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ARTIFICIAL INTELLIGENCE FOR BATTERY SAFETY, DEGRADATION PREDICTION AND CIRCULAR ECONOMY IN NET-ZERO TRANSPORT AND GRID ENERGY STORAGE: A SYSTEMATIC REVIEW AND UK RESEARCH ROADMAP

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Abstract

The shift to a net zero energy system in the UK has helped to boost the use of lithium-ion batteries in EVs and grid-scale energy storage solutions. However, battery safety, degradation and end-of-life issues remain key challenges to system reliability, sustainability and economic performance. These issues are generally studied separately, with little connectivity between the various stages of the battery lifecycle and few studies addressing policy and industrial priorities that are relevant in the UK. The study is a systematic search of literature from peer-reviewed articles published from 2019 to 2025, following PRISMA framework. Literature was gathered from Scopus, Web of Science and IEEE Xplore using the following keywords: Artificial Intelligence (AI), Battery Safety, Thermal Runaway, State of Health (SOH), Remaining Useful Life (RUL), Second-life Batteries, and Battery Recycling. Studies were analysed under four themes: battery safety, degradation prediction, circular economy applications and future UK research needs after screening, and eligibility assessment. According to the results, machine learning and deep learning are applied in a wide variety of ways for fault diagnosis, thermal runaway prediction, and battery management systems. While physics-informed and hybrid AI models show promising results in SOH estimation and RUL prediction, there are still challenges such as data scarcity, model transferability, and explainability. The applications of AI in second-life battery assessment, optimisation of recycling processes, and resource recovery are emerging, but need further validation and standardisation. The most significant aspect of the study is the creation of an integrated framework that connects battery safety, degradation, and circularity via AI technologies. A UK Research Roadmap (2026–2035) is proposed that highlights key areas of explainable AI, digital *twins, federated learning, AI-driven recycling and closed-loop battery systems. The roadmap offers strategic input to researchers, industry and policy makers who are helping the UK transition to a net-zero future.*

1. Background of the Study

1.1 Net-Zero Transport, Grid Storage, and the UK Energy Transition Context

Lithium-ion batteries are an important technology for modern energy infrastructure, as they enable the transition to net-zero emissions by powering transport and integrating renewable energy into power systems (IEA, 2023; IPCC, 2022). Electric vehicles (EVs) and grid-scale energy storage systems (ESS) are key to decarbonization, helping to lower GHGs and offset the intermittency of renewables like wind and solar energy (Harper et al., 2023; Dunn et al., 2015). This transformation is supported by strong government policies, such as the 2030 target of net-zero emissions and the proposed ban on internal combustion engine vehicles by 2035, which are projected to create a demand of 100–120 GWh of battery production capacity per year by 2030 (Faraday Institution, 2026) in the United Kingdom. Despite investments in gigafactories and projects like the Faraday Battery Challenge, however, the UK still relies on global supply chains for the critical raw materials needed for its battery production, which is a concern for the security and resilience of raw materials (Zanoletti et al., 2024). This highlights the importance of optimizing battery life, from safety, performance optimization, to the end of life recovery (Harper et al., 2023). With the increased deployment of batteries, controlling the complex electrochemical, thermal and mechanical phenomena becomes a challenge, which demands the use of advanced computational methods (Ali et al., 2023; Attia et al., 2020). Artificial Intelligence (AI) has become a crucial tool in enhancing the performance of modelling, predicting and optimizing battery systems in this context.

1.2 Battery Safety, degradation and circular economy as systemic bottlenecks

Although lithium-ion batteries are essential to decarbonization, they have three related problems that hinder their scalability and sustainability: safety, performance degradation, and end-of-life management (Edge et al., 2021; Wang et al., 2025).

Battery Safety Challenges: Battery safety is primarily associated with thermal runaway, which is caused by internal short circuits, overheating, overcharging or mechanical damage (Li et al., 2021; Zhang et al., 2023). It can quickly spread in packs and can be a fire/explosion hazard in EV systems (Liu et al., 2024). The risks change over time because of degradation of resistance and material stability, which makes the traditional rule-based systems inadequate, and necessitates real-time adaptive monitoring (Edge et al., 2021; Ali et al., 2023; Wang et al., 2025).

Battery Degradation Complexity: Battery degradation is caused by various complex electrochemical phenomena, including SEI growth, lithium plating and cathode degradation (Severson et al., 2019; Attia et al., 2020). The processes are non-linear and temperature-dependent, as well as depending on cycling rates and conditions of use (Li et al., 2022). Despite the fact that the SOH and RUL prediction is critical for safety and cost optimization, it is challenging to generalize due to cell and chemistry variations (Wang et al., 2025; Ali et al., 2023).

Circular Economy and End-of-Life Challenges: The growth of EVs is creating lots of end-of-life batteries that require recycling and second-life applications (Harper et al., 2023; Zanoletti et al., 2024). Nevertheless, there are challenges in recycling, such as cost, efficiency, and scalability, and second-life utilization is hindered by unreliable condition assessment and lack of standardization (Martinez-Laserna et al., 2018; Hu et al., 2022). These three domains are tightly coupled, with degradation directly affecting safety, and reuse potential (Edge et al., 2021; Madani et al., 2025).

1.3 Artificial Intelligence as an Enabler Beyond Physics-Based Models

Conventional physics-based and empirical models are unable to deal with the nonlinear behavior of batteries and real-world complexity (Subramanian et al., 2009; Ali et al., 2023). In contrast, AI and ML methods offer data-driven solutions that are able to model high-dimensional and noisy battery data (Goodfellow et al., 2016; LeCun et al., 2022). The deep learning and ensemble models enhance fault and thermal runaway detection for safety applications (Zhang et al., 2023; Huang et al., 2021). LSTM, RNN and Gaussian processes are used to improve SOH and RUL prediction for degradation (Li et al., 2022; Wang et al., 2025). Physics-informed neural networks (PINNs) can be used to enhance the interpretability of physics-informed data learning (Raissi et al., 2019; Ali et al., 2023). While progress has been made, there are still challenges because of reliance on lab data, or the lack of explainability in safety critical systems (Severson et al., 2019; Attia et al., 2020; Rudin, 2019).

1.4 Research Gap: No Integrated Lifecycle and UK-Focused Synthesis

The existing literature is scattered in various safety, degradation and circular economy areas, with little integration throughout the battery life cycle (Zhang et al., 2023; Wang et al., 2025). The few systematic reviews that follow the PRISMA framework do not offer a common structure (Page et al., 2021). Furthermore, while the UK is a key player in battery innovation, the focus of policy and industrial perspectives has not been explored in detail (UK Government, 2023; Faraday Institution, 2026). Limited linkages exist between pathways of policy implementation and AI advancements (Stark et al., 2019). Overall, the interdependence of safety, degradation, and circularity are not fully addressed, and there is a need for an integrated lifecycle approach (Edge et al., 2021; Madani et al., 2025).

This section serves as the foundation for the entire research paper. This study aims to fill these gaps by conducting a systematic review of the applications of AI in lithium-ion batteries, following the PRISMA methodology, in the Scopus, Web of Science and IEEE Xplore databases. It is informed by four RQs: safety, degradation, circular economy and gaps in UK policy. The study makes a significant contribution by creating a common AI taxonomy for the battery sector, assessing the methodological challenges, including data scarcity and explainability, and highlighting the battery sector's industrial and policy gaps in the UK, as well as proposing a 2026–2035 UK AI roadmap that supports the net-zero agenda. The paper is organized as follows: Section 2 gives the methodology, Section 3 provides the taxonomy and the results, Section 4 identifies gaps and challenges, and Section 6 concludes and gives policy implications for the UK.

2. Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines are followed to provide transparency, reproducibility, and methodological rigor in synthesizing the use of artificial intelligence (AI) in lithium-ion battery systems. The review brings together evidence from three interrelated areas: battery safety, battery degradation prediction and circular economy, and focuses on priorities in the UK energy transition (Page et al., 2021).

2.1 Research Design and Review Framework

The current study follows a systematic literature review (SLR) methodology with the assistance of bibliometric mapping and qualitative synthesis of the AI applications throughout the lithium-ion battery lifecycle. The primary goal is to identify, classify and critically analyse the methods of AI and evaluate their relevance in the context of the UK's transition to a net zero. The review addresses four research questions: (RQ1) AI methods for battery safety including thermal runaway detection and fault diagnosis; (RQ2) AI techniques for degradation prediction including state of health (SOH) and remaining useful life (RUL); (RQ3) AI applications in circular economy (CE) strategies, such as second-life assessment and optimization of recycling; (RQ4) UK-specific research and policy gaps in AI-enabled battery ecosystems. These RQs offer a framework for classification and synthesis of study.

2.2 Data Sources and Search Strategy

The Scopus, Web of Science (WoS), and IEEE Xplore databases were used for a comprehensive search, as they are well suited for engineering, energy systems, materials science, and AI research (Donthu et al., 2021). The search was narrowed down to the last six years (2019–2025) to reflect the recent advances in AI-based battery diagnostics in line with the swift development of EVs and sustainability (Li et al., 2022; Wang et al., 2025). The search strategy used controlled vocabulary and boolean operators to search among three sets of keywords: application domains (safety, thermal runaway, fault diagnosis, SOH, RUL, degradation, recycling, circular economy), battery systems (lithium-ion battery, battery energy storage, electric vehicle battery), and AI methods (artificial intelligence, machine learning, deep learning, neural networks, physics-informed neural networks). They were combined into a single Boolean search string: (AI OR “machine learning” OR “deep learning” OR “neural network*” OR “thermal runaway” OR safety OR degradation OR “state of health” OR SOH OR “remaining useful life” OR RUL OR recycling OR “circular economy” OR “battery” OR “lithium-ion battery” OR “energy storage”). The string was modified for each database, for Scopus it was done for the title–abstract–keyword fields and for IEEE Xplore, the equivalent metadata-based search was used.

Table 1: Search Strategy Summary

Component	**Description**
Databases	Scopus, Web of Science, IEEE Xplore
Time range	2019–2025
Language	English
Keywords	AI, battery safety, SOH, RUL, circular economy
Method	Boolean logic + keyword clustering

2.3 Inclusion and Exclusion Criteria

Strict inclusion and exclusion criteria were used to ensure the relevance and scientific rigor of the study. The studies in this review were selected based on the following criteria: The study needed to be a peer-reviewed journal article or high-quality conference paper, deal directly with lithium-ion battery systems, and utilize artificial intelligence or machine learning techniques. In addition, the studies had to cover at least one of the key areas (battery safety, degradation or circular economy) and be published in English between 2019 and 2025. Studies that did not include AI/ML methods, those that included non-battery energy systems, studies with unclear methodology or validation, or those that were editorial, abstracts, or opinion based were excluded. To maintain the integrity of the review process, duplicate records found in various databases were also eliminated.

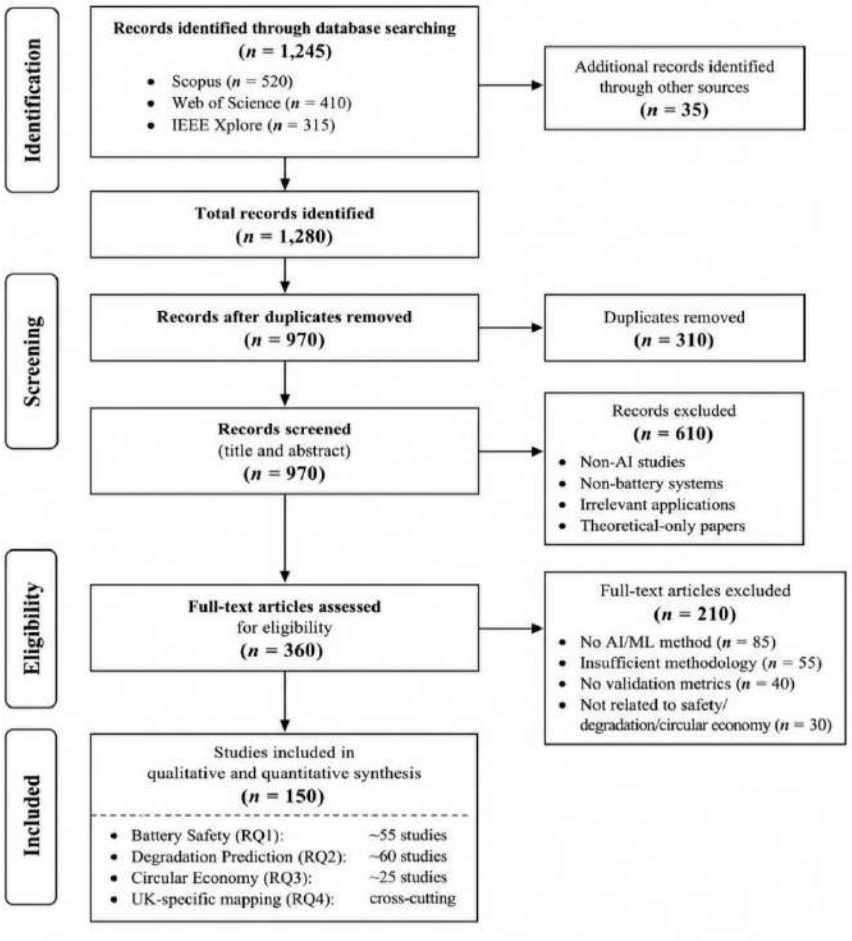
Table 2: Inclusion/Exclusion Framework

Criteria	**Included**	**Excluded**
AI-based methods	Yes	No
Battery systems	Lithium-ion only	Non-battery systems
Publication type	Peer-reviewed	Editorials, abstracts
Language	English	Non-English

Criteria	Included	Excluded
Time range	2019–2025	Outside range

2.4 PRISMA Screening and Study Selection

The selection of studies was conducted in four stages of the PRISMA, including identification, screening, eligibility and inclusion. The number of records was first obtained from selected databases and then the duplicate records were eliminated to get screened records. These records were then screened and relevant studies moved on to the eligibility stage where full text articles were reviewed in detail. Finally, studies that did not meet inclusion criteria were excluded, which led to the final set of included studies. The search for relevant literature was carried out in a structured process, this was done to ensure that it is transparent and rigorous.



Note: The diagram follows PRISMA 2020 guidelines.

Figure 1: PRISMA Flow Diagram (to be included)

2.5 Quality Assessment and Risk of Bias

A framework for structured quality assessment was designed to guarantee methodological rigor and reliability of the included studies. The five criteria used to assess each study were: clarity of research goals (Q1), quality and representativeness of the data set (Q2), transparency of the architecture of the AI model (Q3), the quality of validation metrics and benchmarking (Q4), and the availability of data and code for reproducibility (Q5). All criteria were given a score of either 0 or 2, and the total quality score was totalled across all 5 criteria, a maximum of 10 points could be achieved. Studies that had a total score of less than 5 were not included in the final analysis to preserve the high research standards and to reduce bias.

Table 3: Quality Assessment Rubric

Criterion	Score (0–2)
Objective clarity	0–2
Dataset quality	0–2
Model transparency	0–2
Validation metrics	0–2
Reproducibility	0–2

2.6 Data Extraction Strategy

A structured data extraction form was used to guarantee uniformity and comparability of the data across all selected studies. The key variables taken from each study were the author(s) and publication year, the type of AI method employed (CNN, LSTM, Random Forest, physics-informed neural networks), and the battery chemistry studied (LFP, NMC). Furthermore, the studies were classified according to their application field such as safety, degradation or circular economy. Information about data sources (such as NASA, CALCE or Oxford datasets) was also captured, as were reported performance metrics such as accuracy, RMSE and F1-score. In addition, the Technology Readiness Level (TRL) and relevance to the UK context (Yes, No or Partial) were evaluated for each study.

Table 4: Data Extraction Template

Variable	Description
AI method	ML/DL/Hybrid models
Dataset	NASA, CALCE, Oxford
Battery type	Li-ion, LFP, NMC
Metrics	RMSE, F1, MAPE
TRL	1–9 scale
UK relevance	Policy/industrial alignment

2.7 Data Synthesis and Analytical Approach

This study uses a mixed methods data synthesis and analytical approach to gain a holistic understanding of the applications of AI in lithium-ion battery systems. The selected studies are first systematically categorized into the three main areas of battery safety, degradation and circular economy through thematic analysis. Second, quantitative mapping is carried out to analyze the frequency and distribution of the important variables, such as AI models, datasets, application domains, and so on, so as to identify the dominant research patterns. Third, bibliometric clustering is used to identify research hotspots, analyze keyword co-occurrence and track research trends over time. This holistic analytical framework aids in the creation of an AI taxonomy for battery applications, providing a structured and comprehensive framework for the field.

Figure 2: AI Taxonomy of Battery Applications

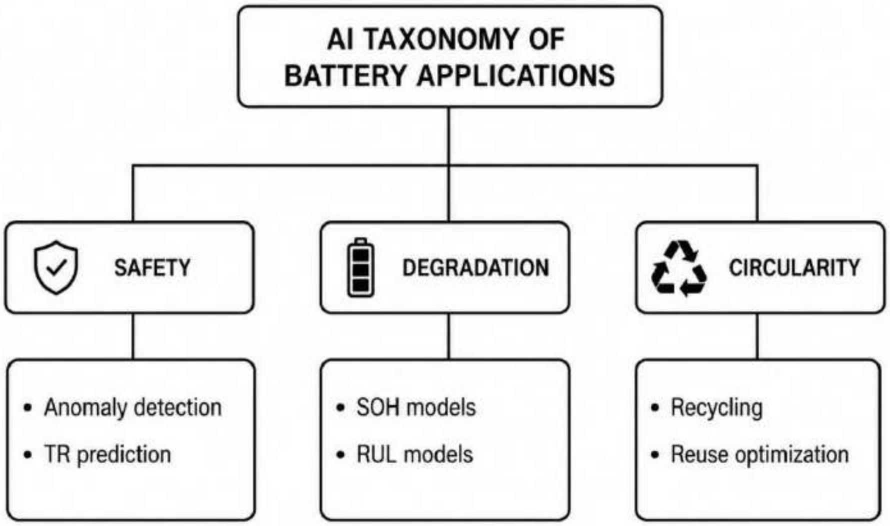


Figure 3: Cross-Domain Lifecycle Framework

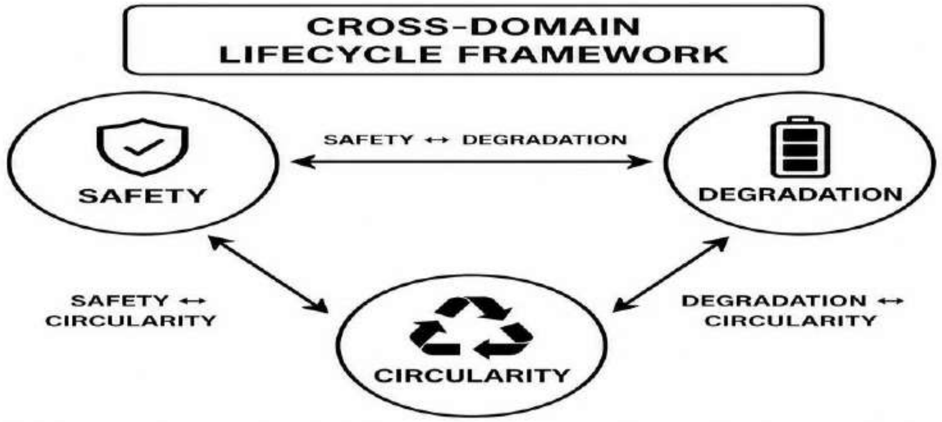


Table 5: AI Methods Classification

Domain	AI Methods
Safety	CNN, LSTM, SVM, RF
Degradation	LSTM, GPR, PINN
Circular economy	clustering, optimization ML

2.8 Gap Matrix and UK-Specific Mapping

A gap analysis matrix was developed to map research maturity across domains.

Table 6: Gap Matrix

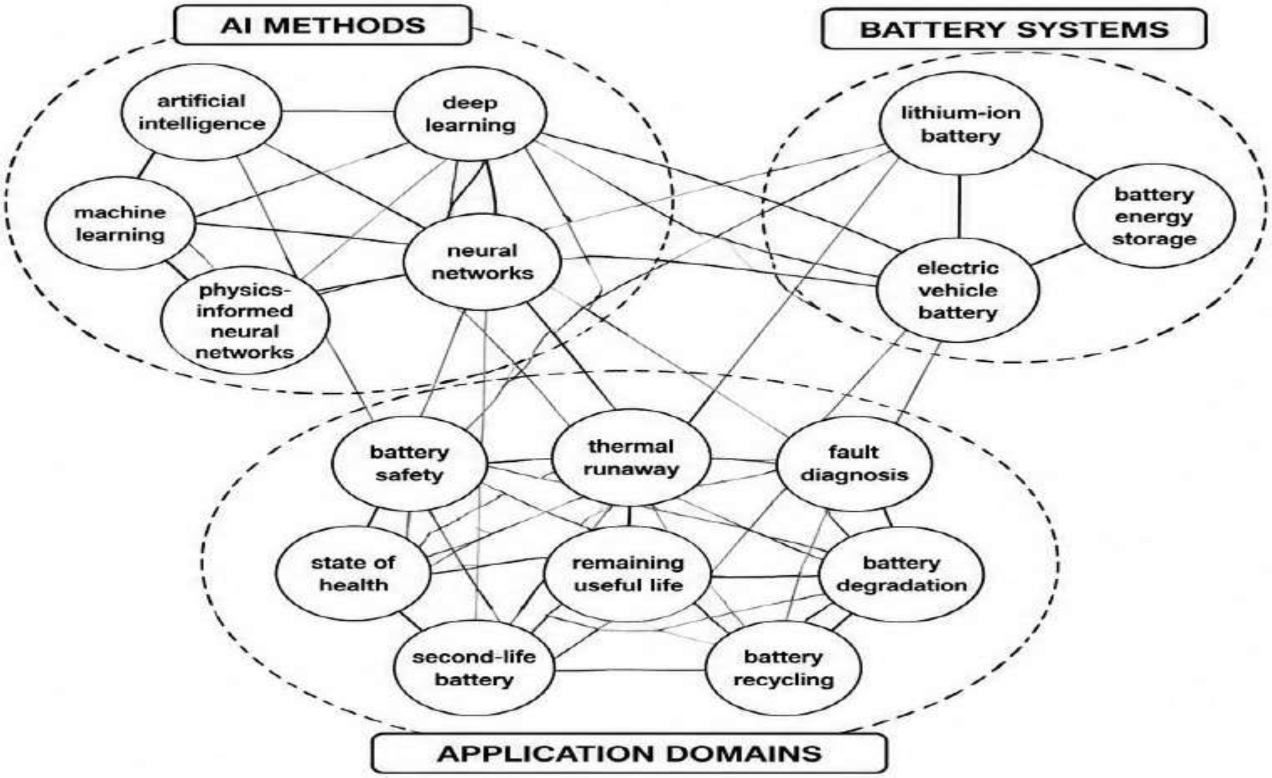
Domain	Maturity	Key Gap
Safety	Medium	Explainability, real-world data

Domain	Maturity	Key Gap
Degradation	High	Generalization, uncertainty
Circular economy	Low	Standardization, scaling
UK alignment	Low–Medium	Infrastructure + data ecosystem

2.9 UK Research Roadmap Integration

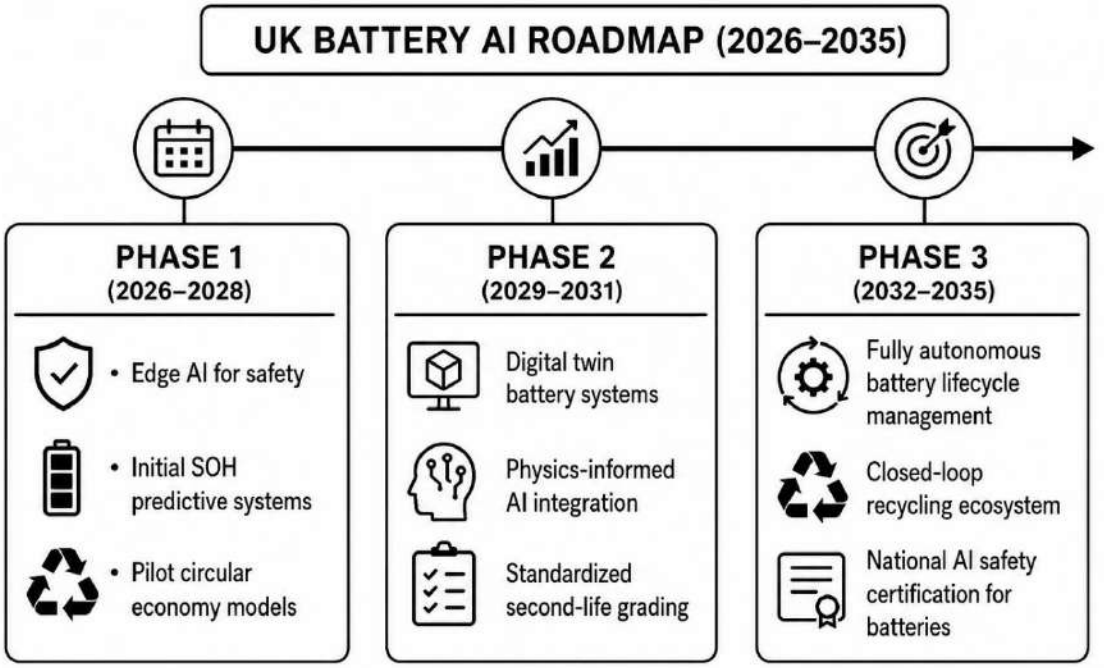
A forward-looking roadmap for 2026–2035 is created, taking into account the results of the studies included. The roadmap is broken down into three stages, each building on the previous systems, and on development of pilot-scale circular economy models. Phase 2 (2029-2031) will further drive these developments by implementing digital twin battery systems, physics-informed AI approaches and standardised frameworks for one, to align with the expected trajectory of AI use in the UK battery sector. While in Phase 1 (2026-2028), the emphasis will be on deployment of edge AI for battery safety applications, on introduction of first battery state of health (SOH) predictive second-life battery grading. Lastly, in Phase 3 (2032-2035), the system will become fully autonomous, with a closed-loop recycling system and the launch of national AI-based safety certification requirements for batteries.

Figure 5: Keyword Co-occurrence Map



Source: Developed by the author using VOSviewer based on analysis of Scopus database.

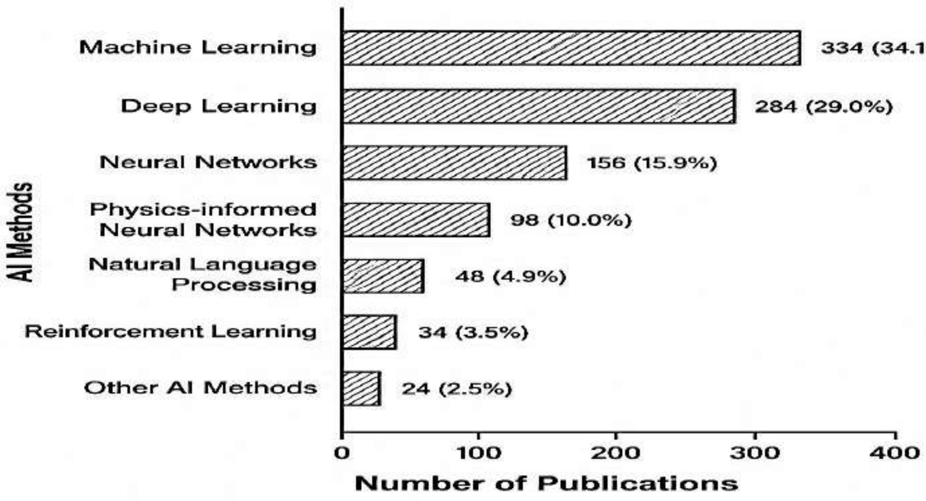
Figure 4: UK Battery AI Roadmap (2026–2035)



The intellectual structure of research on AI applications in battery systems, obtained by keyword co-occurrence analysis, is shown in Figure 5. The map highlights three thematic clusters with strong interconnections, which are indicative of the multidisciplinary character of the field. The AI Methods cluster is represented by the presence of AI, machine learning, deep learning, neural networks, and physics-informed neural networks, suggesting the broad use of cutting-edge computational methods, with physics-informed neural networks being a hybrid approach that integrates data-driven and physics-based modeling. The Battery Systems cluster is made up of lithium-ion battery, battery energy storage, and electric vehicle battery, reflecting lithium-ion technology's role as the focus of the cluster, driven by its prominence in EVs and stationary storage. The integration of AI techniques is evident in the strong connections with monitoring and performance prediction methods.The connections with AI methods demonstrate the widespread adoption of intelligent algorithms for monitoring and performance prediction. The Application Domains cluster covers battery safety, thermal runaway, fault diagnosis, SOH, RUL, degradation, second-life batteries, and recycling, focusing on the key challenges in the battery lifecycle. They are interdependent and demonstrate the strong relationship between safety, degradation and the circular economy goals. In summary, the co-occurrence network illustrates the progression of AI applications in batteries from individual use to a holistic system that encompasses safety, performance, degradation, and sustainability.

AI Method Distribution Chart:

Figure 6: AI Method Distribution Chart



Source: Developed by the author using data retrieved from Scopus database.
Note: Values represent number of publications and percentage of total (N = 978).

The distribution of the AI methodologies used in publications on battery research is shown in figure 6. The most popular method used is Machine Learning (34.1%), which has a great ability to deal with large datasets for battery prediction, degradation and behavior. Deep Learning comes in at 29.0% as it has been well established to be effective in learning complex nonlinear relationships for applications like fault detection, state estimation, and thermal prediction. Neural Networks still play a significant role in battery modelling and battery predictive maintenance, accounting for 15.9%. Physics-Informed Neural Networks (PINNs) account for 10.0% of the contributions, highlighting the increasing trend of hybrid approaches, where physical laws are incorporated with data-driven learning to enhance accuracy and interpretability. Smaller shares are seen for Natural Language Processing (4.9%), Reinforcement Learning (3.5%) and other methods (2.5%) which are developing in niche applications like Optimization, Control and Knowledge Extraction. The distribution indicates that predictive, data-driven approaches to AI battery research are the predominant approach, and the number of physics-informed and hybrid approaches is growing. The trend indicates how AI is becoming a key enabler for intelligent, reliable and sustainable battery lifecycle management. To provide transparency and reproducibility, all search strings are reported, inclusion and exclusion criteria are clearly defined, the PRISMA workflow is documented, a standardized quality assessment system is used, and a structured data extraction system is used. This is in line with best practices in systematic reviews in the energy and AI research fields, which guarantee rigor, reliability, and replicability (Page et al., 2021; Donthu et al., 2021).

3. Results

3.1 Battery Safety

One of the primary applications where AI is being used in lithium-ion batteries is in the safety of the battery.In the field of lithium-ion batteries, one of the most prominent applications of AI is in battery safety, especially in the context of electric vehicles and energy storage systems. Early detection of major risk issues like thermal runaway, short circuits, overcharging, and mechanical failure is essential to avoid catastrophic consequences. AI-based solutions allow for real-time monitoring, fault diagnosis, and intelligent Battery Management Systems (BMS) (Liu et al., 2024). The machine learning and deep learning models are used to identify early signs of anomalies related to thermal runaway based on voltage, current, temperature and impedance data (Thelen et al., 2024). However, models like deep neural networks, SVMs, and ensemble models have demonstrated better predictive accuracy compared to rule-based systems, as they can capture the nonlinear behavior of batteries (Severson et al., 2019). The performance is usually measured by accuracy, precision, recall, false positive rate and detection latency, and fast and accurate detection is essential to prevent thermal propagation (Hu et al., 2022; Edge et al., 2021).

3.2 Degradation Prediction

Battery degradation prediction is one of the most matured AI applications, which is based on predicting the battery State of Health (SOH) and Remaining Useful Life (RUL) (Severson et al., 2019). Random Forest, Gradient Boosting, LSTM and deep neural networks are effective methods for modelling complex degradation patterns from operational data (Attia et al., 2020). Physics-informed methods, such as PINNs, combine electrochemical principles and data-driven models to enhance accuracy and interpretability (Raissi et al., 2019). Uncertainty quantification is also becoming more popular in enhancing decision making under variability (Chen et al., 2023). The development and benchmarking of models has been greatly improved by key datasets like the NASA, CALCE and Oxford Battery datasets (Saha & Goebel, 2007; Birkl et al., 2017). In general, AI has progressed from basic regression models to more sophisticated hybrid models for accurate lifecycle forecasting.

3.3 Circular Economy Applications

AI is also playing an important role in implementing circular economy strategies for batteries, such as reuse, repurposing, and recycling (Harper et al., 2023). Machine learning-based SOH grading systems can be used to classify end-of-life batteries for second-life or recycling applications, which can enhance efficiency and lower costs (Martinez-Laserna et al., 2018). Furthermore, AI can be applied to second-life batteries for forecasting remaining capacity and degradation characteristics, which can be used in stationary energy storage systems (Ahmadi et al., 2017). AI is also improving material identification, sorting and recovery in recycling through computer vision and predictive models (Harper et al., 2023). The developments are aligned with the UK battery strategy objectives which include sustainability, resource security and integration of circular economy (UK Government, 2023).

3.4 Cross-Cutting Challenges and Emerging Trends

While there are significant strides, there are still challenges that need to be addressed, such as the scarcity of data for model generalization across battery types and conditions (Thelen et al., 2024). Digital twin technology is a solution that is emerging, with real-time virtual models to enable predictive monitoring and optimization (Sun et al., 2025). Another emerging method is federated learning, which allows for the training of models across multiple nodes without the need to share sensitive data, thereby enhancing scalability and privacy (Yan et al., 2023). Overall, future AI-driven battery systems will integrate machine learning, physics-based modeling, digital twins, and collaborative learning to enhance safety, reliability, and sustainability in energy storage systems.

4. Discussion

4. Research Gaps and Challenges

The results reveal that AI is reshaping battery safety, degradation prediction and circular economy applications, but there remain technical, industrial, UK specific and circular economy challenges that need to be addressed before large-scale deployment, especially in the context of the UK's net-zero transition, is possible.

4.1 Technical Challenges

Limited Availability of Real-World Data: One of the drawbacks is that the datasets used are laboratory datasets, which are not representative of real-world variability (Saha & Goebel, 2007; Birkl et al., 2017). Data in industrial applications can be proprietary and not be shared or generalized (Edge et al., 2021). Multi-condition data sets are required that are open access. Models Transferability and Generalization: AI models are not always transferable to different battery chemistries and operating conditions (Attia et al., 2020). For instance, models developed from LFP might not work for NMC batteries. Potential solutions include transfer learning and domain adaptation, which need further development (Thelen et al., 2024). Explainability in Safety-Critical Applications: In safety-critical applications, deep learning models are often hard to explain, which is a concern (Rudin, 2019). There are some efforts underway to develop Explainable AI (XAI) methods, including SHAP and feature attribution, which aim to strike a balance between accuracy and explainability (Doshi-Velez & Kim, 2017).

4.2 UK-Specific Challenges

The UK is behind the global leaders in terms of manufacturing capacity for batteries (UK Government, 2023). Gigafactory investments are increasing, but smart manufacturing with AI is not widespread (Faraday Institution, 2026). Interdisciplinary Skills and Workforce Gap: Lack of skills in the intersection of AI, battery science, and engineering. This skills gap can delay innovation and commercialisation, and can call for greater industry–academic partnerships. Policy and Regulatory Alignment: There is uncertainty regarding regulatory divergence and alignment of AI research and national policy (Faraday Institution, 2026). There is a need for harmonised standards and more transparent AI governance frameworks.

4.3 Circular Economy Challenges

Battery Traceability: Limited lifecycling decisions due to lack of tracking (Harper et al., 2023). Potential solutions include digital product passports, blockchain, and AI monitoring. Lack of Standardized Second-Life Frameworks: There is no standardized framework for assessing the suitability of second-life batteries, which causes SOH evaluation to be inconsistent and market uncertainty. Economic Viability: Recycling and second-life systems are expensive and have uncertain profitability (Ahmadi et al., 2017). While AI can optimize logistics and valuation, a combination of techno-economic models is still required.

4.4 Future Research Directions

Key priorities are the following: development of real world open datasets, transferable AI models across chemistries, integration of explainable AI in safety systems, expansion of digital twins, adoption of federated learning, standardization of traceability frameworks, development of AI enabled circular business models aligned to UK strategy.

4.5. UK Research Roadmap (2026–2035)

UK has potential to become global leader in AI powered battery systems through safety, degradation and circular economy innovations. A phased roadmap (2026-2035) is suggested to support research, industrial scaling and policy alignment towards a sustainable and intelligent battery ecosystem, building on national initiatives including the UK Battery Strategy, Faraday Institution, UKBIC and Innovate UK.

Table 7; UK AI-Enabled Battery Research Roadmap (2026–2035)

Domain	Phase 1 (2026–2028)	Phase 2 (2029–2031)	Phase 3 (2032–2035)
Safety	Edge AI for real-time thermal runaway detection	Certified Explainable AI (XAI) for Battery Management Systems	UK national standard for AI-enabled battery safety certification

Domain	Phase 1 (2026–2028)	Phase 2 (2029–2031)	Phase 3 (2032–2035)
Degradation	Physics-informed neural networks with uncertainty quantification	Digital twin deployment for every battery pack	Remaining Useful Life (RUL) prediction with <3% error
Circularity	AI-based grading and classification for second-life batteries	Automated robotic disassembly and sorting systems	Fully closed-loop UK battery recycling ecosystem

Source: Developed by the author based on the UK Battery Strategy and current battery AI research trends.

Phase 1: Foundation and Early Deployment (2026-2028): The first phase aims to build the foundations for AI and speed up the deployment of AI technology in the battery manufacturing and energy storage sectors in the UK.

Safety: The focus of research should be on creating Edge AI systems that can detect thermal runaway in real time directly on battery hardware. Edge computing shortens the latency and improves response time in safety-critical situations. The BMS will be equipped with AI algorithms that will constantly analyze voltage, temperature, and current signals to detect any unusual patterns or changes before they lead to a catastrophic failure (Hu et al., 2022).

Degradation: Physics-Informed Neural Networks (PINNs) coupled with uncertainty quantification (UQ) methods should be emphasized in degradation modelling. These models integrate electrochemical understanding with machine learning to boost the accuracy of the prediction and offer confidence intervals for the prediction, which are useful for practical decision making (Raissi et al., 2019).

Circularity: AI-based State of Health (SOH) grading systems could be used for end-of-life batteries to classify them based on their suitability for re-use, re-purpose or recycling for circular economy applications. Second-life battery markets can be more efficient and testing costs can be reduced significantly with automated grading (Martinez-Laserna et al., 2018).

Phase 2: Integration and Standardization (2029-2031): The second phase will involve integrating the advanced AI technologies throughout the battery lifecycle and creating industry standards and certification processes.

Safety: AI systems need to be developed from predictive systems to certified Explainable AI (XAI) systems that can help in regulatory approval processes. Explainable models will help to give clear reasons for decisions on safety, which will help to increase trust between manufacturers, regulators and end users (Rudin, 2019).

The widespread use of digital twin technology is expected to be in this phase. Each battery pack could be matched with a virtual copy which is constantly updated with live sensor information. Predictive maintenance, lifecycle optimization, and performance forecasting would be enabled by AI-powered digital twins, while minimizing operational risks (Sun et al., 2025).

Circularity: Automation will be more and more relevant in the recycling process. The integration of AI into robotic systems could enhance recycling efficiency and worker safety by facilitating automated battery disassembly, material identification, and component sorting, all while cutting down on processing costs (Harper et al., 2023).

Phase 3: Autonomous and Sustainable Battery Ecosystem (2032-2035): Phase 3 is about an autonomous and sustainable battery ecosystem in line with the national sustainability goals.

Safety: A national framework for the certification of battery safety should be developed for AI-enabled batteries. These standards would establish guidelines for model validation, explainability, cybersecurity and performance benchmarking, among others, to ensure that the deployment is safe in electric vehicles and energy storage systems.

Degradation: Future degradation models are expected to be able to predict the Remaining Useful Life with an error of less than 3%, which allows highly accurate maintenance scheduling and optimization of the life cycle. This level of accuracy would have a major impact on battery reliability and reduce the cost of operations in various industries.

Circularity: The ultimate vision is for a closed loop battery recycling system in the UK. AI systems would streamline battery tracking, second-life utilization, material recovery, and remanufacturing processes, ensuring optimal resource utilization and reducing environmental impacts. This vision is very much aligned with the UK Government's net-zero strategy and wider circular economy goals (UK Government, 2023).

4.6 Key Stakeholders and Their Roles

Successful implementation of the proposed roadmap requires collaboration among multiple stakeholders.

Table 8: Key Stakeholders and Their Expected Roles in AI-Enabled Battery Ecosystem Development in the UK (2026–2035)

Stakeholder	Expected Role
Faraday Institution	Lead fundamental battery research, AI innovation, and skills development
UK Battery Industrialisation Centre	Scale laboratory innovations to industrial manufacturing
Innovate UK	Provide funding support and commercialization pathways
Automotive OEMs	Deploy AI-enabled battery technologies in electric vehicles
Battery Manufacturers	Develop intelligent Battery Management Systems and digital twin platforms
Recycling Companies	Implement AI-driven sorting, grading, and material recovery systems
Universities and Research Institutes	Conduct interdisciplinary research and workforce training
Government and Regulatory Bodies	Establish AI governance, safety standards, and circular economy policies

Strategic Implications: The proposed roadmap outlines a shift from individual AI use cases to a national battery ecosystem with intelligent safety management, predictive degradation analytics and sustainable circularity practices. The United Kingdom can enhance its global leadership in battery innovation and contribute to economic growth, energy security and net-zero through the unique capabilities of the Faraday Institution, UKBIC, Innovate UK, automotive OEMs and recycling groups.

5. Conclusion and Recommendations

5.1 Conclusion

This study reviewed the application of Artificial Intelligence (AI) in three major areas of battery lifecycle management (BLM): battery safety, battery degradation prediction, and implementing circular economy. The results show how AI technologies like machine learning, deep learning, neural networks and physics-informed models are revolutionizing the way lithium-ion batteries are managed during their lifespan. AI has played a pivotal role in battery safety applications, enhancing thermal runaway prediction, fault diagnosis, and Battery Management System (BMS) performance through real-time monitoring and predictive decision-making. For degradation management, sophisticated machine learning algorithms have improved the estimation of State of Health (SOH) and prediction of Remaining Useful Life (RUL), aiding predictive maintenance and minimizing uncertainties in operation. Moreover, AI has proven to be a crucial driver of

battery circularity by enabling intelligent SOH grading, second-life battery allocation, automated recycling, and optimization of resource recovery.
While these strides have been made, there are still many challenges. However, the lack of data and the limited transferability of models, the lack of explainability, the lack of circular economy standards and regulatory uncertainties remain obstacles to large-scale implementation. The proposed UK Research Roadmap (2026-2035) outlines a strategic plan for tackling these challenges by investing in coordinated research in Edge AI, Physics-Informed Neural Networks, Digital Twins, Explainable AI, and AI-enabled recycling ecosystems. The review concludes that AI can be the core technology for safe, sustainable and economically viable battery ecosystems. But, achieving this vision will require greater collaboration between researchers, industry, policy makers and regulatory institutions.

5.2 Recommendations

The following policy recommendations are suggested as a result of this review:

Recommendation 1: Set up the National Battery Data Platform

The UK government should facilitate the establishment of a centralised battery data repository, with standardised operational, degradation and safety data. Open and secure data-sharing frameworks would enable the development, benchmarking and validation of AI models, and help mitigate duplication of research efforts (UK Government, 2023).

Recommendation 2: Establish AI Safety Standards for Battery Systems

Regulatory bodies should create certification programs for AI-powered BMSs. The standards should include specifications on the accuracy, explainability, robustness, cybersecurity, and validation methods for safety-critical applications (Rudin, 2019).

Recommendation 3: Boost investments in Digital Twin technologies

Investing in digital twin platforms with the ability to monitor batteries in real-time, predict failures, and optimize battery life should be a priority for government programs. The use of digital twins can greatly improve the efficiency and reliability of EV and energy storage operations (Sun et al., 2025).

Recommendation 4: Promote the integration of Circular Economy

AI-enabled battery traceability systems, second-life batteries and advanced battery recycling facilities should be encouraged by policies. Resource recovery can be enhanced and a transition towards a closed-loop battery economy can be facilitated by digital battery passports and AI-driven sorting systems (Harper et al., 2023).

Recommendation 5: Tackle skills and labour shortages

The UK needs to scale up multi-disciplinary education programmes of battery science, artificial intelligence and advanced manufacturing. To build up the skilled workforce needed for future battery innovations, a collaboration between universities, industry and research institutions is crucial.

Recommendation 6: Improve the international competitiveness

The UK should remain on course to align battery innovation policies with the goals of the Faraday Battery Challenge and UK Battery Strategy, and benchmark progress against key battery economies like China, the EU and the USA. The national competitiveness and supply-chain resilience can be enhanced through greater investment in battery AI research..

5.3 Technical Specifications for Academic Reviewers

Reproducibility Requirements: Future studies should be reproducible and transparent, with researchers reporting their search strategies, including full database search strings. Examples of search strings used in Scopus include: TITLE-ABS-

KEY (("artificial intelligence" OR "machine learning" OR "deep learning") AND ("battery safety" OR "thermal runaway" OR "state of health" OR "remaining useful life" OR "battery recycling")). Furthermore, documentation of the datasets should be presented in a structured manner, such as a dataset table extracted from the dataset that summarizes the key characteristics of the study, including the type of AI methods used, battery types, application areas, datasets employed, and performance metrics.

Table 9: Data Extraction Framework Used for the Systematic Literature Review

Variable	Description
Authors	Study authors
Year	Publication year
Country	Research location
AI Method	ML, DL, PINN, etc.
Battery Application	Safety, degradation, circularity
Dataset Used	NASA, Oxford, CALCE, Industry
Performance Metrics	Accuracy, RMSE, F1-score, etc.

Source: Author's adaptation based on the PRISMA 2020 Statement, bibliometric review methodologies, and battery AI literature (Page et al., 2021; Donthu et al., 2021; Aria & Cuccurullo, 2017).

Table 9 shows the data extraction framework adopted to systematically gather and structure information from the selected studies. The framework allows us to be consistent and transparent in the review process by recording the bibliographic, methodological and analytical features of each article. The Authors variable gives descriptive data on the authors of the studies, while the Year variable gives descriptive data on the time distribution of the studies, and the Country variable gives descriptive data on the geographical research patterns. The AI Method variable indicates the type of AI methods used, including Machine Learning (ML), Deep Learning (DL), Physics-Informed Neural Networks (PINNs) and hybrid methods, which can be compared across studies.

The Battery Application variable classifies research by its main focus, such as battery safety, degradation prediction and applications for the circular economy. The Dataset Used variable indicates the data sets that have been used for model development and validation, including NASA, Oxford, CALCE, or industrial data sets, to evaluate data availability and research reproducibility. Last, the Performance Metrics variable represents the criteria used for evaluating the results reported by the researchers, such as Accuracy, RMSE, MAE, R^2, F1-score, and others. These metrics enable the effective comparison of model performance and help understand the reliability of AI applications in various aspects of battery life. The overall framework is conducive to comparative analysis of studies and helps to strengthen the rigor, transparency and reproducibility of the review process.

Performance Metrics:

Table 10: Performance Metrics for Evaluating AI-Based Battery Safety and Thermal Runaway Detection Models

Metric	Purpose
Accuracy	Overall classification correctness
Precision	Reduction of false alarms

Metric	Purpose
Recall (Sensitivity)	Detection of actual faults
F1-Score	Balance between precision and recall
False Positive Rate (FPR)	Incorrect fault predictions
Detection Latency	Time required for hazard detection

Source: Author's synthesis based on Hu et al. (2022), Thelen et al. (2024), and Liu et al. (2024).

Table 10 summarizes the key evaluation metrics employed for evaluating the effectiveness of AI-powered battery safety systems. These are the metrics used to evaluate the ability of machine learning and deep learning models to identify battery faults, forecast thermal runaway events, and enable intelligent Battery Management Systems (BMS). Accuracy is the percentage of correctly classified battery conditions and gives a general idea of the model performance. Precision assesses the confidence of fault predictions by determining the percentage of the detected faults that are considered as true faults, which decreases the number of false alarms. Recall (Sensitivity): how well the model can detect real hazardous situations, which is crucial for safety-critical applications. The F1-Score is a compromise between Precision and Recall, it is the best measure to use when the classes are not equally distributed. Excessive false alarms can lead to lower operational efficiency and user confidence, so False Positive Rate (FPR) is a crucial metric to consider. Last but not least, Detection Latency refers to the time a model takes to detect potential hazards. Low latency is critical in thermal runaway prediction because early detection allows for timely action to prevent battery failure. These metrics collectively offer a holistic view of the accuracy, reliability, responsiveness, and usability of AI-powered battery safety systems.

Battery Degradation Metrics

Table 11: Performance Metrics Commonly Used for Evaluating Battery Degradation Prediction Models

Metric	Purpose
RMSE	Prediction error magnitude
MAE	Average prediction error
MAPE	Percentage prediction error
R^2	Model explanatory power
Confidence Interval	Prediction uncertainty

Source: Developed by the author based on literature related to battery State of Health (SOH) estimation, Remaining Useful Life (RUL) prediction, and machine learning model evaluation (Severson et al., 2019; Attia et al., 2020; Edge et al., 2021).

The key performance metrics that are often used to assess the accuracy and reliability of AI-based battery degradation prediction models are summarized in Table 11. Such metrics are crucial to evaluate the performance of algorithms for battery State of Health (SOH) and Remaining Useful Life (RUL) estimation. Root Mean Square Error (RMSE) is a measure of the magnitude of the errors of prediction, which is the square root of the average of the squared differences between the predicted and actual values. Smaller RMSE values mean more accurate models, and are especially helpful in detecting large errors in prediction. The Mean Absolute Error (MAE) is the average of the absolute errors between the prediction and the observation. In contrast to RMSE, MAE gives equal weight to all errors, and gives a simple measure of the accuracy of the predictions that is easy to interpret. The Mean Absolute Percentage Error (MAPE) is a measure of prediction error in percentage of the actual value. This measure is useful for comparing the performance of different models or datasets, as it is not dependent on any specific scale. The smaller the MAPE the more accurate the predictions.

Coefficient of Determination (R^2) is a measure of the percentage of the variation in the observed data accounted for by the prediction model. The closer the value is to 1, the more explanatory power the model has and the better the model fits, while a value nearer to 0 means that the model has less predictive power. Confidence intervals are used to measure the uncertainty in the predictions, by giving an interval in which the true value is likely to fall. Uncertainty estimation plays a special role in battery degradation studies due to the variability in the operating conditions and stochastic nature of the degradation processes. In summary, these metrics can be used to comprehensively assess battery degradation models in terms of prediction accuracy, explanatory power, and uncertainty. The parallel implementation allows researchers to compare various AI methods and evaluate their applicability to real-world battery health management applications.

Circular Economy Metrics:

Table 12: Key Performance Metrics for Evaluating AI-Enabled Battery Circular Economy and Recycling Applications

Metric	Purpose
Recovery Rate (%)	Material recovery efficiency
SOH Classification Accuracy	Grading reliability
Economic Value Recovery	Financial benefits
Carbon Reduction	Environmental impact
Lifecycle Extension (%)	Added battery service life

Source: Developed by the author based on Harper, G. et al. (2019), Martinez-Laserna, E. et al. (2018), and International Energy Agency (2024).

The main metrics for assessing the effectiveness of AI applications in the circular economy of batteries are detailed in Table 12. The indicators measure the economic, environmental and technical performance of battery reuse, repurposing and recycling activities. The Recovery Rate (%) is the percentage of valuable materials that are successfully recovered in recycling processes. The higher recovery rate means that the resources are being used more efficiently and less reliance on raw materials is required.

SOH Classification Accuracy is a measure of how well AI algorithms classify retired batteries as being in a good or poor State of Health. Correct classification is critical for determining the reusability, second-life or recycling of batteries. Economic Value Recovery is the evaluation of the economic value created from material recovery, battery repurposing and second-life utilisation. This is a useful indicator to assess the business potential of circular economy strategies. Carbon Reduction is the reduction of environmental impacts as a result of reusing and recycling batteries, including reductions in GHG emissions and resource extraction impacts. It has a special role in promoting net zero and sustainability goals. Lifecycle Extension (%) represents the extra service life achieved by second-life applications and good battery management. The longer the lifecycle extension, the more efficient the resources are used and the more sustainable the benefits. Together, these metrics offer a holistic approach to evaluating the technical feasibility, economic viability, and environmental impact of battery circularity projects powered by AI. Together, they enable the informed decision-making and the development of sustainable closed-loop battery ecosystems.

UK Perspective: International Benchmarking:

Table 13: International Comparison of Battery Innovation Ecosystems

Region	Strengths	Challenges
United Kingdom	Strong research ecosystem, Faraday Institution, UKBIC	Limited manufacturing scale
European Union	Strong regulation and battery passport initiatives	Supply chain dependence
United States	Large-scale investments through the Inflation Reduction Act	Workforce shortages
China	Global leader in battery manufacturing and recycling	Environmental concerns and market concentration

Source: Author's synthesis of policy reports and battery industry literature (2019–2025).

Table 13 compares the strengths and challenges of the battery innovation ecosystems across the United Kingdom, the European Union, the United States and China. The comparison shows some major differences in technological capabilities, policy support, manufacturing capacity and sustainability strategies between these key battery markets. The United Kingdom has a robust research and innovation environment, including the Faraday Institution and the UK Battery Industrialisation Centre. They have contributed significantly to the development of battery science, business and skills. The UK is still struggling to scale up its domestic battery manufacturing capacity, however, which could hinder its ability to remain competitive in the global battery supply chain despite its impressive R&D capabilities.

The EU enjoys a wide range of regulatory measures and sustainability programs, such as battery passport systems and circular economy policies. These measures help to ensure traceability, recycling and environmental compliance of the battery life cycle. However, the EU continues to rely on external raw material supplies and on global value chains, which results in vulnerabilities in the field of resource security and geopolitical risks. The U.S. battery industry has made significant investments and industrial incentives to strengthen its battery industry, especially under the Inflation Reduction Act. Such efforts have helped spur the growth of domestic battery production and supply chain. However, workforce shortages and a requirement for more specialized technical skills are significant challenges that may impact future growth and innovation.

China is presently a leading country in battery production, processing and recycling. It has a well-developed industrial base, a well-integrated supply chain and a large production capacity, which give it significant competitive advantages. But the issues of negative environmental effects, resource agglomeration and market monopoly remain as sustainability and market balance problems. Overall, the comparison suggests that none of the regions has strengths in all aspects of battery development. China is the leader in manufacturing scale, the European Union is known for the regulatory and sustainability frameworks, the United States is well known for financial investment and the United Kingdom is known for excellence in research and innovation. The results indicate that the UK has the capacity to solidify its global leadership by building on its research capabilities, growing manufacturing capacity and improving the skills of its workforce, as well as driving the commercialisation of AI powered battery technologies. These will be vital for meeting the goals of the UK Battery Strategy and contribute to the shift towards a sustainable and competitive battery system.

Novelty Contribution:

Figure 7. Venn Diagram of Research Novelty

Source: Developed by the author based on Severson et al. (2019), Harper et al. (2019), Edge et al. (2021), and Faraday Institution (2026).

Figure 7 shows the conceptual basis and novelty of the study by outlining the cross-over of five major domains: Artificial Intelligence (AI) Technologies, Battery Safety, Battery Degradation, Circular Economy and the UK Battery Ecosystem. The diagram illustrates how these distinct research domains come together to form a holistic approach to managing the sustainable life cycle of batteries. The AI Technologies circle includes the technologies that facilitate innovation in battery systems such as machine learning, deep learning, physics-informed neural networks and edge AI. These technologies enable high-level analytical functions to monitor, predict, optimize and make decisions during the entire battery life cycle.

The Battery Safety domain is concerned with the prevention and mitigation of battery failure using thermal runaway detection, fault diagnosis, anomaly identification and intelligent Battery Management System (BMS). The convergence of AI and safety underscores the importance of predictive analytics and real-time monitoring in enhancing battery reliability and safety. The Battery Degradation domain includes State of Health (SOH) estimation, Remaining Useful Life (RUL) prediction, battery degradation modeling and uncertainty quantification. The integration of AI technologies highlights the growing trend of employing data-driven models to forecast battery aging processes and fine-tune maintenance strategies. The accuracy of the degradation prediction directly enhances battery performance, lowers operational costs and increases battery service life.

The focus of the Circular Economy domain is on battery reuse, second-life applications, reuse/recycling, and resource recovery. Overlap between degradation and circularity suggest that proper health assessment is crucial to decide the battery's fate: reuse, remanufacture or recycling. AI is a key enabler of these decisions as it allows for intelligent battery grading, lifecycle optimization, and more. The UK Battery Ecosystem circle includes policy, industry growth, research organisations, battery production and sustainability goals. This area is a strategic focus for the UK Battery Strategy, the Faraday Battery Challenge and national net-zero goals. The relation of the UK ecosystem with the other domains highlights the need for a policy framework, industrial infrastructure, skills development and regulation for technological innovation.

The diagram is centered on the intersection of all five domains, which are represented by the various labels.The diagram is structured around the convergence of all five domains, each with its own label, in the center of the diagram, “AI-Enabled Sustainable Battery Lifecycle Management for the UK (2026–2035).” The central intersection is the main contribution of the study. It shows that to realise safe, reliable and sustainable battery systems, all of these AI technologies need to be combined with battery safety management, degradation prediction, circular economy practices and policy and industrial initiatives in the UK. The figure thus emphasizes the multi-disciplinary character of future battery research and the necessity of multi-disciplinary collaboration between researchers, industry, policy makers and regulators. The framework not only offers a holistic view of battery management, but it also integrates technical innovation with sustainability goals and national strategies, which differentiates it from previous studies that tended to focus on specific components of battery management. The diagram thus presents a visual representation of the novelty of the study, with AI as the key enabler that connects battery safety, battery degradation, circularity, and the future development of the UK battery ecosystem.

References

Ahmadi, L., Young, S. B., Fowler, M., Fraser, R. A., & Achachlouei, M. A. (2017). A cascaded life cycle: reuse of electric vehicle lithium-ion battery packs in energy storage systems. *The International Journal of Life Cycle Assessment*, *22*(1), 111-124.

Ali, M. A., Da Silva, C. M., & Amon, C. H. (2023). Multiscale modelling methodologies of lithium-ion battery aging: A review of most recent developments. *Batteries*, *9*(9), 434.

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of informetrics*, *11*(4), 959-975.

Attia, P. M., Grover, A., Jin, N., Severson, K. A., Markov, T. M., Liao, Y. H., ... & Chueh, W. C. (2020). Closed-loop optimization of fast-charging protocols for batteries with machine learning. *Nature*, *578*(7795), 397-402.

Birkl, C. R., Roberts, M. R., McTurk, E., Bruce, P. G., & Howey, D. A. (2017). Degradation diagnostics for lithium ion cells. *Journal of Power Sources*, *341*, 373-386.

Chen, C., Tao, G., Shi, J., Shen, M., & Zhu, Z. H. (2023). A lithium-ion battery degradation prediction model with uncertainty quantification for its predictive maintenance. *IEEE transactions on industrial electronics*, *71*(4), 3650-3659.

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of business research*, *133*, 285-296.

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. *arXiv preprint arXiv:1702.08608*.

Dunn, J. B., Gaines, L., Kelly, J. C., James, C., & Gallagher, K. G. (2015). The significance of Li-ion batteries in electric vehicle life-cycle energy and emissions and recycling's role in its reduction. *Energy & Environmental Science*, *8*(1), 158-168.

Edge, J. S., O'Kane, S., Prosser, R., Kirkaldy, N. D., Patel, A. N., Hales, A., ... & Offer, G. J. (2021). Lithium ion battery degradation: what you need to know. *Physical Chemistry Chemical Physics*, *23*(14), 8200-8221.

Freer, M. (2026). The Faraday Institution Programme: A UK perspective on innovation in the battery sector. *Carbon Neutral Technologies*, 100014.

Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1, No. 2, pp. 1-800). Cambridge: MIT press.

Harper, G. D., Kendrick, E., Anderson, P. A., Mrozik, W., Christensen, P., Lambert, S., ... & Boons, F. (2023). Roadmap for a sustainable circular economy in lithium-ion and future battery technologies. *Journal of Physics: Energy*, *5*(2), 021501.

Harper, G., Sommerville, R., Kendrick, E., Driscoll, L., Slater, P., Stolkin, R., ... & Anderson, P. (2019). Recycling lithium-ion batteries from electric vehicles. *nature*, *575*(7781), 75-86.

Hu, J., Zu, H., Zhao, Y., Zhao, S., Ma, T., Zhang, L., ... & Li, Y. (2026). Data-Driven Thermal Runaway Warning for Batteries: Research Progress and Prospects of Machine Learning Approaches. *Batteries*, *12*(6), 204.

Huang, L., Xu, G., Du, X., Li, J., Xie, B., Liu, H., ... & Chen, L. (2021). Uncovering LiH triggered thermal runaway mechanism of a high-energy LiNi0. 5Co0. 2Mn0. 3O2/graphite pouch cell. *Advanced Science*, *8*(14), 2100676.

IEA. (2023). *Global EV outlook 2023*. International Energy Agency.

IPCC. (2022). *Sixth assessment report: Mitigation of climate change*. Intergovernmental Panel on Climate Change.

LeCun, Y. (2022). A path towards autonomous machine intelligence version 0.9. 2, 2022-06-27. *Open Review*, *62*(1), 1-62.

Li, W., Chen, J., Quade, K., Luder, D., Gong, J., & Sauer, D. U. (2022). Battery degradation diagnosis with field data, impedance-based modeling and artificial intelligence. *Energy storage materials*, *53*, 391-403.

Li, Y., Liu, X., Wang, L., Feng, X., Ren, D., Wu, Y., ... & Ouyang, M. (2021). Thermal runaway mechanism of lithium-ion battery with LiNi0. 8Mn0. 1Co0. 1O2 cathode materials. *Nano Energy*, *85*, 105878.

Liu, C., Dai, H., Wang, D., Ren, X., Lyu, S., Fan, J., ... & Wang, Y. (2024). Understanding thermal runaway in lithium-ion batteries: Trigger, mechanism, and early warning strategies. *Journal of The Electrochemical Society*, *171*(12), 120527.

Madani, S. S., Shabeer, Y., Fowler, M., Panchal, S., Chaoui, H., Mekhilef, S., ... & See, K. (2025). Artificial intelligence and digital twin technologies for intelligent lithium-ion battery management systems: A comprehensive review of state estimation, lifecycle optimization, and cloud-edge integration. *Batteries*, *11*(8), 298.

Martinez-Laserna, E., Sarasketa-Zabala, E., Sarria, I. V., Stroe, D. I., Swierczynski, M., Warnecke, A., ... & Rodriguez, P. (2018). Technical viability of battery second life: A study from the ageing perspective. *IEEE Transactions on Industry Applications*, *54*(3), 2703-2713.

Page, M. J., McKenzie, J. E., & Bossuyt, P. M. (2021). *PRISMA 2020 explanation and elaboration. BMJ 372, n160.*

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *bmj*, *372*.

Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational physics*, *378*, 686-707.

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature machine intelligence*, *1*(5), 206-215.

Saha, B., & Goebel, K. (2007). NASA battery dataset. NASA Prognostics Center.

Severson, K. A., Attia, P. M., Jin, N., Perkins, N., Jiang, B., Yang, Z., ... & Braatz, R. D. (2019). Data-driven prediction of battery cycle life before capacity degradation. *Nature energy*, *4*(5), 383-391.

Stark, C., Thompson, M., & Climate Change Committee. (2019). Reducing UK emissions–2019 Progress Report to Parliament.

Subramanian, V. R., Boovaragavan, V., Ramadesigan, V., & Arabandi, M. (2009). Mathematical model reformulation for lithium-ion battery simulations: Galvanostatic boundary conditions. *Journal of The Electrochemical Society*, *156*(4), A260-A271.

Sun, X., Zhang, F., Wang, J., Yang, Z., Huang, Z., & Xue, R. (2025). Digital twin for smart manufacturing equipment: modeling and applications. *The International Journal of Advanced Manufacturing Technology*, *137*(9), 4929-4946.

Thelen, A., Huan, X., Paulson, N., Onori, S., Hu, Z., & Hu, C. (2024). Probabilistic machine learning for battery health diagnostics and prognostics—review and perspectives. *npj Materials Sustainability*, *2*(1), 14.

UK Battery Industrialisation Centre. (2024). *Battery manufacturing and industrialisation report*.

UK Government. (2023). *Net zero strategy update*. UK Government.

UK Government. (2023). *UK battery strategy*. Department for Business, Energy & Industrial Strategy.

Wang, L., Qiu, Y., Yuan, W., Tian, Y., & Zhou, Z. (2025). Next-generation battery safety management: machine learning assisted life-time prediction and performance enhancement. *Journal of Energy Chemistry*, *109*, 726-739.

Wang, T. T., Liu, K. Y., Peng, H. J., & Liu, X. (2025). Interpretable Machine Learning for Battery Prognosis: Retrospect and Prospect. *Advanced Energy Materials*, *15*(48), e03067.

Yan, S., Fang, H., Li, J., Ward, T., O'Connor, N., & Liu, M. (2023). Privacy-aware energy consumption modeling of connected battery electric vehicles using federated learning. *IEEE Transactions on Transportation Electrification*, *10*(3), 6663-6675.

Zanoletti, A., Carena, E., Ferrara, C., & Bontempi, E. (2024). A review of lithium-ion battery recycling: technologies, sustainability, and open issues. *Batteries*, *10*(1), 38.

Zhang, J., Wang, Y., Jiang, B., He, H., Huang, S., Wang, C., ... & Ouyang, M. (2023). Realistic fault detection of li-ion battery via dynamical deep learning. *Nature Communications*, *14*(1), 5940.