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Analysis of the Performances of Electric Vehicle Batteries: A Systematic Literature Review

Antonio Comi | Ippolita Idone

Department of Enterprise Engineering "Mario Lucertini", University of Rome Tor Vergata, Via Del Politecnico, 1, Rome 00133, Italy

Correspondence: Antonio Comi (comi@ing.uniroma2.it)

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ABSTRACT

Electric vehicles (EVs) are increasingly becoming the main mobility option, with global sales in 2023 driven predominantly by China (60%), Europe (25%) and the United States (10%). This widespread adoption has intensified demand for EV batteries, which exceeded 750 GWh in 2023, marking a 40% year-on-year increase. As EVs expand in number, battery performance and reuse emerge as pivotal challenges in the transition to sustainable mobility. This study presents a systematic literature review focussing on the performance evaluation and life prediction of EV batteries, with a primary emphasis on lithium-ion technology, which is the more common technologies. Using a bibliometric clustering approach by CiteSpace©, the review identifies key research domains and highlights critical gaps, especially the underrepresentation of real-world usage conditions in performance models. This review integrates findings across diagnostic, modelling and field-performance studies to propose a unified framework for evaluating EV battery performance under dynamic operating conditions. Findings reveal that while numerous diagnostic tools and modelling techniques exist, their applicability to dynamic operational contexts remains limited. The results aim to support future innovation in battery management systems (BMSs), second-life strategies and potentially circular economy applications, providing both a scientific foundation and practical guidance for advancing sustainable energy solutions.

1 | Introduction

The global transition towards sustainable mobility has positioned electric vehicles (EVs) as a cornerstone technology in the effort to reduce greenhouse gas emissions and mitigate the environmental impact of transport systems. In 2023, EV sales reached an all-time high, with China, Europe and the United States accounting for approximately 95% (i.e., China, 60%, Europe, 25% and the United States, 10%) of the global demand. This unprecedented growth reflects not only consumer interest and supportive policy frameworks but also the rapid evolution of battery technologies, charging infrastructure and energy systems integration. As a direct consequence of this market expansion, the global demand for EV batteries exceeded 750 GWh in 2023, marking a 40% increase over the previous year. This growing reliance on lithium-ion batteries, while enabling decarbonisation goals, raises a series of complex and interrelated challenges concerning performance, durability, safety and environmental sustainability.

Battery performance is influenced by a range of technical and external factors, including cell chemistry, battery size, thermal conditions, usage intensity and long-term ageing processes. In particular, degradation phenomena such as capacity fade and increased internal resistance can compromise vehicle efficiency and user satisfaction. In this context, the proposed review focuses on operational and usage-related causes of deterioration (i.e., temperature, driving behaviour, charging cycles, environmental stress), as well as diagnostic and predictive modelling approaches. Aspects such as packaging architecture, specific chemistry comparisons and proprietary battery-management system (BSM) protocols are acknowledged, but they remain outside the core scope of this study.

Moreover, the diversity of operational scenarios, ranging from urban stop-and-go traffic to high-speed highway travel, introduces significant variability in the way batteries behave and degrade over time. Factors such as driving style, temperature fluctuations, irregular charging habits and different load profiles contribute to dynamic stress patterns that are often not captured in standardised laboratory tests.

Although numerous studies have examined battery behaviour under controlled conditions using standard driving cycles (e.g., NEDC: New European Driving Cycle, US06, WLTP: New European Driving Cycle), these protocols offer a simplified and often idealised view of real-world usage. In reality, EV operation is shaped by nonlinear and context-specific variables that interact in unpredictable ways, making it difficult to generalise laboratory findings to practical conditions. As a result, many existing performance models lack the robustness required to accurately estimate key indicators such as state of health (SoH), state of charge (SoC) and remaining useful life (RUL) across diverse usage profiles.

Addressing these gaps requires a more integrated research approach, capable of synthesising both quantitative and qualitative insights from a wide body of literature. As said, this paper presents a systematic literature review under the point of view of transport engineers/planners, aimed at evaluating current methodologies for assessing and forecasting EV battery performance, with particular emphasis on studies that consider operational variability, ageing processes and predictive health estimation. A bibliometric clustering technique is combined with in-depth content analysis to map the major research trends, identify knowledge gaps and assess the evolution of the scientific discourse over time.

As detailed below, the review identifies six key factors that significantly affect battery performance in real-world scenarios: operating temperature and environmental conditions, charge and discharge cycling patterns, driving behaviour, charging methodologies, internal degradation mechanisms and AI-based predictive modelling techniques. These elements form the backbone of a more holistic understanding of battery dynamics, and their interdependence highlights the need for multidimensional models that go beyond siloed assessments.

Ultimately, this study aims to contribute to the development of more accurate, adaptive and sustainable battery management systems (BMSs), while supporting broader objectives related to energy efficiency, battery reuse and potentially circular economy principles. By offering a structured synthesis of the literature, the paper also provides guidance to researchers, policymakers and industry stakeholders seeking to advance innovation in the management of EV battery and promote long-term sustainability in electrified mobility systems.

2 | The Proposed Methodology of Analysis

Researchers can employ bibliometric analysis, a quantitative method used to examine and synthesise published studies, to assess academic research on a specific topic [1–6]. This technique relies on secondary data from digital databases, providing an objective, data-driven perspective. Bibliometric analysis enables a systematic, transparent and replicable approach to reviewing the literature, thus enhancing the reliability of the review. The methodology used in this study, depicted in Figure 1, consists of the following steps:

- *initialisation*; i.e., creation of a scientific dataset based on predefined inclusion and exclusion criteria to ensure the relevance and quality of the selected studies;
- *identification*; i.e., definition of relevant keywords and the use of Boolean operators to optimise search results within databases;
- *screening and eligibility*; i.e., selection of relevant studies, with the removal of duplicates and irrelevant ones;
- *data analysis*; i.e., detailed examination of the selected studies, including a review of their content and emerging trends.

In addition to the quantitative clustering process, each identified thematic group/cluster of studies is manually reviewed to validate the coherence of representative papers and to identify potential overlaps among disciplines. This validation step helped capture the cross-domain nature of the topic, where engineering, environmental science and artificial intelligence (AI) frequently intersect in the study of EV battery performance.

3 | The Results

Following the methodology outlined, the literature review has been systematically developed, progressing through the predefined stages as detailed in the following sections.

3.1 | Initialisation

The initial phase consisted of defining the specific field of inquiry. Based on this, a scientific dataset was built to align with the aims of the study. The relevant keywords were then identified, focussing on the assessment of the impact of EVs in the context of vehicle usage. The literature search has been carried out using both Web of Science (WoS) and Scopus, since WoS offers extensive historical records and Scopus provides broader journal coverage. Clear inclusion and exclusion criteria have been established to guide the selection process, ensuring the relevance and quality of the studies considered. The search was limited to publications in English, although this choice could exclude relevant studies published in other languages. This choice is made to ensure consistency in screening and interpretation, but it can introduce a geographical bias in the reviewed literature. These criteria are presented in Table 1.

3.2 | Identification

After selecting the relevant keywords, the data collection process has been refined through the use of Boolean operators (OR, AND), allowing for strategic combinations of terms to optimise search outcomes across the chosen databases (WoS and Scopus). The search aimed at the title, abstract and keyword fields to ensure the retrieval of a comprehensive and well-focused dataset. More details on keyword combinations and search strategy are

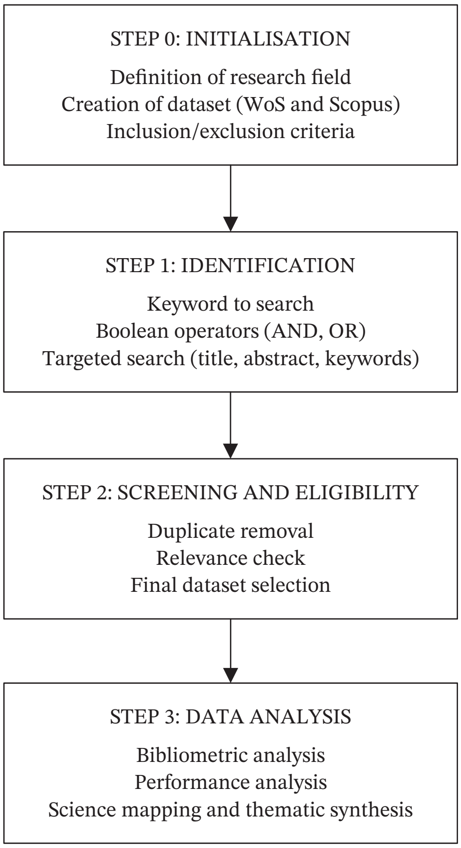

FIGURE 1 | Proposed literature review methodology.

provided in Table 2. Although no keywords have been introduced on the concentration of lithium-ion batteries, the fairly large number of identified studies refer to them.

3.3 | Screening, Eligibility and Inclusion

An initial screening has been carried out by including only studies written in English and published from 2010 onwards. The results of the search process are summarised in Table 2, with a total of *8657* publications identified as relevant for review. The final stage involved examining the selected studies to conduct the bibliometric analysis, which included both performance analysis and science mapping. Performance analysis typically assesses the impact and significance of publications, authors, journals, institutions and countries, often based on citation counts and average citations per publication. Science mapping, on the other hand, includes techniques such as co-citation analysis and the exploration of research development over time. The analysed studies span various publication types. Figure 2 displays the annual distribution of the selected studies, highlighting temporal trends and revealing a steady increase in research activity in recent years. The figure also distinguishes among source types, showing a clear predominance of journal papers compared to book chapters and conference proceedings papers.

TABLE 1 | Inclusion criteria for work/study selection.

Dataset	WoS and Scopus
Analysed field	Title, abstract and keywords
Document type	Article, conference proceedings, book chapter
Language	English
Source type	Peer-reviewed studies
Time interval	2010–2025 (April)

3.4 | Results of the Literature Review

Data analysis allows 11 primary thematic groups to be identified. The primary thematic clusters, shown in Table 3, are those with high silhouette scores and internal coherence [7] because they represent groups of papers with well-defined themes. Table 3 reports the main groups identified along with their silhouette values, the number of studies and the average year.

Although clustering produced distinct thematic groups, overlaps emerged, particularly between engineering, environmental science and AI. For example, studies on real-world stress often integrate AI-based predictive modelling, and BMS research intersects with both environmental management and engineering optimisation.

4 | Performances of Electric Vehicle Batteries

Bibliometric analysis carried out using CiteSpace© revealed a structured and diversified research landscape concerning the performance of EV batteries, with 11 major thematic clusters identified. These clusters provide a comprehensive view of the technological, operational and scientific challenges associated with the performance and degradation of lithium-ion batteries in EV applications.

From the synthesis of these clusters, six key factors emerged as central to understanding and evaluating battery performance:

- *operating temperature and environmental conditions*, which affect electrochemical stability, internal resistance and overall efficiency; environmental factors such as humidity, vibration and altitude, though less frequently studied, also appear to influence battery ageing and performance under real-world conditions and are therefore considered as complementary to temperature-related dynamics;
- *charge and discharge cycling patterns*, including frequency, depth of discharge (DoD) and current rates, which influence capacity fade and ageing;
- *driving behaviour and usage patterns*, particularly those associated with acceleration, braking and driving cycle variability, which impact both energy consumption and battery stress;
- *charging methodologies*, including standard, fast and smart charging strategies, as well as battery swapping, which affect thermal load and internal degradation;
- *internal degradation mechanisms*, such as side reactions and chemical ageing that result in irreversible capacity loss and performance decline;
- *predictive modelling and AI-based estimation techniques*, which aim to improve the SoC and SoH predictions and enable proactive battery management.

In addition to these, the role of the BMS emerges as a key enabling component across several of the identified themes. Although not treated as a separate performance factor, the BMS is

TABLE 2 | Summary of the methodology application.

Search string	Documents (studies/works)	To review
("electric mobility" OR "e-Mobility" OR "electric vehicl*" OR "hybrid vehicl*" OR "EV" OR "HEV" OR "PHEV" OR "BEV" OR "automobil*") AND ("battery performance" OR "battery degradation" OR "state of health" OR "health state" OR "SoH" OR "battery aging" OR "health estimation" OR "SoC" OR "state of charge") AND ("real-world" OR "driving" OR "operating" OR "operation*")	5021* 7489** 12,510*** 3853****	8657

* = WoS.
** = Scopus.
*** = total.
**** = duplicates.

instrumental in implementing temperature control, monitoring charge cycles, interpreting usage patterns and executing predictive algorithms for battery diagnostics and optimisation.

4.1 | Operating Temperature and Environmental Conditions

Operating temperature is one of the most influential factors affecting lithium-ion battery performance. Extreme temperatures can alter electrochemical reaction kinetics, increase internal resistance and reduce the accuracy of battery monitoring systems. High temperatures accelerate degradation mechanisms such as solid electrolyte interphase (SEI) growth, while low temperatures hinder ion diffusion, reducing available power [8, 9].

Some studies, such as Xing et al. [10], demonstrated that inaccurate SoC estimations are common under variable thermal conditions. Researchers have proposed a method for estimating the SoC of lithium-ion batteries based on open-circuit voltage (OCV), highlighting how the OCV–SoC relationship varies significantly with ambient temperature and incorporating this variability into the model to improve accuracy.

Environmental conditions beyond temperature, such as humidity, altitude and vibration, also play a key role in battery degradation. Waag et al. [11] found that environmental factors affect internal impedance, with direct implications for both thermal response and SoH estimation.

Thermal and environmental stress must therefore be actively managed, and BMS are critical in this role, providing real-time thermal control and compensation.

4.2 | Charge and Discharge Cycling Patterns

Repetition of the charging and discharging of lithium-ion batteries is a major determinant of long-term performance. Battery degradation is strongly influenced by parameters such as the number of cycles, the DoD, current rates and ambient temperature during cycling. Prolonged exposure to high current densities or deep cycling can cause mechanical stress, structural damage to the electrodes and irreversible capacity loss.

Han et al. [9] offered a comprehensive review of degradation mechanisms, including active material detachment and impedance increase, which occur progressively over the battery lifecycle. In addition to these findings, Severson et al. [12] developed a data-driven approach using early cycling data to accurately forecast battery longevity, revealing that early-stage behaviour can be a reliable predictor of future capacity fade/degradation.

Recent advances have also explored the optimisation of charging profiles to reduce degradation. Attia et al. [13] proposed a closed-

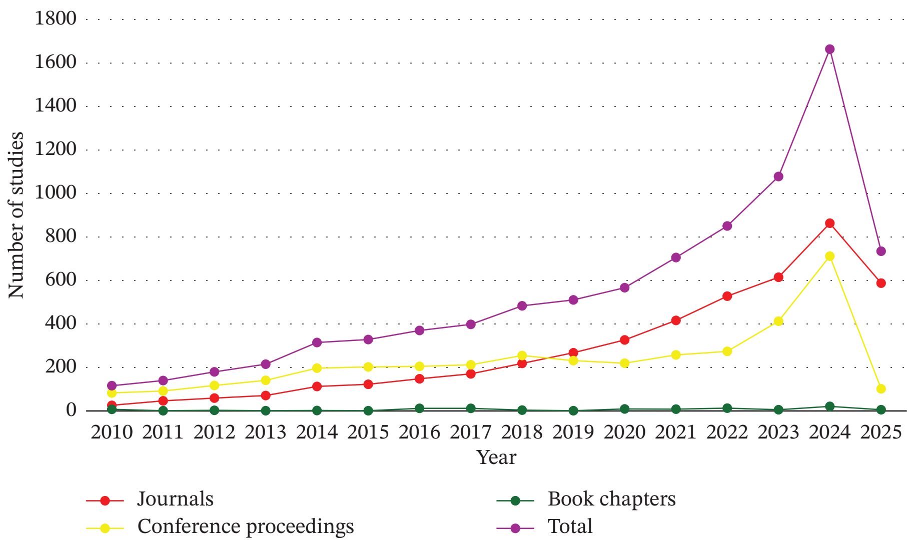

FIGURE 2 | Year-by-year studies.

TABLE 3 | Summary of the 11 largest clusters.

ClusterID	Size	Silhouette	Label (LLR)	Core year
0	142	0.862	AI-based estimation	2019
1	126	0.975	Energy management	2018
3	118	0.842	Real-world state	2021
4	94	0.911	BMS and balancing	2014
5	65	0.921	Deep learning models	2019
6	43	0.932	Hybrid modelling	2014
7	37	1.000	To-grid technologies	2010
8	32	0.993	Side reaction	2011
10	26	0.971	Reduced order	2012
13	12	1.000	Driving behaviour	2012
15	10	0.999	Swapping station	2022

loop optimisation system using machine learning to fine-tune fast-charging protocols while minimising the onset of harmful side reactions.

Therefore, different studies (e.g., [12, 14, 15]) demonstrate that early-cycle data, collected during the first few charge/discharge cycles, can serve as a reliable predictor of the long-term capacity fade and the RUL. This approach leverages initial electrochemical signatures to anticipate degradation trends, enabling proactive battery management strategies.

4.3 | Driving Behaviour and Usage Patterns

Real-world driving behaviour has a significant impact on battery performance. Factors such as aggressive acceleration, frequent braking, stop-and-go traffic, and terrain variability lead to non-uniform discharge profiles and thermal stress. These operating conditions affect not only energy consumption but also long-term integrity of the battery [16]. SoC estimation methods have been developed that incorporate real-time driving parameters, enhancing the robustness of the model under dynamic operating conditions [17]. It has also been shown that incorporating the behavioural patterns into control systems can reduce cumulative degradation by aligning power output with less harmful profiles [18].

A smart BMS, capable of integrating driver behaviour into its control logic, can promote more durable battery usage by dynamically adjusting operational limits. However, integrating real-time driving behaviour into BMS-based SoH estimation remains a challenge. Current systems are limited by onboard hardware capabilities, communication bandwidth and privacy restrictions on telemetry data. Future developments should focus on lightweight data processing, edge-computing integration and privacy-preserving aggregation to enable behaviour-aware SoH estimation in real time.

4.4 | Charging Methodologies

The choice of charging methodology has a direct impact on battery longevity and performance. Conventional, fast and smart charging strategies each involve trade-offs between convenience, safety and degradation. Fast charging, for example, allows for rapid energy replenishment but induces greater thermal and mechanical stress on the cells, often accelerating SEI formation and gas generation.

High-current fast charging has been highlighted to contribute significantly to internal degradation, particularly in the absence of temperature control strategies [19]. In contrast, intelligent or "smart" charging systems, which can adapt to grid conditions and battery state, have shown potential in mitigating these adverse effects.

Beyond conventional and fast charging, some studies address vehicle-to-grid (V2G) and demand response integration. These strategies enable EVs to provide ancillary services but introduce additional cycling and DoD variations, which can accelerate degradation if not properly managed ([19–25]). Smart scheduling and degradation-aware algorithms are therefore essential to balance grid benefits with battery longevity.

At the same time, battery swapping technologies are being investigated as alternatives to conventional charging, particularly in high-use scenarios such as electric fleets and shared mobility services. The planning and operational implications of battery swapping have been reviewed, with particular emphasis on challenges related to standardisation, synchronisation of cell ageing and quality control across interchangeable battery packs [26]. Battery swapping is an accepted and established concept in the EV industry, though its implementation varies significantly by region and use case. It is particularly prominent in China and for commercial fleets but less so for private consumer cars in many Western markets [27, 28]. Both approaches underline that optimised charging practices, supported by advanced BMS and infrastructure design, are essential for preserving battery health in real-world EV applications.

4.5 | Internal Degradation Mechanisms

Internal chemical degradation, often undetectable during regular use, represents one of the most insidious threats to battery performance. Reactions such as SEI thickening, lithium plating and electrolyte decomposition progressively consume active lithium and reduce capacity, contributing to irreversible ageing even under relatively mild operating conditions [29].

A methodology for estimating the density of parasitic side reaction currents using retrospective-cost identification has been proposed as a valuable diagnostic tool for real-time SoH monitoring [30]. An on-board monitoring method for lithium-ion batteries, based on mathematical models and capable of estimating internal resistance and SoH during real-world use using only vehicle-available signals and without additional sensors, has also been developed [31]. These approaches reduce hardware complexity and enable real-time diagnostics under practical conditions.

These approaches underline the increasing relevance of internal diagnostics in battery management. Integration of electrochemical impedance spectroscopy (EIS) and onboard degradation models into the BMS [32, 33] can provide earlier and more accurate warnings of internal failure, supporting predictive maintenance and informed design improvements.

4.6 | Predictive Modelling and AI-Based Estimation Techniques

The integration of AI into battery diagnostics and management systems marks a significant advancement in recent research. Machine learning models, particularly deep learning architectures such as long short-term memory (LSTM) networks and convolutional neural networks (CNNs), are increasingly being used to improve the accuracy of SoC and SoH estimation [34]. The current landscape of AI applications in battery management has been reviewed, emphasising the superior adaptability and precision of data-driven models to handle nonlinear and uncertain conditions. A convolutional autoencoder model trained on electrochemical impedance data has also been introduced, demonstrating reliable SoH predictions even under high levels of signal noise [35].

These developments enable real-time performance forecasting, early fault detection and tailored energy management strategies. Hybrid models that combine physical battery modelling with AI techniques have been proposed as a way to balance interpretability with predictive accuracy [36, 37], representing a key step towards more intelligent and autonomous battery systems.

Although AI-based models are increasingly used for the SoC/SoH estimation, only a limited number of studies explicitly address the adequacy. Some recent works apply XAI tools such as feature-importance analysis, SHAP values or attention mechanisms to improve transparency, but these approaches remain limited. This highlights the need for a more systematic integration of explainability into AI-driven battery diagnostics, especially for safety-critical BMS applications. Besides, hybrid approaches could be used. They typically combine a physical battery model with an AI module that learns residual errors or unmodelled dynamics. Examples include equivalent-circuit models corrected by neural networks or electrochemical models supported by Gaussian-process estimators. These methods improve accuracy and robustness while preserving physical interpretability, but they also require more computation and high-quality data, and their calibration can be challenging.

Advances in AI-driven BMS architectures include autoencoder neural networks and hybrid models that combine physical battery models with machine learning to predict SoH in real time using minimal sensor input [32, 33]. These solutions are designed for onboard implementation, offering non-invasive and computationally efficient estimation suitable for commercial EV platforms.

Recent studies also explore advanced paradigms such as digital twins for real-time battery simulation, generative AI for anomaly detection and predictive maintenance, and federated learning to enable collaborative SoH estimation without compromising data privacy. These approaches, though still emerging, represent a shift towards distributed and adaptive diagnostics suitable for large-scale EV fleets.

5 | Discussion

This systematic literature review provides a structured synthesis of current research on EV battery performance, revealing a highly multidisciplinary and rapidly evolving field. Through bibliometric clustering, six key factors were identified as central to battery behaviour: operating temperature and environmental conditions, charge–discharge cycling patterns, user driving behaviour, charging methodologies, internal degradation mechanisms and predictive modelling approaches.

The bibliometric clustering also revealed several cross-domain interactions, reflecting the inherently multidisciplinary nature of EV battery research. Many studies combine engineering-based performance modelling with environmental or AI-driven analytical approaches. These overlaps highlight that thermal-, mechanical- and usage-related degradation factors are often investigated through integrated methodologies that bridge engineering control, environmental analysis and data-driven diagnostics.

While aspects are often addressed in isolation within the literature, real-world usage of EV introduces significant interactions among them, for instance, how temperature exacerbates degradation during fast charging or how driving style influences cycle depth and stress on cells. The lack of integrated modelling frameworks capable of capturing such complexity limits the effectiveness of many proposed solutions [36].

Environmental stress factors such as humidity, vibration and altitude were found to be only marginally addressed in the reviewed studies. This underrepresentation is mainly due to the experimental and data-related challenges of isolating these effects under controlled conditions. From an engineering perspective, such variables are often embedded within broader operational variability and, therefore, not treated as independent degradation parameters. However, their influence on battery life and safety is non-negligible. Future research should integrate sensor-equipped fleet monitoring, standardised reporting of environment conditions and AI-based data correlation methods to better quantify their role in long-term degradation and second-life use.

A recurring limitation among reviewed studies is the over-reliance on standardised testing protocols (e.g., NEDC, WLTP), which fail to reflect the operational heterogeneity experienced by EV batteries in practice [9, 12]. Consequently, models calibrated on these cycles often misestimate the SoH and the RUL, leading to suboptimal energy management and uncertainty in second-life deployment.

There is also a dominance of laboratory-based ageing tests and the limited validation of machine learning life prediction models under real-world conditions. Most reviewed studies calibrate models using standardised cycles or controlled datasets, which oversimplify operational variability. Consequently, predictive algorithms often fail to generalise to heterogeneous driving patterns and environmental stresses encountered in practice. Addressing this gap requires collaborative validation schemes, integration of fleet telemetry and federated learning approaches to enhance robustness and applicability [9, 12, 36].

Another important limitation concerns the gap between academic modelling and commercial EV platforms. Academic studies typically rely on laboratory data or open-access datasets, which simplify real-world variability and exclude proprietary control strategies. In contrast, industrial systems operate with confidential BMS algorithms and restricted operational data. This discrepancy reduces the transferability of academic findings to commercial contexts. To overcome this limitation, future work should promote collaborative validation schemes, federated learning approaches and anonymised data sharing between research institutions and industry partners.

Although the reviewed studies extensively analyse operational and environmental factors, only a limited number explicitly distinguish degradation behaviour across different battery cell formats (cylindrical, prismatic, pouch). Most contributions treat lithium-ion batteries as a homogeneous category, without isolating the influence of geometry on thermal dynamics or mechanical stress. This lack of format-specific evidence limits the possibility of generalising some degradation mechanisms across all cell types.

In the reviewed literature, electrical parameters (voltage, current, internal resistance) and thermal conditions emerge as the most widely used predictors of battery degradation. These features are often integrated into predictive models, while usage-related variables such as driving behaviour and charging patterns are increasingly incorporated to improve accuracy under real-world conditions.

The integration of digital twins, generative AI and federated learning into battery diagnostics is gaining traction, offering scalable and privacy-preserving solutions for predictive maintenance. These innovations complement traditional AI models and support the vision of intelligent adaptive BMS capable of operating under heterogeneous real-world conditions.

Furthermore, while BMS is recognised as a key enabler technology, it is often treated as a passive monitoring tool rather than an active agent for real-time control, optimisation and adaptation [37]. Bridging this gap requires the integration of advanced data-driven approaches, such as AI-enhanced estimation techniques and hybrid models that combine physical and data-based reasoning into next-generation BMS architectures.

This review also identified several promising avenues for future research: the need to develop models that include environmental and behavioural variability; the fusion of empirical data and machine learning with physics-based battery modelling; and the design of predictive, BMS-centred control systems that are tailored to real-world conditions [26]. These innovations are essential to improve battery durability, optimise reuse potential and support circular economy pathways.

Integration of EVs with external grid services, such as V2G, has been shown to increase ageing rates due to frequent bidirectional energy flows and thermal stress. Predictive models that include the use of V2G consistently report reduced RUL compared to standard operation, highlighting the importance of adaptive BMS and optimised energy management strategies for sustainable deployment.

The trend towards sensor-light SoH estimation reflects a shift from laboratory-intensive diagnostics to practical, real-time solutions. Using existing vehicle signals and AI-enhanced algorithms, these methods reduce cost and complexity while improving predictive accuracy, supporting scalable deployment in next-generation BMS.

Looking ahead, next-generation BMS architectures are expected to integrate all six performance factors (e.g., temperature, cycling patterns, driving behaviour, charging strategies, internal degradation and predictive modelling) into a unified control framework. These systems would combine real-time sensing with digital twin simulations and hybrid physics, i.e., AI models to forecast SoH and RUL dynamically. Adaptive algorithms could adjust charging profiles, thermal management and power delivery in response to operational conditions, while federated learning ensures privacy-preserving collaboration between fleets. This holistic approach would transform BMS from passive monitoring tools into active decision-making platforms for sustainable battery lifecycle management.

Ultimately, this review lays the foundation for a more holistic and realistic assessment of EV battery performance, with significant implications for academic research, industrial applications and sustainable mobility policies.

6 | Conclusions

This study provides a comprehensive and structured review of the current state of research on EV battery performance, using a bibliometric clustering approach to identify key themes and methodological gaps. It highlights six critical factors, operating temperature, charge–discharge cycles, driving behaviour, charging strategies, internal degradation mechanisms and predictive modelling, as essential to understanding battery behaviour in real-world contexts.

The analysis reveals that, while significant advances have been made in modelling and diagnostic techniques, many studies remain constrained by simplified assumptions and standardised test protocols that fail to reflect actual usage scenarios. This limits the effectiveness of current tools in supporting sustainable battery management and second-life planning.

A key contribution of this review is its dual methodological framework, which combines quantitative science mapping with qualitative content analysis. This approach has allowed the identification of underexplored areas, such as behavioural and environmental variability, and has emphasised the need for data-driven, context-aware models.

To advance the field, future research should prioritise the development of hybrid modelling techniques that integrate physical and AI-based methods, grounded in real-world data [35, 36]. Furthermore, intelligent and adaptive BMS should not only be positioned as monitoring tools; the review envisions next-generation BMS as integrated systems that combine electrical, thermal, environmental and behavioural data, leverage hybrid physics, AI models and support adaptive control in real time. Such systems could also enable informed second-life use and integration with grid services [37]. A practical implementation of such integrated BMS would involve multi-source data fusion, edge computing for real-time diagnostics and predictive control loops capable of evaluating the health impact of each operational decision. By embedding these capabilities, future EV platforms can achieve adaptive energy management and extend battery life under heterogeneous real-world conditions.

Future research should prioritise bridging the gap between lab-based protocols and real-world data streams. This includes validating AI-driven life prediction models against field conditions and incorporating dynamic usage profiles into integrated modelling frameworks. By addressing these challenges, researchers and practitioners can develop more robust, accurate and sustainable approaches to battery lifecycle management, with far-reaching implications for electric mobility, energy resilience and environmental impact reduction.

Author Contributions

Conceptualisation, Antonio Comi and Ippolita Idone; methodology, Antonio Comi; software, Ippolita Idone; validation, Antonio Comi and Ippolita Idone; formal analysis, Antonio Comi and Ippolita Idone; investigation, Antonio Comi and Ippolita Idone; resources, Antonio Comi; data curation, Antonio Comi and Ippolita Idone; writing–original draft preparation, Antonio Comi and Ippolita Idone; writing–review and editing, Antonio Comi; visualisation, Antonio Comi and Ippolita Idone; supervision, Antonio Comi; project administration, Antonio Comi; funding acquisition, Antonio Comi.

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All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data are available on request from the authors.

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