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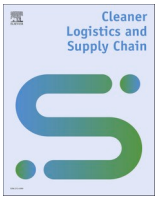

Towards autonomous triaging for end-of-life EV components: a critical review and diagnostic-to-decision framework

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ABSTRACT

The rapid adoption of electric vehicle (EV) has intensified the challenge of managing End-of-Life (EoL) components, particularly the batteries and motors of the EV, which contain both valuable resources and environmentally hazardous materials. This review synthesises emerging tools for the autonomous triaging of the EoL EV components. We critically examine the disconnect between established diagnostic methods (fault diagnosis / condition assessment) and Circular Economy (CE) decision-making. Key findings indicate that while fault detection accuracy is high (over 90% for data-driven methods), the industry lacks standardised thresholds to map these diagnostics to specific CE pathways. To address this, we propose a unified 'Diagnostic-to-CE Decision Framework' and a novel autonomy taxonomy to guide the transition from manual inspection to fully automated triaging systems.

1. Introduction

Global electric car sales reached 17 million in 2024 with 3.5 million more sold compared to 2023, a year-on-year increase of 26% ("IEA (2025), Global EV Outlook, 2025, IEA," 2025). Fig. 1 shows EV sales worldwide over the past 10 years split by Battery vs Plugin Hybrid EV ("International Energy Agency (IEA), "Global EV data explorer – Data tools," 2025). The most recent market updates further indicate that battery EV sales reached approximately 5.93 million units in the first half of 2025, representing a 29.1% year-on-year increase compared with January to June 2024 (Juurikas, 2025). As the number of the EV on the road grows rapidly, so does the volume of aging and end-of-life (EoL) components (e-waste), particularly batteries, and motors. The increase in e-waste raises critical considerations about how to manage or dispose of these e-wastes in a sustainable and economically viable way. However, despite the market momentum, research and validation are constrained by limited EoL data because large scale EV adoption is relatively recent and most vehicles have not yet reached retirement. The U.S. Department of Energy notes that EV batteries are typically expected to remain in service for around 12 to 15 years under moderate climates, often beyond warranty coverage (McAleer, 2026), which delays the availability of retired or degraded components for experimental validation and data collection.

To address these considerations, the concept of a circular economy (CE) has gained broad agreement for its focus on extending product life, minimising environmental pollution, and maintaining functional utility (Geissdoerfer et al., 2017). The CE framework encourages resource efficiency through strategies such as reuse, repair / remanufacture, repurpose, and recycling (Pan et al., 2022; Tiwari et al., 2021). While CE defines the overall recovery pathways, their effective implementation in the EV sector depends on accurate technical evaluation of each component's condition. Condition assessment and fault diagnosis provide this capability by determining the operational state, identifying specific faults, and quantifying degradation levels. For example, the handling of second-life lithium-ion batteries exemplifies how CE strategies can be supported by technical diagnostics and assessments. Reuse (deploying

Abbreviations: AE, Acoustic emission; ANN, Artificial neural network; BMS, Battery management system; CE, Circular Economy; CNN, Convolutional neural network; ECM, Equivalent circuit model; EIS, Electrochemical impedance spectroscopy; EKF, Extended Kalman Filter; EoL, End-of-Life; EV, Electric vehicles; HPPC, Hybrid pulse power characterisation; ICA, Incremental Capacity Analysis; MCSA, Motor-current signature analysis; SoC, State of capacity; SoH, State of health; WEEE, Waste electrical and electronic equipment.

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the battery without modification in another EV), repair / remanufacture (replacing defective modules for use in another EV), and repurposing (using modules for non-automotive applications like stationary energy storage) are increasingly recognised CE pathways (Mrozik et al., 2021). The implementation route for each battery depends on its condition after a series of generic tests, such as visual inspections (corrosion, intrusion, or loose cables), and electrical and mechanical measurements (resistance, capacity) (Kotak et al., 2021). Similarly, e-motors, which include components such as bearings, rotors, and stators, can be evaluated through fault diagnosis and condition assessment to support EoL CE options.

While these efforts mark important progress, many CE strategies still depend heavily on manual inspections and lack intelligent, data-driven decision support systems for determining optimal EoL CE pathway (Tiwari et al., 2021). Most fault diagnosis and condition assessment focus on individual components such as e-motors, battery packs, or wiring rather than the entire electric powertrain (Zhang et al., 2023).

The techniques used for assessing different components also vary considerably. For example, in e-motors, vibration analysis, a model-based method, uses vibration signals to predict machine condition (Ágoston, 2015; Althubaiti et al., 2022; Khaneghah et al., 2023; Tsypkin, 2011), while acoustic emission (AE) techniques rely on acoustic stress waves or ultrasonic signals to assess motor health (Al-Ghamd and Mba, 2006; Glowacz and Glowacz, 2017; Gu and Choi, 2011; Kim and Parlos, 2002). In contrast, many artificial intelligence driven methods require a combination of multiple input parameters, including vibration signals, motor current signals, infrared data, temperature measurements, and thermal images, to meet the requirements for model development (Zhang et al., 2023).

For battery packs, state of capacity (SoC) and state of health (SoH) are two key metrics used to evaluate battery condition. These variables are calculated within the battery management system (BMS), which gathers data from embedded sensors and controllers (Hannan et al., 2017). Typically, batteries are considered for CE pathways when their SoH falls below 70 percent. However, some studies report that batteries can still meet performance requirements even at SoH levels as low as 30 percent (Saxena et al., 2015). The lack of standardisation across methods makes it difficult to decide EoL options. This reflects a broader lack of mature battery recycling technologies and standardised recycling practices within the circular economy framework for EV (Feng et al., 2024).

The connection between condition assessment and CE pathway decision can be strengthened by 'triaging', the French term for sorting (Yancey and O'Rourke, 2023). It was originally used in healthcare for sorting patients depending on the severity of their injuries under resource-constrained environments to prioritise patients that need to be treated (Christian, 2019).

Inspired by the healthcare triaging, the goal in EV component triage is to create a fast and precise decision support to obtain optimal CE pathway for e-wastes. To achieve this, fault diagnosis and condition assessment form the technical foundation of triaging, enabling accurate defect detection and reliable evaluation of component health prior to deciding the optimal CE pathway. It focuses on identifying common, cost-effective, and easily obtainable input data, while selecting processing methods that deliver accurate assessment results quickly enough to guide CE pathways such as reuse, repairing / remanufacturing, repurposing, or recycling.

The proposed triaging process is illustrated in Fig. 2. Following initial disassembly, fault diagnosis is first conducted to identify mechanical, electrical, or system-level faults. However, fault diagnosis alone may not always provide sufficient confidence for CE routing. As shown in Table 1, feedback loops are triggered when the available information is insufficient, uncertain, or inconsistent. A diagnosis refinement loop is activated when the fault type is unclear or inconsistent with condition indicators. The disassembly escalation loop is triggered when

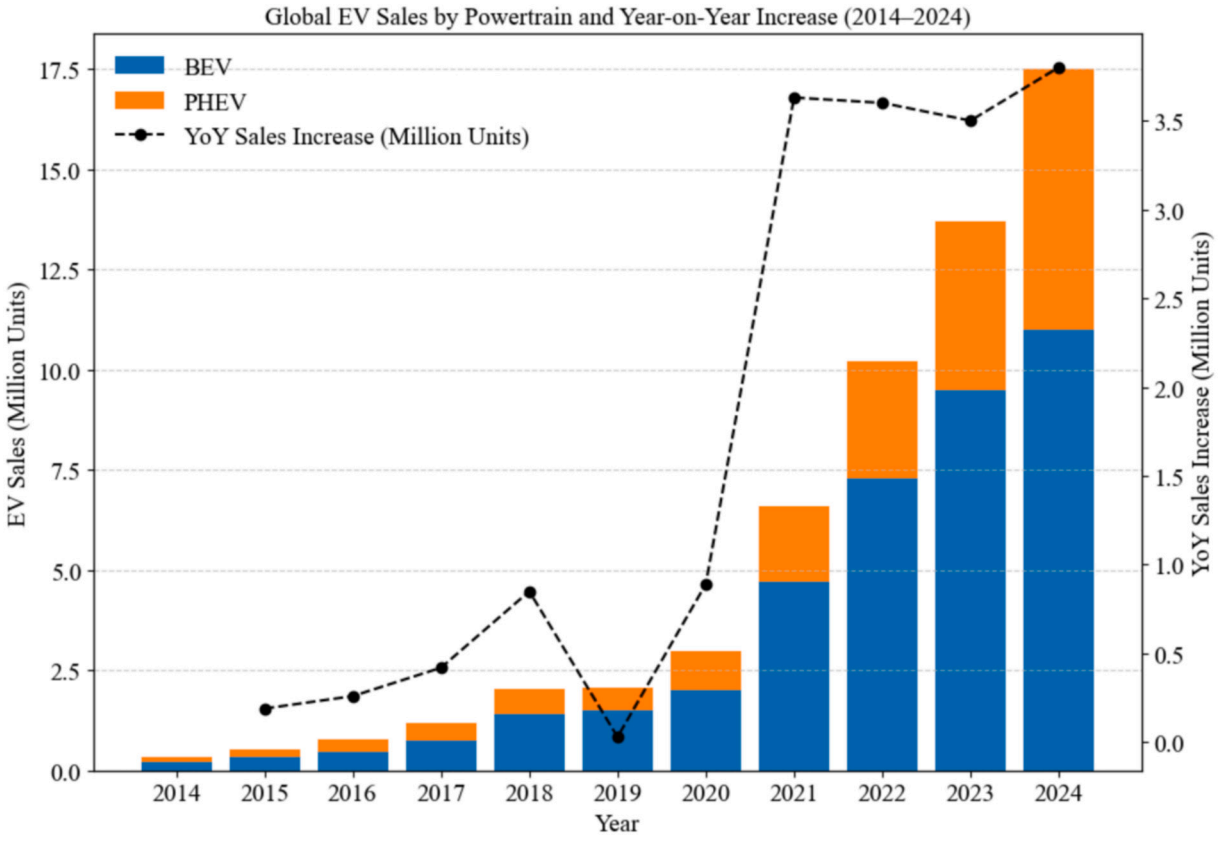

Fig. 1. Numbers of global EV sales by type and YoY (Year-on-Year) sales growth (2014 to 2024) Data sourced from the International Energy Agency (IEA) *("International Energy Agency (IEA), "Global EV data explorer – Data tools," 2025)*

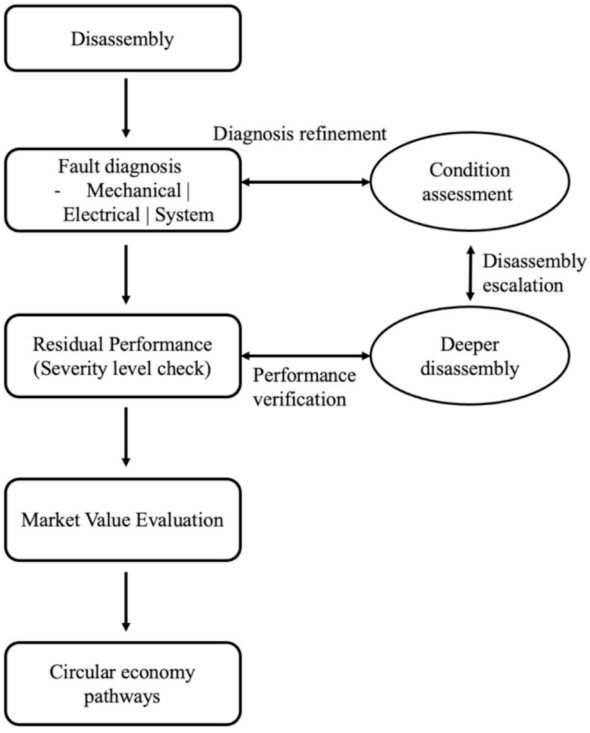

Fig. 2. Conceptual workflow of a triaging system for EoL EV components

Table 1
Triggering conditions, actions, and termination criteria for feedback loops in the proposed triaging workflow

Loop	Trigger	Actions	Termination
Diagnosis refinement	Fault type uncertain or inconsistent with health indicators	Perform additional condition assessment and refine or reclassify the fault diagnosis	Fault class converges with acceptable confidence
Disassembly escalation	Internal defect cannot be confirmed	Expose hidden components for better diagnosis, then repeat diagnosis	Sufficient access or evidence obtained to confirm fault location and severity, or further disassembly is no longer justified
Performance verification	Residual performance uncertain or borderline	Conduct deeper disassembly and reassess hidden damage affecting functional performance	Residual performance estimate reaches acceptable certainty and supports stable CE routing

internal damage cannot be determined at the current inspection depth. Performance verification loop is used when the estimated residual performance is uncertain or does not match the diagnosed severity level. Likewise, condition assessment may require deeper disassembly when accessible features are inadequate for reliable health estimation. Each loop terminates once the diagnosis, assessment, or performance estimate reaches sufficient confidence for the workflow to proceed to market value evaluation and final CE pathway selection.

Accordingly, this review goes beyond summarising fault diagnosis, condition assessment, and circular economy studies as separate research streams. It synthesises these strands into a conceptual Diagnostic-to-Decision framework for autonomous triaging of EoL EV components. The framework links diagnostic evidence, residual performance evaluation, human-machine autonomy allocation, and circular economy pathway selection within a unified decision structure. The purpose is not to present a fully validated industrial system, but to provide a review derived framework that clarifies how technical assessment outputs can be translated into actionable triaging decisions.

2. Method

The objective of this review was to systematically examine the individual technical and strategic building blocks that underpin EV component triaging and to establish a structured understanding of how these elements may be interconnected. Since triaging inherently spans multiple domains including fault diagnosis, condition assessment, circular economy strategies, and autonomous decision making, the search strategy was intentionally designed to investigate each domain independently within the EV context. Rather than presuming an existing integration among them, the review first analysed the fundamental principles, methodologies, input and output structures, evaluation indicators, and decision criteria reported within each area.

As illustrated in Fig. 3, the initial database search identified 444 records. After applying the predefined screening criteria, including English language, peer reviewed status, explicit relevance to end of life EV components, and confirmation that the search terms appeared within the main body of the text, 223 articles published since 2010 were retained for full text analysis. Each article was examined according to its primary technical focus, whether in diagnostic techniques, condition assessment approaches, circular economy strategies, or autonomy related systems. This structured decomposition enabled a clear understanding of the foundational contributions of each domain and provided the analytical basis for synthesising conceptual linkages across them, which underpin the integrated triaging framework developed in the subsequent sections.

The remainder of this paper is organised as follows. Section 3 reviews the CE framework and systematically explains each CE option, clarifying its definition and summarising how these strategies are currently applied in the EV context. Section 4 reviews existing methods for fault detection and condition assessment for e-motors and batteries. This section also reviews the input data requirements and output formats of major diagnostic and assessment methods and by examining how these results can be leveraged to inform CE decision making. Finally, Section 5 discusses current challenges and opportunities for future research in this emerging field.

3. Circular economy

The continued expansion of EV production is driving the future growth of waste electrical and electronic equipment (WEEE), especially batteries and associated power electronics, thereby increasing the urgency of effective EoL management and resource recovery strategies (Fereydoonian et al., 2025; Zhou et al., 2025). These WEEEs often contains both toxic substances (e.g., lead, cadmium) and high-value materials (e.g., platinum, silver, gold, palladium, indium) (Mmereki et al., 2016), making its proper handling not only an environmental necessity but also an economic opportunity (Bressanelli et al., 2020). Unlike those traditional economic development model that relies heavily on the resource consumption and waste generation, CE is a sustainable economic development approach shifts away from single use and disposable practices toward a closed loop model that recaptures product value and reduces waste by keeping WEEE components and materials (Hopewell et al., 2009; Pan et al., 2022). With the CE framework, EoL EV products can be managed more strategically to maximum material recovery, extend product lifecycles, and minimise environmental harm.

Among CE frameworks shown in Fig. 4, the '10R' hierarchy offers a structured spectrum of value retention strategies. While upstream strategies R0 to R2 refuse, rethink, reduce target waste prevention at the design stage, autonomous triaging operates downstream, where products have already reached EoL. Consequently, the present study focuses

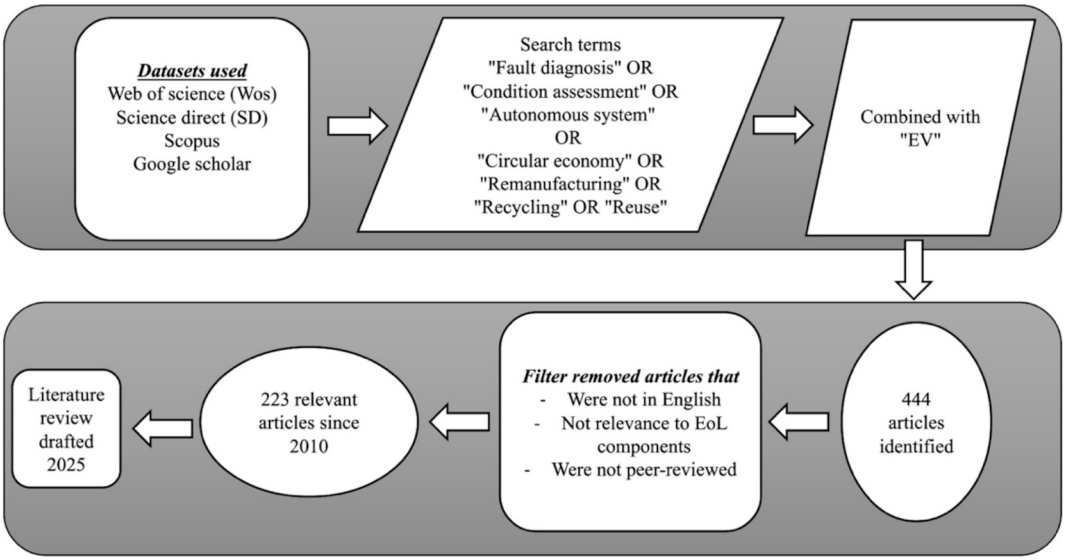

Fig. 3. Literature analysis

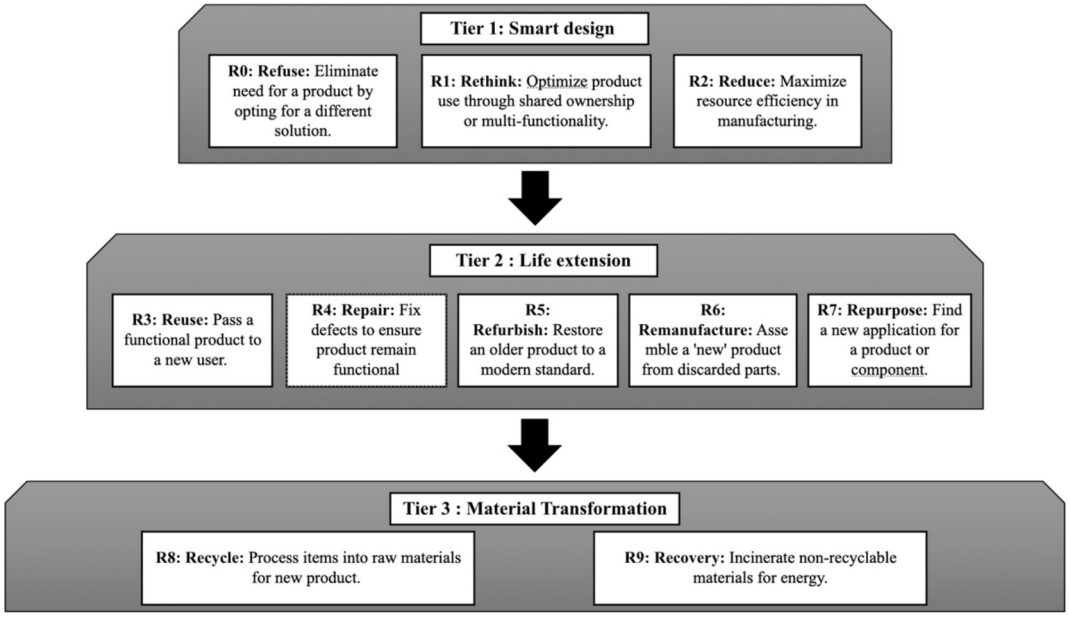

Fig. 4. CE '10R' framework structure (Potting et al., 2017)

primarily on R3 to R9 strategies, where diagnostic evidence determines whether components should be reused, repaired, refurbished, remanufactured, repurposed, recovered, or recycled.

3.1. Life extension (R3 – R7)

Life extension strategies R3 – R7 (Reuse, Repair, Refurbish, Remanufacture, Repurpose) aim to keep EV products and components in service for as long as possible by retaining their functional value rather than recovering only materials (Bressanelli et al., 2019).

In the EV context, this includes reuse of modules and components, repair and refurbishment to restore performance, remanufacturing of high value assembles such as motors or power electronics, and repurposing batteries or subsystems for secondary applications when automotive requirements can no longer be met. Life extension pathways for EV batteries, including reuse, remanufacturing, and repurposing for second-life stationary applications, are evaluated by quantifying the time and cost of disassembly and conditioning from pack level down to cell level (Rallo et al., 2020). Beyond economic feasibility, recent life cycle assessment studies show that used EV batteries can reduce environmental impacts in both reuse and repurposing applications, although these benefits depend on factors such as efficiency fade, used duration, and the electricity mix (Philippot et al., 2022). A techno economic and environmental optimisation model was proposed to plan EV battery disassembly for EoL recovery, selecting the disassembly sequence and the optimal disassembly depth that maximises profit by choosing between life extension options based on the SoH conditions (Alfaro-Algaba and Ramirez, 2020). As discussed, the life extension market for the EV battery often related to the SoH thresholds, where batteries 80% are routed to recycling, those between 80% and 85% are repurposed for less demanding energy system storage, and packs above 85% may still support reuse in smaller EV packs or cell replacement applications (Baars et al., 2020). Similar life extensions opportunity can be proposed for e-motors, since many EoL units may still contain serviceable

subcomponents that could be harvested as spare parts or remanufactured if their conditions meet the criteria.

3.2. Material transformation (R8 - R9)

Material transformation is the final stage in the 10R CE where the product's quality or condition is poor, and the value is recovered primarily at the material or energy level once higher value life extension options are no longer feasible. Specifically, R8 (Recycle) converts EoL products into secondary raw materials for new manufacturing, while R9 (Recovery) extracts remaining value through energy recovery or other residual treatment routes, typically treated as a last resort due to greater value loss compared with reuse-oriented strategies (Potting et al., 2017).

In the EV industry, material transformation happens when life extension options are not technically feasible, unsafe, or economically justified. For the EV components, recycling is the dominant EoL route because packs contain high-value and supply-critical materials. For example: industrial battery recycling typically follows one of three routes: hydrometallurgy (chemical reaction to separate metals) (Jha et al., 2013; Tuncuk et al., 2012), pyrometallurgy (high temperature smelting to concentrate metals) (Ebin and Isik, 2016), or the emerging direct recycling approaches that aim to preserve cathode structure to reduce processing energy and cost (Xu et al., 2023; Yang et al., 2023). Otherwise, EV battery recycling is tightly coupled to safety and logistic, since de-energising, disassembly, and handling damaged cells are non-trivial, which makes the procedure of the recycling complicated (Liang et al., 2025; Wegener et al., 2014; Yun et al., 2018). Beyond batteries, R8 also applies to power electronics and wiring, where copper and aluminium recovery is well established, and to the e-motors as well, where recycling focuses on reclaiming steel, copper windings, and permanent magnets (Liang and Pham, 2025).

R9 is generally treated as a last resort option in EV EoL management because it captures less value than material recycling. In the EV context, recovery most often refers to energy recovery from non-recyclable or contaminated fractions generated during dismantling and shredded, such as mixed plastics, foams, binders, separator residues, and those heavily degraded organic components.

Smart design, Life extension, and Material transformation are treated as interconnected stages within a single closed-loop process. Each stage represents a functional parameter that collectively enables sustainable value retention, resource efficiency, and material recirculation across the EV lifecycle. Building on this framework, the subsequent section focuses on fault diagnosis and condition assessment as the enabling mechanisms that inform stage selection and transition within the CE loop.

4. Fault diagnosis and condition assessment

In the proposed robotic triaging framework, fault diagnosis and condition assessment serve as the critical bridge between the physical inspection of EoL EV components and the selection of the most suitable CE pathway. Before a component can be reused, remanufactured, or recycled, its operational state and residual value must be determined accurately. Fault diagnosis identifies the nature and position of any defects (Gao et al., 2015), while condition assessment detects the component's overall health, performance, and remaining useful life (Liu and Kleiner, 2013). Fig. 5 illustrates how diagnostic outputs (fault type and severity) and condition assessment results (model-based or data-driven) jointly inform the selection of appropriate CE pathways, spanning smart design, life extension, and material transformation. It highlights the feedback between assessment and downstream decisions to support consistent, evidence-based triaging.

A variety of methods have been developed to perform these tasks effectively. Model-based techniques use simplified physics-based models to represent ideal, fault-free behaviour. Faults are detected by comparing measured signals with model outputs, and the differences,

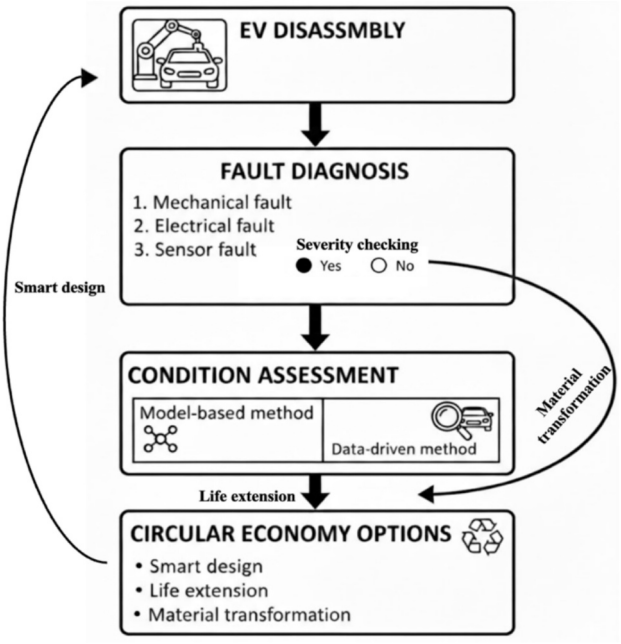

Fig. 5. Conceptual framework linking fault diagnosis, condition assessment with CE decision-making options for EV components

known as residuals, are analysed to determine fault type and severity (Khaneghah et al., 2023). These approaches are well suited to systems with clearly defined parameters and fault modes, making them effective for targeted applications. However, they require accurate system modelling and expert knowledge for parameter tuning, and they are often constrained to single fault detection or scenarios demanding rapid detection (Sabry and Ungku Amirulddin, 2024).

In contrast, data-driven methods bypass the need for explicit system models by learning directly from historical data. Leveraging machine learning and artificial intelligence, these approaches can detect subtle or early-stage faults under varying operational conditions (Choudhary et al., 2019; Farrar and Worden, 2012; Mohanty, 2014). Automated feature extraction, scalability, and adaptability make them powerful for complex and evolving electromechanical systems, especially in large-scale waste processing environments (Khaneghah et al., 2023). Nevertheless, data-driven techniques often require substantial high-quality labelled datasets and can suffer from interpretability challenges, which may limit their acceptance in safety-critical applications (Choudhary et al., 2019).

A review of two key components, e-motors and battery packs, is followed by an evaluation of various fault diagnosis methods and condition assessment techniques. Aiming to highlight their input requirements, strengths, and limitations to guide their practical application in triaging.

4.1. Classification of typical faults in E-motor

E-motors play an important part for the entire EV structure. The quality of e-motors may be influenced heavily on the installation, manufacturing, implementation, vibration during the motion, and other environment factors (Halem et al., 2013). Consequently, robust fault diagnosis and quality measurement of the motor are critical. In e-motors, faults are generally classified into three main categories: mechanical faults, electrical faults, and sensor faults.

4.1.1. Mechanical faults

Bearings, stators and rotors are three main components for an e-motor. Bearings failures are the most common fault, contributing to 40% to 50% (Nandi et al., 2005). The main reasons for causing bearings

failures would be poor lubrication, mechanical vibrations, improper set up of the components, corrosion, shaft misalignment (Khaneghah et al., 2023). Bearing faults can lead to excessive heat and friction, which may result in damage to surrounding components (Nath et al., 2021). If these faults are not detected promptly, they can escalate into more serious issues and potentially cause complete failure of the EV motor (Ewert et al., 2021). The broken rotor bar fault accounts for approximately 5% to 10% of motor failures (Nandi et al., 2005; Uddin and Rahman, 2015). The rotor, which spins to produce electromagnetic induction. Rotor bar faults often occur due to mechanical overstress, thermal fatigue, asymmetry in the feeding current, or design flaws (De Jesus Rangel-Magdaleno, 2021; Gundewar and Kane, 2021). These faults are closely related to those found in the stator, as both components are exposed to high electrical and thermal stresses. The stator is the stationary part of the motor that contains windings responsible for generating the rotating magnetic field. Common stator faults include insulation breakdown, winding short circuits, and thermal degradation. These issues typically arise from overloading, voltage imbalances, or prolonged exposure to high temperatures, which can lead to partial discharge or dielectric failure over time (Gundewar and Kane, 2021). The last type of mechanical fault to discuss is the Air-gap Eccentricity. Air-gap eccentricity in e-motors occurs when the rotor and stator centres are misaligned, leading to an uneven gap. It appears as static eccentricity (constant offset) or dynamic eccentricity (shifting axis during rotation). As shown in Fig. 6, when the rotor symmetry centre (OR), stator symmetry centre (OS) and rotor rotation centre (OW) coincide, presents the air gap is perfectly distributed (Pérez et al., 2025). In the static eccentricity (Fig. 6b), OS mispositions with the OR and OW. In dynamic eccentricity (Fig. 6c), OR misaligns with OS and OW. Common causes include heavy loads, material flaws, or assembly errors, resulting in magnetic imbalance, radial force distortion, and unwanted harmonics (Niu et al., 2023).

Mechanical faults appear first, so early detection and prediction are essential to prevent escalation (Niu et al., 2023). If they are not detected, mechanical issues may trigger secondary electrical faults, increase vibration and energy loss, and in the worst-case lead to complete motor failure and unplanned shutdowns (Khaneghah et al., 2023). Effective monitoring of mechanical health therefore prevents huge damages or failures and reduces downtime (Choudhary et al., 2019).

4.1.2. *Electrical faults*

Electrical faults in e-motors are primarily categorised as inter-turn short circuit and demagnetisation. These failures are commonly triggered by excessive thermal, mechanical, or electrical stresses, which can degrade the insulation and magnetic properties of internal components (Siddique et al., 2005).

Inter-turn short circuit occur when the insulation between adjacent turns in the stator winding break down, often due to overvoltage, thermal overloading, or mechanical vibration. A short between turns creates a low-impedance loop that allows surge currents to flow, generating localised overheating (Kim et al., 2010; Moosavi et al., 2015). This heat can further degrade the insulation, potentially expanding the fault to involve more turns or lead to phase-to-phase or phase-to-ground faults (Kim et al., 2012). A similar fault scenario can also occur in the rotor windings. These windings are typically insulated with materials such as glass laminate and epoxy. When exposed to excessive thermal or electrical stress, the insulation may degrade or break down, leading to rotor winding faults (Sheikh et al., 2022). In severe cases, the resulting overcurrent may also contribute to demagnetisation of the rotor's permanent magnets. Demagnetisation faults are typically induced by high temperatures, aging, reverse magnetic fields, or physical damage to the permanent magnets in the rotor. Inter-turn short circuit can exacerbate this issue by creating reverse magnetic fields that weaken the magnet's flux. Demagnetisation reduces the motor's torque output and efficiency, forcing the system to draw higher currents to compensate, ultimately increasing insulation losses and temperature, which further accelerates degradation.

If undetected, both faults can lead to cascading failures, high repair costs, and safety hazards (Khomfoi and Tolbert, 2007). Therefore, early-stage detection through reliable fault diagnosis technologies is essential (Niu et al., 2023; Sheikh et al., 2022). Identifying harmonic distortions in current signals or monitoring temperature rise and vibration patterns are critical approaches to preventing catastrophic outcomes.

4.1.3. *Sensor faults*

Various sensors, such as current, speed, and position sensors, are employed to acquire measurement signals from the equipment. They provide information and feedback for researchers to monitor the e-motor. Sensors faults happen due to device aging, mechanical vibration, overcurrent, moisture, or even some external circumstances (Choi et al., 2021). These faults including open circuit fault, gain deviation, and noise abnormality (J. H. Xia et al., 2017b). Any of these faults send wrong monitoring data to the terminal and control panel, which result in suboptimal performance and even motor's total failure (Khaneghah et al., 2023).

Table 2 summaries fault types reported in EV motors, together with their underlying causes, poential consequences, and ways in maintenance, thereby providing a foundation for condition assessment.

4.2. *Classification of typical faults in EV battery*

Unlike the faults in e-motors, failures in EV batteries can lead to direct and fast severe consequences, including aging speed, fires or explosions (Kang et al., 2020). Common faults in EV batteries fall into

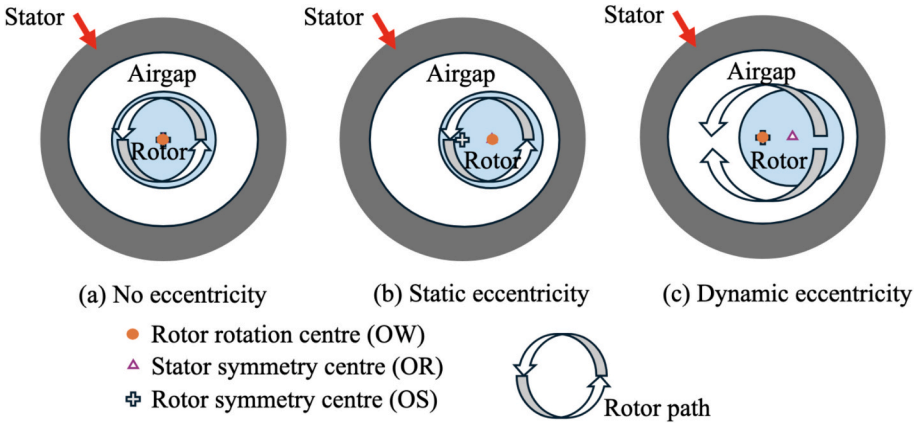

Fig. 6. Air-gap Eccentricity. (a) Healthy machine; (b) Static eccentricity; (c) Dynamic eccentricity. (Pérez et al., 2025)

Table 2
Summary of faults in e-motor.

Fault	Cause/Trigger	Consequence	Maintenance & monitoring	Reference
Bearing	Device aging, misalignment, lubrication failure, corrosion improper set-up, vibration	Excessive friction and vibration, noise, heat, total motor failure	Lubrication schedule, alignment check, vibration testing	(Ewert et al., 2021; Khaneghah et al., 2023; Nandi et al., 2005; Nath et al., 2021)
Broken rotor bar	Overstress, thermal fatigue, asymmetry in the feeding current, manufacturing flaws	Reduced efficiency, unbalanced magnetic pull, rotor heating	Periodic maintenance, components quality check	(De Jesus Rangel-Magdaleno, 2021; Gundewar and Kane, 2021; Nandi et al., 2005)
Stator	Overloading, thermal aging, voltage imbalance, insulation breakdown	Localised heating, uneven flux, phase imbalance	Insulation and polarization tests, thermal imaging, hotspot monitoring	(Gundewar and Kane, 2021)
Air-gap eccentricity	Bent shaft, bearing failure, assembly misalignment	Magnetic unbalance, vibration, mechanical stress, stator collision	Inspect alignments, air-gap measurement	(Niu et al., 2023; Pérez et al., 2025)
Inter-turn short	Insulation degradation, thermal cycling, vibration, overvoltage	Local heating, reduced insulation, risk of cascading failure	Temperature monitoring, phase current balance monitoring	(Kim et al., 2012, 2010; Moosavi et al., 2015; Sheikh et al., 2022)
Demagnetisation	Overheating, external magnetic fields, physical impact, incorrect control	Torque loss, reduced output power, unbalanced flux distribution, overheat	Magnetisation check and maintenance, temperature monitoring	(Khomfoi and Tolbert, 2007; Niu et al., 2023; Sheikh et al., 2022)
Sensor	Aging, vibration, overcurrent, environment impacts, broken wires	Inaccurate readings, control instability, failure to detect real faults	Data check, signal validations, sensor/connector inspection	(Choi et al., 2021; J. H. Xia et al., 2017b)

three categories: mechanical faults (e.g., crushing or penetration damaging internal layers), electrical faults (e.g., overcharging, over-discharging, or short circuits) (Finegan et al., 2017; Lai et al., 2021), and system faults (e.g., sensor failure, thermal system failure). While these fault categories are common across rechargeable battery systems, including lithium-ion (Lithium Iron Phosphate, Nickel Cobalt Aluminium, Nickel Cobalt Manganese) and Nickel-Metal Hydride chemistries, the degradation mechanisms and safety implications differ substantially depending on cathode composition, energy density, and thermal stability. These faults compromise safety, performance, and lifespan of the battery system (Galushkin et al., 2018; Hendricks et al., 2015).

4.2.1. *Mechanical faults*

At the core of an EV battery system is the individual battery cell, the smallest unit responsible for storing and delivering electrical energy. These cells are inherently fragile and susceptible to mechanical damage if not adequately protected. To enhance both power output and structural integrity, multiple battery cells are connected in series or parallel to form a battery module. Several of these modules are then interconnected in series or parallel to construct the complete power battery pack. To ensure safety, EV manufacturers typically install the battery pack within the vehicle's structurally reinforced "safe zone," often located at the lower central section of the chassis (Sun et al., 2020). However, mechanical abuse such as vehicle crashes, sharp object penetration, bending, or external impacts can still lead to serious damage. These incidents may result in internal short circuits, capacity loss, or even electrolyte leakage due to cell deformation or fracture (Zhao et al., 2024).

4.2.2. *Electrical faults*

Electrical abuse refers to conditions in which a battery operates beyond its intended or safe electrical parameters. The main types of electrical abuse involve internal or external short circuit, overcharge, and over discharge (Zhao et al., 2024). The insulator separator is used to prevent the direct touching of the anode and the cathode. The failure of the separator may cause by the high temperature or the cell deformation (Huang et al., 2021). External short circuit occurs when the tabs are accidently connected by a low resistance path (Abaza et al., 2018; Lyu et al., 2019). An internal short circuit results from insulation breakdown between layers within the battery, whereas an external short circuit occurs when the positive and negative terminals of the pack make direct contact (Rheinfeld et al., 2020). Compared with internal shorts, external shorts are usually easier to detect and can cause rapid damage at an early stage (Zhao et al., 2024). Internal short circuit can also lead to a rapid surge of current within the battery cell (Ouyang et al., 2015). This may trigger thermal runaway, a chain reaction that can ultimately result in thermal events like fire or even explosion if not properly managed.

Overcharge and over discharge are two critical forms of electrical faults in EV batteries that pose significant safety and performance risks. Overcharging is often caused by inaccuracies in voltage/current measurements or SoC, and SoH estimations by the BMS (Lelie et al., 2018; Yuan et al., 2015). This leads to lithium plating on the anode, gas generation, and a rise in internal temperature, which may initiate thermal runaway and fire (Huang et al., 2019; Ouyang et al., 2018; D. Ren et al., 2018a). Over discharge, on the other hand, occurs due to prolonged energy extraction, causing copper dissolution from the current collector and migration across the separator, potentially leading to internal short circuits (Fear et al., 2018; Liu et al., 2014). Both conditions are worsened by side reactions such as solid electrolyte interphase film decomposition and cathode degradation, resulting in heat generation and electrolyte instability (Zhao et al., 2024; Zheng et al., 2016). Temperature rise from ohmic heating and exothermic reactions further accelerates failure modes and structural damage, including swelling and rupture (Coman et al., 2017; D. Ren et al., 2018a; Yuan et al., 2015). Especially when the SoC exceeds 180%, internal resistance spikes, triggering extreme thermal conditions ($>220^{\circ}C$) and violent electrolyte reactions, ultimately leading to extremely thermal runaway (Yuan et al., 2015). Therefore, managing these electrical faults is essential to ensure battery safety and prevent catastrophic failure.

4.2.3. *System faults*

System abuse in EV batteries includes faults originating from external equipment and sensor failures, particularly within the BMS. The BMS is a critical component for the safe, efficient, and reliable operation of EV batteries. It is responsible for estimating the SoC and SoH, managing thermal conditions, regulating charge and discharge cycles, ensuring cell balancing, and collecting real-time data (Hu et al., 2020). To achieve these functions, the BMS relies heavily on multiple sensors; primarily current, voltage, and temperature sensors (Samanta et al., 2021).

Thermal system failures, including fan malfunction, sensor errors, or broken fuses, can lead to overheating and thermal runaway, posing severe risks to battery safety (G. Xia et al., 2017a). Heating system faults may also occur at pack level, particularly in low-temperature operating environments where active thermal regulation is required. Inadequate or malfunctioning heating can result in low-temperature stress, reduced

ionic conductivity in the electrolyte, and suppressed lithium-ion diffusion kinetics (Bandhauer et al., 2011). Faults in either cooling or heating subsystems therefore disrupt thermal stability, accelerate degradation, and compromise both performance and safety of the battery system (Zou et al., 2023).

In addition to faults originating within the BMS and its supporting components, many failures can also be attributed to poor system design, substandard manufacturing processes, or deficiencies in electronic control units and power transmission systems (Sun et al., 2020).

Table 3 presents a summary of common EV battery pack faults, their corresponding causes, operational consequences, and maintenance requirements, highlighting key considerations for condition assessment.

4.3. Model-based condition assessments

This section introduces model-based approaches for assessing the condition of e-motors. Condition monitoring enables early detection of faults in EV components and supports maintenance decisions in industrial settings (Choudhary et al., 2019). The following subsections summarise the main methods used for EV assessment.

4.3.1. Vibration analysis

Vibration analysis captures abnormal mechanical behaviour from machine components to detect faults in motor components such as bearings (e.g., pitting, spalling), rotors (e.g., unbalance or eccentricity), and housings, where physical deterioration alters the dynamic response of the system (Althubaiti et al., 2022). There are two primary sources of vibration in e-motors: mechanical (e.g., structural misalignments, coupling issues) and electromagnetic (e.g., radial/tangential forces from rotor-stator interactions) (Tsypkin, 2011). While vibration analysis offers high sensitivity, and the ability to localise faults, it is not without limitations. It may suffer from signal contamination due to structural coupling and ambient mechanical noise, which complicates the isolation of fault-specific features (Khaneghah et al., 2023).

Installing sensors to perform vibration analysis can be expensive, and difficult in compact environments, and signal accuracy may degrade due to long propagation paths and interference from nearby components (Niu et al., 2023). Even ideal systems show baseline vibrations caused by surface roughness or structural imperfections. These vibrations often originate from components like bearings, rotors, or shafts, and require advanced signal processing. The Kurtosis technique could capture impulsive features effectively, enabling it to recognise vibration signals that indicate early fault occurrence (Howard, 1994). Kurtosis method has proven effective in distinguishing between inner and outer race defects under 1450 rpm operating condition (Othman, 2016). With the support of data-driven approaches in analysing the wind turbine shaft bearings, Kurtosis and peak to peak methods have confirmed robust to the noise and effective for detecting early faults (Saidi et al., 2017). Time frequency domain analysis captures features that manifest within specific frequency bands (Xu et al., 2020). Since each fault associated with a characteristic frequency that reflects its unique dynamic behaviour, calculating the frequency intervals between each cycle can provide valuable indicators for identifying fault types (Althubaiti et al., 2022).

While vibration analysis excels at detecting mechanical faults like bearing wear, it struggles with early-stage insulation degradation. Consequently, Acoustic Emission has emerged as a complementary technique for capturing these incipient stress waves.

4.3.2. Acoustic emission (AE) monitoring

AE monitoring is a non-invasive condition monitoring technique used to detect early-stage faults in electrical rotating machines by capturing stress waves generated from material deformation within components. AE systems typically consist of sensors mounted on the surface of the components to detect ultrasonic or audible stress waves generated by the material deformation (Kim and Parlos, 2002). These signals are converted into electrical outputs by transducers and subsequently analysed to identify fault characteristic such as crack initiation, surface wear, or impact damage. This method is especially suitable for detecting bearing-related faults, rotor damage, and stator insulation breakdowns, due to the high sensitivity of AE signals to structural changes (Choudhary et al., 2019; Glowacz and Glowacz, 2017). AE signals can be analysed in both time and frequency domains, and advanced classification methods such as support vector machines, and artificial neural network (ANN) have been employed for feature extraction and fault categorisation (Gundewar and Kane, 2021).

AE analysis is particularly effective in low speed bearing fault detection, where traditional signals may be less informative. However, the oscillatory and complex nature of AE signals make them susceptible to noise from the operating environment, which may influence diagnostic accuracy (Lang et al., 2022). Nonetheless, combining AE with vibration or electrical measurements has shown to improve fault localisation and robustness under variable loading conditions (Stief et al., 2019). Despite some limitations, AE remains a valuable method in fault diagnosis, especially for incipient fault detection in bearings and gears, and is increasingly explored alongside other signals to enhance diagnostic performance.

4.3.3. Motor-current signature analysis (MCSA)

MCSA is an effective technique for fault diagnosis and condition assessment that helps detect early defects in e-motors and implement some maintenance to prevent further deterioration. MCSA captures and analyses the stator current signal, which reflects the internal dynamics

Table 3
Summary of faults in battery pack

Fault	Cause/Trigger	Consequence	Maintenance & monitoring	Reference
Mechanical	External impact, crush, vibration, sharp penetration, bending	Cell deformation, internal short circuit, gas leakage	Physical inspection, fault diagnosis	(Sun et al., 2020; Zhao et al., 2024)
Electrical	Overcharge, over discharge, internal/external short circuit, thermal stress	Heat generation, electrolyte breakdown, separator failure	BMS-data carefully monitoring	(Abaza et al., 2018; Coman et al., 2017; Fear et al., 2018; Hu et al., 2020; Huang et al., 2019, 2021; Lelie et al., 2018; Liu et al., 2014; Lyu et al., 2019; Ouyang et al., 2018, 2015; D. Ren et al., 2018a; Rheinfeld et al., 2020; Yuan et al., 2015; Zhao et al., 2024; Zheng et al., 2016)
Sensor (system)	Temperature/current/voltage sensor failure, poor BMS calibration	Incorrect SoH/SoC, false triggers, overheat or overcool	Sensor maintenance, validation logic needed	(Hu et al., 2020; Samanta et al., 2021; Tran and Fowler, 2020, 2019)
Thermal management (system)	Cooling system: Broken fan, stuck valve, coolant leakage Heating system: Heater malfunction, control relay failure, wiring fault	Overheat, non-uniform temperature distribution Low-temperature stress, internal short circuit	Thermal balance monitoring, maintenance	(Bandhauer et al., 2011; G. Xia et al., 2017a; Zhou et al., 2025)

of the motor. Electrical and mechanical faults such as broken rotor bars, eccentricity, air-gap imbalances, and bearing defects manifest as harmonic distortions or sidebands in the motor current spectrum (Bonet-Jara et al., 2021; Lang et al., 2022).

MCSA's major strengths lie in its non-invasive nature, cost-effectiveness, and suitability for continuous, real-time monitoring under steady-state conditions. It requires no direct mechanical contact with components, making it highly suitable for inaccessible or harsh environments (Bonet-Jara et al., 2021). However, MCSA does present some drawbacks. MCSA is sensitive to power supply variations and requires expertise to accurately interpret spectral features. Additionally, the results are susceptible when face with multiple faults within e-motors (Choudhary et al., 2019).

To overcome these limitations, recent advancements combine MCSA with other sensing or processing techniques. For example, integration with vibration signals has been shown to improve fault classification accuracy, particularly in bearing fault detection (Yakhni et al., 2023). To enhance diagnostic resolution, particularly for non-stationary signals, wavelet-based time-frequency analysis methods such as MCSA-based package decomposition (Teotrakool et al., 2009), MCSA-based continuous wavelet transform (Granda et al., 2017), and MCSA-based short-time Fourier transform (Antonino-Daviu et al., 2018), are employed. These methods offer better time localisation and fault isolation by adapting to variations in signal behaviour under fluctuating loads (Niu et al., 2023).

In practical applications, MCSA has demonstrated high success in early fault detection across domains such as petrochemical plants, automotive systems, mining, and power generation. Its compatibility with sensor fusion and machine learning models ensures it remains a cornerstone of modern condition monitoring systems, especially when enhanced through adaptive algorithms and comprehensive diagnostic frameworks (Singh et al., 2014).

4.3.4. Extended kalman filter (EKF)

EKF is a widely used model-based approach for estimating battery terminal voltage and diagnosing electrical or sensor faults. Unlike the standard Kalman filter that is created to detect sensor faults for linear and Gaussian systems, EKF handles nonlinear dynamics and is therefore suited to battery state estimation and sensor fault diagnosis (Foo et al., 2013; Liu and He, 2015; Sidhu et al., 2015). During operation it can track state degradation and changes in internal resistance, use these to estimate SoC and generate residuals. By exploiting correlations of SoC across adjacent cells, the model can detect short circuit faults under dynamic conditions (Lai et al., 2020; Pradhan and Chakraborty, 2022).

EKF also has high SoC accuracy prediction when open circuit voltage and internal resistance data are available and has been applied to on-board short circuit detection by comparing measured voltages with EKF estimated state of charge (Tian et al., 2023; Yang et al., 2020b). To address model and measurement uncertainty, adaptive EKF methods pair online parameter identification (for example, Recursive least squares for the equivalent circuit model) with automatic adjustment of noise statistics by adapting the prior error covariance, which enables real time tracking of parameter drift and noise and yields more accurate and robust SoC estimation (He et al., 2020).

4.3.5. Evaluation of each model-based condition assessment method

The selection of fault diagnosis methods must balance accuracy, speed, cost, and data complexity to enable real-time, automated decision-making. Vibration analysis offers high sensitivity for detecting mechanical faults such as bearing defects and rotor imbalance, making it suitable for early-stage triaging. However, it requires high-quality sensors and advanced signal processing, which may complicate implementation in automated systems. AE is valuable for detecting incipient faults in components like bearings and stators, but its performance can degrade under environmental noise, limiting its reliability as a standalone method in robotic platforms. MCSA stands out for its non-invasive, low-cost monitoring and is especially effective for electrical fault detection. It's applicable in detecting many mechanical faults inside the e-motor components. Its ease of integration with robotic systems makes it a strong candidate for continuous triaging. EKF measures the SoC of EV batteries from inputs such as terminal voltage, current, and temperature. It achieves high accuracy in detecting electrical and sensor faults because it models nonlinear system dynamics and is robust to measurement noise.

Table 4 provides commonly used EV motor model-based condition assessment methods used in terms of inputs, outputs, cost, time consumption, and detection accuracy.

4.4. Data-driven condition assessments

Data-driven method is implemented using machine learning models that learn from data collected from the EV components. These models require significant computational power for training and testing. During training, the model learns patterns from historical data and is then able to make predictions independently. Unlike traditional model-based approaches, data-driven methods are easy implemented and do not require prior domain knowledge (Lahdhiri et al., 2019). They have gained widespread popularity due to their accuracy and flexibility (Choudhary et al., 2019). Data-driven methods take extensive historical data from the system, using machine learning or advanced statistical modelling to learn patterns and make proper predictions (Dai and Gao, 2013; Gao et al., 2015). In practice, many types of data-driven models are currently used for fault diagnosis and condition monitoring (Saufi et al., 2019). It begins with gathering sensor data from products in both faulty and healthy conditions. This data is then cleaned and analysed to extract meaningful patterns, which are used to train advanced machine learning models capable of accurately identifying and classifying faults.

4.4.1. Data-driven models

Data-driven models are increasingly used to identify faults in EV because they exploit large data sets and strong pattern recognition. As with model-based methods in detecting faults in e-motors, many techniques target specific components or input features (Mehrjou et al., 2011). Acoustic and vibration signals are sensitive to the bearing fault detection (Stief et al., 2019). Electrical signals are more sensitive to the broken rotor bar faults. By combining multiple sensor types and derived features, a condition monitoring system can cover a wider range of fault modes (Stief et al., 2019). For example, a pipeline that couples principal component analysis with a two stage Bayesian sensor fusion framework predicts EV faults with low error across stator, rotor, and broken bar cases. A key benefit is transparency: the global prediction can be traced back to the contributing sensor inputs to see how each sensor responded to a fault. Another study built a multi feature hybrid fusion data-driven model combined with a Random Forest classifier to detect EV battery electrical faults from raw real world daily charge and discharge data (Yifan et al., 2024). The Random Forest grouped cases into different fault categories such as internal short circuit, electrolyte leakage, and overcharge, achieving about 95% overall accuracy in diagnosis.

Neural networks are also widely used in data driven approaches. Computational intelligence techniques have proven effective for automatic diagnosis and fault identification in electrical rotating machines. A multilayer neural network combined with MCSA is applied to detect inter turn short circuit faults: the network learns from motor current signals across different fault severities and load levels, using harmonic and interharmonic features extracted by MCSA to infer the fault condition (Mejia-Barron et al., 2021). The model achieved a goodness of fit above 90 percent on the training cases and above 80 percent on the interpolated case. Convolutional neural network (CNN) can predict demagnetisation faults in e-motors directly from raw stator current data (Skowron et al., 2022). Because cell-level current sensors are often impractical due to space and cost constraints, an ANN was developed to estimate external short circuit cell current from cell-level voltage

Table 4
Comparative summary of e-motors fault diagnosis methods

Method	Input signals	Outputs signals	Time consumption	Cost	Detection accuracy	Reference
Vibration analysis	Vibration-displacement, velocity, acceleration	Time / frequency fault signatures	Moderate – High (depends on the signature processing)	Medium – high (require precise sensors)	Affected by noise (high for mechanical faults)	(Howard, 1994; K.A. Severson et al., 2019; Othman, 2016; Qiu et al., 2002; Ren et al., 2018b; Saidi et al., 2017; Xu et al., 2020)
AE	Ultrasonic / acoustic stress waves	Stress waveform patterns and frequency features	Moderate (sensitive to signal noise)	Medium (AE sensors and analysis tools)	High for incipient faults; less reliable alone	(Gundewar and Kane, 2021; Hongwen He et al., 2011; Jena and Panigrahi, 2015; Kim and Parlos, 2002; Lang et al., 2022; Stief et al., 2019)
MCSA	Stator current signal (time/ frequency domain)	Harmonic content, sidebands, fault frequencies	Low (Fast Fourier Transform -based real -time monitoring)	Low (non-invasive and easy setup)	High for electrical faults; robust with fusion	(Antonino-Daviu et al., 2018; Bonet-Jara et al., 2021; Granda et al., 2017; Singh et al., 2014; Teotrakool et al., 2009; Yakhni et al., 2023)
EKF	Terminal voltage, current, temperature, equivalent-circuit model parameters (identified online)	SoC, predicted terminal voltage	Low – Moderate (recursive real-time for on-board use)	Low (using existing BMS sensors and software)	High for electrical and sensor faults; robust to noise with adaptive EKF	(Foo et al., 2013; He et al., 2020; Lai et al., 2020; Liu and He, 2015; Pradhan and Chakraborty, 2022; Sidhu et al., 2015; Tian et al., 2023; R. Yang et al., 2020b)

measurements. The estimated current is then fed into a 3D electro-thermal model to predict the temperature rise and the spatial temperature distribution (Ruixin Yang et al., 2020). Moreover, to detect e-motors fault without additional sensors, an autoencoder with K mean algorithm was developed to detect any demagnetisation faults (Chang et al., 2020). Extending these learning-based diagnostics to industrial robotic applications, another article proposes an attention guided feature aggregation neural network for servo motor bearing fault diagnosis on industrial robots. This model uses bearing condition signals collected during simple and welding motions, with the attention module emphasising fault relevant features to keep accuracy high across operating scenarios (Raouf et al., 2024). Additionally, using time domain features extracted from vibration signals, support vector machines and proximal support vector machines classifiers assign each record's feature vector to the corresponding bearing fault class (Sugumaran and Ramachandran, 2011).

In the context of triaging systems, the final fault detection of EoL products must be both fast and accurate. Therefore, data quality plays a critical role, as it directly affects the ability to detect faults in e-motors. To ensure reliable inputs, sensors should be directly implemented to capture essential signals. Additionally, the complexity of acquiring and processing these inputs should not be overlooked.

Data-driven methods, such as machine learning or deep learning, provide the highest diagnostic accuracy and adaptability across fault types and subsystems. Yet, they are resource-intensive and dependent on large, labelled datasets, challenges that conflict with the real-time and low-latency requirements of triaging (Ruixin Yang et al., 2020a; Yifan et al., 2024).

4.4.2. SoH and SoC estimating for EV battery

Like the e-motors, the parameters used for battery fault detection are usually voltage, current and temperature. However, EV faults are mainly mechanical or electromagnetic and show up in vibration or current signatures, battery packs are dominated by electrochemical aging and cell imbalance, so diagnostics centre on evolving states such as SoC and SoH (Rezvanizaniani et al., 2014). SoC represents the remaining charge in the battery related to its capacity (Lin et al., 2015), while SoH quantifies the battery's degradation over time and its ability to store and deliver energy reliably (Xiong et al., 2018b). These two parameters directly represent the condition of the battery, and they are continuously monitored and managed by the BMS (Gabbar et al., 2021), which serves as the central controller for safety and reliability. In recent years, a wide range of methods, particularly machine learning and deep learning approaches, have been employed to estimate SoH and detect faults within the battery system effectively.

The following section introduces definitions of SoC and SoH, and reviews key techniques proposed in previous literatures to enhance the accuracy in battery condition predictions.

4.4.3. Measurements of SoC and SoH

The BMS utilises collected operational parameters to estimate the two essential health indicators: SoC and SoH. These parameters directly influence battery performance, safety, and lifecycle planning, making them central to intelligent battery management (Kumar et al., 2023). The SoC is typically calculated using two fundamental approaches, depending on context and accuracy requirements. One widely used equation (Shrivastava et al., 2019) is:

$$SoC = \frac{C_{\text{Remaining}}}{C_{\text{Initial}}} \times 100\% \tag{1}$$

This capacity-based method expresses SoC as the proportion of present accessible charge capacity $C_{\text{Remaining}}$ the battery's original maximum charge capacity C_{Initial}. It is simple and effective when capacity is measurable through full charge–discharge testing, making it ideal for offline diagnostics or benchmarking studies. However, this approach is less suitable for real-time estimation during dynamic EV operation because accurate knowledge of both initial and remaining capacity is often unavailable or imprecise in real-world driving conditions (Shrivastava et al., 2019). For real-time applications, another widely used method is current integration (also known as the Coulomb counting method), where SoC is estimated (Espedal et al., 2021) via:

$$SoC = SoC(0) + \int_0^t \frac{\eta_i I(t) d(t)}{C_{actual}} \tag{2}$$

In the equation (2), i is the instantaneous current, t is time, η is the coulombic efficiency, and the initial SoC is denoted $SoC(0)$. This method tracks the accumulated current input or output over time but suffers from drift and cumulative errors, especially when current sensors are noisy or when the battery exhibits non-linear degradation behaviour (Dini et al., 2024; Zhang et al., 2016). Both methods are employed by BMS platforms depending on the operating context and accuracy requirements.

SoH quantifies the battery's overall condition relative to a new battery, often defined using parameters such as capacity degradation and internal resistance increase (Yao et al., 2021). The equation of SoH (Pradhan and Chakraborty, 2022) according to the capacity of the battery (Ampere-hour counting) is defined as follows:

$$SoH = \frac{Q_{max}}{Q_n} \times 100\% \tag{3}$$

Where Q_{max} is the maximum available capacity, the battery can now hold and Q_n is the nominal capacity when the battery is manufactured.

Lower SoH values indicate increased aging, reduced power output, and limited driving range (Yao et al., 2021). However, accurately measuring battery capacity requires full charge–discharge cycles, which makes the process highly time consuming. Also, it is often difficult to measure capacity with high precision, since a fully charged state cannot be maintained for long (Pradhan and Chakraborty, 2022). In addition, estimating the remaining available capacity relies on advanced electrical probes and can be affected by external factors such as temperature and humidity (Ng et al., 2009). Therefore, more precise methods are required for reliable assessments.

The BMS, as introduced earlier, not only provides the framework for collecting voltage, current, and temperature data but also facilitates the estimation of SoH and SoC. Following the mathematical formulations and definitions discussed, some recent techniques with the using of AI, especially model-based and data-driven methods that leverage this sensor-acquired data to estimate battery condition more precisely under diverse operating scenarios.

Model-based estimation approaches integrate electrochemical knowledge with real time measurements to infer internal battery states. Many of researchers adopt Equivalent circuit model (ECM) or simplified electrochemical model combined with adaptive observers, typically the EKF, to recursively update state variables from current and voltage measurements (How et al., 2019). For example, Thevenin type ECM frameworks estimate SoC by updating internal states such as open circuit voltage and resistance and mapping open circuit voltage to SoC through predefined curves, with filtering used to suppress nonlinearity and measurement noise (Tian et al., 2023). Other work extends this structure by allowing parameters to vary with SoC, temperature, and ageing, enabling indirect SoH inference through resistance growth and capacity fade trends, often implemented via regression or look up tables (Tran et al., 2021).

More physics-oriented variants incorporate frequency or differential features. Electrochemical impedance spectroscopy (EIS) based methods extract impedance signatures and classify degradation states from characteristic Nyquist features (Locorotondo et al., 2021), while Incremental Capacity Analysis (ICA) links voltage capacity derivatives to degradation mechanisms for SoH estimation (Gismero et al., 2023). Although these approaches enhance interpretability and physical consistency, they depend on model structure fidelity, laboratory characterisation, or excitation requirements that may constrain scalability in real world triaging contexts.

Model-based methods can deliver accuracy, and real-time SoC and SoH estimates and are often highly adaptable because they are grounded in strong physical and knowledge (Cacciato et al., 2017). However, this reliance on detailed modelling can also be a limitation since the model typically must be re-identified and tuned for each specific chemistry, design, and manufacture to maintain reliable performance. In addition, deriving the required parameters can be highly time consuming, especially when extensive testing is needed for calibration and validation (Xiong et al., 2018a).

Compared to model-based approaches, data-driven methods do not depend heavily on prior knowledge of battery electrochemistry or ECM. Instead, they leverage patterns learned directly from large volumes of sensor data to estimate battery health states (Chemali et al., 2018). This makes data-driven techniques especially suitable for complex or nonlinear systems where physical modelling may be difficult or computationally expensive (Ghadami and Epureanu, 2022).

Supervised data driven approaches bypass explicit electrochemical model by learning direct mappings between measurable signals and degradation indicators. Using cycling datasets such as the Sandia data, regression models trained on voltage, current, temperature, and capacity measurements demonstrate that SoH can be inferred from operational data alone, provided sufficient labelled histories are available (Das et al., 2024). Deep learning frameworks extend this logic by incorporating cycle indexed voltage features and charging protocol variables to jointly estimate SoH, SoC, and EoL, indicating that neural networks can capture nonlinear degradation trajectories under heterogeneous charging regimes (Pepe and Ciucci, 2023). However, predictive performance remains contingent on dataset diversity and the representativeness of training conditions. More recent work exploits temporal and spatial feature extraction within convolutional architectures. Sliding window segmentation of raw cycling signals enables CNN models to learn degradation signatures without manual feature engineering (Cao et al., 2025). Transfer learning strategies further address cross battery variability by adapting pretrained CNN models to new cells using domain alignment techniques such as maximum mean discrepancy, reducing the need for extensive labelled data in early cycles (Ma et al., 2024). Building on these developments, machine learning frameworks using user behaviour assisted hierarchical features have also been applied to estimate SoH from large scale real world fast charging EV data (Zhang et al., 2025). Similarly, a constant current charging time attenuation labelling method has been proposed for SoH estimation under real operating conditions without requiring full-life degradation experiments (Li et al., 2025). Table 5 summaries the key differences between model-based and data-driven approaches for battery SoC and SoH estimation.

Practical deployment requires consideration of total diagnostic time, defined as the combined duration of signal acquisition and computational processing.

$$T_{diagnositic} = T_{acquistion} + T_{processing} \tag{4}$$

For high throughput triaging lines, decision latency must remain within seconds to, at most, one minute per component. Techniques requiring controlled electrochemical cycling or frequency sweeps inherently violate this constraint.

ICA requires low-rate charge discharge cycling to generate stable differential capacity curves (Dubarry et al., 2012). Given that a full cycle at 0.5C requires approximately two hours of C-rate, acquisition time alone exceeds industrial feasibility. Similarly, hybrid pulse power characterisation (HPPC) (Christopherson, 2015), involves repeated

Table 5
Methodological comparison of model-based and data-driven SoC / SoH estimations.

Category	Model-based	Data-driven
Examples	ECM EKF ICA Multi-condition ECM EIS	SVR, Decision tree, Random Forest CNN Transfer learning
Features required	Terminal voltage Current Internal resistance (R_0, R_1, etc.) SoC (as threshold) Impedance spectrum (EIS) Capacity fade trend	Voltage and current time-series Temperature Cycle number Capacity Charging protocol (e.g., C-rate, SoC thresholds)
Input role in triaging	Requires high-quality signal processing Suitable for systems with fixed sensing architecture Direct mapping to fault parameters (e.g., internal resistance)	Flexible input forms (raw/segmented data) Enables automatic feature extraction from diverse sensors Can adapt to new component types with re-training
Advantages	Physics-informed and interpretable Robust under known conditions Well-suited for real-time systems	Can handle complex, nonlinear degradation Learns directly from raw data Highly generalisable with sufficient data
Limitations	Requires model calibration for each battery type Sensitive to parameter drift May struggle with variable degradation modes	Requires large, labelled datasets Interpretability can be limited Needs careful preprocessing and validation to avoid overfitting

pulse rest sequences across multiple SoC, leading to acquisition durations on the order of tens of minutes. In contrast, observer-based approaches such as ECM combined with EKF operate recursively on streaming voltage and current signals and are routinely implemented in commercial battery management systems with millisecond-level update rates (Xu et al., 2020). Their acquisition requirement is limited to operational data rather than dedicated cycling protocols, making them suitable for real-time triaging environments. Similarly, trained machine learning models (Random Forest, CNN) exhibit negligible inference latency once deployed, with processing times typically below one second on standard industrial hardware (K.A. Severson et al., 2019; Ren et al., 2018b). Their suitability therefore depends primarily on data availability rather than computational speed. Table 6 therefore shifts the comparison from methodological characteristics to deployment feasibility under industrial triaging constrains.

Table 6 summarises the practical feasibility of the reviewed methods for the triaging. The table shows that industrial suitability depends primarily on whether a method can operate on readily available operational data without requiring dedicated cycling or frequency sweep tests. Methods such as ECM and trained machine learning models are therefore more compatible with high throughput triaging than ICA, HPPC, or EIS.

5. Discussion

Building on the preceding review, the proposed Diagnostic-to-Decision Framework can be understood as an integrated structure with three connected layers. The first layer is the diagnostic layer, which includes fault diagnosis, condition assessment, and residual performance evaluation to determine the technical state of the component. The second layer is the decision layer, in which diagnostic outputs are interpreted and mapped to appropriate circular economy pathways such as reuse, repair, remanufacture, repurpose, or recycling. The third layer is the execution layer, which determines the appropriate degree of human or machine involvement in routing and action. In this way, the framework extends beyond diagnosis alone and provides a structured route from technical evidence to practical EoL decision-making.

Critically, the functionality of a triaging system demands both speed and precision. In a high-throughput EoL processing environment, manual inspection and human-mediated decision-making introduce latency, subjectively, and scalability constraints that directly undermine the economic viability of CE recovery. To achieve the rapid, consistent, and evidence-based routing illustrated in Table 6, some degree of autonomy, whether partial or full, is not merely advantageous but necessary. The central challenge, therefore, is no longer whether to automate, but rather what to automate, how much autonomy is appropriate for each decision type, and how to encode engineering diagnostic data into prescriptive CE rules.

The following subsections address these challenges in three parts. Section 5.1 proposes a formal, context-specific definition of autonomy for EoL EV components triaging. Section 5.2 operationalises this autonomy framework through a comprehensive decision matrix that maps diagnostic signatures to CE pathways and corresponding autonomy expected levels. Section 5.3 then synthesises the key barriers and research gaps that constrain the realisation of fully autonomous triaging today.

5.1. Defining autonomy for EoL EV component triaging

Within the proposed framework, autonomy is not treated as a separate concept, but as the execution mechanism through which diagnostic and decision outputs are implemented. Different component conditions, uncertainty levels, and economic consequences require different degrees of human oversight. The autonomy taxonomy therefore defines how responsibility is distributed between AI-based diagnosis, human judgement, and physical routing. Actions, and serve as the governance layer of the framework. The concept of autonomy in EoL component triaging requires clarification, as existing framework such as SAE J3016 (*SAE*, 2021) and Industry 4.0 automation taxonomies are designed for vehicle operation and manufacturing control respectively, and do not directly translate to post use value recovery decisions. Based on the review of existing diagnostic capabilities and manual interventions, we synthesise a four-level taxonomy (Table 7) to categorise the current state of art, defined by the locus of diagnostic interpretation, CE pathway selection, and physical execution. Detailed definitions for each level are provided within the Table 7.

Within this triaging context, autonomy is not binary but graduated; different fault types, component conditions, and economic consequences warrant different levels of machine involvement. The framework explicitly separates decision support, where the human retains full authority, from conditional and full autonomy, where the machine proposes or executes the CE pathway. This distinction is critical because triaging decisions carry significant economic and safety implications that may necessitate human validation even when diagnostic data is reliable. Together, these principles provide the foundation for assigning autonomy levels to specific diagnostic outcomes in the decision matrix that follows.

5.2. A diagnostic to CE decision matrix for autonomous triaging

The autonomy framework established in Table 7 defines how responsibility can be allocated between human and machine, but it does not specify when each level is appropriate, or which diagnostic outcomes should trigger which CE pathways. To operationalise autonomous triaging, these gaps must be bridged by an explicit decision logic that connects the technical evidence of component condition to specific circular economy actions. Table 8 represents the core operational element of the proposed Diagnostic-to-Decision framework. It translates diagnostic signatures, severity classifications, and condition outputs into

Table 6
Industrial feasibility assessment of diagnostic categories for autonomous triaging.

Category	Method	Sensing Type	Acquisition Mode	Dedicated Test Required	Acquisition Duration Nature	Processing Complexity	Industrial Sustainable (T/F)
Model-Based	ECM	Electrical (V, I)	Operational data	No	Continuous, real-time	Low	TRUE
	EKF	Electrical (V, I)	Streaming data	No	Real-time recursive	Low–Moderate	TRUE
	ICA	Electrical (V, Q)	Controlled cycling	Yes	Full/partial low-rate cycle required	Low (post-process)	FALSE
	HPPC	Electrical (Pulse V, I)	Pulse–rest protocol	Yes	Multi-stage protocol across SoC	Moderate	FALSE
	EIS	Electrochemical (Impedance)	Frequency sweep	Yes	Low-frequency excitation required	Moderate	FALSE
Data-Driven	Random Forest/ Decision tree	Electrical time-series	Historical/ operational	No	No additional testing	Low	TRUE
	CNN	Time-series / Image	Historical/ operational	No	No dedicated electrochemical test	Moderate	TRUE

Table 7
Human-robot interaction levels for EoL EV components triaging (Beer et al., 2014; Kim et al., 2024; Lima Junior et al., 2025; Sheridan and Verplank, 1978; Xu et al., 2024)

Level	Designation	Diagnosis	Physical routing	Uncertainty / Failure protocol	Description
L4	Fully autonomous	Machine (AI classifier)	Machine (Robotic sortation)	Human may override	Robots decide and act automatically without the needed of human intervention.
L3	Conditionally autonomous	Machine (AI classifier)	Human (Operator validates and authorises)	Decision held until human confirmation received	Robots propose, human approves. Used where decision rules are well-defined, but execution risk (safety, cost, liability) warrants human oversight.
L2	Semi-autonomous (Decision support)	Machine (Feature extraction)	Human (Operator executes or instructs robot)	Machine provides recommendation and confidence score, human may override	Robots suggest, human decides. Used for complex, multi-modal faults, or where economic/regulatory factors require expert judgement.
L1	Manual	Human (Expert inspection)	Human (Manual handling)	Full expert control	Human performs all tasks. Used for catastrophic damage, novel fault modes, or low / high value components.

specific circular economy routing options and corresponding autonomy levels. In contrast to much of the existing literature, which often terminates at fault identification, this matrix explicitly links technical evidence to downstream decision outcomes. Therefore, it functions as the decision layer of the framework, bridging the gap between diagnosis and actionable triaging.

In practical terms, the framework operates by first identifying the fault type and severity of a given component, then interpreting the likely residual functional value, and finally assigning both a recommended CE pathway and an appropriate level of human-machine involvement. To apply this framework to other EoL components, researchers should define relevant fault modes, select validated diagnostic methods, establish severity thresholds reflecting degradation progression, and assign CE pathways and autonomy levels using the same value-based and responsibility-based logic.

5.3. Critical barriers and opportunities

The decision matrix presented in Table 8 consolidates over fifty diagnostic entries spanning two decades of condition monitoring research. In constructing this matrix, however, a recurring pattern became evident: while the technical literature provides rich and well validated methods for detecting and classifying faults, it almost entirely terminates at the point of diagnosis. Few studies extend their findings to recommend what should be done with a component once its condition is known. This is significant because high diagnostic accuracy alone does not complete the triaging process; the diagnostic result must be converted into a downstream recovery action if it is to support CE rather than stand-alone inspection practices. This reflects a broader shift in the field where earlier research was largely driven by diagnostic accuracy, while current industrial and sustainability demands increasingly rapid, reliable, and scalable EoL decision making into CE outcomes. The gap between diagnostic capability and CE decision execution is therefore not merely a missing detail, but the central barrier to autonomous triaging. The subsections below disaggregate this barrier into three specific challenges: data scarcity, threshold standardisation, and economic acceptance.

5.3.1. Data scarcity paradox - limited availability of EoL EV components for data-driven decision making

This limited availability of EoL components and degradation data creates a fundamental challenge for developing reliable triaging systems, particularly at the early stage focused on fault detection and condition assessment. It also motivates the discussion that follows, where data scarcity is used as a lens to compare data-driven and non-data-driven approaches. Data-driven methods typically require extensive and diverse datasets spanning operating conditions, manufactures, component variants, and fault modes, while model-based methods can operate with less training data but depend on accurate modelling assumptions and calibration. The same issue constrains e-motors life extension in practice, since a key barrier to reuse and remanufacture is the lack of dependable information about the condition of returned motors, for example whether the unit suffers a mechanical fault such as a damaged shaft or an electrical fault such as insulation degradation, which increases uncertainty in both diagnosis and CE pathway selection.

5.3.2. No proper threshold in choosing the optimal CE pathway

Although e-motors can, in principle, follow multiple circular pathways, robust selection remains difficult for large e-motors because EoL decision-making still depends on detailed condition information and agreed thresholds. This scenario happens on the EV battery as well because the degradation of the battery is driven by coupled chemical and electrochemical mechanisms that require nuanced health assessment beyond simple capacity loss. Existing work has proposed several promising approaches, including discrete event simulation to evaluate battery remanufacturing as spare parts by decoupling battery and vehicle lifetimes (Huster et al., 2022). Other efforts compare reuse and recycling and commonly suggest that packs within a 70% - 80% SoH window may be suitable for second-life applications. However, the literature also shows that SoH alone is not a decisive indicator of 'fitness for purpose': an electro-thermal aging model that re-examines the widely used 70% SoH threshold reports that many cases still perform adequately below level, and that limiting mechanisms differ by pack size and duty cycle (Etxandi-Santolaya et al., 2024). As a result, practical questions such as whether a battery at 68% SoH should be repurposed, remanufactured, repair, or recycled do not have universally agreed answers, and current practice still tends to default toward recycling because it has clearer pathways and compliance structures.

Overall, although many publications describe individual CE strategies and some offer pairwise comparisons for EV batteries and motors, there is still no unifies, condition aware decision solution that links diagnostic outputs with economic and environmental criteria to select the optimal CE pathway under real operating uncertainty. This absence of clearly defined, context dependent decision thresholds directly limit the effectiveness of intelligent triaging, because diagnosis results cannot be mapped consistently to CE actions. Therefore, further research is needed to develop robust decision support frameworks that translate rich condition assessment data into explicit application specific thresholds and decision rules, enabling consistent and optimal CE routing across diverse battery designs, usage histories.

5.3.3. Economic trade-offs and customers dependent decision-making

A final but critical challenge in implementing effective triaging for EV components lies in the economic feasibility and user acceptance of the proposed circular economy strategies. Even if a battery or motor is technically suitable for reuse, repair / remanufacturing, repurposing, or recycling, the cost of these processes may outweigh the perceived benefit. In some cases, remanufacturing a component can be more expensive than purchasing a new part or even a new vehicle, making the circular option unattractive in practice. Moreover, this decision-making process is not only driven by technical and financial considerations, but also by customer expectations and risk perception. Some end users may

Table 8
Diagnostic to CE pathway decision matrix for autonomous triaging of EV components.

Component	Fault mode	Diagnostic method	Key diagnostic signature / Feature	Severity classification	Optimal CE pathway	Autonomy level	Reference
Motor Stator	Inter-turn short circuit	MCSA	Sideband harmonics; Third harmonic component	Incipient (Mild)	Repair (Local insulation rework)	L2	(Kotak et al., 2021; Mejia-Barron et al., 2021; Zhang et al., 2023)
		MCSA	Harmonic distortion; Current imbalance	Moderate	Refurnish (Partial rewind)	L1	(Kotak et al., 2021; Mejia-Barron et al., 2021)
		MCSA + Thermal imaging	Hotspot development; Multiple sidebands	Severe	Remanufacture (Full rewind) / Recycle	L1	(Mejia-Barron et al., 2021; Zhang et al., 2023)
	Stator insulation degradation	AE	Root mean square voltage; Burst rate; Energy content	Early stage	Condition monitoring	L3	(Choudhary et al., 2019; Glowacz and Glowacz, 2017; Kim and Parlos, 2002)
	Stator winding open circuit	MCSA / Voltage sensing	Zero current in phase; Open circuit detection	Catastrophic	Remanufacture / Recycle	L1	(Khaneghah et al., 2023; Sheikh et al., 2022)
Motor Rotor	Broken rotor bar	MCSA	Lower sidebands	Single bar broken	Reuse (Accepts if load margin permits)	L3	(Lang et al., 2022; Niu et al., 2023)
		MCSA	Multiple sidebands	Multiple bars broken (2-3)	Remanufacture (Bar replacement)	L2	(Niu et al., 2023)
		MCSA + Vibration	Broadband noise; Torque ripple	>3 bars; End-ring crack	Recycle (Material recovery)	L1	(Choudhary et al., 2019; Khaneghah et al., 2023)
	Demagnetisation	MCSA / Current monitoring	Reduced back EMF; Increased current	Mild	Repair (Remagnetise)	L2	(Khaneghah et al., 2023; Niu et al., 2023)
		CNN	Data features training; Classifications	Moderate – Severe	Remanufacture (Magnets replacement)	L3	(Skowron et al., 2022)
		Autoencoder + K-means	Reconstruction error; Cluster distance	Severe	Recycle (Material recovery)	L2	(Chang et al., 2020)
Motor Airgap	Static eccentricity	MCSA	Sidebands at Rs ± fr	Minor	Reuse (Acceptable tolerance)	L3	(Niu et al., 2023; Pérez et al., 2025)
		Vibration	2 * line frequency component	Moderate	Repair (Realign)	L2	(Khaneghah et al., 2023; Pérez et al., 2025)
	Dynamic eccentricity	Vibration	Rs ± fr components; Rotor orbit analysis	Severe	Remanufacture (Replace bearings / shaft)	L1	(Niu et al., 2023; Pérez et al., 2025)
	Mixed eccentricity	Vibration + MCSA	Multiple spectral components; Combined signatures	Critical	Recycle	L1	(Niu et al., 2023; Pérez et al., 2025)
Motor Bearing	Surface fatigue / Pitting	Vibration (Kurtosis)	High Kurtosis >4	Incipient	Repair (Regrease, monitoring)	L4	(Althubaiti et al., 2022; Othman, 2016; Saidi et al., 2017)
		AE	Burst emissions; Energy envelope	Early	Condition based maintenance	L3	(Choudhary et al., 2019; Kim and Parlos, 2002)
	Spalling / Flaking	Vibration (Envelope)	Modulated sidebands; Acceleration amplitude	Moderate	Repair (Replace bearing)	L2	(Althubaiti et al., 2022; Ewert et al., 2021; Qiu et al., 2002)
		AE	Continuous high-amplitude emission	Advanced	Remanufacture (Bearing + Seal)	L1	(Choudhary et al., 2019; Jena and Panigrahi, 2015; Kim and Parlos, 2002)
	Cage fracture	Vibration	Random impacts; Unstable phase; Broadband excitation	Severe	Remanufacture / Recycle	L1	(Khaneghah et al., 2023; Nath et al., 2021)
	Locked rotor / Welding	Current monitoring / Vibration	Startup current persists; No rotation detected	Catastrophic	Recycle	L1	(Khaneghah et al., 2023; Sheikh et al., 2022)
Motor Sensor	Offset / Gain error	EKF / Residual analysis	Residual mean; Persistent bias	Calibration drift	Repair (Recalibrate)	L4	(Choi et al., 2021; Foo et al., 2013; Liu and He, 2015; J. H. Xia et al., 2017b)
		Parameter estimation	Slowly drafting parameter estimate	Degradation	Condition based maintenance	L4/L3	(Liu and He, 2015; Sidhu et al., 2015)
	Noise / Abnormality	Signal processing	Signal-to-noise ratio degradation; Random spikes	Intermittent	Repair (Connection check)	L2	(Choi et al., 2021; J. H. Xia et al., 2017b)
	Open circuit / Stuck	BMS self-diagnostic / Voting	Constant reading; Zero variation	Hard fault	Replace sensor	L2	(Choi et al., 2021; Tran and Fowler, 2020, 2019)
	Multiple sensor failure	BMS / Voting logic	Inconsistent estimates; conflicting data	System level	Derate / Safe mode	L1	(Liu and He, 2015; Tran and Fowler, 2020, 2019)
Battery		EKF / SoH estimation	$\frac{Q_{max}}{Q_n}$, SoH > 80%	Grade A	Reuse (2nd EV)	L3	(Baars et al., 2020; Etxandi-Santolaya et al., 2024; Kotak et al., 2021; Rallo et al., 2020; Saxena et al., 2015; Yun et al., 2018)
	Capacity fade	ICA	Peak shift; Area under curve; IC curve	Grade B	Repurpose (Stationary storage)	L3	(Alfaro-Algaba and Ramirez, 2020; Etxandi-Santolaya et al., 2024; Gismero et al., 2023;

(continued on next page)

Table 8 (*continued*)

Component	Fault mode	Diagnostic method	Key diagnostic signature / Feature	Severity classification	Optimal CE pathway	Autonomy level	Reference
			distortion; SoH (60% – 80%)				Kotak et al., 2021; Rallo et al., 2020; Saxena et al., 2015)
		Multi-condition ECM	Rapid fade trend; Resistance growth; SoH < 60%	Grade C	Recycle	L2	(Etxandi-Santolaya et al., 2024; Feng et al., 2024; Kotak et al., 2021; Mrozik et al., 2021; Saxena et al., 2015)
	Internal short circuit	EKF (SoC correlation)	Voltage divergence; SoC inconsistency	Incipient	Repair (Module replacement)	L2	(Huang et al., 2021; Lai et al., 2020; Ouyang et al., 2015; Zhao et al., 2024)
		Voltage / Temperature monitoring	Sudden DV; Self discharge; Local heating	Critical	Recovery	L1	(Ouyang et al., 2015; Sun et al., 2020; Zhao et al., 2024)
	External short circuit	ANN + 3D thermal model	Estimated cell current; Temperature prediction	Severe	Isolate / Recycle	L1	(Ruixin Yang et al., 2020)
	Overcharge	BMS voltage monitoring	Voltage exceeds V_{max}	Abuse event	Inspect / Recycle	L2	(Ouyang et al., 2018; Yuan et al., 2015; Zhao et al., 2024)
	Over discharge	BMS voltage monitoring	Voltage below V_{min}	Abuse event	Inspect / Recycle	L2	(Fear et al., 2018; Liu et al., 2014; Zhao et al., 2024; Zheng et al., 2016)
	Lithium plating	ICA / EIS	Voltage plateau distortion; Impendence change	Aging-related	Derate / Repurpose	L4	(Gismero et al., 2023; Ren et al., 2018b)
	Sensor fault (BMS)	EKF / Parameter identification	Residual generation; Parameter estimation error	Various	Diagnose / Repurpose	L2	(Liu and He, 2015; Sidhu et al., 2015; Tran and Fowler, 2020, 2019)
Battery System	Thermal management system failure	Temperature monitoring	Inter cell Decision tree; Absolute temperature rise / drop	Overheat / Overcool	Repair (Fan / Pump / Coolant / Heater)	L2	(Bandhauer et al., 2011; Xia et al., 2017a; Zou et al., 2023)
		Thermal imaging	Hotspot identification; Spatial gradient	Localised	Remanufacture (Module replacement)	L1	(Khaneghah et al., 2023; Zhang et al., 2023)
	Cell imbalance	Voltage sensing	Cell voltage variance; Standard deviation	Progressive	Repair	L3	(Hu et al., 2020; Zhao et al., 2024)
	Connector / Busbar degradation	Resistance measurement	Contact resistance increases	Resistive heating	Refurbish (Clean / Tighten / Replace)	L1	(Khaneghah et al., 2023; Sun et al., 2020)

be unwilling to adopt reused or remanufactured EV components due to concerns about hidden faults, reduced performance, or long-term reliability. These psychological and safety-related hesitations create additional resistance to CE-based solutions, even when they are economically and technically sound.

This presents a multi-stakeholder optimisation challenge, where the final decision is shaped by the priorities and risk thresholds of different stakeholders. A solution that is viable in theory may still be rejected in practice due to personal, commercial, or regulatory preferences. Therefore, integrating economic viability, user behaviour, and perception-based factors into the robotic triaging system is essential to ensure that the chosen CE pathway is not only optimal but also acceptable and implementable in real-world conditions.

6. Conclusion

In the proposed triaging framework, the outputs from fault diagnosis and condition assessment provide detailed information on a component's technical state, including defect type, performance degradation, remaining useful life, and overall health status. However, there is currently no established methodology for translating this diagnosis data into a definitive CE pathway.

A comprehensive review of the steps in the triaging in the EV has been provided within this paper review including the circular economy, fault categories, condition assessment, and connections between each stage in EV. This review proposes the emerging potential of robotics-enabled triaging systems as a novel engineering pathway to support CE strategies, particularly within the context of EV components. The discussion has traced a clear progression from the environmental and technical imperatives for managing EoL EV parts, through the role of fault diagnosis and condition assessment in generating accurate, data-driven insights, to the application of CE frameworks for determining optimal recovery pathways. While substantial progress has been made individually in fault diagnosis, condition assessment, and CE strategy development, the integration of these elements into a unified, intelligent triaging system remains underdeveloped. Bridging these stages requires establishing robust methods for translating diagnostic outputs into actionable CE decisions, ensuring that the earlier technical evaluations directly inform the final sustainability outcomes.

Key challenges have been identified, including the limited availability of EoL components, the absence of standardised thresholds for CE decision-making, the computational demands and limitations of existing machine learning models, and economic or perception-based barriers that hinder adoption. These factors collectively constrain the practicality and scalability of automated triaging systems.

To advance the field, future work should emphasise the development of adaptive and multi-layered decision frameworks that account for technical, economic, and behavioural factors. The success of triaging depends not only on engineering innovation but also on the ability to create systems that are cost-effective, safe, and aligned with user expectations across the entire product lifecycle.

CRediT authorship contribution statement

Rui Li: Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Chaozhi Liang:** Writing – review & editing, Methodology. **Richard Fox:** Writing – review & editing. **Gustav Jonsson:** Writing – review & editing. **Farzaneh Goli:** Writing – review & editing. **Emel Aktas:** Writing – review & editing. **Yongjing Wang:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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