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Ai-Driven Closed-Loop Supply Chains: A Systematic Review Of Operational Mechanisms And Performance Outcomes In Battery Recycling

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Abstract

Introduction: In response to the global rise in new energy vehicles and the accompanying surge in battery waste, this study systematically reviews the integration of artificial intelligence (AI) in closed-loop supply chains (CLSC) for battery recycling. Methods: The study draws upon 134 peer-reviewed articles published from 2015 to 2025 and adopts the PRISMA framework alongside a hybrid screening protocol to investigate dominant AI technologies, performance evaluation frameworks, and key implementation barriers in battery recycling closed-loop supply chains. Findings: The findings show that deep learning and genetic algorithms dominate technical applications across CLSC stages such as recycling, disassembly, and remanufacturing, improving efficiency and reducing operational costs. However, performance assessment suffers from inconsistent metrics and limited socio-environmental integration. While AI significantly enhances material recovery and traceability, its industrial scalability remains constrained by data fragmentation, algorithmic opacity, and policy-technology mismatches. Conclusion: The study concludes by identifying critical research gaps, particularly in the areas of blockchain-AI integration and hybrid intelligent systems, and proposes future research directions to unlock the projected USD 17.8 billion market value by 2030.

Key Words: *AI; Closed-loop supply chain; Power battery; Systematic literature review.*

1. INTRODUCTION

In recent years, governments of various countries have successively introduced a number of policies to promote green economy and sustainable development. Such as China's "14th Five-Year Plan for the Development of Circular Economy" issued in 2021, the EU's "Carbon Border Adjustment Mechanism" officially effective in October 2023. Against this background, new energy vehicles have flourished. By January-February 2025, global new energy vehicle sales reached 2.28 million, a year-on-year increase of 27% (data source: Gaogong Industry Research Institute). This has also brought about a surge in battery use. By 2024, global power battery shipments have increased by more than 55% year-on-year. Power battery recycling has brought tremendous pressure on global sustainable development.According to statistics, China's new energy vehicle power batteries have entered the retirement stage since 2018 (Lai, et al., 2025). It is estimated that by 2030, the global recycling volume of retired batteries is expected to exceed 830GWh, and the market space will exceed 100 billion yuan (data source: CITIC Securities). Battery recycling management, as a sub-field of closed supply chain management, is also an important link in achieving sustainable development. Artificial intelligence can significantly improve the efficiency and resilience of closed-loop supply chains, providing new growth opportunities for enterprises' green transformation and sustainable development.

This study makes some unique contributions to the existing CLSC literature. First, through a systematic literature review, it integrates the intersection of AI, CLSC, and green economic benefits, filling an important academic gap. Second, compared with other review studies that only delve into the details of a few individual studies, this study covers a broad knowledge system with several sub-fields, providing insights from enough individual studies in each sub-field. Currently, there are few literature reviews that construct a three-level framework of "AI-battery field CLSC-performance evaluation" to explore the application of AI in CLSC. The exploration of this study helps to determine the AI application and performance evaluation framework in the CLSC battery field. Finally, based on the systematic literature review, this study proposes four research directions for future research.

The rest of this paper is shown in Figure 1 below: 2. The theoretical background of AI application and performance evaluation in CLSC in the battery field is introduced. 3. The literature data sources and data processing methods are introduced. 4. Descriptive Analyses and Explanatory Analyses are performed respectively. 5. The knowledge gaps and breakthrough directions for future research are provided.

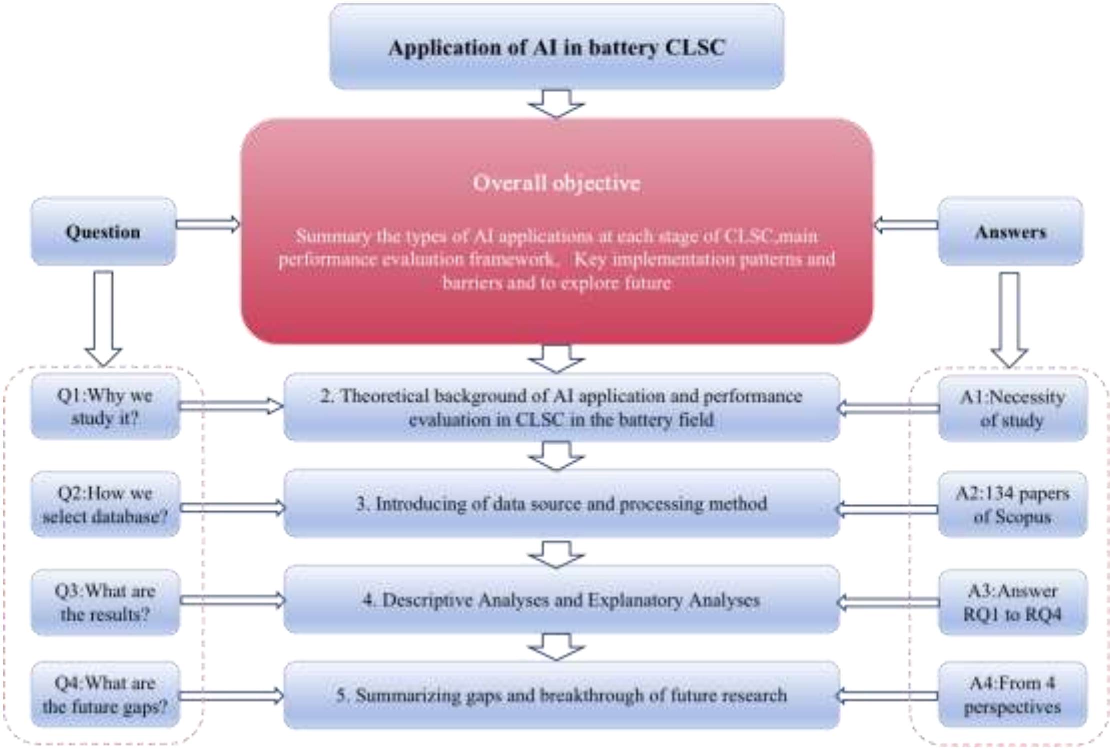

Figure 1. Research framework

2. THEORETICAL BACKGROUND

2.1 Closed-Loop Supply Chains and Sustainability

A CLSC refers to a system designed to maximize resource efficiency by integrating forward logistics with reverse logistics (Govindan et al., 2017). CLSCs aim to minimize waste, reduce environmental impact, and enhance economic viability through product recovery processes. In the context of battery recycling, CLSCs play a critical role in addressing the growing demand for sustainable energy storage solutions and mitigating the environmental hazards of battery waste (Liu et al., 2022). Recent reviews emphasize that CLSCs are increasingly adopting multi-objective optimization frameworks to balance economic, environmental, and social goals, though challenges persist in operationalizing these frameworks (Özkır & Başlıgil, 2013).

2.2 AI in CLSCs

AI technologies, including machine learning (ML), genetic algorithms (GA), and reinforcement learning (RL), have emerged as pivotal tools for enhancing CLSC efficiency. These technologies address complex operational challenges such as demand forecasting, network design, and disassembly sequence planning (Gao, 2024; Kannan, 2010; Islam & Huda, 2018). For instance, AI-driven predictive analytics improve the accuracy of battery health monitoring (Li et al., 2025), while optimization algorithms enhance logistics planning for waste electrical and electronic equipment (WEEE) recycling (Islam & Huda, 2018). A systematic review by Bhattacharya et al. (2024) identifies ten dominant AI techniques in CLSCs, with genetic algorithms and fuzzy logic being widely applied to handle uncertainties in recycling processes. However, advanced AI methods like natural language processing (NLP) and digital twin technologies remain underexplored in CLSC contexts, limiting their potential for real-time decision-making(Hu & Ghadimi, 2023; Bhattacharya et al., 2024).

2.3 Performance Outcomes in Battery Recycling

The integration of AI into battery recycling CLSCs has demonstrated measurable performance improvements. Key outcomes include enhanced recovery rates, reduced operational costs, and lower carbon footprints. For example, AI-enabled robotic disassembly systems improve the precision and safety of lithium-ion battery (LiB) recycling, addressing challenges such as heterogeneous battery conditions and hazardous material handling (Antony Jose et al., 2022). Blockchain technology further complements AI by ensuring transparency in battery supply chains, thereby reducing risks of illegal disposal and enhancing traceability (Centobelli et al., 2022). Despite these advancements, existing reviews highlight persistent gaps. For instance, while AI optimizes technical processes, its application to social sustainability—such as labor displacement and ethical sourcing—remains understudied (Muldoon et al., 2023). Additionally, most AI models focus on single-objective optimization (e.g., cost minimization), neglecting the interplay between economic, environmental, and social objectives (Hassouna, et al., 2022).

2.4 Research Gaps and Theoretical Contributions

Prior reviews collectively underscore critical limitations in current research. First, AI applications in CLSCs often prioritize technical feasibility over practical implementation, with limited empirical validation in industrial settings (Bhattacharya et al., 2024; Sharma et al., 2022). Second, while uncertainty management (e.g., demand fluctuations, quality variability) is a recurring theme, existing studies predominantly rely on isolated methods (e.g., fuzzy logic or stochastic models) rather than hybrid approaches (Chaki, 2023; Bressane et al., 2024). Third, the role of emerging technologies—such as IoT and big data analytics—in augmenting AI-driven CLSCs remains underexplored, despite their potential to enhance data availability and system resilience. Finally, few studies holistically address the lifecycle of batteries, from production to second-life applications, within an AI-integrated CLSC framework (Pregowska et al., 2022; Zhou et al., 2024).

This study addresses these gaps by systematically synthesizing the operational mechanisms and performance outcomes of AI-driven CLSCs in battery recycling. By integrating insights from multidisciplinary reviews, we provide a unified framework that links AI technologies to CLSC sustainability metrics, thereby advancing theoretical understanding and guiding future empirical research.

Table 1 Summary of previous literature on AI and CLSC.

Title	Author	Jounral	Summery
Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future	Kannan Govindan et al. (2015)	European Journal of Operational Research	Summarizing the research results in the field of reverse logistics (RL) and closed-loop supply chain (CLSC) from 2007 to 2013, it is found that the research mainly focuses on the fields of design and planning, investigation, pricing and coordination, production planning and inventory management, and lacks the application research of exact solutions and approximate algorithm.
Understanding value creation in closed loop supply chains – Past findings and future directions	Maren Schenkel et al. (2015)	Journal of Manufacturing Systems	This paper reviews 144 studies on value creation in closed-loop supply chains (CLSC) from 1998 to 2014, identifying four types of value and their specific manifestations: economic, environmental, customer, and information. The study also summarizes six concepts of value creation:
A review of closed-loop supply chain models	Saman Hassanzadeh Amin et al. (2020)	Journal of Data, Information and Management	This paper studies 225 closed-loop supply chain (CLSC) related papers from 1997 to 2020 and summarizes the research status and trends of CLSC networks. The study found that research in the CLSC field mainly focuses on deterministic optimization models, but the use of uncertain optimization models and game theory models has gradually increased in recent years.

Uncertainty factors, methods, and solutions of closed-loop supply chain — A review for current situation and future prospects	Hui Peng et al. (2020)	Journal of Cleaner Production	Summaring 304 papers from 2004 to 2018, identifies 12 major types of uncertainty factors, and summarizes the three main uncertainty research methods (fuzzy method, random method and interval method) and their advantages and disadvantages.
Application of optimization methods in the closed-loop supply chain: a literature review	Luttiely Santos Oliveira and Ricardo Luiz Machado (2021)	Journal of Combinatorial Optimization	Summarizing 354 papers on closed-loop supply chain optimization from 2008 to 2020 and analyzes the application status and trends of optimization methods.
Towards Long Lifetime Battery: AI-Based Manufacturing and Management	Kailong Liu et al. (2022)	Journal of automatica sinica	The study covers 15 papers, summarizing the application of AI in battery manufacturing optimization, intelligent battery data monitoring, battery health diagnosis, and health-conscious charging management
Applications of artificial intelligence in closed-loop supply chains: Systematic literature review and future research agenda	Sourabh Bhattacharya et al. (2024)	Transportation Research Part E: Logistics and Transportation Review	This paper comprehensively reviews the current status of artificial intelligence (AI) applications in closed-loop supply chains (CLSCs), identifies the 10 most commonly used AI technologies, and analyzes the application effects of these technologies in different sub-fields of CLSCs.
Application of AI in the whole process of WEEE recycling and reuse	Xiaoyun Xiong et al. (2025)	Environment, Development and Sustainability	A total of 84 relevant papers from 2009 to 2023 were summarized to explore the application of artificial intelligence (AI) in the whole process of recycling and reuse of waste electrical and electronic equipment (WEEE).

3. METHODOLOGY

This study adopts a systematic literature review method. The primary reason is that it can guarantee the rigor and scientific nature of the literature review process (Denyer & Tranfield, 2009).As suggested by Denyer and Tranfield (2009), this study conducts a literature review in five steps: i) formulating research questions(s), ii) positioning the research, iii) research selection and evaluation, iv) analysis and synthesis, and v) reporting the results (see Figure 2).

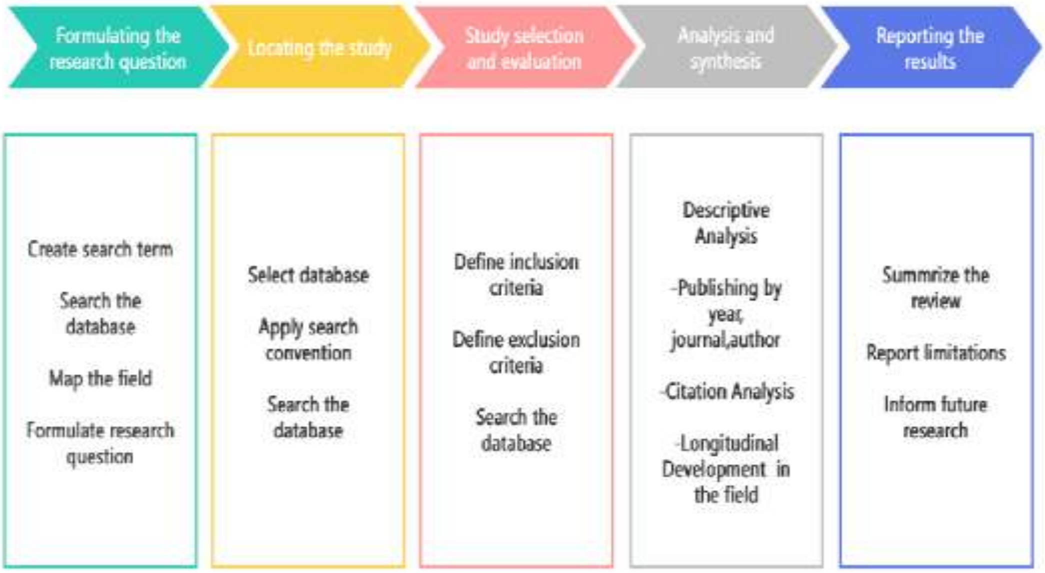

Figure 2. Systematic Literature Review Process.

3.1. Formulating the research question

This section delineates the systematic process of developing the research questions (RQs) through an iterative cycle of database exploration, domain mapping, and evidence synthesis. We used AI, CLSC and battery-related keywords to search for literature in the SCOPUS database. The specific search steps are discussed in detail in 3.2. After a brief investigation of the preliminary retrieved literature, we came up with the research questions of this study:

RQ1:What are the dominant AI technologies applied across battery CLSC stages, and how do they align with operational requirements?

RQ2:What multidimensional frameworks assess AI's CLSC impacts?

RQ3:What are the current implementation patterns and critical barriers to AI adoption in battery CLSCs?

RQ4:What underexplored research areas can advance AI-enabled circularity in battery ecosystems?

3.3. Literature Screening Methodology

This study employed a Tri-Phase Hybrid Screening (TPHS) protocol to address the dual challenges of scale and precision in AI-CLSC literature review. At the same time, the PRISMA framework was used to ensure the transparency and repeatability of the literature screening process. As shown in Figure 3.2, the systematic review process includes four stages: literature identification, screening, eligibility assessment, and inclusion.

3.3.1 Information Sources and Automated Pre-screening

This study is based on the SCOPUS database. Enter the above operation password to search for literature. After the password is entered, 1876 documents are obtained. After we limit the time from 2015-2025, 1747 documents are obtained. In addition, in order to ensure the scientific nature of the research and avoid repeated citations, we also restrict the search conditions as follows:

i. Document type: Article.

ii. Language: English.

iii. Source Type:Journal

After these limit,the number of literature has been 1156.

Finally, in order to ensure the quality of the literature and avoid the interference of too many irrelevant literatures, this study screened the journals based on four dimensions: influence, disciplinary relevance, stability, and compliance, and finally retained 38 high-quality journals (Table 2). The specific decision logic is shown in Figure 3.

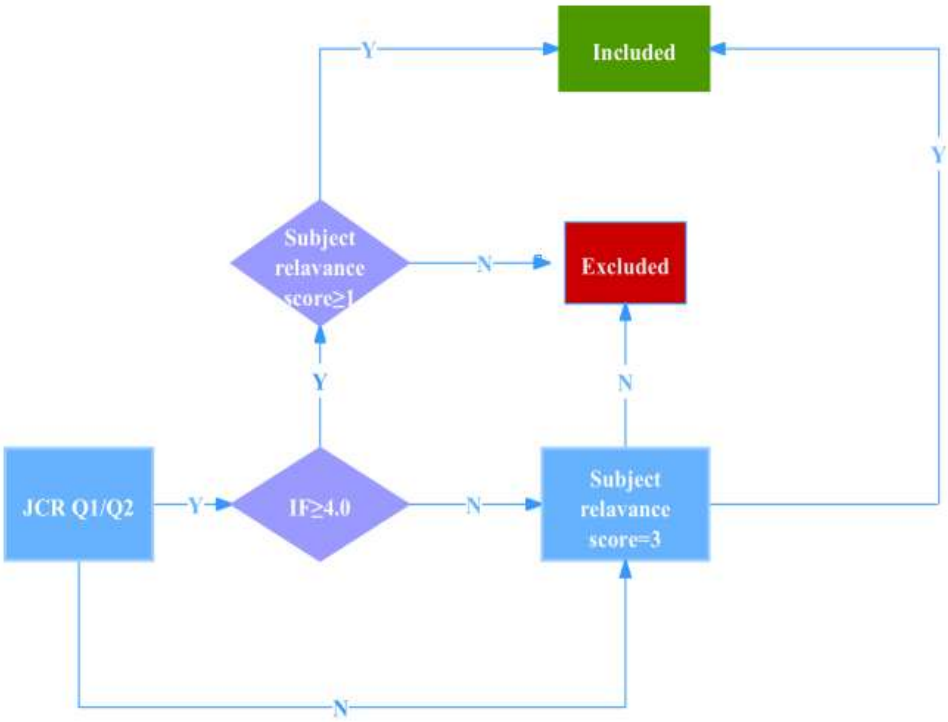

Figure 3. Flowchart of Journal Decision-making Process.

3.3.2. Title/Abstract Screening

This section mainly describes the manual screening process after the above-mentioned automatic screening process. The manual screening process of this study is divided into two steps: first, preliminary screening is performed based on the title and abstract; then, the qualification of the literature is evaluated through full-text reading, and the literature that meets the criteria is included in the analysis. The screening criteria are determined with the help of the PICO framework and structured matrix to score the literature. By pre-defining PICO, researchers can reduce subjective bias and improve the reproducibility of the screening process (Page et al., 2021). Finally, 134 articles were included in the research scope. The screening criteria and structured scoring matrix of this study are as follows:

i. Inclusion criteria:

Topic relevance: studies that explicitly address AI applications in battery recycling CLSCs (e.g., predictive maintenance, disassembly optimization).

Technical specificity: detailed description of the AI approach.

Empirical validation: quantitative/qualitative performance metrics.

Methodological rigor: clear reporting of data sources and validation protocols.

ii. Exclusion criteria:

Domain relevance: applications other than battery recycling.

Non-AI methods: studies using rule-based systems or manual decision making.

Data deficiencies: lack of measurable outcomes or sample size <100 for quantitative analysis.

Table 2 Structured Scoring Matrix of Article screening

Criterion	Weight Threshold	Weight Threshold
Thematic Relevance	40%	≥3/5
Technical Depth	30%	≥2/5
Data Completeness	30%	≥2/5

(Studies scoring ≥7/10 (n=168) proceeded to full-text review.)

The article search, selection, and evaluation process is shown in Figure 4.

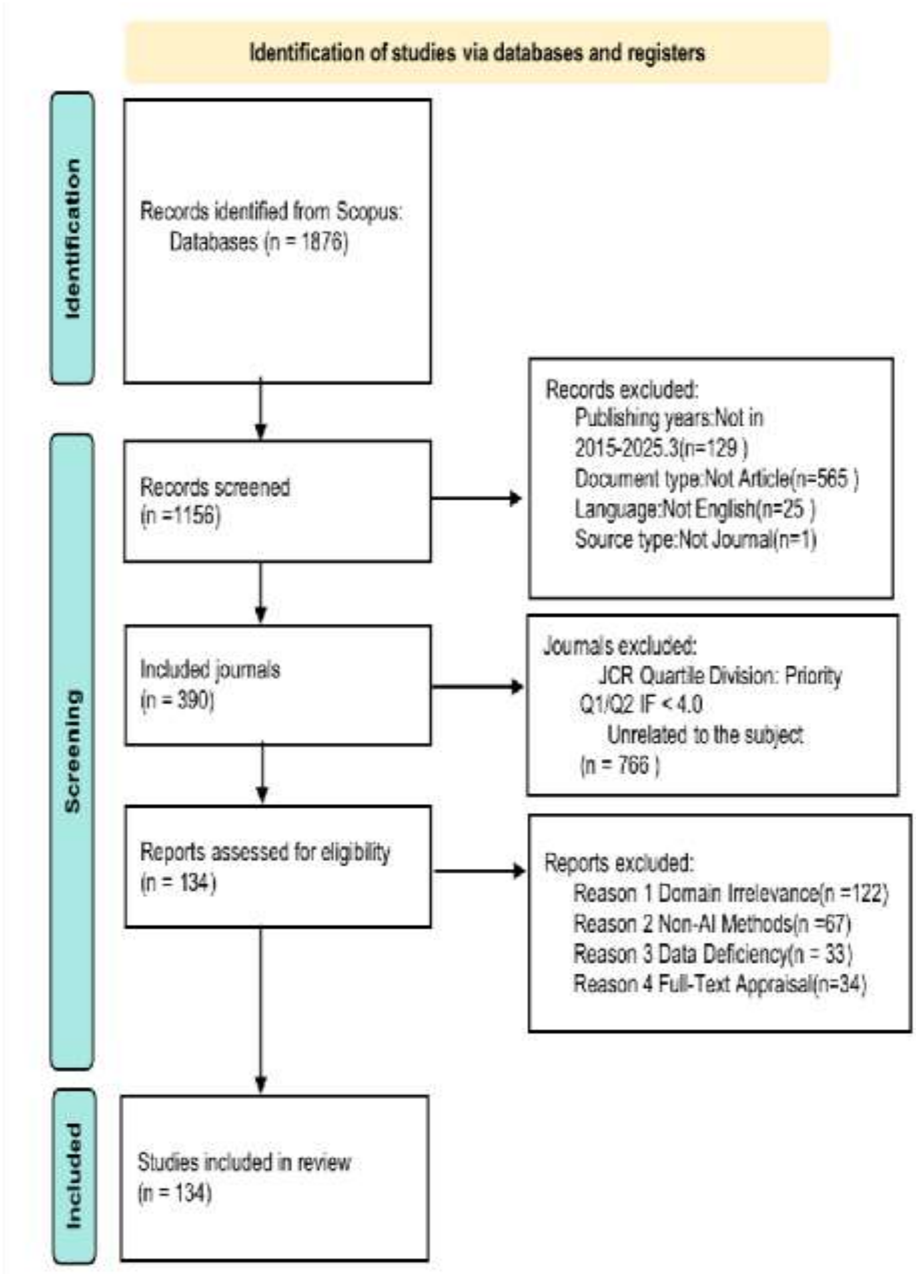

Figure 4. PRISMA Flowchart of Literature Screening Process.

4. RESULTS AND ANALYSIS

4.1. Descriptive Analyses

In order to understand the macro situation of the literature, this stage first conducted a descriptive analysis from the following aspects: (i) keywords, titles and abstracts of papers to identify the core themes and technical connections in the research field; (ii) time trends of paper publication to reveal the evolution of research enthusiasm and policies; (iii) identification of high-impact papers to locate foundational research in the field and knowledge diffusion paths; (iv) the subject areas and distribution of journals to locate the core knowledge output platform and interdisciplinary characteristics.

4.1.1 Keyword Co-occurrence

Based on the Scopus database, the keywords of the 134 selected literatures were used to perform keyword network co-occurrence analysis using Vosviewer, and keywords with a threshold of ≥ 3 were extracted. The co-occurrence network revealed three main clusters (Figure 5). Cluster 1 (red) is related to the CLSC stage, green is centered on AI technology, and cluster 3 (blue) emphasizes the performance evaluation indicators of AI applications in the field of battery recycling.

As shown in the figure,dominating the red cluster are keywords such as circular economy, closed-loop supply chain, and reverse logistics, which collectively anchor the discourse in the strategic alignment of AI with CLSC operational priorities.

The green cluster, centered on machine learning and deep learning, reveals a techno-centric paradigm shaping AI applications in battery recycling. The co-occurrence of metaheuristic optimization methods with MCDM underscores a methodological shift toward hybrid AI systems that combine predictive analytics with operational decision frameworks.

The blue cluster's focus on material recovery cost per unit and sustainable value-added reflects a growing emphasis on quantifying AI's dual impact on economic efficiency and environmental outcomes.

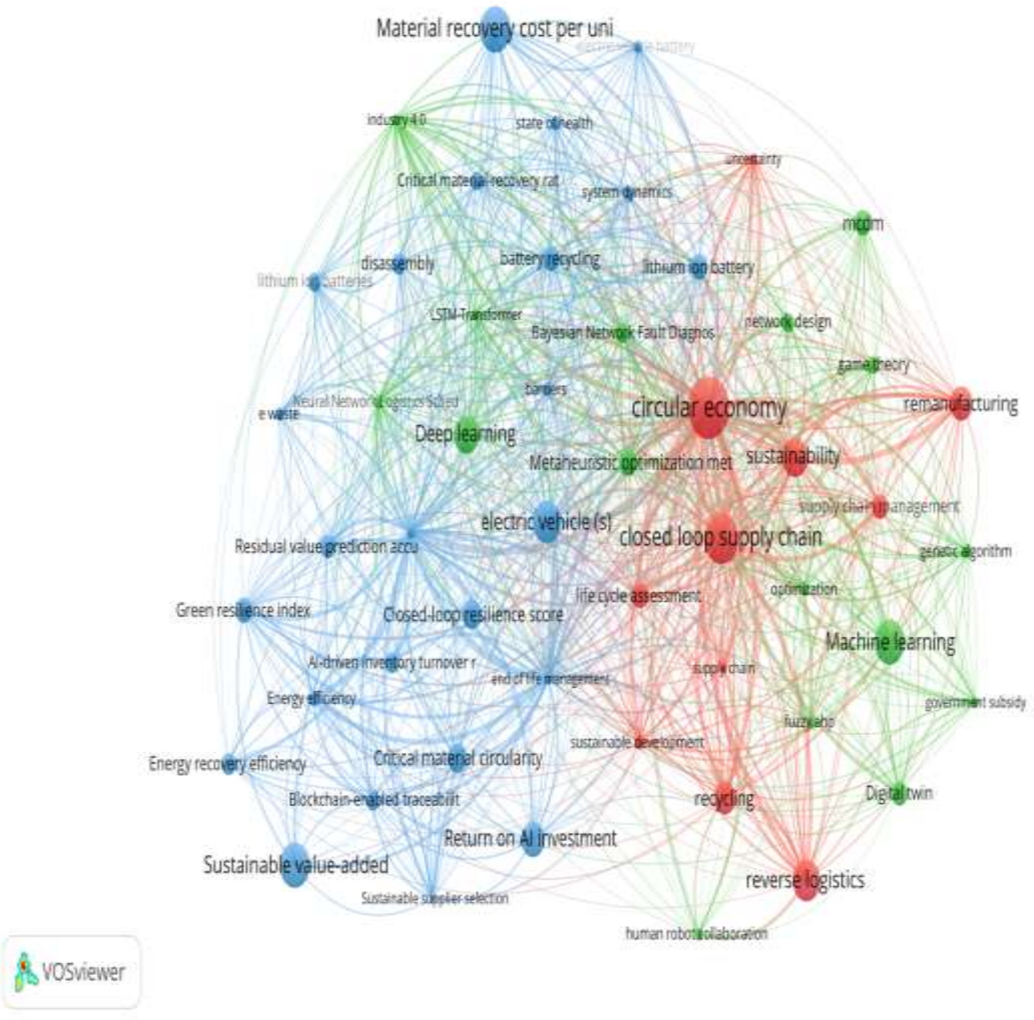

Figure 5. Keyword co-occurrence network diagram

4.1.2 Temporal Trends

The temporal trajectory of academic outputs (Figure 6) unveils three evolutionary phases in AI-CLSC research for battery recycling, each demarcated by inflection points aligning with technological breakthroughs, market shifts, and regulatory interventions. By synthesizing publication volumes with contextual drivers, this analysis elucidates the field's maturation and underscores unmet research priorities.

Phase 1: Bud Stage (2015–2017) – Nascent Exploration

The foundational period recorded 33 publications, averaging 11 articles/year, reflecting embryonic interest in AI-CLSC integration. This phase coincided with early policy signals, notably the EU's Battery Directive 2013/56/EU amendments (2015) mandating 45% recycling efficiency for lithium-ion batteries, and China's 13th Five-Year Plan (2016) prioritizing NEV infrastructure.

Phase 2: Transition Stage (2018–2021) – Methodological Diversification

Publication outputs surged to 91 articles, averaging 22.8/year, marking a 107% growth from the Bud Stage. This acceleration paralleled two key developments:

i. AI Commercialization: Widespread adoption of TensorFlow/PyTorch frameworks (2018–2019) enabled complex applications like CNN-based battery defect detection.

ii. Policy-Market Synergy: The EU's Green Deal (2019) and China's NEV subsidy reforms (2018–2020) tied fiscal incentives to recycling efficiency, spurring corporate R&D.

Phase 3: Outbreak Stage (2022–2025) – Industrial-Scale Validation

The period from 2022 to Q1 2025 witnessed exponential growth, with 270 publications, averaging 90/year—a 295% increase over the Transition Stage.

The above data indicate that the study of AI-CLSC performance in the field of battery recycling is a relatively new and increasingly popular field.

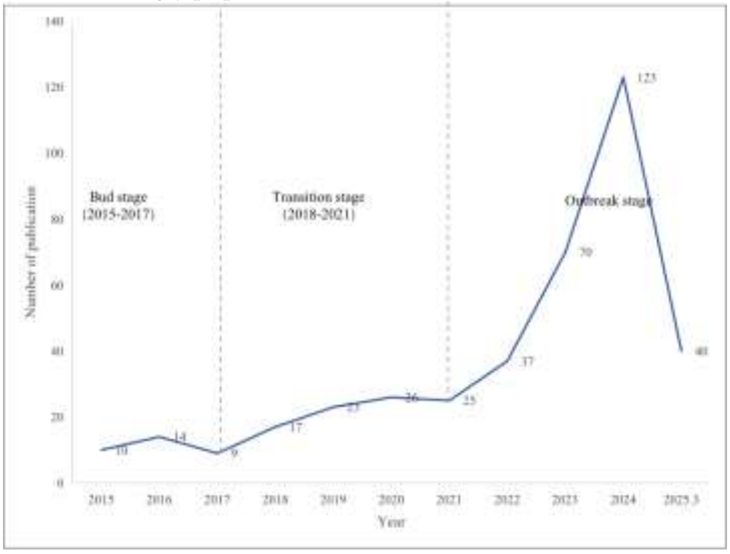

Figure 6. Number of publications changing over years

4.1.3 High-Impact Literature

Therefore,this study identified high-impact literature and located foundational research and knowledge diffusion paths in the field. Firstly,The identification of high-impact literature was conducted through CiteSpace's betweenness centrality analysis, with a threshold of > 0.01 to capture pivotal knowledge brokers. Among the 134 analyzed references, only 6 studies exceeded this centrality threshold.

Then,the use of Citespace to analyze the burst strength of top 25 cited references (Figure 7) reveals three dominant knowledge diffusion pathways: policy-Responsive Innovations, Technological Convergence, Metric Standardization.

References	Year	Strength	Begin	End	2015 - 2025
Harper G, 2019, NATURE, V575, P75, DOI 10.1038/s41586-019-1682-5, DOI	2019	3.05	2021	2025	
Alfaro-Algaba M, 2020, RESOUR CONSERV RECY, V154, P0, DOI 10.1016/j.resconrec.2019.104461, DOI	2020	1.62	2021	2025	
Golmohammadzadeh R, 2018, RESOUR CONSERV RECY, V136, P418, DOI 10.1016/j.resconrec.2018.04.024, DOI	2018	1.31	2021	2021	
USGeological Survey, 2020, MINERAL COMMODITY SUMMARIES 2020, V0, P0, DOI 10.3133/MCS2020, DOI	2020	1.31	2021	2021	
Wu TF, 2022, WASTE MANAGE, V144, P513, DOI 10.1016/j.wasman.2022.04.015, DOI	2022	2.44	2023	2025	
Hjorth S, 2022, ROBOT CIM-INT MANUF, V73, P0, DOI 10.1016/j.rcim.2021.102208, DOI	2022	2.44	2023	2025	
Xu WJ, 2020, ROBOT CIM-INT MANUF, V62, P0, DOI 10.1016/j.rcim.2019.101860, DOI	2020	1.74	2023	2025	
Chen MY, 2019, JOULE, V3, P2622, DOI 10.1016/j.joule.2019.09.014, DOI	2019	2.16	2024	2025	
Tan WJ, 2021, INT J ENERG RES, V45, P8073, DOI 10.1002/er.6364, DOI	2021	2.16	2024	2025	
Chu ML, 2023, J MANUF SYST, V69, P271, DOI 10.1016/j.jmsy.2023.06.014, DOI	2023	1.73	2024	2025	
Meng K, 2022, RESOUR CONSERV RECY, V182, P0, DOI 10.1016/j.resconrec.2022.106207, DOI	2022	1.73	2024	2025	
Hathaway J, 2023, FRONT ROBOT AI, V10, P0, DOI 10.3389/frobt.2023.1179296, DOI	2023	1.73	2024	2025	
Baazouzi S, 2021, BATTERIES-BASEL, V7, P0, DOI 10.3390/batteries7040074, DOI	2021	1.73	2024	2025	
Choux M, 2021, METALS-BASEL, V11, P0, DOI 10.3390/met11030387, DOI	2021	1.73	2024	2025	
Kay I, 2022, ENERGIES, V15, P0, DOI 10.3390/en15134856, DOI	2022	1.73	2024	2025	
Hellmuth JF, 2021, J MANUF SYST, V59, P398, DOI 10.1016/j.jmsy.2021.03.009, DOI	2021	1.73	2024	2025	
Huang J, 2021, COMPUT IND ENG, V155, P0, DOI 10.1016/j.cie.2021.107189, DOI	2021	1.73	2024	2025	
Xiao JH, 2023, J MANUF SCI E-T ASME, V145, P0, DOI 10.1115/1.4062235, DOI	2023	1.73	2024	2025	
Rosenberg S, 2022, ENERGIES, V15, P0, DOI 10.3390/en15155324, DOI	2022	1.29	2024	2025	
Zhou L, 2021, ENERGY STORAGE, V3, P0, DOI 10.1002/est2.190, DOI	2021	1.29	2024	2025	
Yu JP, 2022, J MANUF SYST, V62, P347, DOI 10.1016/j.jmsy.2021.12.006, DOI	2022	1.29	2024	2025	
Klohs D, 2023, RECYCLING-BASEL, V8, P0, DOI 10.3390/recycling8060089, DOI	2023	1.29	2024	2025	
Liu Q, 2019, INT J PROD RES, V57, P4027, DOI 10.1080/00207543.2019.1578906, DOI	2019	1.29	2024	2025	
Shahjalal M, 2022, ENERGY, V241, P0, DOI 10.1016/j.energy.2021.122881, DOI	2022	1.29	2024	2025	
Li HC, 2023, BATTERIES-BASEL, V9, P0, DOI 10.3390/batteries9030187, DOI	2023	1.29	2024	2025	

Figure 7. Top 25 References with the Strongest Citation Bursts

4.1.4 Thematic & Journal Mapping

The analysis of subject distribution can well demonstrate the interdisciplinary characteristics.The disciplinary distribution of AI-CLSC research in battery recycling (Figure 8) reveals a tripartite knowledge structure anchored by Engineering (24.8%), Environmental Science (21.8%), and Business/Management (17.1%), collectively constituting 63.7% of total publications. This triad reflects the field's inherent tension between technological feasibility (Engineering), ecological imperative (Environmental Science), and operational viability (Business).

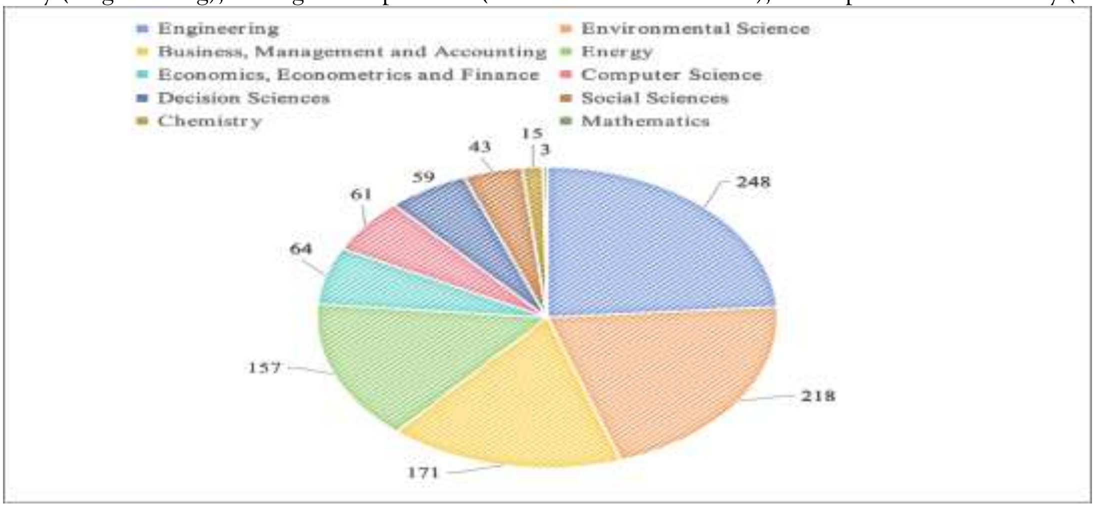

Figure 8. Research direction distribution map

Next, the journal distribution of the 134 articles was analyzed to locate the core knowledge output platform. This section selected 8 journals with ≥5 articles related to the topic (Figure 9).Through analysis, this study identified three cognitive centers:

i. Sustainability Nexus: Journal of Cleaner Production (90 papers) and Resources, Conservation and Recycling (39 papers) dominate, emphasizing system-level sustainability assessments. Their prevalence (combined 45.3% of top-journal publications) underscores the field's policy-responsive character, particularly post-EU Battery Regulation (2020).

ii. Technical Specialization: Journal of Energy Storage (26) and Journal of Manufacturing Systems (12) focus on AI applications in battery health prediction and robotic disassembly, yet exhibit limited engagement with circular business models.

iii. Operational Optimization: Expert Systems with Applications (16) and Annals of Operations Research (15) pioneer hybrid algorithms (e.g., genetic algorithm-LSTM).

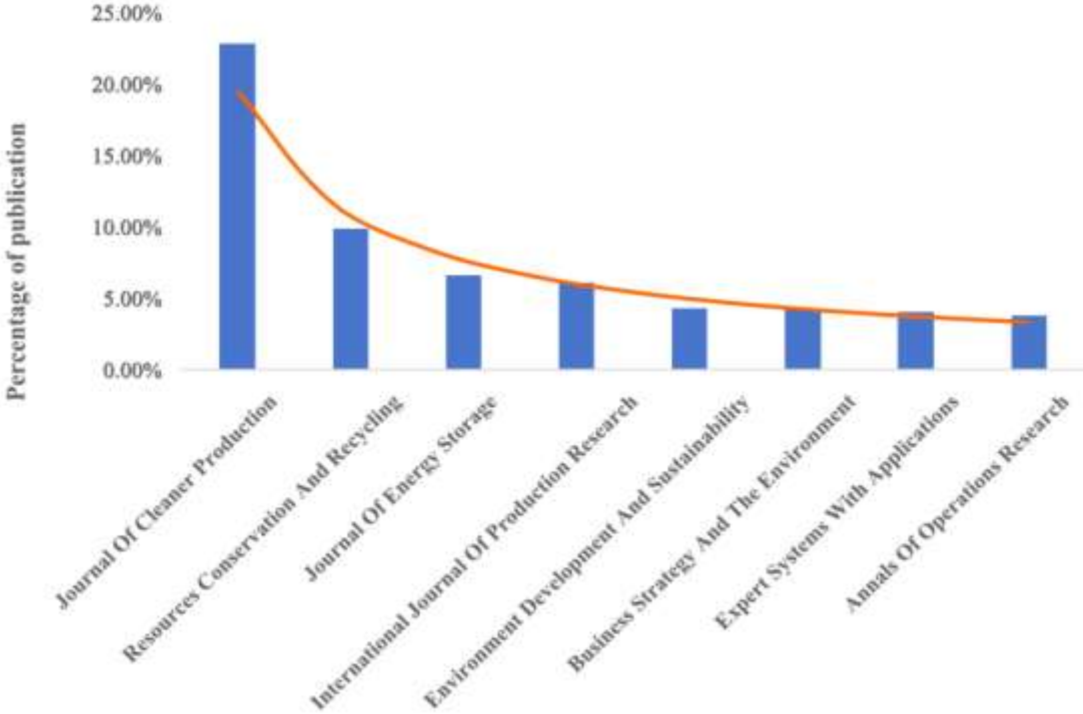

Figure 9. Journal distribution percentage of 134 papers

4.2. Explanatory Analyses

4.2.1 AI Technologies in Battery CLSC Stages: Alignment with Operational Imperatives

Based on Figure 10, we can draw the conclusion of RQ1:

Although AI technology has been widely used in various stages of CLSC, there are certain differences in the AI technologies commonly used in different links. Genetic algorithms (mentioned in 28 papers) are most used in the recycling stage to optimize the reverse logistics network with multiple objectives to quickly identify the chemical system of retired batteries and improve classification accuracy.

In the disassembly stage, the adaptive genetic algorithm (AGA) is dominant, which can dynamically schedule disassembly tasks and reduce downtime. Secondly, deep reinforcement learning (DRL) is used to realize the robot's autonomous disassembly decision (such as screw positioning). In addition, computer vision (CV) technology is also widely used in the disassembly stage to maximize the identification of battery component damage and assist in disassembly path planning. The ant colony algorithm (ACO) is mentioned in a small number of literatures to help optimize the path.

In the remanufacturing stage, LSTM network and genetic algorithm technologies were mentioned many times. In this link, the most used branch technology of LSTM network is remaining life (SOH) prediction, which is used to evaluate the secondary life of the battery and match the cascade utilization scenario; the most mentioned branch technology of genetic algorithm is differential evolution (DE), which is used to optimize the remanufacturing process parameters (such as crushing particle size and material ratio). The next technology mentioned more is digital twin, which can simulate the remanufacturing process and predict equipment failure. Cluster analysis is less mentioned, but it can still be applied to the remanufacturing stage to accurately distinguish and sort the quality grades of recycled materials.

The multi-objective genetic algorithm (MOGA) is most widely used in the redistribution stage to optimize pricing strategies (manufacturer-distributor game) and balance profits and recycling volume; blockchain technology and demand forecasting models are second, which are conducive to enhancing redistribution transparency (such as battery performance certification) and market demand forecasting, and optimizing inventory management; finally, reinforcement learning is used to realize dynamic adjustment of distribution channel strategies.

Digital twins dominate the second-life utilization stage, and their dynamic simulation models are most widely used in this stage, which can simulate the performance of retired batteries in energy storage systems (such as charging and discharging efficiency); simulated annealing (SA) optimizes battery grouping strategies through its multi-objective optimization algorithm (high SOH batteries are used for peak regulation); Monte Carlo simulation is often combined with LSTM to predict the potential for second-life utilization (such as cobalt and nickel demand in 2035); computer vision (CV) can also screen battery modules suitable for second-life utilization through its defect detection (such as crack recognition) technology in this link.

In the scrapping treatment stage, the selective leaching process optimization technology in genetic algorithms (GA) is widely used to maximize material recovery rate (such as lithium and cobalt leaching concentration); cluster analysis, especially its Gaussian mixture model (GMM), can help establish a pollution fingerprint library (VOC/heavy metals) and monitor emissions in real time; dynamic adjustment of processing parameters by reinforcement learning can optimize the harmless treatment process (such as incineration temperature control); blockchain is also mentioned in this link to ensure that compliance processing records cannot be tampered with.

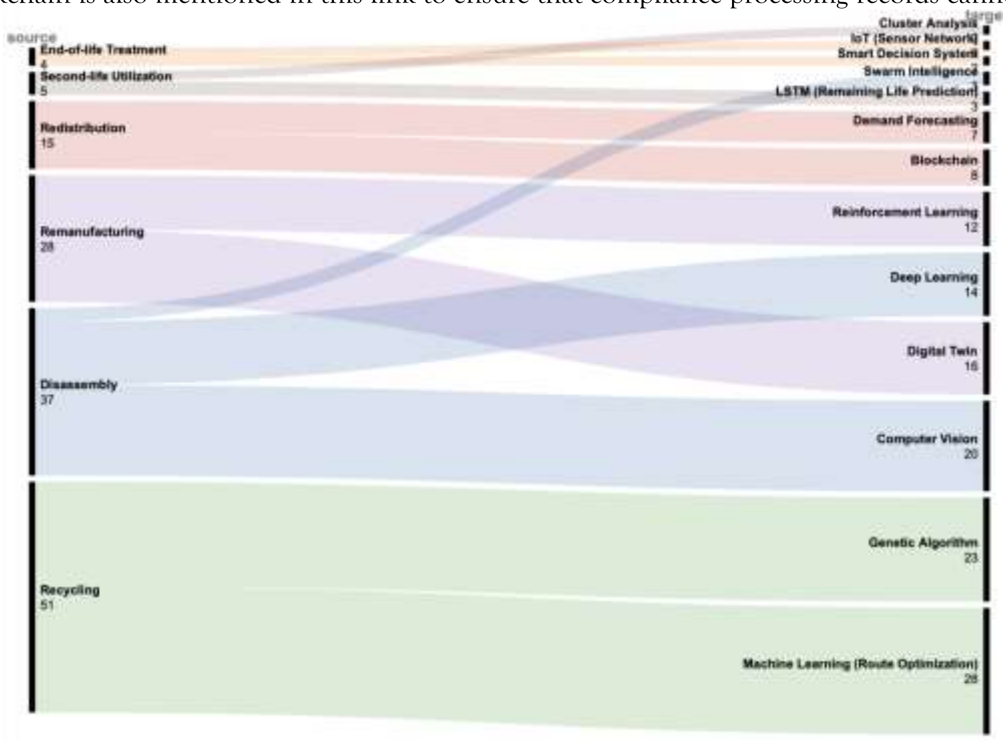

Figure 10. AI application in each stage of CLSC

4.2.2 Performance Evaluation Frameworks

To address RQ2, this section synthesizes the extant literature on AI-driven closed-loop supply chains (CLSCs) for battery recycling, focusing on operational mechanisms and performance outcomes. We identify three dominant evaluation frameworks—Triple Bottom Line (TBL), Circular Economy (CE), and Technology Readiness Level (TRL)—and critically examine their applications, limitations, and interdependencies in assessing AI's role in enhancing CLSC efficiency.

i. Triple Bottom Line (TBL)

The TBL framework remains the most widely adopted lens for evaluating AI-driven CLSCs, as it holistically integrates economic, environmental, and social performance metrics (Reddy et al., 2022). In terms of economic performance, studies emphasize AI's capacity to reduce operational costs through predictive maintenance (He et al., 2024) and robotic disassembly (Jiao et al., 2024). Secondly, from the perspective of environmental impact, AI optimizes resource efficiency, especially in carbon footprint reduction and material recycling rate. Finally, from the perspective of social equity, while less studied, AI mitigates occupational hazards (e.g., reducing manual battery dismantling by 40% in Meng et al., 2022).

ii. Circular Economy (CE)

The CE framework prioritizes closed-loop material flows, with AI acting as an enabler for: Initially, metal recovery efficiency. For instance, deep learning models increase lithium recovery accuracy to ±2% (Peng Y. et al., 2024). Subsequently, second-Life Utilization like AI-predicted State-of-Health (SOH) extends EV battery reuse by 2–4 years (Dewalkar & Nangrani, 2020). Ultimately waste minimization, as epitomized by Sterkens et al. (2022), computer vision reduces misclassification errors in battery sorting to <5%, minimizing landfill reliance (Burke & Akhtar, 2023).

iii. Technology Readiness Level (TRL): Assessing Implementation Feasibility

TRL-based evaluations reveal gaps between lab-scale AI prototypes and industrial deployment. Primarily, in terms of algorithm accuracy, reinforcement learning achieves 90–95% precision in disassembly planning, yet real-world noise degrades performance by 10–15% (Allagui et al., 2025). Concomitantly about scalability challenges, only 8% of studies (Khan & Abonyi, 2022; Pan, et al., 2021; Al-Rakhami & Al-Mashari, 2022) address data interoperability across supply chain tiers.

4.2.3 Industrial Adoption Landscape

This section mainly answers RQ3. For barrier intensity analysis, we conclusion the top 3 obstacles account. Firstly,the Data Heterogeneity, this manifests itself in different battery chemistry records and siloed lifecycle data (e.g., OEM vs. recycler). Then,the Algorithmic Opacity, currently 89% of small recyclers lack in-house MLops capacity, leading to "black box" distrust (Dobbe & Wolters, 2024). Finally, the Policy-Technology Misalignment. There are regional differences in this factor,for example EU's stringent Extended Producer Responsibility (EPR) laws drive AI adoption, whereas fragmented US state regulations inhibit ROI calculations (Tong et al., 2024).

In conclusion,while multinationals lead in AI sophistication, policy scaffolding and interoperable data standards emerge as universal scalability prerequisites—a gap underscored by only 12% of studies addressing cross-border data governance.

5. Future research

Firstly, integrating human expertise with machine learning. Current AI models overly rely on data-driven methods in battery recycling scenarios and lack the integration of implicit knowledge of domain experts (Patil & Mahalle, 2024; Valizadeh et al., 2024; Tao et al., 2024). Future research needs to develop a "human-in-the-loop" architecture to enhance decision transparency through an interactive learning framework (Ma et al., 2024; Rastegarpanah et al., 2025). Secondly, integration of blockchain and AI. Although blockchain technology has been proposed to track battery life cycle data, its synergistic potential with AI has not yet been fully explored (Xing et al., 2024; Faria et al., 2025; Yu & Wang, et al., 2025). Priority directions include dynamic smart contract design and cross-chain interoperability protocols. Then, geopolitical risks are increasingly affecting battery CLSC, but existing AI models mostly assume a stable supply chain environment and dynamic smart contract design (Wang, 2024; Afroozi, 2025). In the future, we can focus on multi-agent simulation platforms and adaptive inventory strategies.

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