance EV battery capacity prediction, future research should focus on several key areas. Enhanced data collection through partnerships with manufacturers and fleet operators can provide diverse, real-world operational data to improve model accuracy. Developing universal models that adapt across battery chemistries, using techniques like transfer and federated learning, will ensure broader applicability while maintaining data privacy. Models should also integrate varied operational factors, such as user behaviour and environmental conditions, to capture comprehensive degradation patterns. Optimising models for real-time deployment through computational techniques will support practical battery management applications. Long-term studies on battery performance under diverse conditions will refine predictions for capacity loss, while multidisciplinary research incorporating materials science and engineering can deepen understanding of degradation. Integrating thermal management in degradation models can further enhance safety and battery lifespan. Emerging machine learning techniques, including reinforcement learning and explainable AI, may improve performance and transparency. Testing models across a range of climates and driving conditions will ensure scalability, while data from recycling and second-life applications will support more sustainable battery management and life cycle practices.

5. Conclusions

This research has provided a thorough exploration of the trends shaping battery technology, which is foundational to the future of electric vehicles (EVs). By using a hybrid methodology that combines DTM and content analysis, this study identifies major advancements in battery materials, design, and manufacturing, highlighting innovations such as solid-state and lithium–sulphur batteries as well as improvements in lithium-ion chemistries. These advancements address critical EV challenges, including energy density, safety, and sustainability, while targeting limitations in range, charging time, and safety—key factors for the widespread adoption of EVs. By analysing these emerging technologies, this study offers essential insights into how battery development aligns with EV industry needs.

Additionally, the study evaluates methodologies for predicting remaining battery capacity, revealing a strong trend towards machine learning and data-driven approaches to improve prediction accuracy. Techniques such as deep learning, transfer learning, and advanced signal processing are gaining prominence in real-time battery health monitoring, allowing for more accurate and timely capacity assessments. These data-centric methodologies support more effective battery management systems, potentially extending battery lifespans and ensuring that EVs remain reliable and efficient over time. Such advancements in capacity prediction contribute to optimising EV performance and addressing concerns surrounding battery reliability and life cycle costs.

This literature review also delves into factors impacting battery capacity degradation, identifying key influences such as temperature extremes, depth of discharge, state of charge, charging rates, and overall operating conditions. Managing these factors is crucial for maintaining battery health and lifespan, and the study emphasises the role of advanced battery management systems, thermal regulation, and optimised charging protocols in achieving sustainable life cycle practices. These insights are timely and relevant, not only to researchers but also to policymakers and industry leaders who are tasked with establishing standards and creating supportive frameworks for sustainable EV growth. By integrating perspectives from materials science, engineering, and environmental policy, this study bridges essential knowledge gaps in battery life cycle management.

In conclusion, this research presents a comprehensive analysis of battery technology developments, methodologies for capacity prediction, and factors affecting battery degradation, directly addressing the core research questions. The findings hold significant implications for the EV sector's role in achieving sustainability goals. As the EV industry continues to evolve, aligning battery advancements with environmental targets is imperative. This research underscores the need for ongoing innovation, interdisciplinary collaboration, and life cycle-focused approaches to ensure that EVs fulfil their environmental potential, contributing to the broader goals of carbon neutrality and a resilient energy future for generations to come.

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