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Review
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Nondestructive sensing and failure diagnosis technologies for lithium-ion battery aging and safety

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Abstract: The large-scale deployment of high-energy-density lithium-ion batteries (LIBs) in electric transportation and grid storage has imposed increasingly stringent requirements on battery safety, reliability, and intelligent management. However, the limited observability of internal electrochemical, thermal, and mechanical states remains a fundamental challenge, leading to persistent safety risks, degraded low-temperature performance, and accelerated aging, which collectively hinder the scalable adoption of electrified systems. To overcome these challenges, conventional battery management systems (BMSs) are evolving beyond voltage-current-temperature measurements toward high-fidelity state estimation enabled by advanced nondestructive sensing technologies, including emerging internal and implantable diagnostic concepts. Based on a comprehensive analysis of physical signals associated with material aging and failure mechanisms, this review provides a systematic and critical assessment of nondestructive testing techniques for battery state monitoring. Beyond a conventional technique-oriented summary, recent advances in battery state diagnosis and lifetime management algorithms are examined, with a particular emphasis on multisource physical feature fusion strategies. More importantly, this review establishes a unified framework linking degradation mechanisms, internal physical signals, and state estimation strategies, offering a cross-scale perspective to guide the codesign of advanced sensing technologies and intelligent algorithms, thereby facilitating the development of next-generation BMSs.

Key words: Nondestructive sensing; Lithium-ion battery; Multiphysics data fusion; Smart battery; Aging mechanism

1 Introduction

Driven by global efforts toward carbon neutrality and sustainable development, efficient, reliable, and safe energy storage technologies have become essential to the ongoing energy transition (Williams et al., 2012; Hepburn et al., 2021). Among various electrochemical energy storage technologies, LIBs have become the dominant choice for electric transportation and grid-scale storage. This is mainly attributed to their high energy density, long cycle life, and mature manufacturing infrastructure (Schmuch et al., 2018; Mallapaty, 2020). Nevertheless, electrochemical and thermomechanical processes during battery operation inevitably induce irreversible aging, structural degradation, and increasing safety risks. These coupled processes collectively challenge the long-term reliability and operational safety of lithium-ion battery (LIB) systems (Feng et al., 2018; Feng et al., 2020; Bang et al., 2025). Meanwhile, growing demands for fast charging, higher energy density, and longer service life require increasingly accurate awareness of battery states throughout the entire lifecycle (Liu et al., 2017; Longchamps et al., 2022).

Battery operation is governed by tightly coupled electrochemical, thermal, and mechanical processes (Fig. 1). Continuous ion transport, phase transitions, and interfacial reactions drive ongoing structural and morphological evolution in electrode and electrolyte materials. These internal changes are indirectly reflected in measurable signals such as voltage, current, temperature, and pressure (Liu et al., 2019; Lin et al., 2021; Xin et al., 2023). Accurate interpretation of these signals is essential for

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state-of-health (SOH) estimation, remaining useful life (RUL) prediction, and timely safety intervention (Feng et al., 2020). However, conventional data acquisition strategies suffer from intrinsic limitations in resolving internal degradation pathways. Electrical signals measured from external circuits are frequently distorted by internal polarization and parasitic side reactions, obscuring underlying electrochemical kinetics (Deng et al., 2022; Li et al., 2024a). Similarly, temperature and pressure signals measured by surface-mounted sensors are subject to spatial averaging and temporal delays, arising from internal heterogeneity and complex transport pathways. Consequently, localized degradation and incipient failure events often remain undetected (Lee et al., 2013; Jia et al., 2024). Advanced in situ characterization techniques, such as synchrotron radiation and magnetic resonance imaging, provide valuable mechanistic insights into battery aging and failure. However, their reliance on large-scale facilities, high operational costs, and lengthy measurement procedures limits their suitability for scalable, real-time battery monitoring (Wang et al., 2024; Moradian et al., 2025).

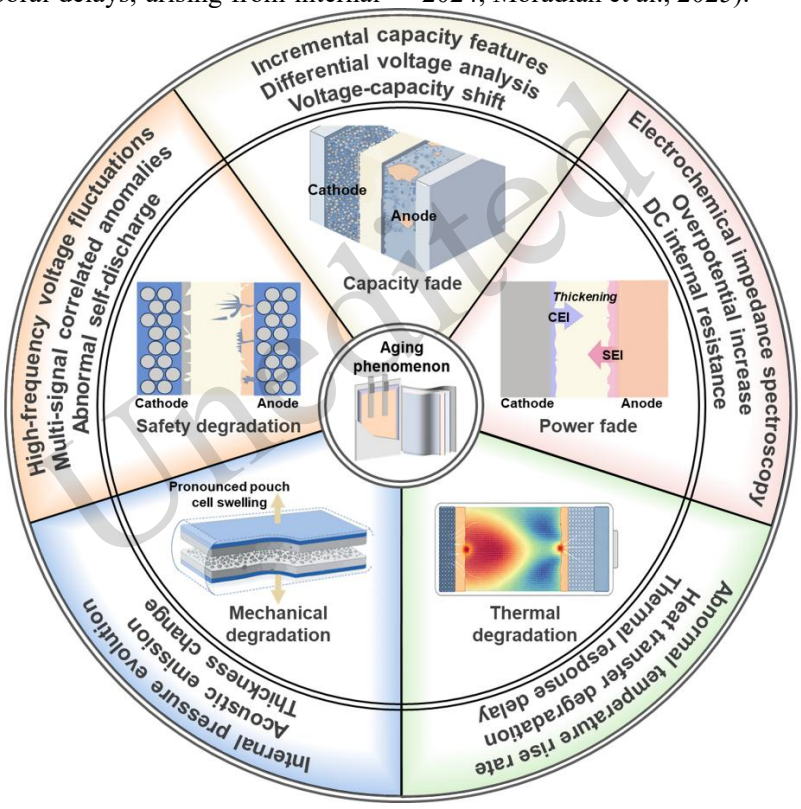

Fig. 1 Coupled aging mechanisms and detectable signal signatures in LIBs.

To overcome these limitations, advanced sensing technologies and intelligent data analytics are increasingly being integrated into next-generation smart BMSs (Guo et al., 2023; Lu et al., 2023; Wang et al., 2024; Guo et al., 2025b). This development follows two complementary directions. First, advances in micro/nanofabrication and functional materials have enabled seamless sensor integration within battery systems. Sensors can be deployed on cell surfaces, embedded inside batteries, or integrated with current collectors and separators. These approaches enable in situ monitoring of temperature, pressure, strain, and local chemical composition with high spatial resolution, providing direct access to previously inaccessible internal states (Zhang et al., 2021; Li et al., 2024b). Second, machine learning and related algorithms are increasingly employed to extract meaningful features from large and heterogeneous datasets. By integrating multisource physical information, these methods improve the accuracy of state estimation, lifetime prediction, and thermal-runaway warning. As a result, battery management is gradually shifting from reactive control to proactive and health-aware operation (Lv et

al., 2021; Geslin et al., 2023; Li et al., 2024a; Gao and Onori, 2025).

Despite rapid progress, translating laboratory-scale innovations into practical applications remains challenging. For embedded sensing, long-term electrochemical, chemical, and mechanical stability remains a major challenge. Sensors must operate reliably under harsh conditions, including high potentials, elevated temperatures, corrosive electrolytes, and repeated mechanical stress (Wang et al., 2024; Yu et al., 2024). In addition, interference-free and decoupled measurements of multiple physical signals remain difficult. Noncontact diagnostic techniques face different challenges, such as limited miniaturization, slow acquisition rates, insufficient system integration, and high cost. These factors restrict their scalability and suitability for real-time field applications. Ultimately, practical implementation of intelligent and nondestructive battery diagnostics requires balancing monitoring performance, system complexity, cost, reliability, and minimal disturbance to battery operation (Wan et al., 2023; Liu et al., 2025b).

This review establishes a unified framework linking degradation mechanisms, internal physical signals, and state estimation strategies for LIB aging (Fig. 2). Based on this framework, recent advances in nondestructive information acquisition and failure diagnosis technologies are systematically reviewed. First, the fundamental electrochemical, thermal, and mechanical aging mechanisms of LIBs are discussed, together with their relationships to key state variables. This analysis provides a physics-informed basis for correlating measurable signals with performance degradation and failure evolution. Next, state-of-the-art sensing and diagnostic technologies are critically evaluated with respect to their operating principles, observability, and limitations. Recent progress in integrating diagnostic and lifetime prediction algorithms into intelligent BMS architectures is also summarized, with emphasis on multisource data fusion and decision-oriented health assessment. Finally, key challenges and future opportunities in technological convergence, standardization, and scalable deployment are discussed. These perspectives aim to support the development of next-generation intelligent BMSs capable of reliable state awareness, early failure warning, and safe long-life operation of advanced energy storage systems.

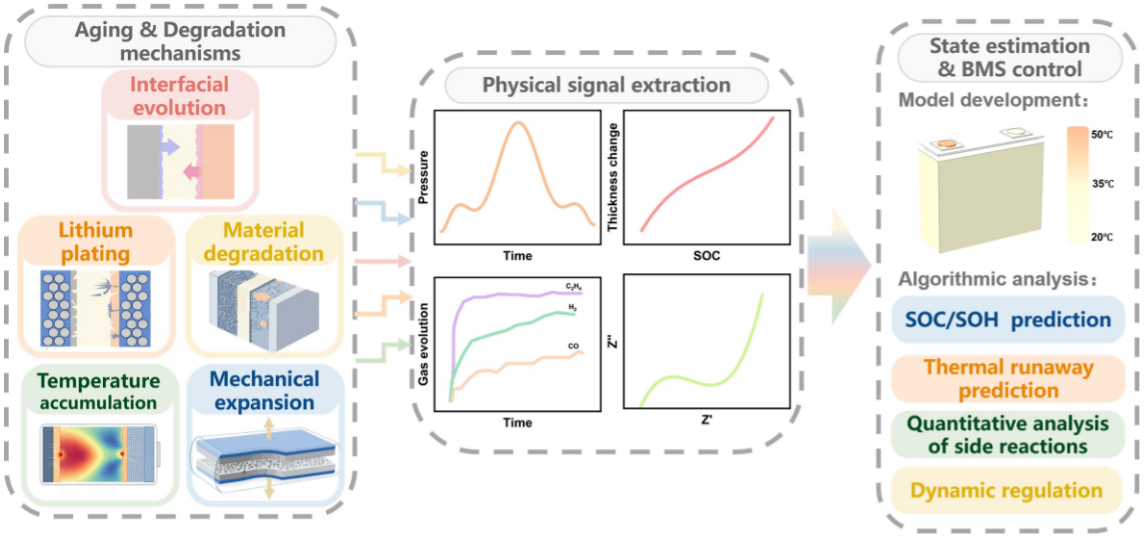

Fig. 2 Framework linking degradation mechanisms, internal signals, and state estimation in LIB aging.

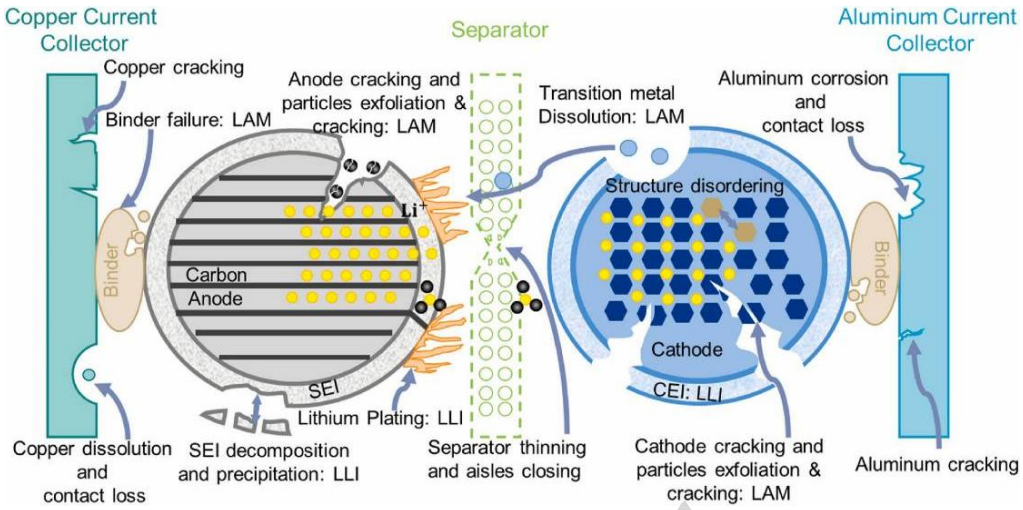

Fig. 3 Bulky and interfacial aging mechanisms in LIBs (reprinted from (Liu et al., 2025a), Copyright 2026, with permission from Elsevier).

2 Overview of LIB aging and failure mechanisms

2.1 Common phenomena and mechanisms of LIB aging

Understanding LIB aging mechanisms provides the physicochemical basis for constructing reliable state monitoring and failure diagnosis frameworks. During operation, LIBs inevitably undergo irreversible aging and degradation processes, which manifest at the cell level as capacity fade, increased internal resistance, and, in severe cases, mechanical deformation or swelling. These phenomena originate from a cascade of coupled physicochemical transformations occurring at the material and interface levels, including the growth of the solid electrolyte interphase (SEI) and cathode electrolyte interphase (CEI), electrolyte consumption and degradation, and the structural degradation of electrochemically active materials. Collectively, these processes are commonly manifested as loss of lithium inventory (LLI) through irreversible lithium trapping and parasitic side reactions, as well as loss of active material (LAM) associated with the mechanical, chemical, and electrochemical deterioration of electrode phases (Fig. 3). The following sections systematically review the aging mechanisms associated with the key battery components: cathode, anode, electrolyte, separator, and current collectors.

2.1.1 Cathode aging

Cathode material degradation plays a central role in governing the aging behavior of LIBs. Contemporary cathode materials, including layered transition-metal oxides such as $LiNi_{1-x-y}Co_xMn_yO_2$ (NCM) and $LiNi_{1-x-y}Co_xAl_yO_2$ (NCA), lithium-rich manganese-based layered oxides ($xLi_2MnO_3\cdot(1-x)LiMO_2$), spinel $LiMn_2O_4$, and olivine $LiFePO_4$, exhibit distinct aging pathways rooted in their crystallographic structures and chemical stability. In general, cathode degradation originates from the coupled interplay of bulk structural degradation, interfacial side reactions, and transition-metal dissolution and migration (Dong and Li, 2022).

Layered oxide cathodes (NCM/NCA) demonstrate composition-dependent trade-offs between capacity and stability but undergo complex degradation. These include microcracking induced by anisotropic volume changes in polycrystalline particles, degrading power capability (Nam et al., 2019; Shen et al., 2024); cation mixing under deep delithiation or extended cycling, blocking Li^+ diffusion; oxidative side reactions at the cathode-electrolyte interface, leading to CEI growth and increased impedance; and dissolution of transition metals that migrate to the anode and destabilize the SEI, accelerating active lithium loss (Guo et al., 2025a). Lithium-rich manganese-based layered cathodes deliver exceptionally high capacity but suffer from pronounced structural instability. In addition to degradation modes shared with

conventional layered oxides, their aging is strongly coupled to anion redox activity, which can trigger irreversible oxygen release, oxygen-vacancy accumulation, and phase transformations from layered to spinel-like structures (Zhang et al., 2019), accompanied by lattice distortion and transition-metal dissolution (Zhan et al., 2025). Spinel $LiMn_2O_4$ degrades predominantly through manganese dissolution and Jahn-Teller distortion. A high Mn^{3+} fraction induces a cubic-to-tetragonal phase transition during lithiation, generating localized strain and promoting Mn^{3+} disproportionation into soluble Mn^{2+} species (Thackeray, 2020). The dissolved Mn^{2+} subsequently migrates to the anode, catalyzing SEI growth, and the capacity fades (Leung, 2016). In contrast, olivine $LiFePO_4$ exhibits excellent bulk structural robustness, with aging dominated by interfacial processes (Liu et al., 2026). Long-term cycling results in progressive SEI thickening and active-lithium trapping (Li et al., 2016). Under elevated temperatures, trace Fe can dissolve and migrate to the anode, where metallic-iron deposition within the SEI catalyzes further electrolyte decomposition (Zeng et al., 2025).

2.1.2 Anode aging

The anode serves as the primary host for lithium storage and exchange, and its degradation directly impacts the overall performance. Common anode materials, including graphite, silicon-based compounds, and lithium titanate (LTO), exhibit aging features predominantly governed by interfacial instability and cycling-induced mechanical damage.

Graphite anodes experience pronounced electrochemical-mechanical coupling during aging. Repeated lithium intercalation and deintercalation induce anisotropic volume changes, which generate microcracks within and between particles, thereby degrading electrical percolation networks and mechanical integrity (Kwak et al., 2007). More critically, the associated strain accumulation and crack propagation disrupt the fragile SEI, triggering repeated cycles of fracture and reformation. This process progressively thickens the SEI, irreversibly consumes lithium and electrolyte, and leads to persistent capacity fade and increasing interfacial impedance (Börger et al., 2017; Lin et al., 2017). Silicon-based anodes offer exceptionally high theoretical capacity but suffer from extreme volume expansion exceeding 300%, which remains the primary obstacle to their practical implementation (Vorauer et al., 2020). The large cyclic swelling prevents stable SEI formation, causing it to repeatedly rupture and regenerate into a thick, non-uniform passivation layer. This process not only accelerates lithium and electrolyte depletion but also severely impairs ion and electron transport due to increasing interfacial resistance (Foss et al., 2025). LTO anodes are often described as “zero-strain”; however, they are not immune to degradation. Under elevated temperatures or high-rate operation, interfacial side reactions still occur, leading to SEI formation and gradual thickening. The resulting increase in interfacial impedance hinders lithium-ion transport, ultimately reducing the rate capability and accessible capacity (Huang et al., 2019; Bank et al., 2020).

In summary, although degradation pathways differ among anode chemistries, they share a common underlying theme: mechanically induced interfacial instability coupled with continuous SEI evolution. This convergence highlights the critical importance of material designs and protective strategies that simultaneously accommodate cyclic mechanical strain and stabilize the interfacial chemistry.

2.1.3 Electrolyte aging

The electrolyte functions as the ion-conducting medium and undergoes depletion and degradation across the cell lifecycle. Electrolyte aging primarily manifests as irreversible decomposition, driven by reduction and oxidation reactions at electrode surfaces, which lead to the formation and growth of SEI and CEI layers and immobilize both lithium ions and electrolyte components. In addition, thermodynamic and electrochemical instabilities of the electrolyte further contribute to degradation. For example, $LiPF_6$, a common lithium salt, is susceptible to hydrolysis and thermal decomposition, generating corrosive byproducts such as HF that attack electrode materials and exacerbate interfacial deterioration (Abellan et al., 2014). The combined loss of electrolyte volume and alteration of its composition results in reduced ionic conductivity, increased polarization, and ultimately accelerated performance fade (Lechtenfeld et al., 2024).

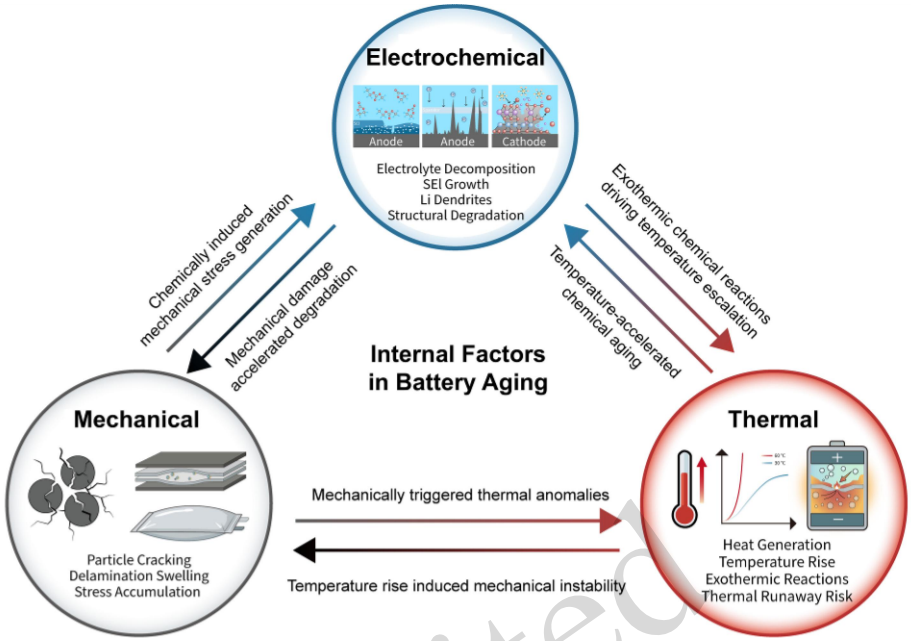

Fig. 4 Coupled chemo-mechanical-thermal aging mechanisms in LIBs.

2.1.4 Separator aging

Separator degradation critically influences both the safety margins and internal resistance. Principal aging mechanisms can be broadly classified into three categories: physical pore blockage and porosity reduction occur when electrode debris, dissolved transition-metal species, or SEI-derived particles generated during cycling accumulate within the separator, obstructing ionic pathways and increasing cell resistance; mechanical penetration may arise from the growth of lithium dendrites, which can pierce the separator and induce internal microshort circuits, potentially triggering thermal runaway; and thermochemical degradation of polyolefin-based separators under elevated temperatures, including shrinkage, melting, or oxidative decomposition, which compromises insulation (Huang and Hitt, 2013). Collectively, these degradation modes substantially erode battery safety margins and accelerate performance decay over prolonged cycling.

2.1.5 Current collector aging

The aging of metal current collectors in lithium-ion batteries typically involves a combination of mechanical damage, corrosion, electrochemical dissolution, and side reactions with the electrolyte. First, during charge/discharge cycles, the collectors undergo volume expansion and contraction, leading to microcracks or deformation, which reduces their electronic conductivity and structural integrity (Waldmann et al., 2014). Second, aluminum and copper collectors can be corroded by the electrolyte, producing dissolved metal ions. This not only alters the surface morphology of the collectors but also leads to deposition on the electrode surface, causing local electrochemical imbalances (Guo et al., 2021). Third, under high-voltage or high-temperature conditions, the collectors react with the electrolyte to form passivation layers or corrosion products, further increasing the interfacial resistance and accelerating aging (Kabir and Demirocak, 2017). Finally, the synergistic effects of mechanical damage, chemical corrosion, lithium dendrite deposition, and HF-induced corrosion significantly reduce the electronic conductivity of the collectors and the cycle life of the battery (Wen et al., 2021). In summary, the aging of current collectors is not caused by a single corrosion or mechanical damage process but rather results from the interplay of multiple physicochemical factors.

2.2 Internal correlating factors of LIB aging and failure processes

LIB aging and failure can be broadly categorized into performance degradation and safety failure.

Performance degradation typically manifests as capacity fade, power loss, and eventual attainment of end-of-life criteria, whereas safety failure is predominantly characterized by thermal runaway and its subsequent propagation. As described above at the component level, these macroscopic failure modes originate from a set of strongly coupled underlying mechanisms that can be broadly grouped into chemical, mechanical, and thermal factors (Fig. 4).

Chemical factors constitute the intrinsic origin of aging. Their essence lies in a series of irreversible side reactions occurring between electrode materials and electrolytes during electrochemical cycling. These reactions continuously consume cyclable lithium, destabilize electrode crystal structures, and increase interfacial resistance, thereby directly driving capacity loss and resistance growth. Key chemical processes include SEI evolution, electrolyte decomposition, lithium dendrite formation, and cathode degradation. Mechanical factors arise mainly from repeated volume changes during Li extraction. Accumulated internal stresses drive chemo-mechanical fatigue, degrading the structural integrity of electrodes and separators and ultimately contributing to both performance loss and safety risks. Characteristic manifestations include electrode swelling, particle cracking, interfacial delamination, and mechanical failure of the separator. Thermal factors are pervasive throughout the whole life of batteries. Heat is an inherent by-product of electrochemical and parasitic reactions, while temperature governs reaction kinetics and material stability. Consequently, effective thermal management is indispensable for sustaining stable performance and operational safety. When heat generation exceeds dissipation, the resulting temperature rise can activate a cascade of exothermic reactions and accelerate structural degradation, ultimately culminating in thermal runaway.

Critically, these internal failure mechanisms do not operate in isolation but are intricately interconnected through strong multiphysics couplings. Battery aging and failure are inherently nonlinear, driven by the concurrent and interdependent evolution of chemical, mechanical, and thermal fields. Understanding these coupled interactions is fundamental for accurately predicting, diagnosing, and managing health. The following sections revisit the three factors and illustrate their mutually reinforcing triangular relationships (Jia et al., 2026).

2.2.1 Chemical-mechanical coupling

Chemical processes generate mechanical stress. The accumulation of gases generated by electrolyte decomposition in the confined cell elevates internal pressure and induces swelling, thereby imposing additional loads on electrodes and separators (Wang et al., 2019). Concurrently, uncontrolled SEI growth, dead lithium accumulation, and the dissolution, migration, and redeposition of transition-metal species continuously deposit solid/byproducts within pore structures and on separator surfaces, altering local stress distributions (Rufino Júnior et al., 2024). In addition, repeated lithium intercalation and deintercalation induce electrochemical strain through cyclic volume changes of active materials. Mechanical damage, in turn, markedly accelerates chemical degradation (Vetter et al., 2005). Stress concentration and gas-driven expansion can fracture particles and delaminate electrodes, exposing fresh, highly reactive surfaces that lack a protective SEI. Direct contact between these surfaces and the electrolyte triggers intensified parasitic reactions, whose kinetics are significantly faster than those occurring on passivated interfaces (Barré et al., 2013). In graphite anodes, mechanically induced layer exfoliation further disrupts lithium intercalation kinetics (Dong and Wei, 2021). Moreover, the continued thickening of interfacial layers increases charge-transfer resistance and impedes ion transport (Khan et al., 2025), while pressure-induced microdeformation of separators modifies local ion pathways and current distribution, promoting electrochemical heterogeneity (Ai et al., 2022). Collectively, these interactions create a self-reinforcing feedback loop between chemical degradation and mechanical damage.

2.2.2 Thermal-mechanical coupling

Mechanical damage often triggers thermal anomalies. A representative mechanism involves lithium dendrites, which form due to nonuniform lithium deposition on the anode surface. Given their high mechanical rigidity, dendrites can penetrate the separator and cause internal short circuits, generating

significant Joule heat (Rosso et al., 2006). Additionally, cell swelling or deformation can degrade interfacial contact between internal components, elevating contact resistance and creating localized hotspots. Increasing temperature severely compromises mechanical stability. Elevated temperatures soften polymeric binders, weaken electrode cohesion, and accelerate active material detachment (Che et al., 2023). Although conventional polyethylene (PE) and polypropylene (PP) separators offer chemically stable and mechanically robust properties, their relatively low melting points render them vulnerable to thermal shrinkage under overheating, dramatically increasing short-circuit risk. Mismatches in thermal expansion among components further induce internal stresses and microcracking. As a result, mechanical damage and thermal events mutually reinforce one another, driving a self-accelerating, cascading failure progression.

2.2.3 Thermal-chemical coupling

Temperature serves as a potent accelerator of chemical aging. According to the Arrhenius law, increasing the temperature exponentially enhances the kinetics of key side reactions, such as SEI decomposition and electrolyte redox processes. As most of these reactions are exothermic, the released heat further amplifies the temperature rise, constituting the intrinsic driving engine of thermal runaway. Under internal shorts or localized overheating, initial Joule heating accelerates SEI reorganization and transition-metal dissolution. Once the system enters a critical temperature window of approximately 60-80 °C, rapid SEI decomposition occurs, exposing highly reactive electrode surfaces and triggering violent exothermic reactions between the electrodes and the electrolyte, thereby initiating a self-sustaining heating regime (Kim et al., 2025). As the temperature continues to rise beyond the thermal tolerance of the separator, large-scale internal short circuits develop. Simultaneously, cathode decomposition releases lattice oxygen, which reacts vigorously with gaseous electrolyte components, driving the temperature above 700 °C (Feng et al., 2018). At very high temperatures, aluminum current collectors at the cathode can participate in thermite-type reactions, releasing additional heat and completing the transition from chemical instability to a full thermal explosion (Liu et al., 2025d). Throughout this progression, each stage unlocks higher-activation-energy reactions, creating an irreversible, self-reinforcing cascade toward catastrophic failure.

In summary, chemical, mechanical, and thermal factors are bidirectionally coupled, with each pair of factors mutually promoting and amplifying one another. They constitute a highly interdependent triangular positive-feedback network. LIB aging and failure emerge from the evolution of this network, transitioning from localized interactions to a system-wide, runaway process once internal thresholds are surpassed.

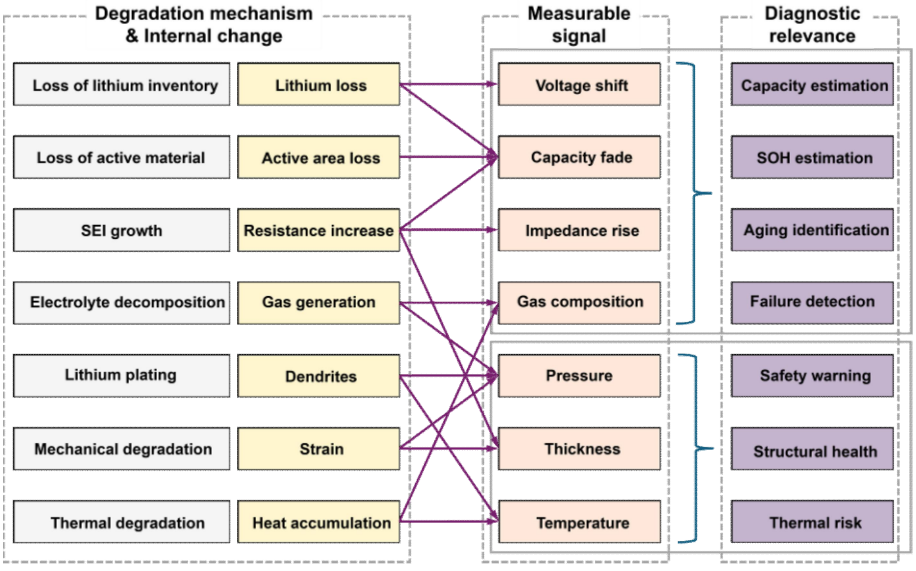

Fig. 5 Mapping between degradation mechanisms and measurable signals in lithium-ion batteries.

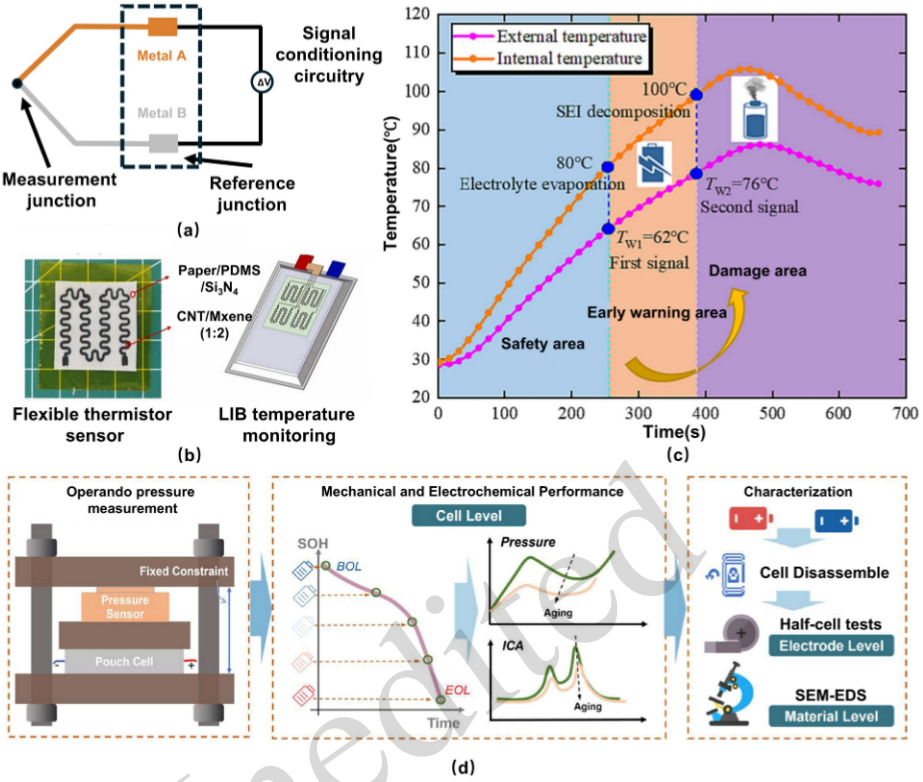

Fig. 6 Surface sensing technologies for nondestructive monitoring of LIBs. (a) Schematic illustration of the operating principle of a thermocouple based on the Seebeck effect for temperature measurement; (b) Schematic diagram of a flexible temperature sensor (FTS) array attached to the surface of LIBs (reprinted from (Sun et al., 2024), Copyright 2026, with permission from Elsevier); (c) The two-level warning signals for thermal runaway of LIBs (reprinted from (Jia et al., 2024), Copyright 2026, with permission from Elsevier); (d) Schematic illustration of the experimental setup for operando pressure measurement during long-term cycling, together with multiscale analysis including pseudo-open-circuit voltage curves at the cell level and degradation characterization at the electrode and material levels (reprinted from (Ding et al., 2025), Copyright 2026, with permission from Elsevier).

3 Multiphysics correlating factors and internal state perception of LIB aging

Given the intricate coupling and self-reinforcing feedback among chemical, mechanical, and thermal factors, LIB aging and failure evolve from localized anomalies to system-wide collapse, driven by multiphysics interactions (Fig. 5). Consequently, accurate and timely acquisition and interpretation of internal battery states are fundamental to precise health management, early fault warning, and enhanced reliability and safety. Achieving these objectives critically depends on the development of efficient, reliable, and practically deployable technologies for internal state monitoring. Based on sensor integration strategies and underlying operating principles, existing and emerging battery sensing approaches can be broadly categorized into four distinct types: surface-attached sensing, implantable sensing, in situ integrated design, and noncontact characterization. This classification provides a systematic framework for comparing their observability, invasiveness, technical maturity, and suitability for intelligent battery management applications.

3.1 Surface sensing technology

Surface-attached sensors offer straightforward integration and enable noninvasive, real-time monitoring of batteries. By detecting external physical signals, these sensors provide indirect information for inferring internal electrochemical states. During cycling, repeated lithium intercalation and deintercalation induce volumetric changes in the

electrode materials, commonly known as the breathing effect. These internal chemo-mechanical dynamics propagate to the cell exterior, manifesting as variations in surface temperature, stress, strain, and overall package deformation. Monitoring these surface-level responses allows for the capture of key indicators related to internal aging processes and failure mechanisms.

Temperature sensing is one of the most widely adopted surface monitoring techniques and is typically implemented using thermocouples, thermistors, and resistance temperature detectors (RTDs). Thermocouples exploit the Seebeck effect to infer temperature from the electromotive force generated at a heated junction (Fig. 6a), while thermistors and RTDs rely on the predictable temperature dependence of electrical resistance. To enhance spatial resolution and enable systematic monitoring, arrays of commercial sensors are often distributed across the battery surface to map temperature fields under different operating conditions, supporting model-based estimation of internal temperature distributions (Mevawalla et al., 2020). However, in practical applications, particularly at the module and pack levels, such dense sensor deployment is often constrained by cost, complexity, and integration limitations. In most operational systems, including electric vehicles and large-scale energy storage, only a limited number of temperature sensors are typically installed per module, which restricts the achievable spatial resolution and may compromise the accuracy of temperature field reconstruction. Therefore, the scalability and practical feasibility of high-density sensor arrays remain important considerations for real-world implementation. Beyond conventional devices, flexible temperature sensors have emerged, such as one based on a carbon nanotube and MXene composite that exhibits a high temperature coefficient of resistance of 0.52% $°C^{-1}$ (Fig. 6b). This sensor enables high-resolution mapping of surface temperature distribution on a pouch cell, capturing gradients from tabs to distal regions (Sun et al., 2024).

Pressure and strain sensing on battery surfaces is more complex, as the measured mechanical signals reflect a combination of contributions from internal electrochemical processes and the external mechanical environment (Fig. 6d). Isolating deformation induced by the intrinsic breathing effect and converting it into a quantifiable signal typically requires rigid or flexible clamping fixtures (Guo et al., 2025b). These approaches, implemented using customized fixtures and sensor arrays, have been employed to characterize surface pressure distributions on pouch cells, thereby elucidating the impact of external pressure on electrochemical performance and aging behavior (Müller et al., 2019; Li et al., 2023). Beyond purely mechanical characterization, variations in surface pressure can sensitively reflect key electrochemical aging processes, including electrode structural evolution, lithium inventory loss, active material degradation, and lithium deposition. When combined with complementary techniques such as electrochemical impedance spectroscopy, pressure monitoring facilitates early diagnosis and prediction of specific aging modes (Ding et al., 2025; Fang et al., 2025). Advanced developments have led to integrated, multipoint sensing systems. One example employed a 3×3 array of piezoelectric/pyroelectric sensors based on poly(vinylidene fluoride-trifluoroethylene) (PVDF-TrFE) attached directly to a pouch cell surface, enabling simultaneous measurement of pressure and temperature. However, this design suffers from temperature-induced signal drift, which compromises the measurement accuracy (Hu et al., 2020). To address this critical cross-sensitivity issue, subsequent flexible integrated sensors with multilayer architectures incorporating positive and negative temperature coefficient materials have been developed. These designs enable real-time decoupling of temperature and pressure signals, allowing precise monitoring of operational breathing dynamics and providing early warning of thermal runaway (Zhang et al., 2025). However, it should be noted that pressure and strain signals are influenced not only by temperature but also by multiple factors, including cell manufacturing processes, electrode heterogeneity, packaging constraints, and external boundary conditions. These coupled effects complicate the direct attribution of mechanical responses to specific internal aging mechanisms, limiting their use for precise mechanistic analysis. Nevertheless, pressure and stress evolution remain strongly correlated with electrochemical processes during charge – discharge and aging, enabling

effective tracking of internal state variations. From an engineering perspective, such signals provide a practical and robust means of accessing internal information in real time, even if their interpretation is not strictly mechanism specific. As a result, pressure-based sensing serves as a valuable complementary approach for state monitoring and early warning in battery systems.

Beyond conventional electrical and mechanical sensing approaches, fiber-optic sensing provides a complementary strategy for high-resolution surface monitoring. Unlike traditional electrical sensors, fiber-optic techniques rely on optical interactions, such as absorption, scattering, and reflection, between guided light and the surrounding environment. This enables highly precise measurements of temperature and strain, with inherent immunity to electromagnetic interference. The key strength of fiber-optic sensing lies in its distributed "single-line, multipoint" capability, typically realized by inscribing fiber Bragg gratings (FBGs) or tilted fiber Bragg gratings (TFBGs) along a single optical fiber (Han et al., 2021; Wu et al., 2023). When attached to battery surfaces, FBG arrays enable high-spatial-resolution mapping of temperature fields and strain evolution during operation. In addition to thermal sensing, the high sensitivity of FBGs to strain allows accurate tracking of surface deformation associated with electrode expansion and contraction. When combined with electrochemical analysis and modeling, such measurements have been quantitatively correlated with degradation processes, including lithium deposition and active material loss (Li et al., 2022b; Xia et al., 2025).

While surface sensing offers operational convenience and ease of integration, measurements are susceptible to distortion and attenuation from signal transmission delays, interfacial contact resistance, and material heterogeneity. A critical limitation is the pronounced temperature nonuniformity across the battery surface and through its bulk; interior-surface temperature differences can exceed 30°C (Fig. 6c) during high-rate operation (Lee et al., 2013; Jia et al., 2024). Similar limitations also apply to surface-mounted fiber-optic sensors, where interfacial coupling and external disturbances may affect measurement fidelity. Consequently, mitigating surface heterogeneity and identifying optimal sensor placement are key objectives for achieving more efficient and representative surface-based data acquisition.

3.2 Implantable sensing technology

Advances in sensor miniaturization and fabrication constitute a pivotal advancement in battery sensing technology. These innovations enable the integration of highly sensitive and precise sensing elements within the confined internal or surface spaces of batteries. Advanced micro- and nanofabrication techniques allow the realization of microsensor arrays with high integration density while preserving sensing accuracy and reliability (Lee et al., 2015). Compared with conventional bulk sensors, thin-film sensors offer superior flexibility, scalability, and conformability, facilitating large-area deployment and close adhesion to curved battery surfaces or direct internal embedding. Such distributed and spatially resolved measurements effectively overcome the intrinsic limitations of point-based sensing by enhancing sensitivity to internal heterogeneity and simplifying external measurement architectures.

Beyond geometric and integration advantages, implantable sensing technologies enhance the fidelity of internal state information. By embedding miniaturized sensors directly within the battery, they enable direct monitoring of internal states while minimizing uncertainties caused by signal transmission and interface effects. Recent advances in integrated microsensor technologies have enabled real-time, microscale monitoring of internal battery states. Early proof-of-concept studies demonstrated the feasibility of embedding thin-film microelectromechanical system (MEMS)-based sensors within the separator of coin cells (Fig. 7a), enabling simultaneous in situ monitoring of voltage, current, and temperature under high-rate cycling conditions (Lee et al., 2017). Alternatively, customized arrays of commercial pressure sensors encapsulated on the inner surface of pouch cells, when coupled with in situ X-ray characterization, enabled distributed monitoring of internal pressure and its correlation with performance fluctuations (Liu et al., 2025c). To further minimize intrusion into battery performance, strategies such as integrating

electrically insulated thermocouples during cell assembly have been pursued. By correlating signals from internal and external sensors, the spatial and temporal distributions of temperature fields were systematically mapped under different states of charge and cycling rates (Li et al., 2013).

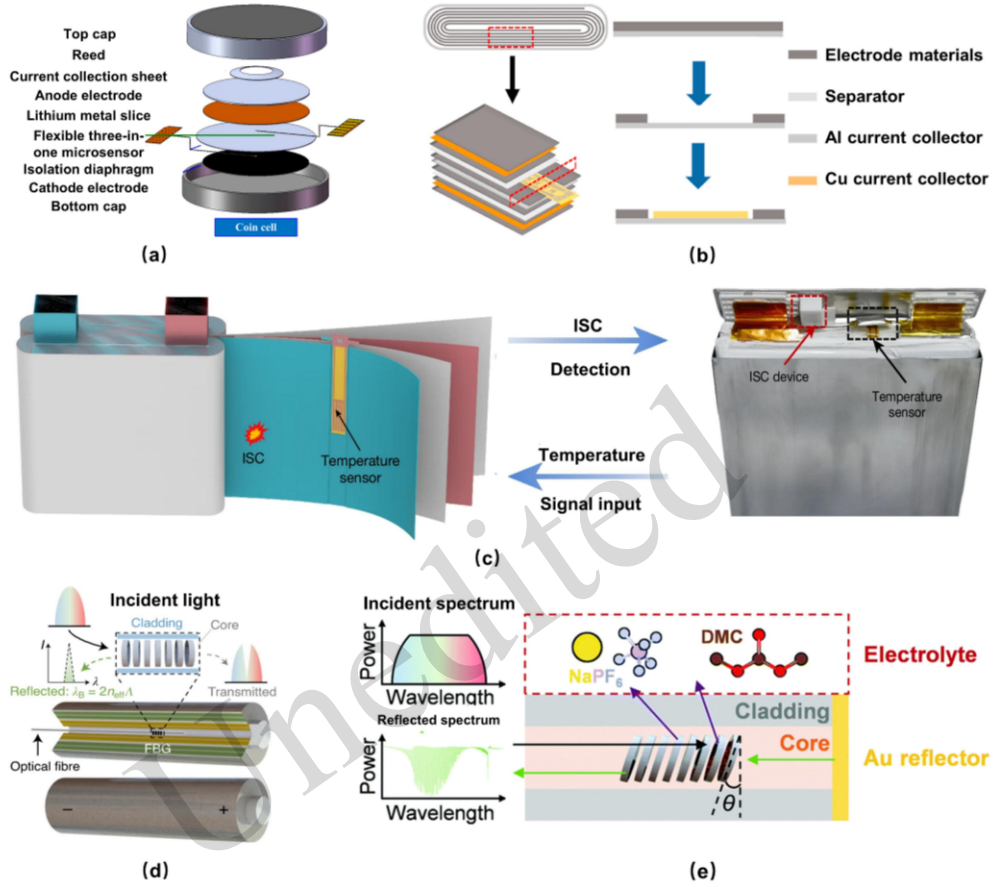

Fig. 7 Implantable and fiber-optic sensing technologies for in situ monitoring of LIBs. (a) Schematic diagram of the package assembly of the embedded flexible three-in-one microsensors in a coin cell (reprinted from (Lee et al., 2015), Copyright 2026, with permission from MDPI); (b) Schematic illustration of a thin-film sensor implanted into a pouch battery, where a localized region of active material is selectively removed to accommodate sensor integration (reprinted from (Zhu et al., 2020), Copyright 2026, with permission from Elsevier); (c) Schematic illustration and optical photograph of Internal Short Circuit (ISC) device and temperature sensors assembled in the prismatic battery (reprinted from (Fan et al., 2025), Copyright 2026, with permission from Springer Nature); (d) A schematic of the integration of an optical fiber into the large central void (~1500 μm) of the jelly roll-type battery (reprinted from (Huang et al., 2020), Copyright 2026, with permission from Springer Nature); (e) Schematic illustration and representative spectra of TFBG, where the grating plane is tilted by an angle γ relative to the fiber axis, enabling multiparameter sensing (reprinted from (Huang et al., 2021), Copyright 2026, with permission from Royal Society of Chemistry).

More recently, ultrathin sensing layers with thicknesses below 50 μm, fabricated via photolithography and magnetron sputtering in microreserved electrode regions, have been embedded into cylindrical and stacked pouch cells (Fig. 7b). These sensors enable in situ measurement of internal strain and pressure with negligible impact on electrochemical performance (Zhu et al., 2020). Subsequent research has further enhanced system-level integration by incorporating wireless data transmission and self-powered operation using energy harvested from the host battery. Demonstrated on large-format prismatic cells (Fig. 7c), such miniaturized sensing systems have supported the development of early-warning models for internal short circuits and thermal runaway (Fan et al., 2025). In parallel, sensor deployment within electrochemically inactive regions has emerged as a

pragmatic strategy to mitigate performance interference while retaining diagnostic sensitivity. For example, implanting temperature sensors into void spaces of pouch and cylindrical cells has enabled systematic investigation of internal thermal behavior across different battery architectures (Fleming et al., 2019). Additionally, mounting thin-film sensors on the exterior of cell stacks or the inner walls of casings further improves long-term stability and reduces intrusion. Notably, these externally mounted sensors remain capable of sensitively capturing critical signatures such as cyclic breathing-induced deformation (Chen et al., 2023; Chi et al., 2025).

In addition to microelectronic sensors, fiber-optic sensing has also been explored for implantable configurations, offering unique advantages for high-fidelity internal diagnostics. Owing to their chemical inertness, small diameter, and immunity to electromagnetic interference, optical fibers can be embedded within battery structures to directly probe internal physicochemical states while minimizing uncertainties associated with signal transmission and interfacial effects (Lu et al., 2022). For example, the implantation of optical fiber sensors into Swagelok-type and commercial 18650 cells has enabled in situ monitoring of internal stress evolution during cycling (Fig. 7d), providing direct insight into electrode mechanics and degradation processes (Huang et al., 2020; Betermier et al., 2023). This approach has also enabled nontraditional characterization of processes such as SEI formation and effective heat capacity. Furthermore, advanced configurations such as TFBGs have enabled sensitive probing of electrolyte properties through refractive index and spectral response variations (Fig. 7e), enabling indirect detection of chemical evolution, including electrolyte composition changes (Huang et al., 2021).

Despite their clear advantages in signal fidelity and spatial resolution, implantable sensing technologies continue to face several critical challenges, including long-term electrochemical and mechanical stability in complex and reactive battery environments, devising minimally intrusive integration schemes that preserve cell performance and cycle life, and balancing fabrication cost, sensitivity, and overall system reliability. These challenges are particularly pronounced for implantable fiber-optic sensors, where improper integration may induce local stress or disrupt electrode integrity (Fortier et al., 2017; Gardner et al., 2022). Moreover, in highly dynamic application scenarios such as electric vehicles, sustained high-frequency mechanical vibrations can induce interfacial fatigue at the junctions between embedded sensors and external circuitry. Without robust packaging strategies and effective stress-relief designs, such vibration-induced degradation may lead to intermittent or permanent signal loss, thereby undermining the continuity and reliability of data acquisition throughout the battery lifecycle. Addressing these issues is pivotal for translating implantable sensing from laboratory demonstrations into practical solutions.

3.3 In situ integrated design

The in situ design of smart batteries establishes an advanced framework for nondestructive monitoring by embedding sensing functionalities directly into intrinsic battery components or incorporating them as structural elements during manufacturing. The primary objective is to achieve real-time, in situ awareness of internal states while preserving the core architecture and electrochemical integrity of the cell. More rigorously, in situ integrated sensing is characterized by functional integration rather than mere embedding, whereby key battery components simultaneously fulfill their primary electrochemical or mechanical roles while enabling signal transduction, and the sensing process shares components or transport pathways with the battery itself, for example, by utilizing the electrolyte for signal transmission or employing current collectors as part of the sensing circuitry, rather than relying on fully isolated sensor units. By seamlessly integrating sensing functions into key components such as current collectors, separators, and packaging materials, this approach fundamentally mitigates the interference, compatibility, and stability challenges commonly associated with externally attached or implanted sensors (Wei et al., 2022). Recent advances in precision printing, micro/nanofabrication, and functional materials engineering have further accelerated the practical feasibility of this intrinsically integrated design paradigm.

The integration of sensing functionalities into

critical battery components represents a major trend toward compact, multifunctional monitoring systems. One representative strategy focuses on current collectors. For example, a composite current collector (Cu -PP-Cu) modified with feather keratin functional layers (Fig. 8a) serves simultaneously as an electrical conductor and a temperature-responsive safety element, autonomously interrupting the circuit when

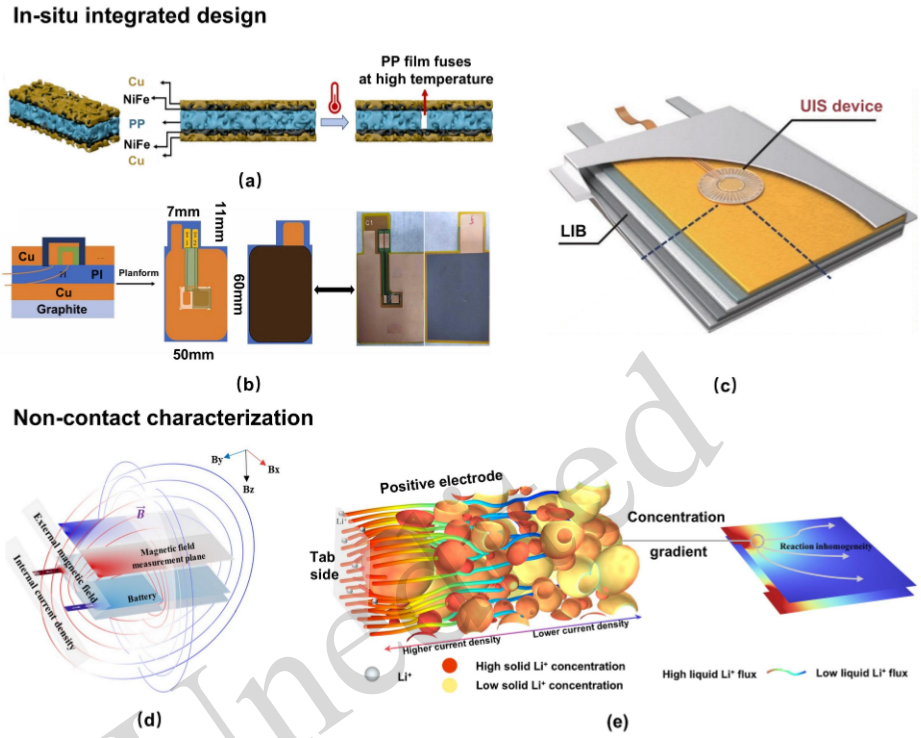

Fig. 8 In situ integrated sensing designs and noncontact characterization techniques for LIBs. (a) Schematic illustration of the working principle and safety management mechanism of a Cu-PP-Cu structure integrated within LIBs (reprinted from (Xu et al., 2025), Copyright 2026, with permission from Elsevier); (b) Cross-section, top-view, and sample image of the Lithium Battery Pressure/Temperature Monitoring Sensor (LBPTMS) based on the PVDF-TrFE film coated on one side of the flexible printed circuit (FPC) (reprinted from (Peng et al., 2022), Copyright 2026, with permission from Elsevier); (c) Scheme of the pouch cell with an in situ ultrathin integrated sensor (UIS) device for pressure monitoring (reprinted from (Chang et al., 2025), Copyright 2026, with permission from Oxford University Press); (d) and (e) Schematic of the relationship between internal current density distribution and the external magnetic field, highlighting how internal reactions induce measurable magnetic field patterns on an external observation plane; Schematic illustration of inhomogeneous reaction kinetics at the positive electrode, showing spatial variations in current density and corresponding concentration gradients of solid- and liquid-phase lithium (reprinted from (Zhao et al., 2025), Copyright 2026, with permission from Elsevier).

temperatures exceed approximately 150°C (Xu et al., 2025). In a related approach, piezoelectric/pyroelectric thin-film sensors were integrated into flexible printed circuit current collectors (Fig. 8b), enabling simultaneous real-time detection of external mechanical impacts, battery swelling, and internal temperature rise (Peng et al., 2022). Separator functionalization provides another effective pathway for sensor integration. A sandwich-structured separator incorporating a nanoscale copper layer as a third electrode has been designed to generate a distinct voltage signal upon contact with penetrating lithium dendrites, providing early warning of internal short circuits (Wu et al., 2014). Similarly, an electrochemical sensor directly printed onto a separator has been designed to selectively detect Mn^{2+} species, enabling in situ monitoring of electrolyte degradation and cathode dissolution with minimal impact on the overall energy density (Paljk et al., 2023). While these strategies enable sensing with minimal additional footprint by leveraging intrinsic battery components, they are inherently constrained by the original functions and operating conditions of these components. As a result,

such approaches are typically designed to respond to specific and extreme events, such as lithium dendrite penetration, internal short circuits, or thermal runaway, rather than providing continuous and comprehensive monitoring of internal states. This event-triggered nature limits their ability to extract real-time, quantitative information throughout normal operation.

Beyond electrochemically active components, packaging and auxiliary structures offer a complementary, less intrusive route. Microscale RTD sensors embedded into battery spacers via additive manufacturing exhibit faster response and higher accuracy than conventional surface-mounted sensors (Li et al., 2019). Building on this concept, a fully printed multifunctional sensor array has been developed. It can be conformally attached to the inner wall of battery packaging foil to simultaneously monitor temperature, pressure, and gas leakage signals with negligible weight to the cell (Sun et al., 2025). Pushing integration even further, a unified iontronic sensing mechanism has been proposed (Fig. 8c), in which the battery electrolyte itself functions as the sensing medium. This approach enables the construction of in situ pressure sensors without discrete sensing components or complex encapsulation, representing a conceptual shift toward the genuine codesign of sensing and electrochemical functionalities (Chang et al., 2025).

Despite their appealing noninvasive monitoring potential, the widespread adoption of in situ integrated designs faces formidable challenges. Chief among these is the integration of complex micro/nanofabrication or functional material preparation processes into existing large-scale battery manufacturing lines in a cost-effective and highly reliable manner. Equally important is ensuring the long-term electrochemical, thermal, and mechanical stability of functionalized components under prolonged cycling and harsh operating conditions. Moving forward, fostering coinnovation among materials, manufacturing processes, and battery system design will be key to reducing costs and enabling the scalable application of this technology.

3.4 Noncontact characterization

Noncontact sensing and characterization provide a vital route toward truly noninvasive and global monitoring of internal battery states. Unlike integrated or contact-based sensors, noncontact sensing techniques rely on the interaction between externally applied fields (e.g., X-rays, magnetic fields, and acoustic waves) and internal battery materials to probe internal states, structural evolution, and degradation processes. By probing structural, chemical, and transport-related responses without physical intrusion or perturbation of cell operation, noncontact methods enable in-depth visualization and mechanistic analysis of material evolution, reaction heterogeneity, and failure processes. As such, they play an indispensable role in fundamental studies and advanced diagnostics of battery aging and safety.

Among these approaches, X-ray-based techniques have emerged as particularly powerful tools for resolving structural evolution in electrode materials and the spatial distribution of lithium. Spatially resolved X-ray diffraction (XRD) has been applied to systematically investigate the heterogeneous deposition of lithium dendrites during extreme fast charging. By correlating this spatial heterogeneity with the local state of charge (SOC), the specific contribution of irreversible lithium plating to capacity fade can be quantified (Paul et al., 2021). Extending this capability, the Li inventory mapping of electrodes (LIME) technique, which couples XRD with fluorescence spectroscopy, enables in situ, simultaneous, and spatially resolved measurement of lithium content in both solid electrode materials and the liquid electrolyte of an intact cell. It provides clear insights into the origins of mass transport limitations during fast charging (Dawkins et al., 2023).

In parallel, noninvasive magnetic-field imaging techniques have been developed to dynamically map internal current-density distributions in commercial batteries during operation (Fig. 8d,e). These studies revealed self-regulating feedback mechanisms for reaction currents and demonstrated that battery structural design and internal mechanical stress significantly influence reaction uniformity, highlighting the potential of magnetic-field imaging for identifying manufacturing defects and localized performance bottlenecks (Zhao et al., 2025). Beyond single-physics probing, multisignal synchronous monitoring systems represent a focused approach for the early warning and mechanistic study of failure

processes, particularly the chain reactions preceding thermal runaway. For example, a sealed diagnostic platform capable of real-time acquisition of voltage, temperature, pressure, and gas concentration signals was developed to monitor batteries before and after internal short-circuit initiation. Comparative analysis across different cathode chemistries identified voltage and temperature as the most sensitive early warning indicators, elucidating the influence of material chemistry on short-circuit evolution pathways (Xin et al., 2023).

Beyond these conventional signals, gas evolution provides a sensitive and mechanism-relevant indicator of internal state transitions. The composition and onset of vent gases evolve systematically with degradation and temperature rise, enabling their use as diagnostic features. In the early stages, low-boiling electrolyte vapors dominate, reflecting mild heating. At 35-80°C, lithium dendrite formation and SEI decomposition generate H_2, CO_2, and C_2H_4, indicating interfacial instability. At approximately 120°C, anode-electrolyte reactions produce hydrocarbons and CO, marking accelerated side reactions. At 150°C, coupled cathode-electrolyte decomposition releases O_2, CO_2, CO, and HF, associated with thermal runaway onset, while further H_2 evolution at higher temperatures reflects intensified reactions. These gas signatures can be mapped to distinct degradation stages, enabling multistage state estimation from early instability to thermal runaway. When combined with temperature and pressure signals, gas sensing can further improve the sensitivity of early warning, although challenges remain in selectivity, quantification, and practical integration (Wang et al., 2019; Kong et al., 2022; Li et al., 2025).

In summary, noncontact characterization techniques are distinguished by their holistic perspective, high spatial resolution, and minimal intrusion into battery operation. They have proven indispensable for deciphering complex internal processes and failure mechanisms. However, their reliance on large-scale, sophisticated instrumentation typically precludes direct integration into BMSs for onboard, real-time monitoring. Consequently, their principal contribution lies in supplying foundational data and physical insights to inform battery design, model development, and failure analysis, thereby complementing embedded and in situ sensing approaches. Future progress hinges on advancing these techniques toward greater portability and cost-effectiveness, which is essential for broadening their practical applicability in both research and industrial settings.

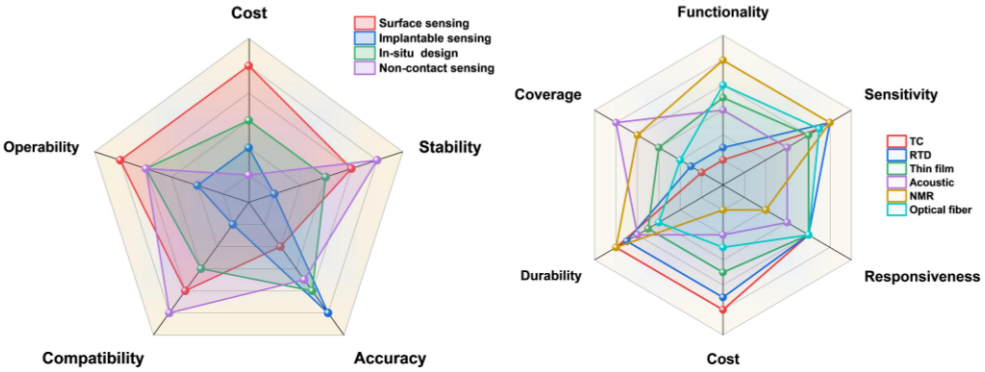

Fig. 9 Comparative radar analysis of sensing strategies and sensor modalities.

Table 1 Comparative evaluation of sensing diagnostic methods and parameters for battery monitoring.

Method	Surface	Implantation	In situ	Non-contact
Sensor Cost (USD)	10^0~10^2	10^2~10^4	10^1~10^4	>10^4
Stability	★★★★★	★☆☆☆☆	★★★☆☆	★★★★☆
Accuracy	★★★☆☆	★★★★★	★★★★☆	★★★★☆
Compatibility	★★★★★	★☆☆☆☆	★★★☆☆	★★★★★
Operability	★★★★★	★☆☆☆☆	★★★☆☆	★★★★★

Parameter	Temperature	Pressure	Voltage	Gas
Detectability	★★★★★	★★★★★	★★★☆☆	★★☆☆☆
Anti-interference	★★☆☆☆	★★★☆☆	★★★★★	★★★☆☆
State Correlation	★★☆☆☆	★★★★☆	★★★★☆	★★★☆☆
Warning Capability	★★★★☆	★★★★☆	★★★☆☆	★★☆☆☆

3.5 Comparative evaluation of sensing technologies

Following the above discussion, a quantitative comparison of surface-attached, implantable, intrinsically integrated, and noncontact sensing technologies is essential for assessing their engineering viability. As summarized in Fig. 9 and Table 1, these approaches exhibit different characteristics in terms of sensor cost, stability, accuracy, compatibility, and operability. Meanwhile, different sensing parameters exhibit varying performance in terms of detectability, anti-interference capability, correlation with battery states, and early-warning capability. (Lu et al., 2023; Deng et al., 2025; Guo et al., 2025b; Moradian et al., 2025).

Surface-attached sensors remain the most practical solution for current BMS implementations due to their low cost, high maturity, and ease of deployment. However, their ability to resolve internal states is inherently limited, and their effectiveness strongly depends on sensor placement. Optimizing installation locations to capture representative thermal and mechanical signatures while minimizing redundancy is therefore critical for improving monitoring accuracy under practical constraints. Implantable sensors improve signal fidelity and enable localized diagnostics; however, their introduction as foreign bodies raises critical concerns regarding long-term compatibility, including disturbance to ion transport, stress accumulation, and potential impacts on cycle life and safety. Intrinsically integrated sensing offers superior compatibility and minimal intrusion by embedding sensing functions within native battery components, making it a promising pathway toward scalable and durable monitoring. Nevertheless, challenges in manufacturability, cost, and technology readiness currently limit large-scale adoption. Noncontact methods provide noninvasive, system-level diagnostics suitable for large battery packs but are constrained by relatively low spatial resolution, susceptibility to environmental interference, and typically higher system cost associated with specialized equipment and signal processing requirements.

From an engineering perspective, no single approach optimally satisfies all performance metrics. Practical deployment, therefore, requires balancing sensing fidelity, cost, scalability, and impact on battery performance. A promising direction is to minimize sensing overhead through optimized sensor placement and reduced device count while adopting low-intrusion or functionally integrated designs that are compatible with existing manufacturing processes, thereby limiting impacts on energy density and cycling stability. Under such constraints, the information content obtained from individual sensing modalities is often limited, which necessitates the integration of heterogeneous data sources and the development of model-assisted inference frameworks to reconstruct internal states with higher fidelity.

4 LIB state diagnosis and lifetime management via multisource feature fusion

The widespread deployment of LIBs in electric transportation and energy storage systems necessitates high-fidelity SOH estimation and robust RUL prognostics. Accurate SOH estimation is essential for predictive maintenance, optimized charging/discharging protocols, and mitigating severe safety risks such as thermal runaway (Ge et al., 2021). However, battery degradation is a nonlinear, time-dependent process driven by multiple coupled mechanisms, including SEI growth, loss of active material, and mechanical stress (Ge et al., 2021; Li et al., 2022a). In conventional BMS implementations, monitoring has largely relied on easily accessible electrical signals, such as voltage, current, and surface temperature (Liu et al., 2025b). Although these signals are convenient to acquire, they provide only indirect and limited insight into internal degradation processes and early-stage failure evolution, effectively rendering the battery a “black box” during operation. Building upon recent advances in sensing

technologies, including embedded sensors, fiber-optic sensing, in situ integrated designs, and noncontact characterization, there is a growing emphasis on multisource feature fusion to enhance state observability and diagnostic fidelity. The following sections, therefore, focus on how these heterogeneous sensing inputs can be transformed into actionable intelligence through systematic feature engineering, predictive modeling, and intelligent diagnostic frameworks, ultimately enabling proactive health management and lifetime prediction.

4.1 Feature signal-based battery lifetime prediction models

Accurate battery lifetime prediction, encompassing SOH estimation and RUL prediction, critically depends on the extraction of health indicators (HIs) that reflect degradation evolution. These indicators should capture key aging effects, such as capacity fade and internal resistance increase, commonly observed during battery operation (Li and Xue, 2025).

4.1.1 Evolution and trends of physics-based models

Before delving into data-driven frameworks, it is imperative to outline the development and current trends of physics-based models, which serve as the fundamental baseline for battery state estimation. Historically, equivalent circuit models (ECMs) have been widely adopted in BMSs due to their computational simplicity, yet they inherently lack electrochemical interpretability. To accurately capture internal degradation mechanisms, electrochemical models, notably the pseudotwo-dimensional (P2D) model (Doyle et al., 1993; Fuller et al., 1994) and the simplified single particle model (SPM) (Li et al., 2018), were developed. These models explicitly describe lithium-ion diffusion, intercalation kinetics, and SEI growth based on porous electrode theory (Christensen and Newman, 2004). Currently, the developmental trends of physics-based models are predominantly characterized by two directions. First, to bridge the gap between high-fidelity simulation and real-time computational constraints, advanced order-reduction techniques, such as the Padé approximation and orthogonal collocation, are extensively investigated, enabling the deployment of complex electrochemical models on onboard microcontrollers. Second, physical models are evolving from one-dimensional electrochemical formulations into multiphysics coupled frameworks, incorporating electrochemical, thermal, and mechanical interactions (Yang et al., 2019). This transition is essential to accurately simulate localized thermal hotspots and stress-induced particle cracking under high-dynamic operating conditions (Christensen and Newman, 2006; Li et al., 2018). Ultimately, the modern paradigm is shifting toward hybrid integration, where these advanced physical models serve as boundary constraints for deep learning or digital twins (Severson et al., 2019; Zeng and Berecibar, 2025), ensuring that data-driven predictions strictly adhere to fundamental thermodynamic and kinetic laws.

4.1.2 Extraction of key degradation features

SOH is typically defined as the ratio of the current available capacity to the rated initial capacity. However, direct capacity measurement requires full charge/discharge cycles and is impractical for online applications. As a result, indirect HIs are commonly extracted from measurable signals (Li and Xue, 2025). Incremental capacity analysis (ICA) and differential voltage analysis (DVA) are widely used to derive degradation-related features from voltage profiles. These methods convert voltage plateaus into characteristic peaks that are sensitive to internal electrochemical processes such as phase transitions and SEI growth (Vetter et al., 2005; Barré et al., 2013). As aging proceeds, the peak positions and amplitudes of ICA/DVA curves shift, correlating with capacity loss and resistance increase (Birkl et al., 2017). However, ICA/DVA typically require standardized low-rate charge/discharge conditions, and differentiation tends to amplify measurement noise. Consequently, the integration of advanced denoising and signal processing frameworks is indispensable to ensure diagnostic robustness against measurement artifacts. Compared to these high-fidelity but noise-sensitive differential methods, statistical and temporal HIs (e.g., constant-current (CC) charging duration) offer a more computationally efficient alternative. While the latter simplifies real-time implementation, the trade-off is a relative

lack of deep electrochemical interpretability regarding internal phase transitions. Differential thermal voltammetry (DTV) further incorporates temperature information and provides thermal-related features useful under dynamic operating conditions.

In addition to differential-based methods, HIs can also be directly extracted from charging/discharging curves using statistical and temporal characteristics. Common statistical features include the mean, standard deviation, skewness, and kurtosis of voltage, current, or temperature over selected intervals. Temporal features, such as the duration of CC and constant-voltage (CV) phases or the time required to reach a specific voltage during discharge, have been shown to correlate with SOH (Severson et al., 2019). Compared with differential-based features, statistical and temporal HIs are easier to implement and require less computational effort. This makes them more suitable for practical BMS applications, especially when sensing and processing resources are limited.

4.1.3 Advanced prediction architectures

Battery lifetime prediction aims to extrapolate degradation trends beyond observed data. Before the widespread adoption of data-driven approaches, physics-based models, including P2D models, SPM, and ECMs, served as the foundation for battery state estimation (Mevawalla et al., 2020; Dong and Wei, 2021). These models provide profound interpretability by explicitly describing internal electrochemical kinetics, mass transport, and thermal dynamics. Recent advancements have focused on order-reduction techniques to enable the real-time execution of complex electrochemical models on BMS microcontrollers. However, the performance of pure physics-based models remains fundamentally constrained by the difficulty of accurately parameterizing internal variables that continuously evolve with aging, as well as their high computational overhead. Traditional machine learning methods (Gaussian process regression (GPR), support vector regression (SVR), random forests (RF)) have been widely used for SOH and RUL prediction due to their relatively simple structures and moderate data requirements (Severson et al., 2019; Attia et al., 2020). However, these models often depend on carefully engineered features and may struggle to capture complex temporal dependencies. Deep learning approaches, especially recurrent neural networks (RNNs) and their variants, such as long short-term memory (LSTM) and gated recurrent units (GRUs), are commonly employed to model sequential degradation data. These networks can learn temporal dependencies from historical measurements, including charging voltage profiles and extracted HIs. When provided with time-series inputs, RNN-based models can iteratively predict future SOH or RUL. However, their performance depends on the data quantity, operating condition variability, and generalization ability.

To improve robustness under limited or heterogeneous data conditions, physics-informed neural networks (PINNs) have been introduced. PINNs integrate empirical degradation models or state-space equations as physical constraints during training. For instance, recent progress involves embedding governing equations, such as SEI growth kinetics or Arrhenius thermal constraints, directly into the loss function of neural networks (Christensen and Newman, 2004). By embedding mechanism-related constraints into the learning process, PINNs can reduce physically inconsistent predictions and improve generalization across different battery types and operating scenarios (O'Kane et al., 2022). Effectiveness, however, hinges on the accuracy of the underlying physical assumptions and parameter identification. Recently, transformer-based architectures have been explored for battery lifetime prediction. These models leverage attention mechanisms and sequence-to-sequence learning to capture long-range dependencies in degradation trajectories (Wang et al., 2025). Some studies show that transformer-based models can forecast future degradation trends with limited early-cycle data and map predicted trajectories to SOH and RUL through dedicated estimators. Although promising, these methods generally entail higher computational complexity and require further validation for large-scale real-time BMS applications.

4.2 Multisource information fusion for advanced fault diagnosis

While the approaches summarized in Section 4.1 effectively capture macroscopic degradation trends (SOH and RUL), they primarily rely on standard

electrical signals (voltage, current, surface temperature). These signals are macrolevel reflections of complex internal physicochemical changes and often lag behind the onset of degradation, potentially limiting sensitivity to early safety precursors such as lithium dendrite growth, electrolyte depletion, or microcracking.

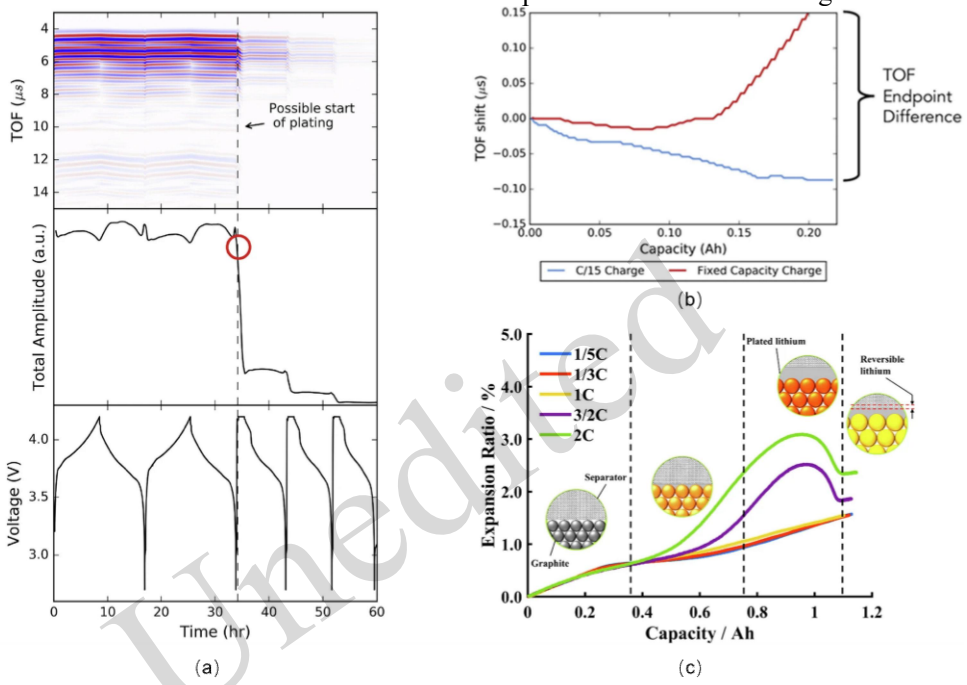

Fig. 10 Overview of sensor data and extracted features used for lithium plating detection (reprinted from (Zeng and Berecibar, 2025), Copyright 2026, with permission from Springer Nature). (a) Acoustic signal evolution during high-rate charging, showing rapid attenuation associated with the onset of lithium plating; (b) Acoustic time-of-flight (TOF) shifts under different charging protocols, where deviations at high C-rates indicate lithium plating behavior; (c) Battery volume expansion ratio as a function of charging capacity at different C-rates, with overshoots at high rates suggesting lithium plating and stripping.

chemical, mechanical, and thermal domains. Taking lithium plating detection as a representative case, Fig. 10 summarizes sensor-derived features such as acoustic attenuation, time of flight (TOF) shifts, and expansion-ratio overshoots. These features can be correlated with plating onset and subsequent stripping behavior, illustrating how multimodal sensing signals may provide earlier warning than conventional voltage or surface-temperature thresholds. Unlike individual signals that may be ambiguous, the temporal correlation between internal temperature rise and expansion ratio overshoots provides a more specific indicator to isolate lithium plating from normal breathing dynamics (Wang et al., 2024; Sun et al., 2025). By explicitly linking these multiphysics signatures to underlying degradation pathways, such as correlating pressure deviations with LAM and acoustic attenuation with LLI, the diagnostic framework transitions from general anomaly detection to precise, mechanism-informed fault isolation (Moradian et al., 2025). In practical diagnostic frameworks, such multidimensional signals can be further integrated using sequence-learning architectures, such as CNN-LSTM models, to identify coupled failure modes under dynamic operating conditions.

Electrochemical impedance spectroscopy (EIS) provides valuable diagnostic insights by mapping frequency-domain features to the internal states of a battery (Birkl et al., 2017). Key HIs include ohmic

4.2.1 Multiphysical sensor integration

Early and reliable fault diagnosis requires decoding multiple physical features that emerge prior to observable anomalies in external electrical signals. The transition from healthy operation to failure states, such as internal short circuits or thermal runaway, imprints subtle but distinct signatures across electro-

resistance, SEI resistance, and charge-transfer resistance (Zhang et al., 2020; Fang et al., 2025). For example, a sudden phase-angle change at mid-to-low frequencies can serve as an early warning for lithium plating or SEI decomposition, offering a longer detection window than surface temperature thresholds. Recent studies have further demonstrated the potential of EIS for online fault diagnosis, state estimation, and early safety warning when combined with equivalent circuit modeling, distribution of relaxation times (DRT) analysis, and machine-learning algorithms (Birkl et al., 2017; Fang et al., 2025). Nevertheless, several challenges remain for practical deployment. Conventional EIS measurements typically require frequency sweeping over a wide range, resulting in relatively long acquisition times that are difficult to accommodate during normal battery operation. In addition, impedance responses are strongly influenced by temperature, SOH, and cell-to-cell variations, complicating the interpretation of degradation-related features (Knott et al., 2024). The nonuniqueness of equivalent circuit fitting and the overlap of multiple electrochemical processes may further reduce diagnostic robustness. Therefore, future developments should focus on fast-acquisition EIS techniques, physics-informed feature extraction, and integration with BMSs to enable reliable real-time monitoring and fault detection in practical applications (Wang et al., 2018).

Mechanical stress–strain signal deconvolution involves analyzing data from fiber-optic sensors and thin-film strain gauges to identify chemo-mechanical signatures. Algorithms detect characteristic peak shifts and rates of change, which are deconvoluted to distinguish normal breathing (lithium intercalation) from abnormal expansion due to gas generation or lithium dendrite growth (Li et al., 2018). As evidenced in Fig. 10c, an overshoot in the battery expansion ratio at high C-rates serves as a clear precursor for lithium plating and stripping events. Thermal-temporal correlation features are derived by processing internal temperature data from embedded or acoustic/ultrasonic sensors to identify thermal gradients and heat generation rates. By analyzing the differences between internal and surface temperature evolution, diagnostic models can detect localized hotspots that are often masked by thermal inertia in conventional monitoring. Acoustic and ultrasonic signature analysis involves examining the interaction of ultrasonic waves with internal battery layers to extract features related to changes in density and modulus (Fig. 10a). Variations in TOF and signal attenuation can indicate electrolyte exhaustion or dead lithium accumulation (Fig. 10b), which are critical precursors to electrode degradation.

4.2.2 Fusion models for fault diagnosis

After acquiring multiphysical signals, appropriate fusion models are needed to distinguish normal operation from various fault modes. Given the complexity and coupling of battery failure mechanisms, data-driven approaches are widely used to integrate heterogeneous sensor information and improve diagnostic performance.

In supervised frameworks, models are trained with labeled data from experiments or simulations. A common approach is to establish a healthy reference behavior using historical voltage or current data and compare it with real-time measurements. Parallel to purely data-driven baselines, advanced physics-based models, particularly electrochemical-thermal coupled models, are increasingly employed to generate high-fidelity reference states (Abada et al., 2016). By dynamically comparing the physically expected temperature or voltage against actual sensor measurements, robust residual signals are generated for early fault isolation and thermal runaway warning (Yang et al., 2019). The resulting residual signals (e.g., voltage differences) are fed into classification models. Convolutional neural networks (CNNs), sometimes augmented with attention mechanisms, have been used to identify fault types such as internal short circuits and capacity anomalies. These methods can classify faults across different severity stages (early, intermediate, and advanced) by estimating the likelihood of abnormal behavior. Despite their high diagnostic accuracy under laboratory conditions, supervised approaches face fundamental barriers to large-scale engineering deployment. Their effectiveness critically depends on the availability of extensive, high-quality labeled datasets that comprehensively cover diverse and often rare failure scenarios. In practical electric transportation systems, such labeled failure data are intrinsically scarce (Zeng and Berecibar, 2025), costly to obtain, and difficult to

generalize across cell designs and operating conditions. Consequently, the reliance on labeled data significantly limits scalability and robustness. From an industrial perspective, unsupervised or weakly supervised multimodal frameworks are more attractive, as they learn system behavior directly from normal-operation data and detect anomalies without requiring explicit fault labels, effectively alleviating the long-standing "label scarcity" bottleneck in BMS. Unsupervised or weakly supervised diagnostic frameworks have been developed to address this issue (Zhang et al., 2023). These frameworks typically combine numerical features (e.g., charging resistance, time-accumulated indicators) with signal representations from other domains (e.g., time-frequency features from short-time Fourier transform (STFT)). Anomaly detection models, such as autoencoders or local outlier detection methods, are trained on normal operation data and used to identify deviations. Time-accumulated features, including trend-based indicators from relative voltage signals, can highlight gradual changes that simple threshold-based monitoring may miss. Such multimodal frameworks are considered suitable for real-world deployment where fault patterns are diverse and evolving.

4.3 Low-cost monitoring strategies and feature engineering

4.3.1 Low-cost monitoring strategies

The deployment of advanced sensing and diagnostic techniques in large-scale electric vehicle and energy storage systems is often constrained by cost, complexity, and hardware integration. Consequently, many studies aim to reduce sensing and computational requirements while maintaining acceptable diagnostic and prognostic performance. A widely adopted and practical strategy is to exploit standard electrical signals, such as voltage, current, and temperature, that are already available in most BMSs. Degradation-related information can be extracted from these signals without introducing additional sensors, for example, through statistical and temporal features derived from short segments of charge – discharge data for SOH estimation. Additionally, trend-based anomaly detection applied to normalized voltage signals can highlight abnormal behavior and support early detection of potential internal short circuits using only low-cost measurements (Yuan et al., 2023). To further address the limited computational capability of onboard BMS units, adaptive cloud-edge collaborative system architectures have been increasingly proposed. In such frameworks, computationally intensive tasks, such as model training, parameter optimization, and fleet-level analysis, are performed in the cloud. Lightweight optimized models are then run on embedded BMS hardware for real-time inference and monitoring (Attia et al., 2020; Ward et al., 2022). This approach enhances diagnostic capability while reducing local computational burden. Transfer learning is often used to adapt trained models to new battery chemistries or operating conditions with limited additional data. Beyond signal-based approaches, ongoing research is exploring low-cost and integrated sensing concepts based on miniaturized sensor designs. Printed and integrated multifunctional sensor arrays can provide multiphysical measurements with minimal impact on cell weight and packaging. Although large-scale commercialization remains challenging, these approaches demonstrate the potential of combining low-cost sensing with feature reduction and data fusion for future battery monitoring systems (Lu et al., 2022; Che et al., 2023).

4.3.2 Feature dimensionality reduction, selection, and multisource data fusion

In practical BMSs, advanced sensing modalities, such as impedance spectra, acoustic signals, and time-frequency representations, often generate high-dimensional data. Direct utilization of such data is typically infeasible in real-time applications due to constraints in computation, memory, and communication bandwidth (Che et al., 2023). These challenges are further intensified in multisource sensing scenarios, where heterogeneous data streams with different sampling rates, formats, and noise characteristics must be processed simultaneously (Shu et al., 2025; Wei et al., 2023). Consequently, feature selection and dimensionality reduction are essential for enabling efficient and deployable diagnostic frameworks.

Despite the capability of deep learning models to automatically extract features, explicit feature selection remains widely used in BMS applications

due to its interpretability and lower computational cost. Feature relevance is commonly assessed through correlation analysis with target variables such as SOH or RUL using metrics such as the Pearson correlation coefficient. Features with weak relevance or high redundancy are removed to improve robustness and reduce overfitting. More systematic approaches, such as recursive feature elimination (RFE), further enable the identification of compact and informative feature subsets while maintaining predictive performance, which is particularly important for resource-constrained embedded systems (Tian et al., 2025). To further compress the feature space, dimensionality reduction techniques are employed. Linear methods such as principal component analysis (PCA) and nonlinear extensions such as kernel PCA (KPCA) project high-dimensional data into lower-dimensional representations while preserving dominant patterns (Zhou et al., 2024). In multimodal diagnostics, these approaches facilitate the transformation of heterogeneous features into unified numerical representations, thereby enabling efficient data integration and reducing computational burden.

Building on this feature engineering foundation, multisource data fusion can be categorized into three levels. Data-level fusion combines raw signals and requires homogeneous sensing or strict temporal synchronization, making it mainly applicable to electrical measurements such as voltage and current; feature-level fusion, the most widely adopted strategy, integrates extracted features (e.g., IC/DV peaks, impedance parameters, temperature gradients) within a unified model, offering a balance between flexibility and robustness; decision-level fusion aggregates independent state estimates (e.g., SOC, SOH) from multiple models or sensors through higher-level algorithms, such as probabilistic frameworks (Chen et al., 2025; Yun et al., 2025). However, while algorithmic fusion provides enhanced diagnostic capability, its practical deployment in large-scale electric vehicle and energy storage systems is fundamentally constrained by hardware integration. Current BMS architectures primarily rely on low-bandwidth communication protocols, such as controller area networks (CANs) or daisy-chain serial peripheral interfaces (SPIs), which are designed for low-frequency voltage and temperature monitoring (typically < 10 Hz). In contrast, emerging multiphysical sensing modalities generate heterogeneous data streams with substantially higher bandwidth requirements. For example, acoustic emission and optical fiber sensors often operate at kilohertz-to-megahertz sampling rates, which exceed the capacity of conventional BMS infrastructures. Bridging this gap requires coordinated advances in both hardware and system architecture. At the interface level, bulky external interrogation systems must be replaced by miniaturized application-specific integrated circuits (ASICs) capable of on-site signal digitization and preprocessing, thereby reducing noise and transmission burden. At the communication level, high-bandwidth architectures (e.g., Automotive Ethernet) combined with precise time synchronization protocols (such as IEEE 1588) are needed to align multirate data streams in the time domain. Without such synchronization, the computational cost of data alignment at the edge becomes prohibitive.

Despite ongoing progress, the lack of standardized sensor interfaces and multisource data fusion protocols remains a key barrier to industrialization (Moradian et al., 2025; Zeng and Berecibar, 2025). These limitations highlight that scalable deployment of intelligent battery diagnostics depends not only on advances in algorithms but also on the codesign of sensing hardware, data acquisition systems, and communication architectures. Future research should therefore emphasize modular, standardized system frameworks that enable seamless integration of multiphysical sensing technologies.

4.4 Key challenges in scalable intelligent battery diagnostics

Despite the operational convenience of sensing, its fidelity is substantially challenged in practical automotive and energy storage environments. High-frequency electromagnetic interference (EMI) generated by motor drives can obscure subtle electrochemical signatures in conventional electronic sensors (Huang et al., 2021; Wang et al., 2024), while large temperature fluctuations under high-power operation often induce calibration drift. For instance, integrated piezoelectric sensors exhibit pronounced temperature-dependent signal instability, necessitating sophisticated compensation strategies to

maintain diagnostic accuracy (Hu et al., 2020). More broadly, these limitations underscore a fundamental gap between laboratory-level sensing performance and real-world operating conditions, highlighting the difficulty of translating sensing innovations into reliable engineering solutions.

Beyond sensing fidelity, the scalable deployment of intelligent diagnostic systems is fundamentally constrained by material, manufacturing, and mechanistic complexities. A primary bottleneck lies in the long-term stability and integration compatibility of advanced sensor devices within the harsh electrochemical environment of batteries, characterized by elevated temperature and pressure, corrosive electrolytes, and significant volume fluctuations. Meanwhile, embedding sensors into battery materials and production workflows introduces additional process complexity and potential failure modes, posing challenges for manufacturing scalability, yield, and consistency control. Battery aging is inherently governed by strongly coupled electrochemical, thermal, and mechanical processes, which introduce substantial challenges for reliable diagnostics (Yang et al., 2019; O'Kane et al., 2022). In particular, disentangling the origins of measured signals, identifying the dominant degradation drivers, and establishing quantitative relationships between observable features and specific failure mechanisms remain largely unresolved.

From a system and algorithmic perspective, the industrialization of intelligent battery diagnostics is further hindered by data heterogeneity, resource constraints, and the need to balance performance with practicality. While conventional battery management systems rely on standardized voltage and temperature measurements, emerging multiphysical sensing modalities such as optical fibers, strain gauges, and acoustic transducers generate data streams with disparate sampling rates, formats, and signal-to-noise characteristics. The real-time integration and interpretation of such data impose substantial demands on data acquisition architectures, computational resources, and algorithm design (Che et al., 2023; Lu et al., 2022). At the same time, high-resolution diagnostics typically require dense sensor networks, increasing system cost and complexity while compromising energy density and power capability. Meanwhile, early-stage degradation signals are inherently weak, easily masked by noise, and further attenuated across cell-to-system hierarchies. Consequently, achieving reliable early-stage fault detection with low false-positive rates while maintaining cost effectiveness and minimal intrusion into battery performance remains a central challenge for large-scale deployment (Abada et al., 2016).

5 Conclusions and perspectives

This review systematically surveys recent advances in nondestructive information acquisition for LIB aging and failure diagnosis, together with their integration with intelligent algorithms. Grounded in aging mechanisms, it correlates the evolution of key physicochemical signals with underlying aging processes and critically evaluates approaches ranging from conventional electrical measurements to advanced in situ sensing and noncontact characterization, highlighting their principles and limitations. The development of next-generation intelligent BMSs fundamentally relies on high-fidelity, multidimensional perception of internal states combined with predictive data analytics. Despite substantial progress, translating these technologies from laboratory studies to reliable, large-scale engineering applications remains a significant challenge. To bridge this gap, a coordinated, system-level optimization across materials, device architectures, and algorithms is emerging as a dominant paradigm, following a staged, application-oriented roadmap (Fig. 11):

(1) Integrated and minimally intrusive sensing. Efforts should focus on low-cost, minimally intrusive solutions that can be seamlessly integrated into current systems. Key priorities include optimizing sensor placement and reducing sensor count, improving the quality of conventional signals (e.g., voltage, temperature, pressure), and leveraging model-assisted inference to enhance state estimation under limited sensing conditions. Compatibility with existing manufacturing processes and scalability at the module and pack levels remain critical.

(2) Multisource information fusion and digital twin deployment. With increasing sensing diversity, integrating heterogeneous data streams with

physics-based models and data-driven algorithms will be essential. The development of battery digital twins capable of capturing degradation dynamics and decoupling key parameters will enable more accurate lifetime prediction and early fault detection. Achieving a balance between model fidelity, computational efficiency, and real-time applicability is a central challenge at this stage.

(3) Fully integrated and intelligent battery systems. Future systems are expected to evolve toward intrinsically integrated sensor-battery architectures combined with cloud-edge collaborative frameworks, enabling self-powered sensing, autonomous monitoring, and closed-loop regulation. Such systems will support system-level optimization across diverse applications, including energy storage and electrified transportation, ultimately enabling highly reliable, adaptive, and intelligent battery management.

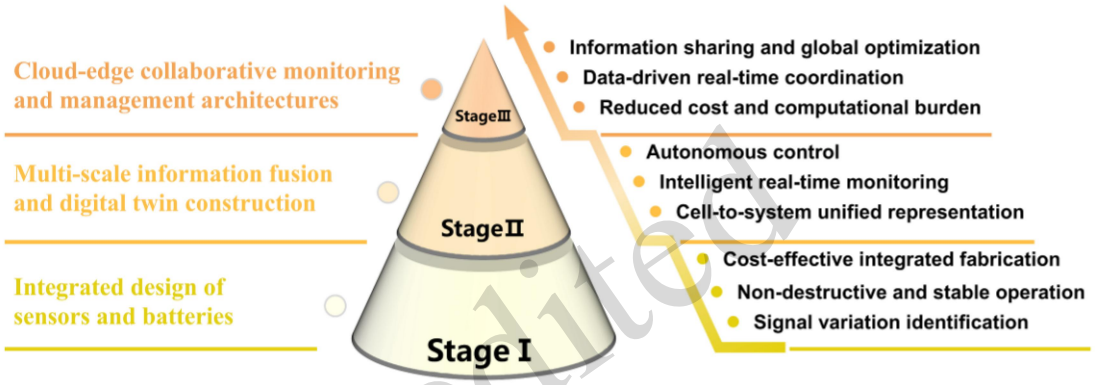

Fig. 11 Staged roadmap for system-level optimization of nondestructive diagnosis in LIB aging.

In summary, nondestructive information acquisition and failure diagnosis for LIB aging are undergoing a fundamental transition from external and indirect observation toward direct internal state perception and from predominantly passive management to proactive and anticipatory early warning strategies. Addressing persistent bottlenecks in sensor technologies, signal interpretation, algorithm integration, and system-level engineering will substantially enhance the safety, reliability, and operational lifetime of battery systems. Looking ahead, the continued convergence of advanced sensing, multisource feature fusion, and intelligent diagnostic frameworks is expected to play a pivotal role in enabling next-generation smart batteries. Collectively, these developments will underpin the sustainable evolution of energy storage technologies and support the broader energy transition necessary to achieve carbon neutrality and global decarbonization goals.

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Author contributions

Debo CHEN drafted the outline of the review paper under the guidance of Yingying LU. Debo CHEN, Zebing SHOU, Xin YANG, and Song CHEN wrote the initial draft of the manuscript. Yingying LU, Debo CHEN, and Xin YANG revised and edited the final version.

Conflict of interest

Debo CHEN, Zebing SHOU, Xin YANG, Song CHEN, and Yingying LU declare that they have no conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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中文概要

题　目： 锂离子电池老化与安全性的无损感知与失效诊断技术

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概　要： 高能量密度锂离子电池在电动交通和电网储能中的规模化应用，对电池的安全性、可靠性和智能化管理提出了日益严苛的要求。然而，电池内部电化学、热学和力学状态的可观测性受限仍是一个根本性挑战，导致安全风险持续存在、低温性能下降以及加速老化等问题，共同阻碍了电气化系统的规模化应用。为克服这些挑战，传统电池管理系统正从电压-电流-温度测量模式，向由先进无损感知技术实现的高保真状态估计演进，其中包括新兴的内部感知与植入式诊断概念。基于对与材料老化及失效机制相关的物理信号的全面分析，本文对电池状态监测领域的无损检测技术进行了系统而批判性的评述。并且，进一步审视了电池状态诊断与寿命管理算法的最新进展，并特别强调了多源物理特征融合策略。更重要的是，本文构建了一个将退化机制、内部物理信号和状态估计策略

联系起来的统一框架，提供了跨尺度视角以指导先进感知技术与智能算法的协同设计，从而推动下一代电池管理系统的发展。

关键词：无损检测；锂离子电池；多物理场耦合；智能电池；老化机制