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Performance Evaluation of Reverse-Recycling Supply Chains for Traction Batteries via the Entropy Method:Evidence from BYD

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ABSTRACT

As China's NEV fleet expands rapidly, the scale of retired traction batteries continues to grow, making the construction of an efficient and sustainable reverse-recycling supply chain critical for automakers to gain cost and green competitiveness. Taking BYD as the focal firm, this paper develops an evaluation framework across four dimensions—economic benefit and cost efficiency, recovery scale and network coverage, environmental/public-interest input, and technological innovation and efficiency—operationalized by ten secondary indicators. Based on firm data compiled for 2022–2024, we apply the entropy method for normalization, objective weighting, and composite measurement to quantify each indicator's impact on recycling performance. The results show that"recovery scale and network coverage"carries the highest weight, followed by"economic benefit and cost efficiency."At the secondary level, annual recovery volume, number of outlets, employment effects, and environmental/public inputs contribute more to performance, whereas"recovery cost"acts as a negative constraint. Benchmarking against industry leaders indicates that BYD still has room to improve in total recovery throughput and outlet density; volatility in patent output and insufficient automation in second-life testing limit the release of technological efficiency. Accordingly, we propose an integrated optimization path that aligns scale, network, and technology, supported by organizational incentive mechanisms. This study contributes a reusable indicator framework with objective weights to support data-driven optimization of automakers'reverse supply chains; limitations include a short sample window and partially estimated indicators, which future research can address by expanding samples and methods for robustness checks.

KEYWORDS

Traction battery recycling; reverse supply chain; Entropy method; indicator weighting; Second-life utilization; Cost efficiency

1 Introduction

Under the "dual-carbon" targets and the producer responsibility(EPR)regime, reverse-recycling supply chains shoulder a dual mission of resource regeneration and regulatory compliance. For battery OEMs, recycling not only affects raw-material self-sufficiency and cost flexibility, but also shapes green brand image and risk management. Current practice reveals structural tensions among scale–network expansion, cost efficiency, and technology commercialization:(i)recovery volumes and site density have risen quickly, yet regional coverage and collection radius remain uneven;(ii)labor-intensive nodes and hazardous-materials transport constraints keep unit treatment costs elevated; (iii)insufficient integration of automated dismantling, AI-assisted sorting, and second-life utilization limits the conversion of patents into economic returns. Against this backdrop, this paper takes BYD as the study case, builds a "four-dimension, ten-indicator" evaluation system, and applies the entropy method for objective weighting to quantify dominant bottlenecks, followed by implementation-oriented optimization strategies. The contributions are: a replicable evaluation framework with objective weights; year-over-year comparable composite performance measures; and a mapping from diagnostic results to actionable organizational and process improvements.

2 Theoretical framework

2.1 Reverse logistics and closed-loop supply chains

Reverse logistics and closed-loop supply chains emphasize the continuous circulation of materials and products across the full life cycle—from forward manufacturing→use→reverse collection→reuse/remanufacturing→re-entry into the market. This model transforms the traditional "linear economy" into a circular one, minimizing waste and maximizing resource recovery.

For traction-battery systems, closed-loop supply chains add unique complexity and value. Material recovery helps hedge against raw-material price volatility, especially for critical metals such as lithium, nickel, and cobalt. Meanwhile, second-life(cascade)utilization extends the economic lifespan of battery assets by redeploying partially degraded packs into energy storage or low-speed mobility applications. Beyond cost and efficiency gains, regulatory compliance and the resulting brand reputation effects reinforce a firm's green competitiveness in the new-energy ecosystem.

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2.2 Extended producer responsibility(EPR)and performance dimensions

The Extended Producer Responsibility(EPR)framework integrates recycling obligations directly into the manufacturer's operational scope,shifting the accountability for end-of-life products from consumers and governments to producers.This regulatory mechanism encourages firms to internalize environmental and social externalities while pursuing profitability. Within this context, the performance evaluation of reverse-recycling supply chains should encompass four core dimensions.First,economic benefit and cost efficiency capture profitability,resource utilization,and cost management.

Second, recovery scale and network coverage measure the breadth, accessibility, and density of the collection infrastructure that enables material flow. Third, environmental and social value reflects a company's contributions to employment, pollution reduction, compliance, and community welfare. Finally, technological innovation and efficiency assess how effectively R&D, patents, and automation translate into operational performance and circular-economy outcomes.Collectively,these dimensions form a balanced scorecard that aligns corporate,societal,and sustainability goals.

2.3 Entropy method for objective weighting

The entropy method provides a quantitative approach to determining indicator weights based on their degree of dispersion across observations. Indicators with greater variability contain more information and thus receive higher weights. Unlike subjective weighting methods—such as expert scoring or analytic hierarchy processes—the entropy method minimizes human bias, enhancing objectivity and reproducibility. In the context of supply-chain performance evaluation,this approach is particularly suitable because it can handle multi-indicator,cross-scale,and heterogeneous data. By quantifying the contribution of each indicator to overall system variance, the entropy method allows researchers to objectively identify the most influential factors shaping supply-chain efficiency and sustainability. This makes it a robust tool for empirical analysis and strategic optimization in reverse logistics and circular economy research.

3 Research design and methods

3.1 Indicator system and attributes

This study builds an evaluation framework with four first-level dimensions—A:economic benefit and cost efficiency,B: recovery scale and network coverage,C:environmental and social value,and D:technological innovation and efficiency.The corresponding second-level indicators are: A1 R&D investment(positive), A2 revenue related to rechargeable(secondary) batteries(positive), A3 recovery cost(negative); B1 annual battery recovery volume(positive), B2 number of nationwide recovery outlets(positive),B3 number of partner enterprises(positive);C1 employment generated by the recycling business (positive),C2 intensity of environmental/public-interest input(positive);D1 number of patents related to battery recycling (positive),D2 second-life utilization rate(positive).This system jointly covers four targets—operational performance,scale–network, green/social value, and technological capability—so that overall performance can be characterized through a composite measure rather than being biased by improvements in a single indicator.Regarding indicator attributes,only A3 is defined as a negative indicator;all others are positive.No"optimal level"(e.g.,inverted-U)indicators are set in this paper.

3.2 Data sources and sample period

The sample period spans 2022–2024.Data are drawn from publicly disclosed corporate reports(annual/ESG disclosures, technical notes)and the original calculation sheets supplied by the project sponsor. Before analysis, we harmonize units, currencies,and time bases(e.g.,converting capacities to tons,normalizing monetary values to the 2024 price level with the official CPI deflator, and aligning fiscal to calendar years where necessary). Variables are mapped to a common data dictionary to ensure that each indicator has a stable definition across years; when multiple sources exist, we apply a documented source-of-truth rule(primary disclosures>audited reports>third-party aggregators).

To ensure interannual comparability, missing values and definition inconsistencies are handled under unified rules: (i) linear interpolation for interior gaps when trends are smooth and bounded;(ii)year-on-year growth approximation when only endpoints are available and business context supports monotonic change;(iii)winsorization($\pm$1%)or casewise review for suspicious extremes, accompanied by consistency checks against operational narratives(e. g., capacity additions, network rollout).All adjustments are logged with variable-level comments,and the appendix provides detailed definitions ("caliber"),transformation formulas,and snapshots of the original tables for traceability.

Quality control includes a three-step pipeline: schema validation(type/range checks), structural validation(cross-totals, identity constraints such as outlets$\geqslant$partnerships where applicable),and temporal validation(flagging implausible swings relative to historical volatility).We also record data provenance(file name,date,version)and compute reproducible hashes for each table used in the study. Sensitivity analyses report how alternative, reasonable treatments—e. g., no deflation, median imputation instead of interpolation—affect weights and scores; results are materially unchanged under these variants,supporting the robustness of the baseline dataset.

3.3 Variable normalization and weighting procedure

To remove scale effects and assign objective importance to indicators,we adopt the entropy-weighting method.Let the raw data matrix be

$$X=\left(x_{ij}\right)_{m\times n},$$

where i indexes the observation(year: 2022/2023/2024, so $m=3$)and j indexes the indicator(ten second-level indicators, so $n=10$).

(1) Normalization.For positive indicators,use

$$z_{ij}=\frac{x_{ij}-\min x_j}{\max x_j-\min x_j}+\epsilon,$$

and for negative indicators,use

$$z_{ij}=\frac{\max x_j-x_{ij}}{\max x_j-\min x_j}+\epsilon,$$

with$\epsilon=10^{-4}$to ensure $\ln(\cdot)$is defined in subsequent steps. In the computed results, most positive indicators in 2024 have$z_{ij}\approx 1.0001$, while the negative indicator "recovery cost" (after reversal)approaches 0.0001, indicating simultaneous improvement on scale and cost in 2024.

(2) Proportion matrix.

$$p_{ij}=\frac{z_{ij}}{\sum_{i=1}^{m}z_{ij}},\quad\sum_{i=1}^{m}p_{ij}=1\left(\forall j\right).$$

Empirically, many positive indicators(e. g., annual recovery volume, number of outlets, employment impact)show higherp_{ij}in 2024 than in earlier years,meaning information mass concentrates in the highest-performing year.

(3) Entropy of each indicator.

$$e_j=-k\sum_{i=1}^{m}p_{ij}\ln p_{ij},\quad k=\left(\ln m\right)^{-1}.$$

Typical values include an entropy around$e_j\approx 0.4925$ for annual recovery volume(high dispersion→high information), with outlet count and employment impact also exhibiting informative dispersion.

(4) Diversification and weights.

$$g_j=1-e_j,\quad w_j=\frac{g_j}{\sum_{j=1}^{n}g_j},\quad\sum_{j=1}^{n}w_j=1.$$

This yields the first-level weight ordering: B(scale&network)≈ 0.3177 > A(economic benefit&cost efficiency)≈ 0.2795 > C (environmental&social value)$z=0.2074$ > D(technological

innovation&efficiency)≈ 0.1954.At the second level, annual recovery volume≈ 0.1211, nationwide outlets≈ 0.1013, employment impact≈ 0.1058, and environmental/public input≈0.1016 rank highest; recovery cost is negative but still sizable(z 0.0952),implying a meaningful constraint on performance.

(5) Composite score.For year i,the overall performance is

$$S_i=\sum_{j=1}^{n}w_j z_{ij}.$$

Contribution analysis$\left(w_j z_{ij}\right)$shows 2024 gains are driven by recovery volume, outlets, partnerships employment, environmental input, and second-life utilization, while the negative drag from recovery cost is minimal after reversal-consistent with cost management and process redesign in that year.

Robustness checks. We apply±1%winsorization and vary$\epsilon\in\left[10^{-6},10^{-3}\right]$.The first-level ranking remains B>A>C>D, and top second-level rankings are stable, indicating that weights and composite ordering are insensitive to outliers and parameter perturbations.

4 Empirical results and analysis

4.1 Weighting results

Using the entropy method, the first-level dimensions rank B: recovery scale&network coverage>A: economic benefit&cost efficiency>C: environmental&social value>D: technological innovation&efficiency. Dimension B carries the highest weight(0.3177), indicating that scaling effective throughput and densifying the network produces the greatest marginal lift in composite performance at this stage of industry development.Dimension A follows(0.2795),reflecting the hard, near-term constraint of cost discipline and profitability on firm behavior. Although lower in rank, C(0.2074)and D (0.1954)together account for nearly 40%of the total, underscoring that green externalities(employment, public/ environmental inputs)and technological efficiency(automation, second-life readiness)contribute meaningfully to the overall assessment and should not be deprioritized in managerial planning. In short, the weight structure portrays a system where scale remains the primary engine, cost the operative constraint, and environmental/technological factors the indispensable complements that sustain long-run competitiveness.

Table 1 Entropy-based weights(first-and second-level)

Level	Indicator	Attribute	Weight
First	A Economic benefit&cost efficiency	—	0.2795
	B Recovery scale&network coverage	—	0.3177
	C Environmental&social value	—	0.2074
	D Technological innovation&efficiency	—	0.1954
Second	B1 Annual recovery volume	Positive	0.1211
	C1 Employment impact of recycling	Positive	0.1058
	B2 Nationwide recovery outlets	Positive	0.1013
	C2 Environmental/public-interest input	Positive	0.1016
	D2 Second-life utilization rate	Positive	0.1002
	A2 Revenue from rechargeable batteries	Positive	0.0955
	A3 Recovery cost	Negative	0.0952
	B3 Partner enterprises	Positive	0.0952
	D1 Patents related to recycling/second-life	Positive	0.0952

At the second level, "scale–network" (B1, B2) and "social/green spillovers" (C1, C2) dominate the ranking, while technology and cost indicators sit in the middle band. This pattern implies that scale effects remain the primary driver of performance, yet employment and public/environmental inputs have become endogenous to evaluation and visibly shape the composite score. Although recovery cost (A3) is negative, its non-trivial weight (0.0952) means small marginal changes can materially shift overall performance—making cost control a binding constraint and a priority lever in subsequent strategy design.

4.2 Year-over-year composite scores and contribution decomposition

Multiplying the weights by the normalized values and summing yields the annual composite performance $S_i = \sum_j w_j z_{ij}$. The trajectory is monotonic—2024>2023>2022—indicating that improvements are broad-based rather than idiosyncratic. Decomposing the total into contribution scores ($w_j z_{ij}$) pinpoints where the lift comes from: (i) scale—network indicators post the largest gains in 2024, consistent with accelerated throughput and denser coverage; (ii) the negative drag from recovery cost (A3) is minimized in 2024, so its suppressing effect on the total score is visibly reduced and no longer offsets the scale benefits. In cumulative terms, the top two scale items (B1, B2) account for a dominant share of the year-over-year delta, while green/social (C1, C2) and technology utilization (D2) provide supportive, second-order increments. This pattern aligns with the strategic reading from Section 4.1: scale remains the engine, with cost discipline as the binding constraint and ESG/technology factors as stabilizers of long-run performance.

Table 2 Year-over-year comparison of key contribution scores ($w_j z_{ij}$)

Indicator	2022	2023	2024
B1 Annual recovery volume	~0.0000	0.036349	0.121136
B2 Nationwide recovery outlets	~0.0000	0.049049	0.101357
A3 Recovery cost(negative,after reversal)	High drag	Medium drag	Lowest drag

As Table 4-2 shows, the step-change in B1 and B2 explains most of the 2024 uplift; cost control further amplifies the net effect by shrinking A3's headwind. These score dynamics are consistent with observed operations: recovery volume climbs from ~2,000 t (2022) → 5,000 t (2023) → 12,000 t (2024), outlets expand from ~20 → 35 → 51, and partnerships from ~15 → 28 → 37. In parallel, unit recovery cost declines year by year, converting scale gains into realized performance rather than being diluted by rising expenses. Managerially, this decomposition suggests that marginal resources allocated to throughput growth (B1) and network densification (B2) yield the highest return on the composite score, provided that A3 remains tightly managed to prevent erosion of gains.

4.3 Key bottlenecks and sensitivity diagnostics

Robustness checks. We implement two diagnostics to test whether results depend on artifacts of the data or modeling choices: (1) ±1% winsorization of each indicator to dampen the influence of outliers; and (2) sensitivity tests on the numerical stabilizer ε over [10-6, 10-3]. Under both checks, the first-level ordering remains B>A>C>D; the Top-5 second-level indicators (B1, C1, B2, C2, D2) retain their relative ranking; and the annual composite scores continue to satisfy 2024>2023>2022. These patterns indicate that the weighting structure is not driven by extreme observations or parameter settings, and that our conclusions are highly robust to reasonable perturbations. What the sensitivity says operationally. The stability of results under winsorization implies that improvements are broad-based rather than driven by a few exceptional observations. The ϵ-grid stability shows that conclusions are numerically well-posed and not an artifact of logarithmic safeguards, which strengthens managerial confidence in prioritizing B1/B2 while enforcing hard controls on A3.

Actionable implications.To unlock the next tranche of performance:(1)densify the network with micro-collection nodes and dynamic siting to shorten the median collection radius; (2)automate pre-sorting and dismantling, and integrate hazmat time-window routing to compress cycle time and reduce A3;(3)standardize SOH diagnostics and traceability to raise effective D2,ensuring that R&D outputs flow into second-life deployment.Together,these moves align the largest weights(B1,B2)with binding constraints(A3)and convert technological inputs(D1)into measurable gains(D2).

5 Conclusions and recommendations

Conclusion 1.The empirical results show that scale–network exerts the strongest marginal pull on performance:the weights of annual recovery volume and outlet density are significantly higher than those of cost,green,and technology dimensions.This implies that,at the current stage,expanding effective recovery volume and optimizing spatial coverage are the primary levers for improving reverse-recycling supply-chain performance.

Conclusion 2.Although the year-over-year composite score increases monotonically,the negative constraint from unit recovery cost remains evident,and the improvement in technology commercialization is limited by insufficient process integration.As a result,scale expansion has not yet fully translated into net performance gains;cost and technology remain the key bottlenecks for the next stage.

Conclusion 3.An integrated strategy of"scale expansion—network densification—process reengineering—technology substitution—data-driven pricing"can sustain growth while compressing unit costs,and—through standardized residual-value assessment and data-enabled circulation—unlock second-life premiums,thereby jointly enhancing cost efficiency and green performance.

Policy and Practice Recommendations.To convert the weighting evidence into operational gains, the reverse-recycling system should first deepen cross-industry collaboration and regional crowdsourcing. Long-term take-back agreements with automakers, mobility platforms, logistics firms, and repair networks can create predictable retirement curves, while piloting micro-collection nodes in lower-density counties shortens the average collection radius and reduces empty backhauls. These partnerships should carry explicit service-level targets—such as pickup lead times and node uptime—linked to incentives so that last-mile touchpoints densify where material flows actually arise. In parallel, a full-lifecycle data backbone is needed to standardize State-of-Health (SOH) assessment and accelerate asset circulation. A unified digital passport covering manufacture, use, collection, testing, second-life deployment, and materials recovery ensures interoperability across OEMs and recyclers, enables event-level traceability (chain-of-custody, diagnostic results, residual-value quotes), and supports transparent pricing.

On the operations side, automation and process intensification should target the cost bottleneck directly: automated dismantling, AI-assisted sorting and diagnostics, and high-efficiency material extraction must be funded against clear unit-cost and throughput KPIs (cycle time per pack, first-pass yield, energy per ton) so technology spend converts into measurable reductions in recovery cost and higher second-life release rates. Regulatory fine-tuning can reinforce these gains by updating hazardous-materials transport rules to permit time-window routing, modular containers, and pre-approved corridors, while risk-based outlet admission and performance-linked subsidies lower compliance costs without compromising safety. Finally, market mechanisms for residual value—standardized auctions or price bands indexed to certified SOH, chemistry, and cycle count—can speed matching between supply and second-life demand in stationary storage and low-duty mobility; financial institutions and insurers can underwrite these trades once data quality thresholds are met. A supporting workforce and governance layer is essential: multi-skill training in hazmat handling, automation maintenance, and SOH testing, coupled with dashboards that track cost-to-serve and patent-to-revenue conversion, and a cross-functional steering group that reviews network density, unit cost, and second-life placement rates on a monthly cadence, will keep execution aligned with the highest-weight drivers identified by the model.

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