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Artificial intelligence for battery reusing, recycling, and remanufacturing

Shengyu Tao[1, 2, 3], Scott Moura[2], Daniel Brandell[4], Zhiyuan Han[1],
Shafiq Urréhman[5], Changfu Zou[3, *], Xuan Zhang[1, *], Guangmin Zhou[1, *]
[1] Tsinghua Shenzhen International Graduate School, Tsinghua University, Shenzhen, 518055, China
[2] Department of Civil and Environmental Engineering, University of California, Berkeley, CA, 94720, USA
[3] Department of Electrical Engineering, Chalmers University of Technology, Gothenburg, 41296, Sweden
[4] Department of Chemistry-Ångström Lab, Uppsala University, Lägerhyddsvägen 1, Uppsala, 75121, Sweden
[5] Motor Vehicle Manufacturing, Zeekr Technology Europe AB, Gothenburg, 41755, Sweden
* changfu.zou@chalmers.se (C. Zou);
* xuanzhang@sz.tsinghua.edu.cn (X. Zhang);
* guangminzhou@sz.tsinghua.edu.cn (G. Zhou).

Key Points:

1. Data scarcity and data heterogeneity across battery material types, format designs, operation profiles, environmental conditions, and ownership change can limit effective battery diagnostics, prognostics, and lifecycle-aware decision-making.
2. AI supports battery lifecycle safety, efficiency, economic feasibility, and environmental friendliness by informing decisions across manufacturing, first-life service, second-life repurposing, raw material recovery, and system-level remanufacturing.
3. AI model development and deployment must adapt to diverse data availability, specifically, physics-based modeling when data is absent, field testing when data is limited, and federated learning when data sharing is restricted.
4. Emerging solutions such privacy-protected data sharing, data sufficiency evaluation, data-efficient field diagnostics, automated disassembly, and battery passports address multi-layered challenges in data curation, model development, model deployment, battery management practice, and policy engagement.
5. Physics knowledge integration and data sufficiency evaluation improve AI model in accuracy, stability, generalizability, interpretability, and cost-effectiveness.
6. Standardized performance evaluation from multi-perspectives such as battery data, models, systems, practices to policies are critical for both industrial-scale practice and cross-institutional academic research outcome benchmarking of AI-powered battery reusing, recycling, and remanufacturing.

Abstract:

Lithium-ion batteries are often retired while still retaining 70–80% of their rated capacity, creating economic and environmental challenges across their supply chain. Although reuse, recycling and remanufacturing offer alternatives to recover this otherwise under-utilized value, their implementation is hindered by the lack of reliable data on battery condition at retirement, making it difficult to determine whether, when and how these alternatives should be applied. In this Perspective, we discuss how artificial intelligence (AI) can help to overcome data barriers by enabling adaptive, data-informed decision-making throughout the battery life cycle. AI tools can be tailored to battery data scarcity and heterogeneity contexts, and integrated with data curation, model establishment and model deployment. For example, physics-based modelling can be used when data are unavailable, field-sensing when data are limited and federated AI when data sharing is restricted. Management of retired batteries can benefit from AI tools that are adequately accurate, stable, interpretable, transferable and deployable under these data uncertainties. Further adoption of AI into retired battery condition inspection, pretreatment, reutilization and governance could offer a framework towards safe and efficient battery life-cycle management at scale.

Glossary

Reusing

The process of cell, module, pack-level repurposing used or end-of-life batteries from their original applications, such as electric vehicles, to generally less-demanding secondary application scenarios, such as stationary energy storage, household energy storage and low speed vehicles.

Recycling

Recycling is the process of material-level recovering valuable materials, such as lithium, nickel, cobalt, and copper, from used batteries through mechanical, thermal, or chemical treatment, so that these materials can be reintegrated into new battery production and primary resource extraction and environmental impact can be reduced.

Remanufacturing

The process of electrode and cell-level restoring used or end-of-life batteries to a like-new condition through disassembly, replacement of degraded components, reassembly, and quality verification to extend product life and recover functional value as newly produced module or pack-level batteries.

State of charge (SOC):

The ratio of the battery's currently available electrical energy to its maximum available electrical energy under the current state of health and a specified temperature, typically expressed as a percentage.

State of health (SOH):

The ratio of a battery's available full-charge capacity to its original full-charge capacity, indicating the degree of aging or degradation.

State of power:

The maximum power output a battery can deliver under current operating conditions, considering its thermal and electrical limitations.

State of temperature:

The internal or surface temperature of a battery, which influences its efficiency, safety, and degradation behavior.

Remaining useful life (RUL):

The estimated duration or number of charge-discharge cycles over which a battery is expected to operate reliably within predefined performance thresholds.

Degradation trajectory:

The temporal evolution of performance indicators, such as capacity, internal resistance, or efficiency, which characterizes how a battery degrades under specific operating conditions.

Material type:

The specific composition and formulation of materials used in battery electrodes and electrolytes, including both the class of active materials and their internal proportions or doping configurations.

Degradation mechanism:

The underlying physical and chemical processes that lead to battery aging and performance decline. Common examples include loss of lithium inventory, loss of active materials, and growth of solid–electrolyte interphase.

Consistency:

The degree of uniformity in performance metrics such as voltage, capacity, or thermal behavior among individual cells within a battery module or pack.

Knee point:

A critical inflection point in a battery's aging curve at which the rate of degradation increases notably.

Thermal runaway:

A critical failure mode in which elevated temperatures initiate self-sustaining exothermic reactions within battery components, potentially resulting in thermal instability, fire, or explosion.

Charging behavior:

The electrical and thermal response of a battery during charging, including voltage profile, current acceptance rates, and heat generation.

Disassembly:

The use of robotic or mechanical systems to separate battery components without manual intervention, aiming to improve safety, efficiency, and material recovery in recycling or remanufacturing processes.

Data augmentation:

A technique for expanding datasets by generating additional samples or applying transformations, used to improve the robustness and generalizability of AI models under data scarcity and heterogeneity.

1 Introduction

Lithium-ion batteries (LIBs) are widely used in electric vehicles and energy storage systems, supporting the integration of intermittent renewable energy sources such as wind and solar into smart grids[1-3]. However, LIBs are typically retired from electric vehicles while still retaining up to 70-80% of their initial capacity, due to concerns about safety, driving range, and performance under cold-start conditions[4]. This underutilization poses economic and environmental difficulties to materials suppliers, battery manufacturers, electric vehicles companies, and end users[5-9].

[G] Reusing, [G] recycling, and [G] remanufacturing represent three complementary approaches for extending the value of retired batteries. Reusing refers to repurpose batteries with sufficient remaining capacity for less-demanding applications such as stationary or household energy storage[10]. Recycling recovers valuable materials including lithium, nickel, cobalt, and copper via mechanical, thermal, hydro or chemical treatments, reducing raw-material demand and associated environmental impact[11]. Remanufacturing restores used batteries to near-new performance via [G] disassembly, component replacement, and reassembly, achieving high functional recovery[12]. However, key questions, such as whether, when, and how these processes should be carried out to ensure reliable and efficient battery lifecycle-aware decision-making, have not yet received definitive answers[13]. This uncertainty largely stems from the lack of reliable field data on battery states at the point of retirement, which is crucial for data-informed lifecycle decision-making[13]. However, critical information, such as state of charge[14], remaining capacity[15], remaining energy, [G] material types[16], and [G] degradation mechanisms[17], is usually not readily accessible at test sites.

The EU Battery Directive, effective from July 2023, aims to promote sustainability through battery lifecycle management, and the Battery Passport is envisioned as a digital record of battery attributes to secure information traceability and data integrity[18-20]. However, the data recorded in the Battery Passport is static and does not accommodate the frequent changes in battery ownership and usage post-retirement. This limitation underscores an urgent need for dynamic methods to acquire and make available such battery information[21]. Artificial intelligence (AI) has demonstrated potential for assessing field states of batteries at retirement, leveraging available existing data and affordable to-be-curated data. Compared to their first life, retired batteries face unique challenges because of data scarcity and data heterogeneity. Data scarcity often arises due to restrictions on battery management system data usage or privacy concerns related to historical battery usage information[16,22-24]. Data heterogeneity is another issue, as retired batteries are usually collected in batches, with each batch containing batteries of different material types, physical formats, capacity designs, and degradation mechanisms shaped by varying usage histories[13,15,16]. Finally, reselling retired batteries for second-life use will require warranties, with cost depends markedly on accurately predicting remaining residual values and failure distributions[25,26].

In this Perspective, we examine data challenges associated with battery reusing, recycling, and remanufacturing, focusing on data scarcity and data heterogeneity resulted from different battery chemistries, formats, and usage conditions. We present an overview of how AI tasks, AI tools allocation can support battery lifecycle-aware decisions by enabling effective diagnostics and prognostics with limited or fragmented data access. We discuss key lifecycle stages and AI focuses, objectives, tools and limitations, highlighting stage-specific opportunities in reusing, material recovery, and system-level remanufacturing. We also discuss remaining challenges and data-informed strategies matched to data availabilities, and map these approaches to data curation, model development, battery management system integration, industrial implementation and policy implications of battery reusing, recycling, and remanufacturing.

2 Battery data constraints

Across the lifecycle of LIBs, from research and development stage to primary-life, second-life and post-retirement processing for material recycling, effective decision-making regarding battery residual value and internal states depends critically on high-quality and standard battery data[27-29]. These data support key processes such as health estimation, residual value assessment, sorting decisions, and application matching. However, each stage faces distinct data limitations that collectively hinder the effective adoption of advanced data-driven approaches (Figure 1).

These data constraints emerge from four interrelated aspects. First, operational and management barriers restrict data flow across stakeholders, leading to fragmentation and traceability loss[30]. Second, the variability in material compositions, physical formats, and module or pack designs results in inevitable inconsistencies that complicate the dataset comparability[31,32]. Third, real-world environmental and usage diversity introduces uncontrolled conditions and measurement noise that reduce data reliability[33-35]. Finally, these factors culminate in a data scarcity and data heterogeneity, undermining the scalability and generalizability of battery management system design and deployment.

Data scarcity refers to the lack of sufficient, high-quality, and context-rich battery data. While early-stage testing in manufacturing can be data-rich, most of this information is proprietary and inaccessible. During field use, critical data are often withheld by manufacturers or fragmented across platforms due to privacy concerns[36]. In reusing and recycling stages, historical data are frequently missing or unusable, and testing is often constrained by resource limits and unknown battery states[15,37,38]. As a result, large-scale datasets that cover diverse chemistries, formats, and aging conditions remain rare since publicly available datasets report around 7,000 cells, surprisingly only equivalent to the number of cells in a Tesla electric vehicle. Data heterogeneity arises from inconsistencies in materials, formats, applications, and user behaviors. Field-collected data vary in sampling frequency, feature definition, and quality, leading to considerable data distributional shifts that challenge model transferability[39,40]. Without unified labeling or testing standards, combining or comparing datasets across multiple sources remains difficult. In summary, data scarcity limits data coverage, while data heterogeneity undermines comparability. Their combination hinders the development of generalizable algorithms for reliable battery diagnostics and prognostics.

2.1 Operation and management barriers

Effective battery lifecycle management relies heavily on transparent, traceable, and continuous data access. Yet in practice, operational and institutional constraints create notable friction in achieving this goal (Figure 1). One major barrier stems from the proprietary nature of battery material formulations, which are treated as commercial secrets. Without disclosure of exact material compositions or design parameters, even well-instrumented algorithms remain opaque to downstream processing of these batteries. Closely related is the restricted access to battery management system, where high-resolution and battery quality-relevant operational data, such as voltage, internal resistance, and fault logs, are stored but frequently locked by manufacturers due to commercial and cyber-security reasons[41-43].

Compounding these issues are concerns around battery data privacy and liability. In both consumer electronics and electric vehicles, usage patterns are coupled to personal or proprietary information such as driving behavior, [G] charging behavior, and origin-destination information, creating reluctance in sharing historical records even when batteries are decommissioned from their first-life use[39,44-48]. Batteries can also experience uncontrolled processing post-retirement (for example, suboptimal test parameters), causing secondary damage during disassembly or transport, which complicate the data curation[49].

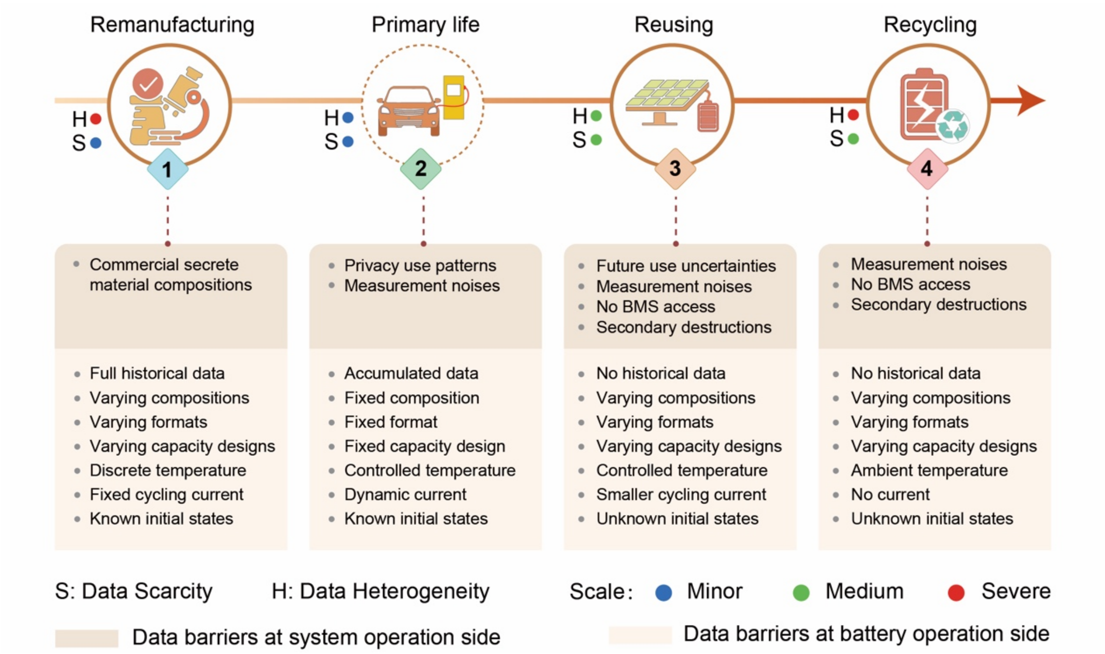

Figure 1 Stage-specific data constraints hinder safe, economical, and environmental-friendly battery management decisions for reusing, recycling and remanufacturing, due to weak observability into battery states. Data constraints arising from multiple aspects such as data accessibilities, operation diversities, and measurement challenges, including composition secrets, privacy use patterns, future use uncertainties, measurement noises, secondary destructions, no battery management system access. Each phase including manufacturing (remanufacturing), primary life, reusing for second life, recycling for materials and remanufacturing for near-new cells, modules and packs, faces distinct levels of data scarcity and data heterogeneity, highlighting systematic bottlenecks in value-aligned lifecycle decisions. Note that manufacturing and remanufacturing share a lifecycle stage due to their products are battery cells, modules, and packs, while taking different lifecycle functions, i.e., manufacturing refers to the process of fabricating batteries from materials or electrodes, and remanufacturing refers to the process of producing near-new cells, modules and packs from refurbished components. It is worth noting that the flow of life stages from left to right, i.e., remanufacturing, primary life, reusing, and recycling, is not unidirectional, as different life cycle stages can be directly connected without the demonstrated sequential flow. For example, batteries undergoing remanufacturing may be sent directly to recycling due to defects, and batteries in their primary life stage may also be directly recycled without reusing if they have irreversible degradations. BMS: battery management system.

Moreover, the lack of standardized end-of-life handling protocols and clearly defined second-life application scenarios makes it difficult to anticipate future operating conditions, such as current intensity, temperature range, and usage patterns. This uncertainty not only hinders direct prediction of battery states but can also complicate physics- and scenario- based simulations, as the absence of representative use scenarios limits the assumptions and inputs required for reliable modeling[50].

Lastly, standardized testing methods such as constant current constant voltage test are often applied without necessary knowledge of battery-specific parameters like cutoff voltages or C-rates. Given diverse material types, operation conditions and unknown states of batteries, such standardized protocols can lead to noisy measurements, reducing the data reliability[51-53].

2.2 Material and design variability

Beyond operational and management factors, intrinsic diversities in material composition, physical formats and capacity designs also contributes notably to inconsistencies in battery data[15,54]. First, the differences in electrode chemistry, such as lithium iron phosphate (LFP), nickel cobalt manganese (NCM), or lithium nickel cobalt aluminum oxide (NCA), result in distinct voltage profiles and aging behaviors[55-57]. These electrochemical and mechanical variabilities affect how voltage-based features are derived and interpreted[58,59]. As a result, algorithms trained on one chemistry consistently fail to generalize to others without sophisticated adaptation methods[60].

Second, even when materials are nominally the same, differences in physical structure, such as cylindric, pouch, prismatic and blade formats affect mechanical stress distribution, thermal distribution, and current density, leading to varying internal states, and thus external signatures[61-63].

Third, batteries of the same chemistry and format factors often differ in nominal capacity designs, depending on their targeted application (for example, consumer electronics, electric vehicles, and grid storage). This system capacity difference impacts both inner- and inter-cell uniformity of electrochemical, thermal and electrical behaviors, with this difference even amplified with battery degradations[64,65]. Besides, additional variability can also arise from factors such as tab configuration, separator type and thickness, electrolyte additive type and concentrations, type and amount of binder and carbon additives in the electrode, and pack-level thermal or [G] consistency management[66-70].

2.3 Environmental and usage variability

Real-world environmental conditions and usage patterns introduce substantial variability in battery behavior and measurement outcomes. These uncontrolled factors, especially prevalent in primary- and second-life stages, often lead to deviations in expected degradation from manufacturing in a laboratory setting, complicating performance analysis and modeling. First, ambient and internal temperature play a pivotal role in battery performance and degradation behavior, while also mechanical conditions such as vibrations cause battery ageing. Elevated temperatures accelerate side reactions such as solid-electrolyte interphase and electrolyte decomposition, leading to capacity fade and shortened [G] thermal runaway time[71]. In contrast, low temperatures suppress lithium-ion diffusion and increase polarization, and thus increasing impedance and charging under low temperatures cause Li plating on the anode[72]. Moreover, temperature fluctuations introduce nonuniform aging across cells within the same module and pack (for example, thermal gradients causing accelerated degradation in edge-facing cells)[73]. These thermal effects are compounded by the absence of precise thermal control in second-life or off-grid environments, where passive cooling is common[74]. Second, current intensity and cycling profile have direct impacts on degradation modes and estimation fidelity. High C-rate charging promotes lithium plating and mechanical stress accumulation at the anode, while low-rate partial cycling tends to amplify calendar aging[53,75]. Irregular or user-specific charging behaviors, such as frequent fast-charging, shallow cycling, or prolonged idle storage, introduce distributional shift in voltage and current signatures[75-77]. Unfortunately, most public datasets are generated under controlled laboratory cycling, and thus do not capture the diversity of real-world current profiles despite a few recent datasets that aim to characterize fluctuating loads in hybrid mobility systems or household energy storage[78,79]. Third, initial state uncertainties, such as unknown prior usage history, severely affect the interpretability of observed behaviors. For example, two batteries with similar open-circuit voltages can differ in capacity, yet such differences are hard to resolve without prior labels. In reusing and recycling scenarios, where batteries are collected from disparate sources with varying operational histories and initial states, the lack of initialization data becomes a bottleneck for accurate state reconstruction or performance forecasting[37,80].

3. AI's role in sustainable battery lifecycle

The circular utilization of LIBs hinges on the ability to make safety-, economy- and carbon-informed decisions at every stage of the lifecycle, from manufacturing and primary-life to second-life, recycling, and remanufacturing, while being challenged by the aforementioned data constraints (i.e., data scarcity and data heterogeneity). A central problem of these challenges is a lack of visibility into the internal states of batteries given scarce and heterogeneous battery data. AI addresses these two challenges by analyzing external measurements with algorithmic inference to estimate key states thus guiding informed decisions. Importantly, the role of AI focus, objective, tools and limitation evolve across the lifecycle (**Figure 3** and **Table 1**). In manufacturing, AI aims to support defect detection (quality inspection), early failure screening, consistency assessment, and manufacturing process optimization. In primary life, such as service in electric vehicles, AI aims to support degradation monitoring. risk early warning and fault (or anomaly) detection. In reusing, AI seeks to support residual evaluation, sorting and regrouping and risk-aware reuse decision. In recycling, AI can support material type identification, degradation mechanism inference, recycling process routing decision, optimal reaction agent and dose design, and recovered material quality prediction. In remanufacturing, AI can support automated disassembly and assembly, module or pack reconstruction, and high-demand consistency improvement. Such variation in AI task focuses necessitates deliberate AI task allocation, where algorithms are aligned with lifecycle-specific goals, constraints, and available data. Matching AI tasks and available tools to stage-dependent challenges is key to realizing intelligent, circular, and high-value battery equipment and material flow management (**Figure 2**).

3.1 Manufacturing

As the industry and academia push for batteries with longer lifetimes, higher energy densities, faster charging capabilities, and lower carbon footprints, precision control and defect minimization in the manufacturing process become imperative. For example, foreign matter defects in lithium-ion batteries can be effectively detected by combining random forest models with out-of-bag error analysis using data collected from pilot manufacturing lines[81]. Lithium-plating-type defects were further identified during battery manufacturing by analyzing formation and capacity grading data[82]. Electrode-level defects during manufacturing were successfully detected using computer vision-based deep learning approaches, particularly using convolutional neural networks[83]. Battery electrode heterogeneity assessment, manufacturing process optimization, and multi-objective manufacturing optimization under data scarcity and heterogeneity were achieved through a series of simulation- and AI-based methods, including Gaussian process regression[84],, Gaussian naive Bayes[85], and Bayesian multi-objective optimization[86], with synthetic data generated from physics-based simulations. In addition, data-efficient screening of promising charging protocol designs was enabled by physics-informed learning and generative models that integrate simulation outputs with limited experimental data, significantly reducing testing time and cost[17].

Following initial cell fabrication, early-stage fault detection has been enabled through charging behavior prediction based on voltage-time and differential capacity analyses, which reveal irreversible anomalies associated with lithium plating or loss of active materials, allowing defective cells to be rejected prior to system integration[17,87]. However, conventional quality inspection remains largely dependent on post-production sampling, which is insufficient to capture localized or process-induced variability across large manufacturing volumes. AI provides a pathway toward inline quality monitoring, defect detection, and performance prediction during manufacturing. Microstructural defects can be identified from imaging data, such as CT, X-ray, or transformed time-series signals, enabling prediction of the [G] remaining useful life (RUL), degradation trajectories, and degradation mechanisms [88-90]. Sudden performance drops, including the emergence of the [G] knee point, have been inferred from early-cycle voltage and capacity evolution well before macroscopic degradation becomes observable [91]. By learning nonlinear mappings between subtle early-cycle signatures and long-term degradation outcomes, a range of AI models, including random forest for feature importance extraction[92], Gaussian process regression for uncertainty-aware trajectory prediction[93], and support vector machines for early-stage anomaly separation, enabling proactive identification of cells prone to rapid aging or instability [94].

Once individual cells pass quality screening, their assembly into modules and packs requires a high degree of performance consistency to prevent imbalance-induced degradation and localized thermal stress. To this end, AI-based clustering and hierarchical classification approaches have been used to group cells with similar capacity fade patterns and impedance growth, thereby reducing intra-pack heterogeneity and improving pack-level uniformity, safety, and operational lifetime[95,96].

3.2 Primary service life

Unlike the controlled environment of manufacturing, the operating conditions during primary-life are highly dynamic and uncertain. Battery systems experience irregular load profiles, varying ambient temperatures, and user-specific behaviors[97]. Furthermore, as batteries are deployed at the module or pack level, internal inconsistencies, both within individual packs (cell-to-cell variability) and across systems, become more pronounced, increasing the complexity of AI tasks for monitoring and control[98]. In addition to the common quality-relevant tasks in manufacturing, the primary life focuses heavily on the estimation of internal battery states, such as [G] state of charge (SOC), [G] state of health (SOH), [G] state of power, and [G] state of temperature[99-102]. In contrast, advanced AI methods aim to infer internal battery states that cannot be directly measured by learning relationships between externally observable signals and latent electrochemical conditions. These approaches typically take time-resolved voltage, current, and temperature measurements from on-board battery management systems as inputs, and output continuous or probabilistic estimates of internal states, such as SOC, SOH, RUL, or risk indicators associated with abnormal operation[103-107]. The inferred states are used to support real-time monitoring, adaptive control, safety warning, and lifetime-aware decision-making under dynamic and uncertain operating conditions.

However, purely data-driven models can suffer from reduced robustness and limited generalizability when operating conditions deviate from the training distribution, particularly under unseen temperatures[17], load profiles[108], or aging modes[109]. To address this limitation, physics-informed neural networks and hybrid digital twins explicitly embed electrochemical degradations, such loss of active materials, loss of lithium inventory, or voltage-current derived indicators into AI architectures, thereby constraining model behavior to remain physically consistent while retaining the flexibility of AI models[17,110-113].

3.3 Reusing for secondary life

The reusing of retired LIBs offers an economically and environmentally favorable path toward resource efficiency by deploying these batteries in less-demanding contexts, including grid-scale storage, residential energy systems, uninterruptible power supplies, and low-speed electric mobility[18,114-116]. Unlike primary-life, second-life usage scenarios are highly heterogeneous and can involve sequential redeployment across multiple application domains, a process often termed cascaded utilization or echelon utilization[117]. Before any reusing, decommissioned battery packs must undergo a controlled discharge to lower their energy content, ensuring safe transport and storage[118,119]. In this context, estimating the SOC becomes essential, while not to indicate range or availability as in electric vehicles, but to prevent excessive deep discharge that could trigger secondary degradation or safety incident such as thermal runaway. This requires AI models capable of inferring SOC under unknown prior usage and incomplete monitoring data[38,120]. Another critical step before reusing is disassembly and performance evaluation such that cells with comparable performance are regrouped into new modules or packs, while underperforming ones are directed to material recycling. AI-enabled battery sorting methods that leverage supervised classification, anomaly detection, or physics-informed clustering, have been shown to enhance grouping efficiency and pack reliability[11,137-139]. Currently, battery disassembly is predominantly with manual labor, which exposes workers to electrical, chemical, and ergonomic hazards, thus automation via robotics and AI vision systems is gaining traction[121]. Emerging techniques including battery object detection, module edge image separation, health-aware disassembly decision-making, learning-based robotics and non-destructive cell separation are attracting growing interests as these methods address core challenges of battery disassembly with limited observability of internal structures and large variability in battery designs [122-126]. Another particularly challenging issue in second-life is the unknown or mixed origin of battery materials. Specifically, unlike first-life systems where chemistry and design are standardized, reused batteries are sourced from varied manufacturers and chemistries. Accurate material type identification is critical for battery performance prediction, reusing decisions, and downstream material recycling[16]. Solutions under exploration include X-ray imaging, mass spectrometry, laser-induced breakdown spectroscopy, and electrochemical signal decoding using federated learning, which preserve data privacy while enhancing classification accuracy across distributed sources[16,127-129].

3.4 Recycling for material

Recycling refers to recovering valuable materials from spent batteries to minimize environmental harm and conserve critical resources[119]. In Figure 2, rather than landfilling or incinerating, batteries are processed through several key recycling techniques such as pyrometallurgy, hydrometallurgy, and direct recycling. Pyrometallurgy melts battery components at high temperatures to extract critical metals such as cobalt and nickel; however, it is energy-intensive and results in considerable emissions[130,131]. Hydrometallurgy, on the other hand, uses chemical solutions to leach metals in a controlled environment, which can achieve high recovery rates at lower temperatures but often produces secondary waste[132,133]. Direct recycling is gaining notable attention for its ability to lower energy consumption and reduce environmental impact compared to traditional methods like pyrometallurgy and hydrometallurgy[134-137]. The direct recycling reduces material degradation and maintains higher-value components, making it both cost-effective and environmentally friendly[138,139]. Common direct recycling techniques include solid-phase regeneration and hydrothermal repair[140,141], involving mixing spent cathode materials with a supplement lithium source and heating at high temperatures to restore their original structure. Hydrothermal repair, on the other hand, uses aqueous solutions under high pressure to replenish lithium and repair defects in the cathode material[142,143].

However, for recycling to be feasible, efficient, economical and profitable, it requires detailed information about internal chemical compositions of the batteries[16,135,144,145]. Critical internal information includes material type, degree of material degradation and physicochemical properties such as phase transitions in the cathode, lithium depletion, crystal structure defects, the presence of Li plating, and the state of solid electrolyte interphase on the anode [138,146-149]. Understanding these factors is crucial because they determine whether, and how electrode materials can be repaired or reused. Cathode material types of massive retired lithium-ion batteries were accurately identified using a federated and collaborative learning framework that supports both homogeneous and heterogeneous data access while preserving data privacy across collaborators [16]. The discovery of deep eutectic solvents for lithium-ion battery cathode recycling was accelerated by applying conditional generative adversarial networks, effectively bypassing the conventional trial-and-error process in chemical agent optimization [150]. Thermodynamic and kinetic losses within batteries were further identified using physics-integrated neural networks, enabling more precise scrap material classification and targeted recycling prior to large-scale battery production [17].

The quality of recycled materials can be enhanced by integrating artificial neural network models into the regeneration process of spent lithium iron phosphate cathodes, where optimal regeneration temperatures were predicted to improve the long-term performance of regenerated batteries to lifetimes of up to 1100 cycles [151]. In addition, the economic viability of material recycling was improved through generative data augmentation using variational autoencoder models, which enabled efficient health estimation of massive retired batteries and reduced electricity consumption during battery deactivation by up to 50% prior to recycling [37].

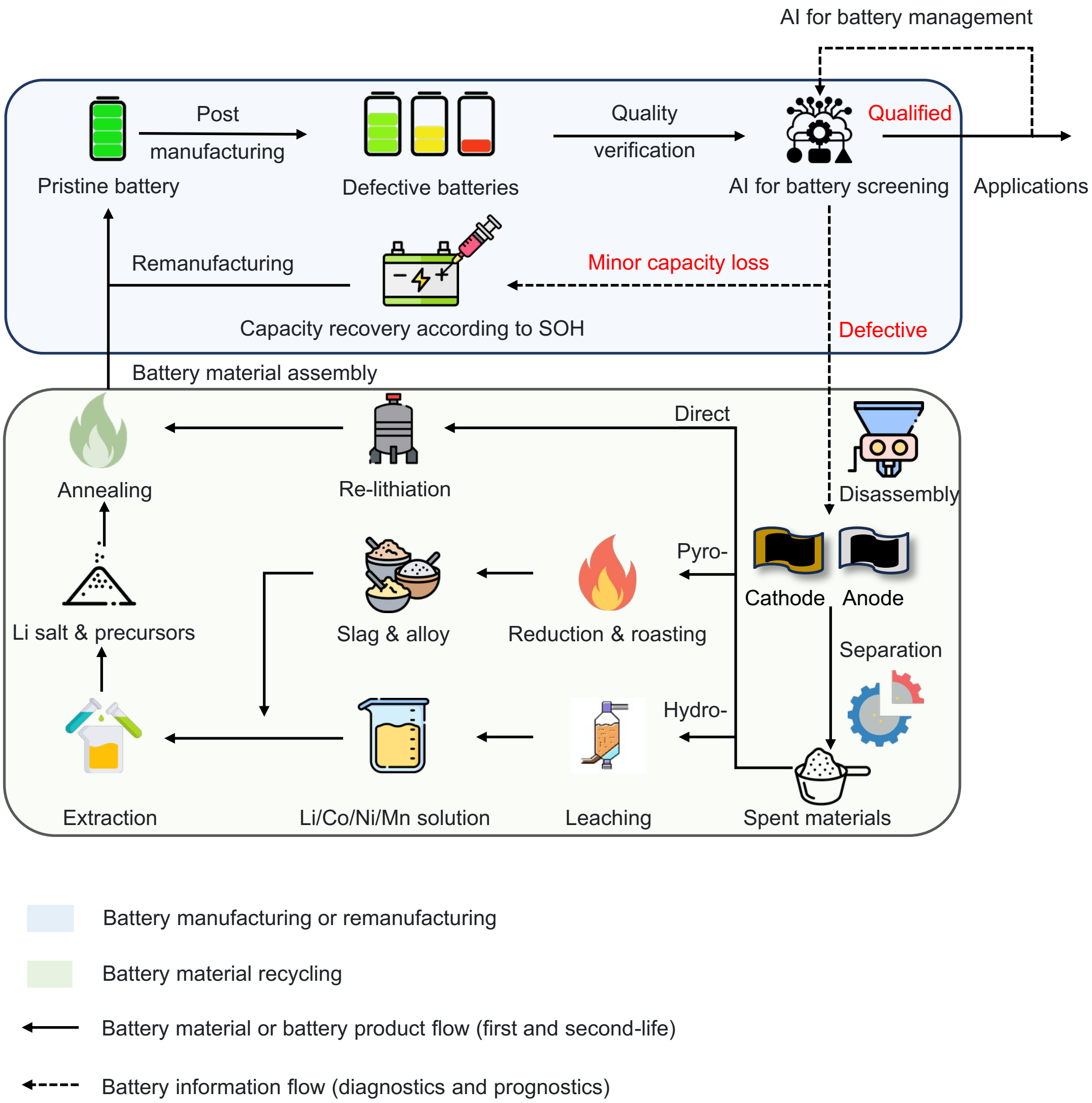

Figure 2 AI-enabled pathways routing for battery reusing, recycling, and remanufacturing. In battery manufacturing and remanufacturing loop, pristine batteries undergo quality verification to distinguish qualified products from defective ones. Defective batteries with minor capacity loss can be remanufactured based on their health states to recover capacity and re-enter the application cycle (including primary life and reusing). Battery material recycling routes, such as direct regeneration, pyrometallurgical, and hydrometallurgical processes, include disassembly, separation, leaching, reduction, and re-lithiation steps. In this way, AI can support battery diagnostics and prognostics, ensuring traceable battery information flow with material circulation. It is worth noting that this diagram does not emphasize general use case of AI in battery reusing, recycling, and remanufacturing, but rather emphasizes the role of AI in remanufacturing and recycling as details for primary life and reusing for other applications are not highlighted in this diagram. Together, these AI enabled processes establish a closed-loop framework that improves material recovery efficiency, quality of recycled materials and extends application lifetime. AI: artificial intelligence;

SOH: state of health.

3.5 Remanufacturing for modules and packs

Remanufacturing can take two principal forms, each entailing distinct AI requirements. When remanufacturing starts from recycled materials, the process closely mirrors traditional manufacturing[152]. In this case, AI tasks resemble those described in Table 1 for battery manufacturing stage. These AI tasks are essential to ensure that the regenerated cells meet stringent quality standards, and defective cells must be screened and rejected before integration into application systems.

When remanufacturing proceeds from retired modules or packs, it involves disassemble, refurbishing and reassemble used cells into new modules or packs for reuse in high-demand scenarios such as electric vehicles[153]. This form of remanufacturing shares similarities with second-life applications, however, it should be noted that unlike reusing, which repurposes batteries for lower-demand applications, remanufacturing focuses on returning battery to its original performance for high-demand uses in battery module or pack[12,154]. While reusing emphasize maximizing the use of remaining capacity without addressing cell-level details, remanufacturing involves detailed, rigorous testing and component refurbishment to ensure that remanufactured batteries are at near-new conditions[155].

Recent research increasingly conceptualizes battery remanufacturing as a system-level decision and execution problem, in which automated disassembly, task planning, and human-robot collaboration must jointly address structural uncertainty and safety constraints. Early advances have focused on perception-enhanced disassembly, where the integration of computer vision-aided neural networks with online thermal sensing enabled battery type classification, cutting temperature prediction, and defect detection during dismantling, thereby supporting closed-loop control that improved operational safety and cutting quality in automated disassembly processes [156]. Building on perception-driven automation, subsequent work has emphasized disassembly sequence optimization under uncertainty. Battery disassembly has been formulated as a dynamic decision-making process, with multi-agent reinforcement learning applied to optimize task sequences in human-robot collaborative settings, resulting in significant reductions in disassembly time and tool-switching frequency compared with rule-based planning approaches [157]. To explicitly address partial observability in real disassembly environments, the problem has further been modeled as a partially observable Markov game, where Q-learning-based deep reinforcement learning frameworks enabled optimized human-robot task allocation, achieving higher global efficiency and reduced labor costs [158].

Beyond purely learning-based optimization, knowledge-guided and hybrid approaches have been introduced to improve robustness and interpretability. Neuro-symbolic task-and-motion planning frameworks that integrate visual perception, force sensing, and symbolic reasoning have enabled the generation of flexible disassembly primitives, supporting accurate screw removal and enhanced adaptability to diverse battery designs [159]. In parallel, digital twin-driven strategies have emerged to bridge planning and execution, where the combination of dynamic Petri nets with multi-agent deep Q-learning allowed real-time adjustment of disassembly sequences across multiple scenarios, improving both efficiency and safety in complex remanufacturing workflows [160]. Uncertainty in disassembly outcomes has also been explicitly addressed through probabilistic modeling. Dynamic Bayesian networks have been employed to represent uncertain disassembly structures and optimize sequencing decisions, demonstrating improved adaptability across heterogeneous battery packs [161]. Complementarily, extended Petri nets integrated with self-adaptive Q-learning have been used to identify near-optimal disassembly plans under uncertain component quality, achieving faster convergence and higher value recovery compared with static planning methods [160]. Collectively, these developments illustrate a clear evolution from perception-enabled automation toward uncertainty-aware, AI-driven, and human-robot-integrated remanufacturing systems.

3.6 AI task allocation for lifecycle management

Given distinct operational goals and data environments across the battery lifecycle, AI tasks must be carefully allocated to align with stage-specific challenges and decision-making needs. More detailed AI task allocations and focus can be found in the lower left part of Figure 3.

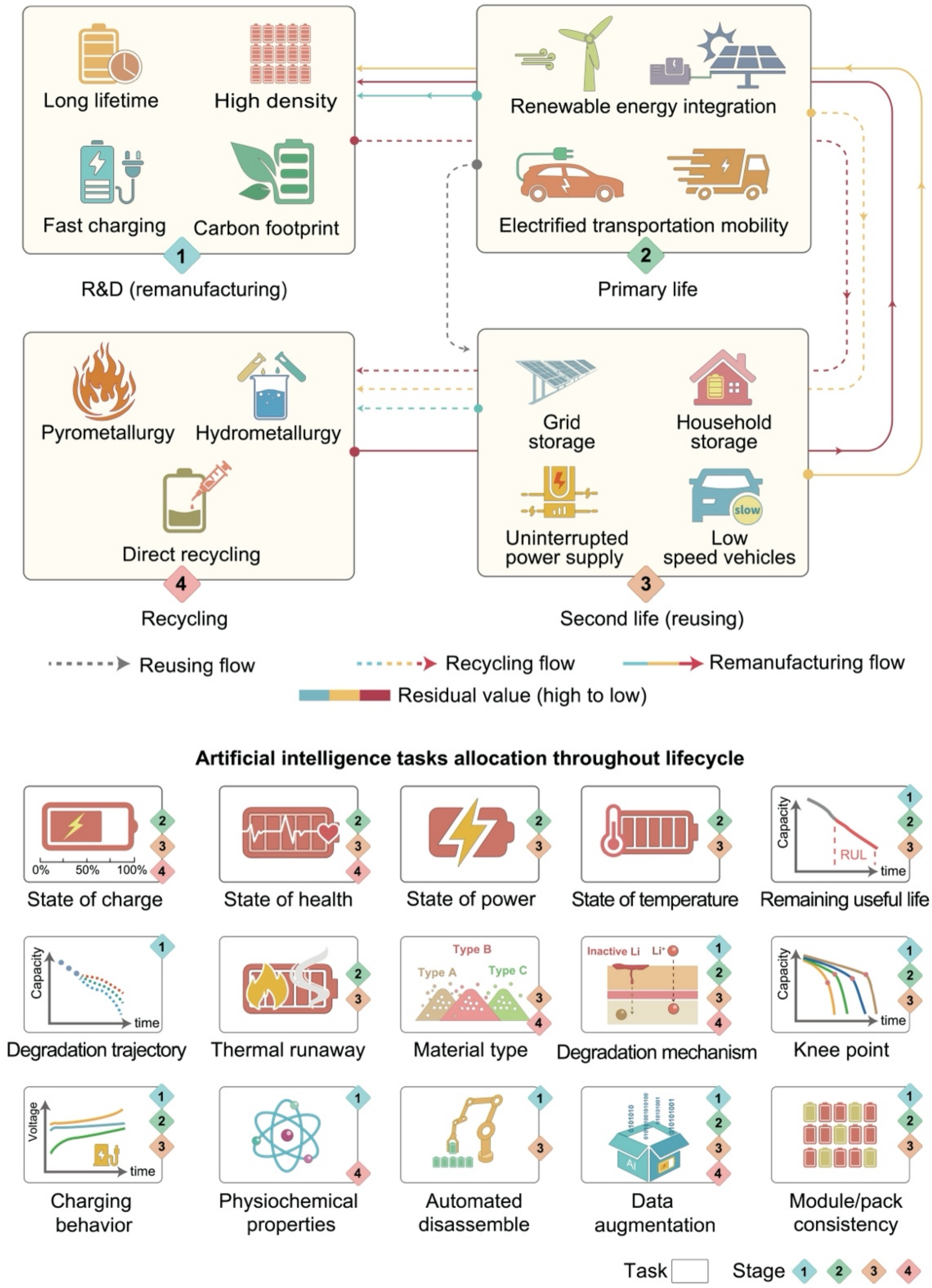

Figure 3 Lifecycle-specific artificial intelligence (AI) tasks enable adaptive battery value flow allocation. Battery

manufacturing, primary life, second life (reusing), recycling and remanufacturing involve diversified applications from mobility to stationary storage, other less demanding second-life application scenarios and material recycling, where corresponding AI tasks should be matched with lifecycle stages to maximize residual value, safety assurance and lifecycle sustainability. The stage icons indicate which lifecycle stages require the corresponding AI tasks. Different from **Figure 1** and **Figure 2**, this diagram completely illustrates all possible material flows at each stage of battery reusing, recycling, and remanufacturing in the top part, encompassing reusing flow, recycling flow, and remanufacturing, rather than depicting a specific possible case. It is noted that the AI task allocations emphasize the dimensions that are recommended to be considered for specific life cycle stage, instead of any specific AI tools that be adopted in that stage. For the available AI tools, **Table 1** further gives an exemplified summary of the mapping between AI task focus, AI tools, and their limitations. R&D: research and development.

In the manufacturing stage, the priority is defect detection and quality prediction, where AI helps ensure first-pass yield and early screening of substandard units through imaging and early-cycle data. During the primary service life, AI shifts toward state estimation (for example, SOC, SOH, state of power, state of temperature) and risk early warning, with dynamic monitoring enabling proactive management of degradation and prevention of failure events such as thermal runaway. In second-life reusing, the emphasis moves to residual value evaluation and cell/module sorting. AI enables rapid screening of decommissioned batteries under uncertainty and supports regrouping into consistent packs for extended utilization. In the recycling stage, AI is applied to material identification and degradation mechanism analysis. Accurate classification of electrode types and their degradation levels support efficient process routing and enhances the quality of regenerated materials. Finally, remanufacturing requires module and pack reconstruction with a focus on balancing performance and safety. AI ensures consistency across reused components and facilitates automation in the system rebuilding. It is noted that AI task allocation merely accounts for the dimensions that are recommended to be considered for specific life cycle stage, instead of any specific AI tools that be adopted in that stage. A detailed allocation of AI tools into life cycle stages can be found in **Table 1**.

Table 1 AI task focuses, tools, and limitations across battery lifecycle.

	AI task focuses	AI tools	Limitations
Manufacturing	- Defect detection and quality inspection for early rejection of defective cells into product delivery - Early failure screening to prevent defect propagation into battery system integration - Consistency assessment and manufacturing process optimization to improve yield through uniformity control	Random forest[81] Autoencoder with classifier [82] Convolutional neural network [83] Support vector machine [162] Gaussian process [85] Gaussian naives Bayes [84] Bayesian multi-objective optimization [86]	Data scarcity: Limited access to high-resolution in-line manufacturing and defect data Data heterogeneity: Process-induced variability across materials, equipment, and production lines
Primary service life	- Continuous degradation diagnostics and fault detection under changing conditions for safe operation - Continuous state estimation and anomaly identification for risk early warning	Dynamical deep learning [163] Long short-term memory neural network [164] Spatio-temporal transformer [165]	Data scarcity: Restricted availability of long-term, high-fidelity field operation data and the responding

	- Continuous monitoring of electrical, mechanical and thermal behaviors for failure prevention		ground truth of labeled outputs Data heterogeneity: Highly variable usage profiles, environmental conditions, and user behaviors
Reusing for secondary life	- Residual value evaluation under uncertainty for second-life decision-making - Sorting and regrouping to establish performance-consistent second-life systems - Risk-aware screening for safe and economic reuse eligibility	Generative learning [37] Generative transfer learning [14] ResNet [166] K-means[167] Gaussian process regression[168]	Data scarcity: Missing historical usage records and incomplete state labels at retirement Data heterogeneity: Mixed chemistries, formats, degradation states, and unknown prior conditions
Recycling for material	- Material type identification and degradation mechanism inference to support recycling pathway decisions - Process routing and reaction agent dose design for recycling optimization - Material quality prediction to maximize recovery value and reduce energy and resource waste	Federated learning [16] Physics-informed learning [76] Artificial neural network [151] Conditional Generative Adversarial Network [150]	Data scarcity: Lack of internal material state and degradation mechanism information Data heterogeneity: Diverse material compositions and uneven material degradation modes across collected batteries
Remanufacturing for modules and packs	- Automated disassembly and reassembly to improve safety and efficiency - Module or pack reconstruction to restore near-new performance - Consistency improvement to ensure high-demand reliability across rebuilt systems	Convolutional neural network [156] Multi-Agent reinforcement Learning [157] Partially observable deep reinforcement learning [158] Knowledge driven sequence planning [169] Self-adaptive learning [160] Deep Q-learning [170] Dynamic bayesian network [161]	Data scarcity: Insufficient cell- and module-level performance and topology data for reliable reassembly Data heterogeneity: Inconsistent residual capacities, impedances, and thermal behaviors among reused components

4. Data-informed battery management

Despite the fact that data scarcity and data heterogeneity pose fundamental challenges to battery diagnostics and prognostics, such challenges can be categorized into three ways, specifically, (1) one has no experimental data but has physical understandings; (2) one has no experimental data but affords a few field measurements; and (3) one has no experimental data but allows for data collaboration for different entities. To address these challenges, a growing suite of innovative methods now enables data-informed decision-making across battery lifecycle, including data sufficiency evaluation, physics-based methods, data measurement-based methods, privacy-preserving-based methods, and data recording-based methods (Figure 4).

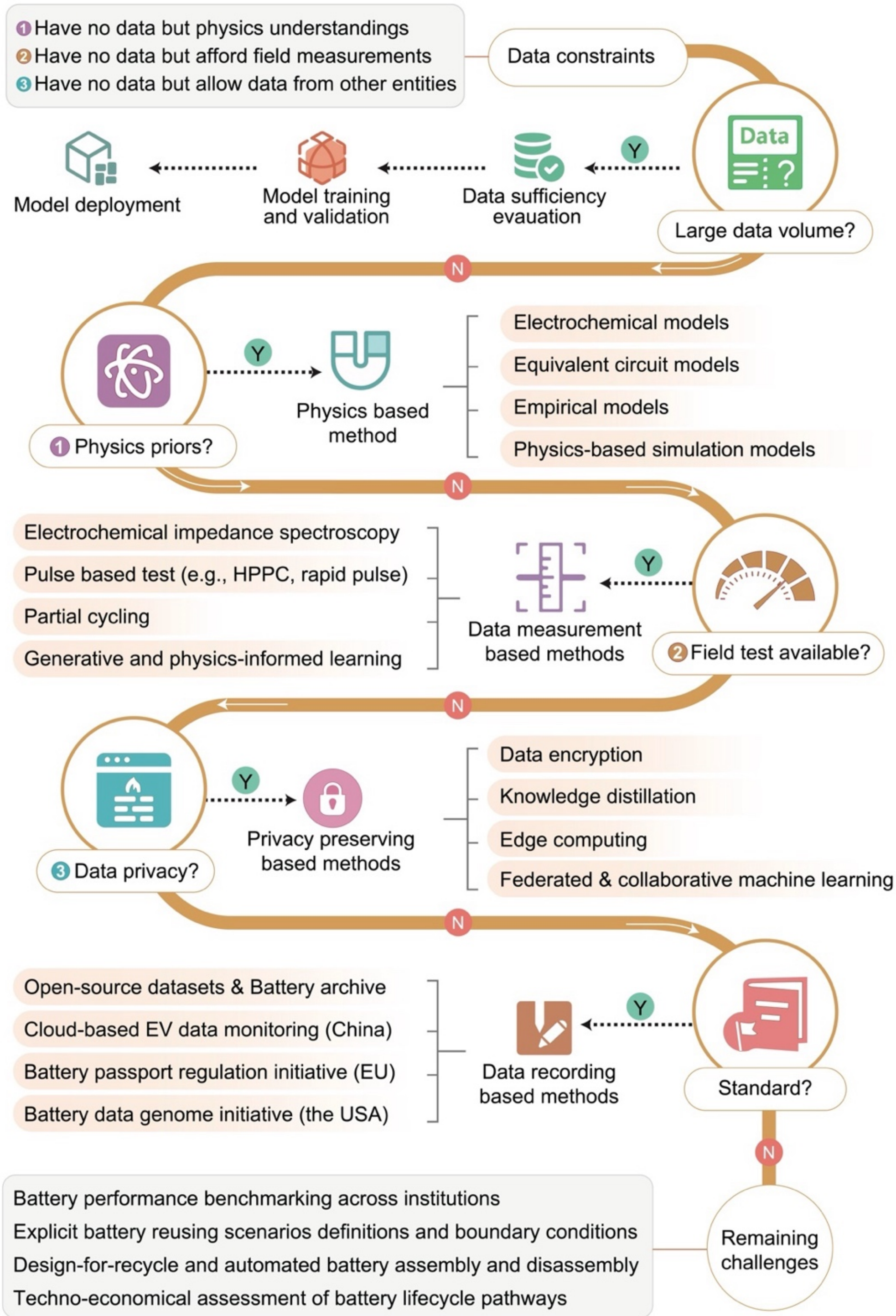

Figure 4 Data-informed management strategies for battery reusing, recycling and remanufacturing under real-world data constraints. Battery management faces diverse data constraint scenarios, specifically, one has no experimental data but physical understandings; one has no experimental data but a few field measurements; and one has no experimental data but data collaboration for different entities. Systematic battery management decision support ranging from data volume check, physics priors, field test availability, data privacy barriers, and standardization gaps are presented. This battery management decision support illustrates how measurement protocols, modeling methods, and AI tools selection adapts to existing data constraints, guiding the use of physics-based, measurement-based, privacy protection based, and data-recording based methods tailored to varying levels of battery information availability. Noted that the decision support can also be in a non-serials manner as presented with multiple measurement protocols, modeling methods, and AI tools combinations. HPPC: Hybrid Pulse Power Characterization.

4.1 Data sufficiency evaluation

Data sufficiency refers to the minimal amount of data required to achieve a target level of accuracy and stability in battery diagnostics and prognostics. If a data volume enables reliable model performance within these criteria, it is deemed sufficient for some AI tasks[171]. The core motivation of data sufficiency evaluation lies in balancing model performance with data efficiency. While larger datasets generally improve prediction accuracy, especially with the rise of battery big data and large-scale AI models, the marginal gain per additional unit of data is unclear. Redundant or homogeneous data can incur notable time and financial costs without yielding meaningful information gain[33]. Early works on RUL prediction demonstrated that long-term degradation could be forecasted using only the first 100 cycles of data, while subsequent research numerical results have pushed this boundary further to smaller cycle numbers, claiming that even the first cycle alone can suffice[91,172-175]. However, such minimal-input models often suffer from instability across varying conditions, raising concerns about generalizability and overfitting. Similar trends are observed in early diagnostic efforts for degradation trajectories and degradation mechanisms, which aim to identify aging modes from early cycling patterns[176-178]. Despite promising accuracy, these models face the same limitations in robustness and transferability when applied beyond the original training distribution. In contrast, other research numerical results have shown that beyond a certain number of cycles, adding more data does not notably enhance AI task accuracy, suggesting a diminishing return effect[33]. This reveals a fundamental trade-off: while less data can suffice for accurate predictions, their generalizability remains limited; conversely, excessive data can add little value beyond certain threshold. However, systematic frameworks to evaluate data sufficiency, especially regarding predictive capability and cross-condition transferability, remain limited[171].

4.2 Physics-based methods

For the as-manufactured batteries or those batteries in operation, physics-based methods are suitable for scenarios with no experimental data available, while with domain knowledge and physical understanding established. These approaches leverage mathematical representations of battery behaviors to enable modeling, simulation, or synthetic data generation under controlled assumptions. Depending on the degree of physical abstraction, physics-based methods can be categorized into electrochemical, equivalent circuit, empirical, and physics-based simulation models. Electrochemical models, such as the single particle model, pseudo two-dimensional model, and Doyle-Fuller-Newman model, simulate battery behavior at the microscale by describing ion transport, charge transfer, and solid-state diffusion[179-181]. These models offer high fidelity for internal state exploration and are often used in physics-based digital twins or battery emulators. By adjusting design parameters and conditions, they can generate synthetic datasets that capture electrochemical dynamics, aiding model training or hypothesis validation. Equivalent circuit models, on the other hand, use combinations of ideal resistors, capacitors, and voltage sources to mimic battery terminal behavior. While computationally efficient and adopted in battery management system design for state estimation or control, Equivalent circuit models are limited in ability to describe internal degradation processes[182]. Nonetheless, they remain effective for generating synthetic data at system level, including voltage, current, and temperature under different load profiles. Empirical models build predictive relationships through interpolation or extrapolation based on limited experimental data[183,184]. Although simple to implement, empirical models lack robustness under varying operating conditions and can fail to generalize beyond their training scope.

For the battery manufacturing process, physics-based simulation modeling approaches such as the coarse-grained molecular dynamics method and the discrete element method have been increasingly adopted to elucidate the complex physical phenomena governing battery electrode process. The coarse-grained molecular dynamics method has been widely employed to describe the slurry equilibration, solvent evaporation, and drying dynamics during electrode coating, enabling the prediction of particle rearrangement and binder migration under realistic process conditions[185,186]. This approach provides mechanistic insight into how the interactions between active material, carbon additive, and binder evolve from the slurry to the dried electrode, directly influencing the electrode microstructure and its transport pathways. In contrast, the discrete element method has been particularly effective in modeling particle-scale contact mechanics, densification, and deformation during subsequent steps such as calendering, compaction, and solvent-free extrusion[187,188]. Moreover, integration of these physics-based simulations with continuum electrochemical models or finite-element-based electro-mechanical analyses has enabled quantitative prediction of performance degradation induced by heterogeneity and pressure gradients[84,155].

4.2 Data measurement-based methods

When physical knowledge of battery is limited or insufficient for modeling, field measurements offer a pragmatic solution for diagnostics and prognostics insight. Data measurement-based methods apply to scenarios where experimental data are scarce but selective field testing is available. Depending on the nature of input signals, these methods can be categorized into electrochemical impedance spectroscopy, pulse-based testing, partial cycling, and generative data augmentation. Electrochemical impedance spectroscopy applies sinusoidal voltage or current perturbations and analyzes the response spectrum to extract information on SOH and degradation mechanisms[189-191]. As the net energy input over time is near zero, Electrochemical impedance spectroscopy is considered quasi-steady and nondestructive. Coupled with equivalent circuit model fitting, electrochemical impedance spectroscopy data enables dissection of battery behavior across frequencies, linking high-frequency arcs to charge transfer resistance and low-frequency features to mass transport[192]. Pulse test involves the application of short-duration current pulses and measurement of resulting voltage response. Variants include hybrid pulse power characterization and rapid pulses. Despite introducing net energy, the short duration renders the tests noninvasive in practice[193]. When integrated with AI models, pulse data have been used for SOC and SOH estimation, degradation mechanism identification, material type sorting, and dead-lithium and active material restoration[15,37,194-196]. Partial cycling allows for measurement under unconstrained SOC windows and flexible current profiles, aligning with real-world battery use. Under varying charge and discharge intensities, partial cycles provide informative voltage and current dynamics that, support SOH and material type estimation with minimal operational disruption[16,197]. Given the limitations of field measurement volume, generative AI are adopted to enhance data richness. Techniques such as conditional vibrational autoencoder, generative adversarial neural network and diffusion models are used to synthetically extend datasets[80,198-201]. More recently, physics-informed neural networks have emerged to combine the flexibility of AI with physical laws, by integrating governing equations or physical constraints into AI architectures, either through feature engineering or loss function integration. For example, Arrhenius law was integrated into transfer learning for cross-temperature [G] degradation trajectory prediction[17]. For another example, encoding degradation mechanism-related features into the loss functions can encourage AI models to learn interpretable degradation patterns, instead of purely statistical correlations that can be hard to be deployed in safety-critical applications[94,110-113].

4.3 Privacy-preserving-based methods

In scenarios where experimental data are unavailable but collaboration across data-holding entities is possible, privacy-preserving-based methods enable shared model development while protecting sensitive information. This is particularly relevant for battery applications where data often involve user behaviors, operational histories, or proprietary system designs that must remain confidential. Battery data privacy protection includes four categories: data-level privacy, knowledge-level privacy, computational-level privacy, and decision-level privacy. Strategies such as data encryption, knowledge distillation, edge computing, and federated learning have been developed to address each of these aspects. For data-level privacy, methods such as differential privacy and homomorphic encryption introduce controlled noise or secure computation mechanisms to obscure raw data without compromising AI task performance[202,203]. The notion of privacy budget has also emerged, defining the maximum level of perturbation that a model can tolerate while maintaining acceptable accuracy, which effectively quantifies the boundary between data utility and data privacy[16]. Knowledge distillation offers an alternative that transfers learned model behavior from a baseline model trained on private data to an transferred model operating on public or less sensitive data, which has been used to estimate SOH, RUL, and SOT while ensuring that the underlying raw data remain inaccessible during training[204-206]. Edge computing enhances privacy by keeping data processing local to battery management system, avoiding direct data transmission to centralized servers. To address the computational constraints of edge devices, hybrid edge-cloud architectures have been proposed for SOH and RUL estimation, optimizing trade-offs between latency, privacy, and model complexity[207]. Decision-level privacy is supported by federated learning, which enables multiple entities to jointly train AI models without exposing local data. Federated learning has been employed for SOH, RUL, degradation trajectory, and material type prediction, especially under conditions of data scarcity and heterogeneity[16,208-212]. The Federated learning of "data available but not visible" allows diverse stakeholders, ranging from manufacturers to operators, to collaboratively develop models while maintaining strict data confidentiality.

4.4 Data recording-based methods

Data recording-based methods aim to establish a robust and interoperable data infrastructure that enables consistent acquisition, management, and exchange of battery-related information across diverse stakeholders and lifecycle stages. These methods are foundational to enhancing model reproducibility, facilitating cross-condition and cross-institution benchmarking, and supporting regulation-compliant battery analytics. Central to this effort is the development of open-access repositories and standardized data formats that ensure semantic consistency and machine-readability. Notable initiatives include publicly available datasets and platforms such as the Battery Archive, which consolidate cycling, aging, and diagnostic data across a broad spectrum of cell chemistries, test protocols, and operational scenarios[213]. At the policy and industrial level, a series of coordinated regulatory frameworks have been introduced to institutionalize battery data collection and usage. In China, the State Key Laboratory of Intelligent Vehicle Safety Technology have advanced the deployment of cloud-based battery monitoring systems for electric vehicles, enabling real-time acquisition of field data under standardized schemas, albeit with anonymization for privacy protection[106]. The European Union's Battery Passport legislation represents a landmark in data traceability, mandating end-to-end digital records of battery manufacturing, usage, and end-of-life handling[18,30]. This aims to improve supply chain transparency and incentivize circular economy practices. In parallel, the United States has launched the Battery Data Genome, which seeks to unify fragmented battery data streams by promoting standardized metadata descriptors, ontologies, and exchange protocols[32]. The initiative envisions a vertically integrated battery data ecosystem that spans research and development, manufacturing, deployment, and recycling, with the goal of accelerating innovation through data-centric collaboration and AI-readiness.

Despite these promising developments, several challenges persist. First, performance evaluation across remanufactured batteries and manufactured batteries with novel chemistries remains inconsistent, with stakeholders often lacking a common benchmarking framework, leading to record-high but uneven and unverifiable claims of reported battery performances [214-216]. Second, although reusing and recycling are widely recognized as pillars of sustainable battery management, there remains a lack of regulatory clarity on technical thresholds that define eligibility for each reusing and recycling pathway[50]. Without clearly defined criteria, inappropriate battery deployment can pose safety and economic risks. Third, current battery pack and module designs rarely consider end-of-life disassembly or reconfigurability, complicating downstream processes such as material recovery and module-level remanufacturing[123]. Finally, techno-economic analyses often overlook the granularity of battery health states, which incorporating these state indicators into such evaluations is essential to support battery-data-informed sustainability assessments and lifecycle decisions[10].

5. Cross-level challenges and emerging solutions

While AI offers powerful tools to enable data-informed battery management, several persistent and interlinked challenges remain across different system layers, from raw data collection and model development to system-level deployment, industry implementations and regulatory framing (Figure 5). These challenges are not isolated, rather form a hierarchy of constraints where upstream issues in data quality and standardization propagate downstream, influencing modeling validity, battery system performance, and eventually large-scale sustainability (economic and environmental feasibilities) outcomes and policy efficiency. Therefore, it is crucial to adopt an integrative perspective that aligns technical, practical, and policy-driven solutions for holistic battery management optimization tailored for their reusing, recycling and remanufacturing. This section outlines these cross-level challenges, and discusses the corresponding emergent respond strategies and actionable pathways.

5.1 Data curation

Effective data curation underpins reliable battery diagnostics and prognostics but is challenged by data heterogeneity, destructiveness, scarcity, and cost. Methods such as feature alignment, distribution metrics, and domain adaptation help unify heterogeneous representations stemmed from variations in chemistries, formats, and testing protocols[33,60]. Non-intrusive methods, for example, electrochemical impedance spectroscopy, X-ray, voltage relaxation, and in-situ/wireless sensors offer safer alternatives for destructive diagnostics like full cycling or abuse testing[189,190,217]. Despite the scarcity arises from limited real-world data coverage, generative models (for example, generative adversarial neural networks, variational autoencoders and diffusion models), contrastive learning, and federated data sharing expand usable data while preserving privacy[201,218-221]. High data cost, especially for long-term or high-fidelity tests, motivates cost-aware sampling and data sufficiency evaluation to maximize information gain per resource cost. Active learning and data sufficiency-aware acquisition strategies can also enable efficient and scalable data collections[171,222]. It should be noticed that one of the main issues is the lack of physics in the data-driven data generation model, therefore, battery data generated by generative adversarial neural networks, variational autoencoders can be unphysical data. Thus, multiple runs of data shuffling and random split of the training and test data should be considered, especially under unseen conditions[37].

Beyond data-driven curation and augmentation approaches, validated physics-based methods can serve as surrogate data generators that produce synthetic yet physically consistent datasets, thereby alleviating experimental data scarcity and accelerating data curation [223]. Hybrid workflows that combine physics-based simulations with deep learning have enabled accurate prediction of electrode drying behavior, showing strong agreement with experimentally derived microstructures and supporting near-real-time manufacturing optimization [224]. Quantitative agreement between simulated and experimental results has also been demonstrated using three-dimensional electrochemical–mechanical models of composite electrodes derived from manufacturing-based coarse-grained molecular dynamics simulations, particularly in capturing electrode swelling and stress evolution during cycling [225]. Furthermore, experimentally anchored physics-based manufacturing simulations have been leveraged to generate high-fidelity synthetic datasets for multi-objective optimization and inverse design of electrode structures [86]. Collectively, these validated simulation frameworks demonstrate that experimentally consistent physics-based models not only enhance physical interpretability but also function as reliable data curation engines, expanding the accessible design space and strengthening the foundation for digitalized, data-informed battery manufacturing.

5.2 Model establishment

Robust model establishment is central to battery diagnostics and prognostics but faces persistent challenges in overfitting, benchmarking, transferability, and explainability. Overfitting risks arise when models capture spurious patterns in limited or homogeneous datasets, leading to poor generalization under real-world variations. Extra validation under unseen operating conditions, together with data augmentation, is critical to simulate extreme operation scenarios and enhance robustness[103,226,227]. Model benchmarking is hindered by the lack of standardized datasets and evaluation criteria. The use of open-access datasets and multi-metric performance evaluation, including accuracy, generalization, and uncertainty, can enable fairer and more transparent model comparisons[31]. Additionally, explainability ensures trustworthy decision-making in second-life applications with increased risk. Explainable feature engineering, SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), layer-wise model weight interpretation could provide insight into model behavior and aligns predictions with physical insights[108,228-232].

Transferability is critical for deployment across battery utilization stages, operation conditions, and battery management tasks. Transfer learning, continual learning, and few-shot learning allow models to adapt to new domains with minimal labeled data, reducing retraining costs and improving model scalability[17,33,60,233,234]. Moreover, transfer learning is promising in addressing the issue of data scarcity and heterogeneity, and they can be used to merge synthetic and experimental data, making them an important tool in this scenario. Data scarcity in battery manufacturing processes has been effectively addressed using transfer learning approaches that leverage pre-existing experimental data together with stochastically generated datasets [235]. The effectiveness of transfer learning has also been demonstrated under extremely limited field data availability for joint SOC and SOH estimation in second-life batteries, as well as for cross-operating-condition battery applications [14,33]. In addition, early detection of defective cells in as-manufactured batteries has been enabled through physics-informed transfer learning, providing a sustainable pathway for recycling battery prototypes prior to large-scale next-generation battery production [17].

5.3 Battery management system systems integration

The complexity of battery management systems integration stems from their hierarchical structure and operational heterogeneity. Addressing challenges such as multi-task coordination, intra-pack inconsistency, and integration barriers is essential for efficient lifecycle management. Parallelizing multiple management tasks requires unified architectures such as multi-task learning and foundational models[236,237]. Graph-based learning and topological modeling allow spatially aware diagnostics by embedding physical structure into AI model to mitigate the inconsistencies[238,239]. Reverse engineering and standardized hardware or software interfaces are crucial for enabling cross-platform integration and upgradability given private protocols across different manufacturers. Besides, the human-robotic collaborative automation and computer vision-assisted disassembly improve precision, safety, and scalability for disassembly and reassembly[121,123].

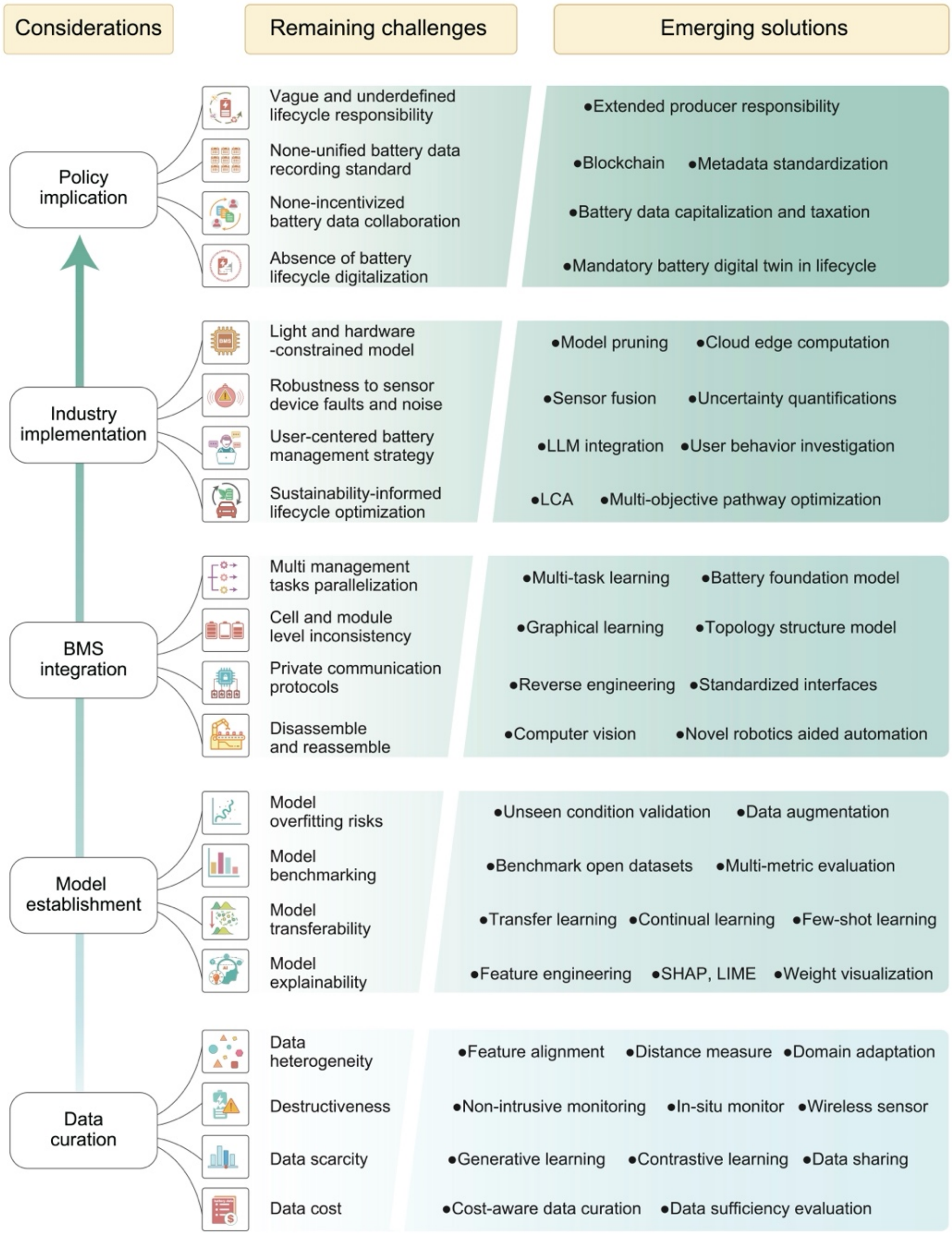

Figure 5 Cross-level considerations, remaining challenges and emerging solutions for battery reusing, recycling and remanufacturing. Battery lifecycle considerations include data curation, model establishment, battery management system (BMS) integration, industrial implementation and policy implication. The remaining challenges of data curation include data heterogeneity, destructiveness, data scarcity and data cost. The remaining challenges of model establishment include model over fitting risks, lack of model benchmarking, transferability and explainability. The remaining challenges of BMS integration include multi-management tasks parallelization, cell and module level inconsistency, private communication protocols, and disassemble and reassemble. The remaining challenges of industry implementations include light and hardware-constrained model, robustness of sensor device faults and noise, use-centered battery management strategy, and sustainability-informed lifecycle optimization. The remaining challenges of policy implications include vague and under defined lifecycle responsibility, non-unified battery data recording standard, non-incentivized battery data collaboration, and absence of battery lifecycle digitalization. LLM: large language model; LCA: life cycle analysis; SHAP: SHapley Additive exPlanations; LIME: Local Interpretable

Model-agnostic Explanations.

5.4 Industry implementation

Translating battery analytics into real-world industry practice requires models and strategies that are both resource-efficient, user-aligned and context-aware. First, lightweighted hardware environments demand compact models that can operate reliably on edge or embedded devices with computation resource constraints[171]. Methods such as model pruning, quantization, and cloud-edge collaborative computing can enable efficient model deployment without sacrificing performance[240,241]. Second, practical systems must remain robust in the presence of sensor faults, data noise, data missing, and operational variability, calling for sensor fusion and uncertainty quantification to ensure resilient and trustworthy decision-making[242-245]. Third, effective battery management system must consider context-aware battery data formats, such as the natural language. Integrating large language models (LLMs) with user-centric battery data helps uncover behavioral patterns and personalize battery management system strategies[227,228,246]. Pre-trained LLMs with engineered prompts have been demonstrating successes in battery management tasks such as data-driven SOH, SOC estimations, model-based electrochemical parameter identification and battery data augmentation[247-251]. Beyond battery management tasks, LLMs signify a broader shift in battery research, from data-driven analytics toward knowledge-centered intelligence. By integrating heterogeneous sources such as literature, experimental logs, and operational data, LLMs hold potential in unifying fragmented knowledge across materials discovery, electrochemical modeling, and lifecycle management[252]. This integration transforms battery research into a context-aware and hypothesis-generating process, where LLM models not only interpret existing data but also propose experimental designs and interpret degradation mechanisms through reasoning[253]. As these reasoning capabilities extend from laboratory to field applications, LLMs are poised to serve as cognitive infrastructures that connect scientific understanding, engineering practice, and user behavior, redefining how batteries are tested in laboratory, used in service life, and recycled for residual value across their entire lifecycle.

5.5 Policy implications

Effective battery lifecycle management is still hindered by fragmented policies and underdefined responsibilities. First, the lack of clearly assigned lifecycle responsibility blurs accountability across manufacturers, users, and recyclers. Policies enforcing extended producer responsibility can ensure that producers remain liable for end-of-life treatment, incentivizing more sustainable design and take-back systems[254-256]. Second, absence of a unified data standard complicates interoperability and benchmarking. Blockchain frameworks and metadata standardization can secure tamper-proof data provenance across the battery lifecycle[29,257]. Third, despite the value of battery data, few incentives exist for stakeholders to share them. Thus, capitalizing battery data as assets and introducing taxation or credits based on battery performance can encourage collaboration while protecting proprietary interests[258]. Moreover, mandating battery digital twins in the lifecycle can enable real-time tracking, predictive maintenance, and policy compliance, laying the foundation for intelligent and accountable battery ecosystems[259]. It is noted that the emerging adoption of AI shows potential in normalizing the data extracted from different sources in the battery manufacturing and recycling process, thus the promotion of AI regarding data standardization and data protection should be considered[16,260].

5.6 Emerging sustainability aspects of AI adoption

To ensure long-term sustainability of batteries, lifecycle sustainability optimization must go beyond energy efficiency consideration during battery operation alone. Life cycle assessment and multi-objective optimization frameworks should be considered to balance safety, performance, cost, and environmental impact[13]. In remanufacturing, physics-informed learning models have been proven useful in early detection of degradation patterns from non-destructive signals, allowing defective prototypes or prematurely aged batteries to be requalified before mass production. By predicting electrochemical trajectory shifts from limited early-cycle data, the reported approach reduces verification time by 25 times and minimizes waste from defective prototypes, unlocking a projected 19.76 billion USD market for recycled materials by 2060[17]. In reusing, life-cycle assessment informed optimization models can identify economically optimal second-life deployment scenarios with different SOH and system capacity configurations. The optimized allocation among grid energy storage, communication base stations, and low-speed vehicles yields up to 58% higher profits and 18% lower carbon dioxide emissions for LFP batteries compared to direct recycling alone[13]. In recycling, federated learning enables battery data collaboration among recyclers, achieving 97% cathode classification accuracy across heterogeneous datasets from 7 simulated manufacturers and 5 chemistries. The resulting AI-assisted direct recycling achieves profits of up to 3,390 USD per ton for NMC and 1,845 USD per ton for LFP, approximately 2.3 times higher than those of conventional pyrometallurgical or hydrometallurgical recycling routes, while reducing energy consumption and carbon emissions by 54% and 18%, respectively[16]. If the data collaboration is prohibitive, the generative learning approaches can synthesize realistic electrochemical signals under unseen retirement conditions, alleviating data scarcity and heterogeneity while potentially saving 4.9 billion USD and 35.8 billion kg CO_2 globally by 2030, using fast pulse test to robustly estimate residual values of retired batteries before massive material recycling investments[37].

6 Summary and future perspectives

This Perspective begins by identifying data scarcity and data heterogeneity as core obstacles that hinder accurate battery diagnostics, prognostics, and economical-environmental-aware decision-making. These issues originate from diverse reasons, including inconsistent operating conditions, variable material compositions, different designs, and fragmented data access across the battery value chain. Building on this foundation, we outline how AI task and AI tool allocations can support sustainable battery management, covering manufacturing, first-life service, second-life reusing, material recycling, and system-level remanufacturing, by allocating different battery management tasks and tools to distinct lifecycle stages. For AI to operate in complex and data-limited contexts effectively, we suggest that data-informed approaches that match different data availability scenarios, ranging from physics-based modeling with no data, to field testing with limited data, and collaborative learning with multi-entity data but while privacy constraints. These methods include data sufficiency evaluation, physics-based modeling, selective-field measurements, federated learning, and open-access data frameworks. Further, we discuss cross-cutting challenges across six interrelated levels: data curation, model establishment, battery management system integration, industry implementation, policy implications and emerging sustainability aspects of AI adoption. Each level presents distinct challenges, spanning destructive data collection, model overfitting, inconsistent communication protocols and underdefined regulatory responsibilities, with each matched with emerging technical or regulatory solutions. By connecting technical innovations with practical deployment needs and policy support, this Perspective provides a forward-looking view for integrating AI into real-world, sustainable battery management tailored for reusing, recycling, and remanufacturing.

Underpinning the vision of AI-enabled circular battery economies are persistent gaps in data, infrastructure, and governance that must be urgently addressed. Despite recent advances, battery data remain fragmented and non-interoperable with respect to inconsistent formats, labeling systems, and metadata schemes across countries and enterprises, hindering reproducible model training and the model performance validation. Future progress hinges on building unified battery data ontologies and dynamic data infrastructures, which evolves from static battery passports toward continuously updated, cloud-linked records that reflect real-time performance and ownership transitions. Equally limiting is absence of longitudinal, scenario-level datasets capturing stochastic evolution of batteries across manufacturing, operation, and reusing, recycling and remanufacturing stages. Coordinated public-private data alliances with transparent governance and embedded sensing will be essential to bridge the gap between laboratory insights and industrial realities. Another unresolved issue is the unclear relationship between data sufficiency and task complexity. Without systematic quantification of how much and what kind of data are needed for specific AI tasks, research risks data inefficiency and overfitting despite the rapidly increasing capability of AI tools. Establishing evidence-based battery data sufficiency examinations before massive data curation, paired with standardized benchmarking and verification protocols, would enable fairer AI model comparison, guide resource allocation, and strengthen industrial confidence. At the system level, automated battery disassembly and remanufacturing remain data-disconnected, where integrating robotics, vision, and material analytics into a closed digital loop could transform static automation process into an adaptive manner holds promise. Meanwhile, the imbalance between model complexity and computational resources, especially at edge device side continues to limit real-world deployment, demanding hierarchical AI architectures that balance accuracy, computation, and latency with cloud-edge infrastructure collaboration and periodical synchronization.

Finally, governance thresholds for reusing, recycling and remanufacturing remain ambiguous, thus key questions such as whether, when, and how to proceed with these processes remain unclear. Evidence-based standards linking technical health indicators of batteries to economical-environmental-societal criteria are urgently needed to align extended battery lifecycle with sustainability goals. Battery data ownership, privacy, and accountability remain ill-defined, particularly across transnational value chains. Establishing dynamic regulatory mechanisms, such as extended producer responsibility, data trusts, and transparent auditing standards, can incentivize responsible data sharing while protecting proprietary interests. International harmonization of certification of reusing, recycling and remanufacturing policies is equally critical to prevent fragmented regional practices. Ultimately, battery governance should evolve from *post-hoc* regulation to proactive coordination, ensuring that AI-enabled battery life cycle decisions are transparent, equitable, and verifiable across their full lifecycle.

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9 Conflicts of interest statement

S.U. is an employee of Zeekr Technology Europe AB, a company that focuses on developing advanced battery technologies, vehicle components, vehicle architectures, and engineering solutions for passenger vehicle design and manufacturing. The views expressed herein are solely those of the authors and do not necessarily reflect the views of Zeekr. The remaining authors declare no competing interests.

10 Author contributions

S.T. wrote the article. S.M., D.B., Z.H., and S.U. contributed substantially to discussion of the content. C.Z., G.Z., and X.Z wrote, discussed and acquired funding for the article. All authors reviewed and edited the manuscript before submission.