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# Circular Investment Risk, Cost, Uncertainty, Impact, and Traceability (CIRCUIT-5): An Evidence-Governed Framework for Robust Techno-Economic and Environmental Screening of Lithium-Ion Battery Recycling

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# Circular Investment Risk, Cost, Uncertainty, Impact, and Traceability (CIRCUIT-5): An Evidence-Governed Framework for Robust Techno-Economic and Environmental Screening of Lithium-Ion Battery Recycling

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**Abstract—** Circular-economy investments require decisions that reconcile economic feasibility, environmental performance, uncertainty, and the credibility of supporting evidence. However, conventional techno-economic and environmental screening approaches rarely distinguish changes arising from competing objectives, input sensitivity, and numerical evidence deficiencies. This study develops CIRCUIT-5, a reproducible five-stage computational framework integrating source-data auditing, techno-economic and environmental assessment, multiobjective trade-off analysis, robustness testing, and evidence-governed screening. Using 18,198 published model-generated lithium-ion battery recycling records covering 337 Chinese cities, six battery chemistries, and nine model years, four screening configurations were evaluated across 3,033 city–year choice sets. Spatial Pareto analysis, carbon-valuation switching thresholds, and assumption-based perturbation experiments were subsequently examined across 54 chemistry–year groups. Results reveal that economic and integrated cost–GHG screening produced identical chemistry selections, whereas minimum-cost and minimum-emission cities differed in all 54 spatial groups. Selecting the minimum-emission endpoint required a median processing-cost premium of 18.33% while reducing modelled GHG emissions by 35.38%. The median first-switch carbon valuation was USD 72.48/t$CO_2$e, with 44 of 54 groups changing their preferred city at USD 100/t$CO_2$e. Under ±5%, ±10%, and ±20% input perturbations, mean selection stability declined to 14.53%, 8.50%, and 4.42%, respectively. All seven controlled evidence-gate tests passed, and 12 published industrial LCA totals were independently reproduced arithmetically. CIRCUIT-5 contributes an evidence-aware, uncertainty-sensitive screening framework that distinguishes objective alignment, environmental trade-offs, and ranking robustness, providing a reproducible foundation for preliminary circular-investment assessment.

**Index Terms—** Circular economy, lithium-ion battery recycling, techno-economic assessment, life-cycle assessment, multiobjective optimization, carbon valuation, decision robustness, evidence governance, sustainable finance.

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## I. INTRODUCTION

The transition toward a circular economy requires investment in technologies capable of recovering valuable materials, reducing primary-resource dependence, and improving industrial resource efficiency. However, the economic and environmental attractiveness of circular technologies is highly sensitive to processing costs, recovery efficiency, energy requirements, material characteristics, and geographical conditions. Ma et al. [1] identify financial performance and risk as central circular-investment concerns, while Mia et al. [2] review barriers to financing circular business models. Financial uncertainty, information asymmetry, and limited technical evidence further complicate appraisal. These challenges are particularly relevant to lithium-ion battery recycling, where economic performance depends on process configurations, input chemistry, material values, and operating conditions [3], [4].

Conventional economic screening prioritizes cost efficiency and financial viability, while environmental assessment evaluates impacts within defined system boundaries. Although these approaches provide essential information, evaluating them independently may conceal trade-offs between economically preferred and environmentally preferred alternatives. A low-cost recycling configuration may not minimize greenhouse gas (GHG) emissions, and the selection of alternatives may change when environmental impacts are assigned an explicit economic value. Consequently, integrated techno-economic and life-cycle assessment (TEA–LCA) requires transparent functional units, compatible system boundaries, and robust sensitivity analysis [3], [5], [6].

Recent advances in battery-recycling modelling provide opportunities to investigate these trade-offs using published numerical evidence. Li et al. [7] present a geographically disaggregated dataset of recycling costs and GHG emissions across Chinese cities, battery chemistries, and model years. Machala et al. [8] provide industrially informed life-cycle assessment results for battery-material recycling. Together, these studies demonstrate the analytical potential of detailed economic and environmental modelling. However, differences in geographical coverage, process boundaries, and functional units require that their results be assessed separately rather than treated as directly interchangeable observations.

A parallel literature emphasizes the importance of sustainability information quality in economic decision-making. Krueger et al. [9] investigate mandatory ESG disclosure, and Huang et al. [10] examine environmental double materiality. Sustainability assurance may also influence financial and investor assessments, as examined by Huang et al. [11] and Sakchuenyos and Haji [12]. Lagasio [13] investigates ESG-washing indicators, while Gorovaia and Makrominas [14] examine potentially misleading sustainability communication. These findings highlight the importance of distinguishing data availability, internal consistency, source provenance, and independent assurance. For computational investment screening, incomplete or inconsistent supporting information may justify verification even when the available numerical indicators appear economically attractive.

Despite these advances, integrating economic–environmental trade-off analysis with explicit evidence-quality controls remains a distinct methodological challenge. Numerical optimization can identify preferred alternatives under specified objectives, but it does not independently establish the reliability of every underlying input. Conversely, evidence-completeness checks can detect specified deficiencies without necessarily changing economic rankings. A useful analytical framework must therefore distinguish changes arising from economic–environmental preferences, uncertainty assumptions, and evidence-governance conditions.

This study develops and evaluates CIRCUIT-5, a five-stage computational framework integrating source-data auditing, techno-economic and environmental assessment, cost–GHG trade-off analysis, robustness testing, and evidence-governed screening. Using 18,198 published model-derived city–chemistry–year records, the analysis compares four screening configurations across 3,033 city–year choice sets. It subsequently evaluates spatial Pareto frontiers across 54 chemistry–year groups, examines carbon-valuation switching thresholds, and tests decision stability under explicitly defined input perturbations. Controlled evidence-defect experiments assess whether the implemented screening rules respond consistently to missing, invalid, or contradictory numerical inputs. A separate industrial LCA benchmark is used to verify selected published environmental calculations.

The study contributes to computational circular-economy assessment in three respects. First, it distinguishes the effects of economic–environmental weighting from those of numerical evidence-completeness screening. Second, it quantifies modelled spatial cost–emissions trade-offs and the carbon valuations at which preferred alternatives change. Third, it integrates ranking robustness and controlled evidence-governance tests within a reproducible decision-screening workflow. The resulting framework provides a transparent basis for examining computational screening.

The remainder of this paper is organized as follows. Section II reviews the literature on circular-economy financing, integrated techno-economic and environmental assessment, sustainability information quality, and decision robustness, establishing the research gap and analytical expectations. Section III presents the CIRCUIT-5 research design, data sources, screening configurations, spatial multiobjective analysis, robustness experiments, and evidence-governance procedures. Section IV reports the empirical and computational findings, including chemistry-level screening outcomes, spatial Pareto trade-offs, carbon-valuation switching thresholds, ranking stability, and numerical validation results. Section V discusses the theoretical, methodological, practical, and policy implications of the findings, together with the study's limitations. Finally, Section VI concludes by summarizing the principal contributions and identifying directions for future research.

## II. LITERATURE REVIEW

### A. Circular-Economy Financing and Battery-Recycling Economics

Circular-economy investment is characterized by interactions among financial feasibility, resource availability, technological performance, and market uncertainty. Ma et al. [1] identify financing arrangements, risk, and financial performance as central dimensions of circular-economy research. Ndoka et al. [15] investigate circular-business-model barriers, Aminullah et al. [16] examine circular practices and financial outcomes among SMEs, and Bourdin and Jacquet [17] study regional implementation conditions. These contributions suggest that circular technologies cannot be evaluated solely through their potential environmental benefits; their economic performance and sensitivity to operating conditions must also be established.

Battery recycling illustrates these challenges. The economic attractiveness of material-recovery pathways depends on battery chemistry, processing requirements, recovery efficiency, material prices, and operational scale. Woeste et al. [3] examine the techno-economic performance of alternative lithium-ion battery recycling processes, while Han et al. [4] address sustainability and robustness in recycling supply-chain network design under uncertainty. These studies demonstrate the importance of clearly specified process assumptions and decision boundaries.

Geographically disaggregated cost and emissions estimates introduce an additional analytical dimension [7]. Differences in modelled processing costs and environmental intensities can create competing preferences across locations, technologies, and time periods. However, geographical rankings derived from processing indicators alone do not fully represent facility-location feasibility, which may also depend on transportation networks, feedstock access, capacity constraints, and regulatory requirements. This distinction motivates the use of spatial comparisons as defined analytical screening experiments.

**B. Integrated Techno-Economic and Environmental Assessment**

Techno-economic assessment evaluates the economic implications of process design and operating assumptions, whereas life-cycle assessment examines environmental impacts across specified system boundaries. Integrating these approaches facilitates the identification of economic–environmental trade-offs and potential conflicts between cost minimization and impact reduction.

The validity of such comparisons depends on consistent functional units, clearly defined process boundaries, and transparent treatment of recycling assumptions. Nordahl and Scown [5] discuss methodological challenges in assessing recyclable materials, while the GHG Protocol provides established principles for emissions accounting [18]. Environmental reporting frameworks, including IFRS sustainability standards and the GRI Standards, provide complementary disclosure structures [19], [20], [21].

Published battery-recycling research demonstrates the importance of these methodological choices. Li et al. [7] model recycling costs and GHG emissions across multiple geographical and technological conditions. Machala et al. [8] examine environmental performance using industrially informed life-cycle inventory information. These datasets offer complementary evidence but represent different assessment boundaries and functional units. Their appropriate use therefore requires separate interpretation and explicit acknowledgement of the level at which numerical findings have been reproduced.

Beyond comparing average environmental and economic performance, multi-criteria analysis can identify non-dominated alternatives for which improvements in one objective require deterioration in another. Pareto analysis and carbon-valued cost functions provide alternative representations of such trade-offs. In particular, assigning an assumed monetary value to GHG emissions can reveal switching thresholds between economically preferred alternatives. These thresholds are conditional analytical results rather than evidence of actual carbon-market obligations or project cash flows.

**C. Sustainability Information Quality and Evidence Governance**

Sustainability disclosure and assurance research identifies information credibility as an important determinant of financial interpretation. Krueger et al. [9] investigate mandatory ESG disclosure, while Huang et al. [10] examine environmental double materiality and firm valuation. Sakchuenyos et al. [22] assess assurance and oversight information in investor judgments. Alkhataybeh et al. [23] examine external assurance in sustainability reporting.

Luu et al. [24] assess mandatory emissions reporting and greenwashing; Li et al. [25] examine discrepancies in decarbonization performance. Siddique et al. [26] investigate sustainability claims and carbon risk. These studies establish the importance of evidence quality but also require careful separation between unsupported information, inconsistent disclosures, and intentional misrepresentation. A missing supporting record does not independently establish that the corresponding environmental claim is false.

For computational assessment, evidence governance can be operationalized through traceability, completeness, numerical reconciliation, and predefined escalation rules.

Foundational assurance research emphasizes the relevance of assurance arrangements and their scope [27]. However, software-based completeness tests should not be conflated with independent sustainability assurance.

This distinction is central to CIRCUIT-5. The framework separates economic and environmental rankings from evidence-eligibility conditions, allowing the analysis to determine whether specified data deficiencies trigger verification rather than automatically generating a revised economic recommendation.

**D. Uncertainty, Robustness, and Decision Screening**

Investment decisions depend on both expected performance and uncertainty surrounding the underlying assumptions. Rikhardsson and Holm [28] examine environmental information in investment allocation, while McDonald and Siegel [29] provide a foundational framework for investment timing under uncertainty. Strong et al. [30] develop approaches for estimating the value of additional information, although such methods require suitable probabilistic assumptions and decision structures.

Uncertainty is equally relevant to environmental comparisons. Heijungs [6] examines methodological considerations in probabilistic life-cycle assessment, emphasizing the importance of simulation design. In computational screening, sensitivity analysis provides a means of evaluating how preferred alternatives respond to variations in costs, emissions intensities, and environmental valuation parameters.

Two distinct forms of analysis are relevant. Preference sensitivity examines changes in selections when the relative economic importance of emissions changes. Input robustness examines whether the preferred alternative remains stable when the underlying numerical indicators are perturbed. These analyses answer different questions: the former concerns decision priorities, while the latter concerns dependence on uncertain inputs.

For evidence-governed screening, a third dimension involves rule consistency under predefined data deficiencies. Controlled missing-value and reconciliation tests can establish whether software responds according to specified requirements. Such tests assess computational reliability rather than empirical predictive accuracy.

**E. Research Gap, Questions, and Analytical Expectations**

Existing research provides foundations for circular-economy financing, battery-recycling TEA–LCA, sustainability information credibility, and uncertainty analysis. However, these literatures emphasize different analytical objectives and validation standards. The present study examines their intersection through a reproducible framework that distinguishes economic–environmental screening, ranking robustness, and numerical evidence governance.

The primary research question is:

RQ: Under what economic, environmental, and evidence-quality conditions do battery-recycling screening decisions change, and how robust are those decisions to alternative valuation and input assumptions?

Four analytical expectations structure the evaluation:

H1: Cost-based and integrated cost–GHG screening can produce different preferred alternatives when the corresponding economic and environmental rankings diverge.

H2: The incorporation of an assumed carbon valuation can change the preferred spatial alternative, with switching thresholds varying across battery chemistries and model years.

H3: Perturbations in modelled processing costs and GHG emissions can alter selection stability, with larger perturbations potentially producing greater ranking instability.

H4: Explicit evidence-eligibility rules identify predefined missing, invalid, or inconsistent numerical inputs that are not independently assessed by cost-only screening.

These expectations are evaluated within the implemented computational and controlled-test environments. They distinguish the analytical behaviour of the screening configurations from independently observed investment performance.

## III. METHODOLOGY

### A. Research Design and Analytical Scope

This study employs a reproducible secondary-data computational design to examine economic–environmental screening and evidence-governed decision rules for lithium-ion battery recycling. The analysis comprises three complementary exercises: chemistry selection within each city–year combination, spatial cost–GHG trade-off assessment within each chemistry–year combination, and controlled tests of input-validation rules. The first two use published model outputs; the third uses deliberately modified numerical records to evaluate software behavior. The five-stage analytical sequence is summarized in Fig. 1.

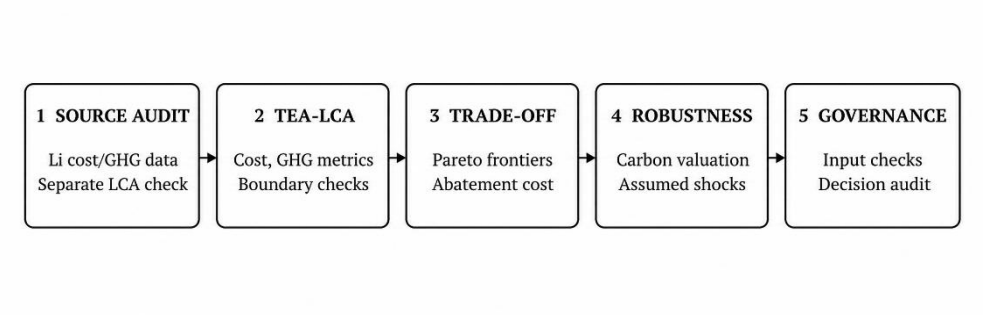



Fig. 1. CIRCUIT-5 five-stage computational assessment workflow.
Note: Li cost–GHG data and the independent industrial LCA benchmark remain separate. All screening outputs are model-based.

### B. Data Sources, Units, and Integrity Checks

The principal dataset is the city-resolved battery-recycling processing-cost and greenhouse-gas (GHG) model published by Li et al. [7]. It contains 18,198 records covering 337 Chinese cities, six battery chemistries, and nine model years between 2020 and 2060. Processing cost is expressed in USD per tonne of battery input, and emissions intensity in tonnes of $CO_2$-equivalent ($tCO_2e$) per tonne of battery input. Year-specific values are outputs of the underlying published model, including projections, rather than observations from distinct operating plants. Component reconciliation checks compare source-level cost and GHG totals against their reported constituent terms. A separate industrial life-cycle assessment (LCA) workbook associated with Machala et al. [8] is used exclusively to reproduce selected published environmental totals; its different product, system, and functional-unit boundaries preclude pooling with the Chinese model panel. Table I specifies provenance and analytical boundaries.

**TABLE I**
**SOURCE DATA AND SYSTEM BOUNDARIES**

| Source | Sample / scope | Functional unit | Evidence status | Analytical purpose |
|---|---|---|---|---|
| Li et al. 2026 Chinese battery-recycling cost/GHG model | 18,198 city x chemistry x year rows | USD per tonne recycled and tCO2e per tonne recycled | modelled/projection panel; not observed facilities | primary paired economic-environmental ranking |
| Machala et al. 2025 industrial LCA publisher source data | 12 Figure-6 aggregated combinations (4 scenarios x 3 metrics) | kgCO2e/kg cathode equivalent; MJ/kg; L/kg | secondary published industrial LCA estimates, underlying proprietary measurements not reconstructed | separate external environmental benchmark; not pooled |

*Note: Data sources use distinct functional units and boundaries; values from the two source studies are not pooled.*

### C. Screening Configurations and Comparison Sets

For each of 3,033 city–year sets, the six chemistry alternatives are assessed using four defined configurations. Configuration A selects the lowest processing-cost alternative. Configuration B selects the alternative minimizing an equal-weight composite of within-set normalized processing cost and GHG intensity. Configuration C applies completeness and arithmetic-consistency eligibility checks before implementing A; configuration D applies the same checks before implementing B. Ineligible records are referred for verification rather than treated as valid inputs. These operational definitions (Table II) are screening rules, not net-present-value (NPV) appraisal or observed investment decisions. Seven alternative normalized GHG weights from 0 to 1 are additionally evaluated for chemistry-choice sensitivity.

**TABLE II**

**FOUR CONFIGURATION DEFINITIONS**

| Configuration | Ranking / comparison | Evidence treatment | v7 observed decision changes |
|---|---|---|---|
| A | minimum cost / city-year chemistry alternative | none | baseline |
| B | 0.5 normalized cost + 0.5 normalized GHG / city-year chemistry alternative | none | 0 of 3033 against A |
| C | A with eligibility filter for missing/inconsistent source components | defer anomalous evidence before ranking | 0 of 3033; all source rows complete |
| D | B with eligibility filter for missing/inconsistent source components | defer anomalous evidence before ranking | 0 of 3033; all source rows complete |

*Note: A/B are ranking rules; C/D add numerical eligibility checks. These are not full NPV or lending-decision models.*

**D. Spatial Multiobjective Analysis**

To examine trade-offs not resolved by chemistry-level screening, each of the 54 chemistry–year sets (six chemistries multiplied by nine years) is evaluated across 337 city-specific model alternatives. A city is classified as Pareto-nondominated when no other city has both a no-higher processing cost and a no-higher GHG intensity, with at least one strict improvement. For each set, the minimum-cost and minimum-emissions endpoints are identified. The endpoint cost premium is the proportional increase in processing cost from the minimum-cost endpoint to the minimum-emissions endpoint; the associated GHG reduction is calculated relative to the emissions of the minimum-cost endpoint. Their absolute cost difference divided by avoided emissions gives the endpoint abatement-cost ratio, expressed in USD/$tCO_2e$.

A carbon-valued screening objective is then specified as

$J_i(\lambda) = C_i + \lambda G_i$, (1)

where $C_i$ is processing cost (USD/t battery input), $G_i$ is GHG intensity ($tCO_2e$/t battery input), and $\lambda$ is an assumed carbon valuation (USD/$tCO_2e$). For each chemistry–year set, the preferred city minimizes $J_i(\lambda)$ at 15 predetermined valuations between USD 0 and USD 5,000/$tCO_2e$. The first positive switching threshold is identified by comparing the baseline minimum-cost city with all strictly lower-emissions alternatives. This exercise measures model-implied ranking changes, not actual facility-location feasibility or compliance costs.

**E. Assumption-Based Robustness and Evidence-Gate Testing**

Ranking stability is assessed under symmetric independent multiplicative perturbations of processing cost and GHG intensity at ±5%, ±10%, and ±20%, alongside an unchanged reference condition. For each nonzero perturbation magnitude, 200 pseudo-random draws per chemistry–year set and carbon valuation (USD 0, 100, and 500/$tCO_2e$) are generated from uniform intervals with fixed random seed 20261108. The outcome is the proportion of draws retaining the unperturbed preferred city. The perturbations define controlled sensitivity experiments and are not statistically estimated confidence intervals or observed facility measurement errors [6].

Numerical evidence-gate behavior is separately tested against seven predefined cases involving missing, invalid, or inconsistent component entries. The tests determine whether the implemented software accepts or flags the altered records according to its rules. They do

not estimate detection accuracy for real-world sustainability documentation or financing dossiers.

**F. Reproducibility and Reporting**

The implemented pipeline uses Python with NumPy, pandas, SciPy, and Matplotlib. Reported exhibits are generated from retained source-derived tables using a reproducible script and machine-readable numerical checks. The study reports processing-cost and GHG screening, rather than full project NPV; spatial comparisons exclude transport-network feasibility, feedstock access, facility capacity, capital requirements, and permitting. All primary model-derived results, independently reproduced industrial figure totals, and controlled software tests are reported as distinct forms of evidence.

## IV. RESULTS

### A. Data Integrity and Modelled Economic–Environmental Heterogeneity

All 18,198 city–chemistry–year records passed the implemented cost- and GHG-component arithmetic checks. Within the 3,033 records available for each chemistry, lithium iron phosphate (LFP) had the lowest mean modelled processing cost (USD 538.38/t) and GHG intensity (0.4948 $tCO_2e/t$). Lithium manganese oxide (LMO) averaged USD 851.06/t and 0.8392 $tCO_2e/t$, whereas nickel cobalt aluminium oxide (NCA) averaged USD 1,158.31/t and 1.3193 $tCO_2e/t$. Table III presents all six chemistries; Fig. 2 decomposes modelled cost and emissions components, and Fig. 3 shows chemistry-specific trajectories across the nine source-model years [7].

**TABLE III**
**MODELLED STATISTICS BY CHEMISTRY**

| Chemistry | N records | Mean cost (USD/t) | Cost SD (USD/t) | Mean GHG (tCO2e/t) | GHG SD (tCO2e/t) |
|---|---|---|---|---|---|
| LFP | 3033 | 538.38 | 98.91 | 0.4948 | 0.0985 |
| LMO | 3033 | 851.06 | 213.43 | 0.8392 | 0.2395 |
| NCA | 3033 | 1158.31 | 224.68 | 1.3193 | 0.3631 |
| NCM-H | 3033 | 1032.65 | 199.97 | 1.1246 | 0.3211 |
| NCM-L | 3033 | 1068.18 | 227.56 | 1.0015 | 0.2756 |
| NCM-M | 3033 | 1039.28 | 212.53 | 1.0473 | 0.2919 |

*Note: Source-model city × year variation; the SDs are NOT observational measurement uncertainty or empirical confidence intervals.*

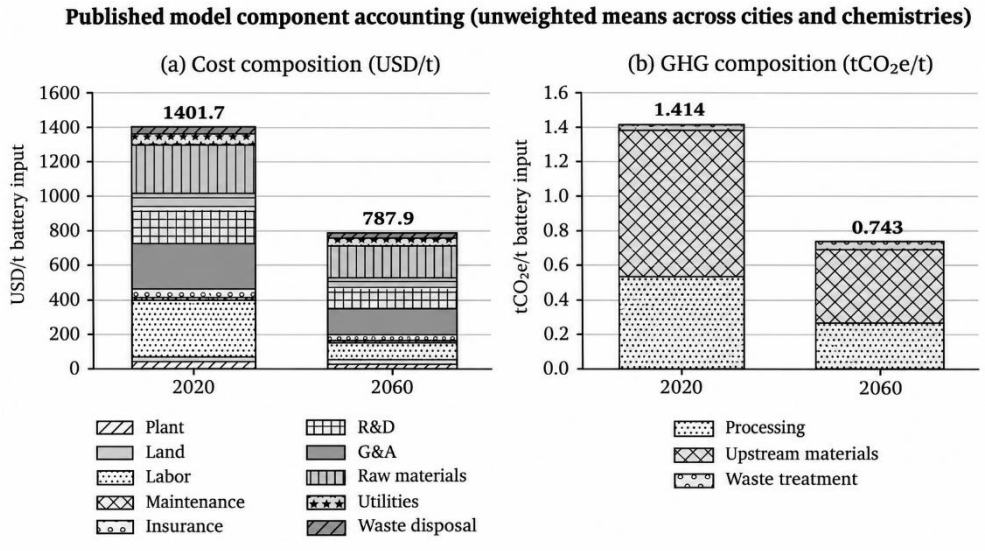



*Fig. 2. Modelled battery-recycling processing-cost and GHG component decomposition.*
*Note: Components originate from the published Li et al. model; panel units and categories must match the underlying source workbook.*

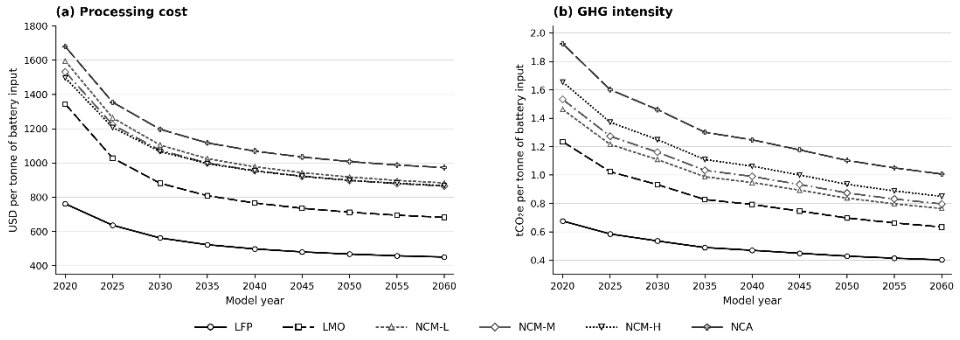



*Fig. 3. Modelled processing-cost and GHG trajectories by battery chemistry and year.*
*Note: Later model years represent projections, not measured future operating results.*

**B. Four-Configuration Chemistry Screening**

Across 3,033 city–year choice sets, configurations A and B selected the same chemistry in every set. Adding source-component eligibility checks produced no intervention under C or D because all supplied records passed the implemented checks. Thus, A versus B, C versus A, and D versus B each yielded zero changed selections. Chemistry rankings also remained unchanged across the seven tested normalized GHG weights. The result establishes identical choices under these specific modelled alternatives and complete-input conditions, rather than an observed investment benefit from the additional screening layers.

**C. Spatial Pareto Structure and Abatement-Cost Trade-offs**

Unlike the chemistry comparison, the 54 spatial chemistry–year comparisons exhibit cost–GHG divergence. The minimum-cost and minimum-emissions cities differed in all 54

groups. The median premium for choosing the minimum-emissions endpoint was 18.331%, accompanied by a median GHG reduction of 35.383% relative to the minimum-cost endpoint. The median Pareto frontier contained eight cities, and the median endpoint cost per tonne of modelled $CO_2$-equivalent avoided was USD 493.30/t$CO_2$e (Table IV). Figure 4 illustrates representative nondominated frontiers. These comparisons characterize source-model geographic differences but do not incorporate logistics or infrastructure constraints [7].

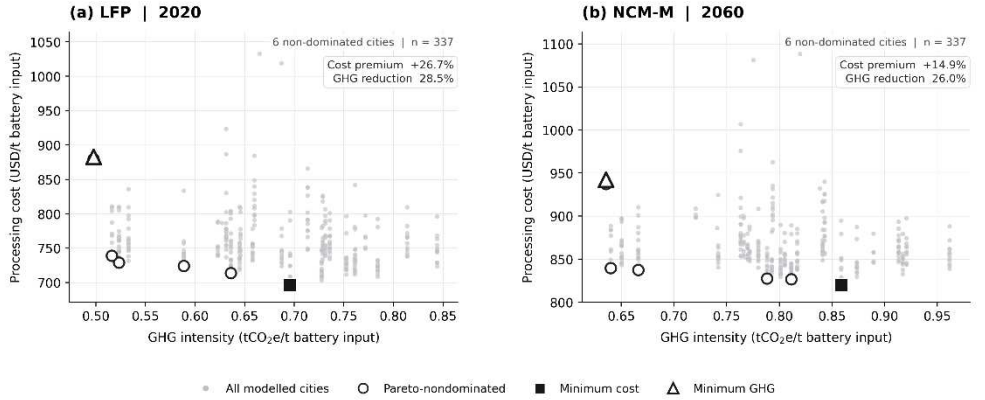



*Fig. 4. Illustrative spatial cost–GHG Pareto frontiers for fixed chemistry–year groups.*
*Note: Non-dominance is defined on modelled processing cost and emissions; transport and facility-siting feasibility are not modelled.*

**TABLE IV**
**SPATIAL SCREENING TRADE-OFFS**

| Indicator | Value |
|---|---|
| Spatial group comparisons | 54 chemistry × modelled year sets |
| City alternatives per group | 337 |
| Different cost-minimum and GHG-minimum cities | 54 / 54 |
| Median cost premium at GHG-minimum (%) | 18.331 |
| Median GHG decrease vs cost-minimum (%) | 35.383 |
| Median non-dominated alternatives per group | 8.0 |
| Median endpoint cost of abatement (USD/tCO2e) | 493.3 |
| Median first-switch valuation (USD/tCO2e) | 72.48 |
| Groups changing city at assumed $100/tCO2e | 44 / 54 |

*Note: Summary statistics cover 54 chemistry–year groups; endpoint abatement cost differs from the first-switch carbon valuation.*

### D. Carbon Valuation and Preferred-Alternative Switching

The median first-switching valuation across the 54 chemistry–year groups was USD 72.48/t$CO_2$e. Relative to the unpriced minimum-cost selection, the minimizing city changed in 4 groups at USD 25/t$CO_2$e, 8 at USD 50/t$CO_2$e, 28 at USD 75/t$CO_2$e, 44 at USD 100/t$CO_2$e, 53 at USD 150/t$CO_2$e, and all 54 at USD 200/t$CO_2$e. The switching profile in Fig. 5 demonstrates that an explicit emissions valuation can change modelled spatial rankings even when the within-city chemistry choice is unchanged. The valuation is a screening parameter, not an observed levy or market price.

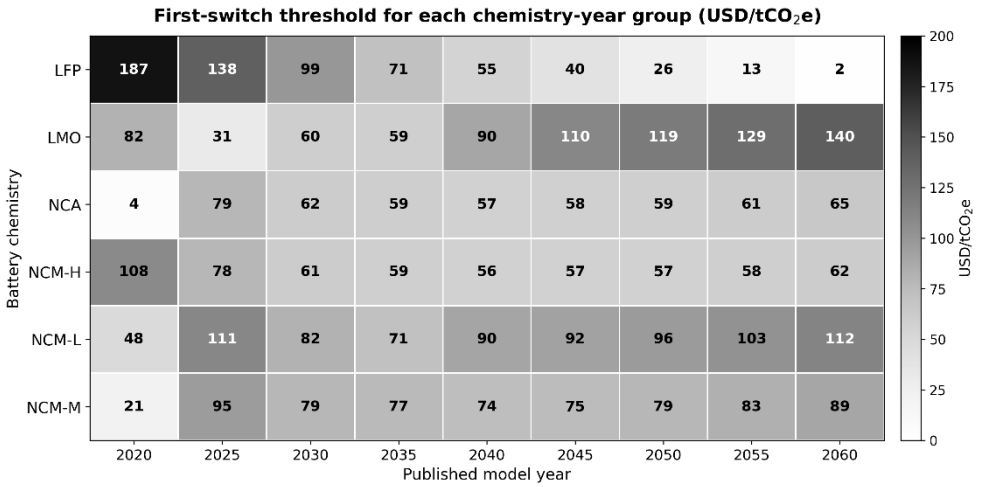



*Fig. 5. First-switch thresholds for changes in minimum-objective spatial selections under assumed carbon valuations across 54 chemistry–year groups.*

### E. Selection Stability under Assumed Input Perturbations

At an illustrative USD 100/tCO₂e valuation, mean retention of the original preferred city declined from 100% without perturbation to 14.53% under ±5% perturbations, 8.50% under ±10%, and 4.42% under ±20%; median retention was 100%, 14.50%, 8.00%, and 4.00%, respectively. The corresponding patterns for USD 0 and USD 500/tCO₂e are reported in Table V and Fig. 6. These retention rates are outcomes of the defined perturbation experiment; they indicate ranking sensitivity, not forecast accuracy or estimated empirical probabilities [6].

**TABLE V**
**ASSUMED-INPUT ROBUSTNESS AT USD 100/TCO2E**

| Assumed perturbation (%) | Carbon valuation (USD/tCO2e) | Median stability (%) | Mean stability (%) | Median distinct winning cities |
|---|---|---|---|---|
| 0.0 | 100.0 | 100.0 | 100.0 | 1.0 |
| 5.0 | 100.0 | 14.5 | 14.53 | 32.0 |
| 10.0 | 100.0 | 8.0 | 8.5 | 49.0 |
| 20.0 | 100.0 | 4.0 | 4.42 | 80.0 |

*Note: Fixed-seed, researcher-defined simulations; values are choice-retention frequencies, not estimated field probabilities.*

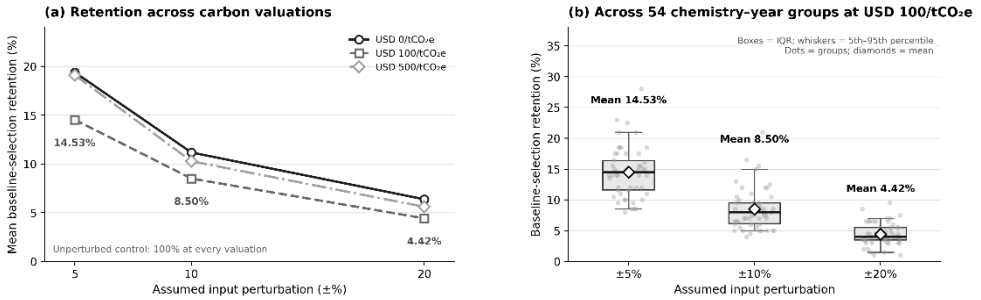



*Fig. 6. Retention of modelled spatial selections under assumption-based cost and GHG perturbations.*
*Note: ±5%, ±10%, and ±20% represent researcher-specified stress ranges; retention rates are not empirical confidence intervals.*

### F. Evidence-Gate Tests and Independent LCA Arithmetic Reconciliation

All seven controlled evidence-gate tests passed, confirming the expected software responses to deliberately missing, invalid, or inconsistent numerical entries. In contrast, no evidence-triggered intervention occurred in the complete source panel because all records satisfied the implemented validation criteria. These findings distinguish successful verification of predefined evidence-governance rules from the unchanged chemistry-level screening decisions.

The separate industrial LCA check reproduced all 12 selected Figure-6 totals reported in the Machala et al. source workbook [8]. For the conventional versus circular California NCA cases, recalculated GHG intensity declined from 21.029 to 4.59529 $kgCO_2e/kg$, energy demand from 262.18 to 45.84969 MJ/kg, and water use from 92.0767 to 25.77926 L/kg. These differences correspond to 78.15%, 82.51%, and 72.00% lower modelled impacts, respectively. In the LCO comparison, the corresponding calculated reductions were 42.21%, 55.21%, and 57.65%. The exercise replicates published figure arithmetic rather than proprietary raw plant measurements. The industrial LCA benchmark remains analytically separate from the Li et al. dataset [7], [8].

### G. Principal Findings

The completed analysis establishes three results. First, cost and GHG rankings coincide for chemistry choice within the tested city–year sets. Second, spatial alternatives exhibit systematic cost–GHG trade-offs, and explicit carbon valuation changes preferred modelled cities. Third, the preferred spatial rankings are sensitive to controlled input perturbations, while evidence checks function as specified in software tests. CIRCUIT-5 therefore provides a reproducible framework for comparing screening rules and exposing modelled cost–environmental trade-offs; demonstrated real-world investment accuracy remains outside the tested scope.

## V. DISCUSSION

### A. Interpretation of the Principal Findings

The CIRCUIT-5 findings demonstrate that the influence of environmental criteria on battery-recycling decisions depends on the alternatives evaluated. Using the geographically disaggregated dataset of Li et al. [49], all 3,033 city–year comparisons produced identical chemistry selections under cost-only and integrated cost–GHG screening. Lithium iron

phosphate (LFP) exhibited the lowest modelled processing cost and emissions intensity across these comparisons. This result indicates that environmental integration does not necessarily alter decisions when economic and environmental rankings coincide. Woeste et al. [23] similarly emphasize the importance of process-specific economic conditions in battery recycling. Conversely, the minimum-cost and minimum-GHG cities differed across all 54 chemistry–year spatial groups. Selecting the lowest-emission endpoint involved a median processing-cost premium of 18.33% and a median emissions reduction of 35.38%. The median Pareto frontier contained eight non-dominated alternatives, demonstrating meaningful trade-offs within the published model. Bourdin and Jacquet [22] highlight the importance of regional conditions in circular-economy implementation, while Han et al. [24] emphasize sustainability and uncertainty in recycling supply chains.

Carbon valuation further influenced spatial preferences. The median first switching threshold was USD 72.48/$tCO_2e$. At USD 100/$tCO_2e$, preferred locations changed in 44 of 54 groups, increasing to all groups by USD 200/$tCO_2e$. These thresholds represent conditional screening outcomes rather than actual regulatory carbon prices. The GHG Protocol [41] provides relevant emissions-accounting principles. Robustness analysis revealed substantial ranking sensitivity. At USD 100/$tCO_2e$, mean selection stability declined from 100% without perturbation to 14.53%, 8.50%, and 4.42% under the implemented ±5%, ±10%, and ±20% input perturbations. Heijungs [28] emphasizes methodological considerations in uncertainty-based environmental comparisons. These results distinguish baseline preference from preference stability under specified assumptions.

**B. Theoretical and Methodological Significance**

CIRCUIT-5 integrates economic–environmental screening, ranking robustness, and numerical evidence governance within a reproducible framework. Ma et al. [18] identify financing risk and financial performance as central circular-economy concerns. Mia et al. [20] further examine financing barriers and research opportunities, while Ndoka et al. [19] identify implementation challenges in developing economies. The first methodological contribution is distinguishing objective alignment from conflicting preferences. Chemistry-level comparisons demonstrated alignment, whereas spatial comparisons revealed non-dominated alternatives. Nordahl and Scown [27] emphasize the importance of assessment boundaries in recycling-related LCA. CIRCUIT-5 extends this perspective through explicit comparative screening and Pareto analysis.

The second contribution is the economic interpretation of environmental preferences through carbon-valuation thresholds. Unlike abstract normalized weights, monetary valuations identify when environmental considerations change modelled economic rankings. The underlying cost and emissions estimates originate from Li et al. [49], while the NGFS climate-scenario framework [48] provides broader context for scenario-based financial analysis.The third contribution concerns evidence governance. Krueger et al. [1] examine mandatory ESG disclosure and information environments. Huang et al. [2] investigate environmental double materiality and firm valuation. Simnett et al. [25] establish the relevance of sustainability assurance, while Sakchuenyos and Haji [4] examine assurance-related investor judgments. These studies support distinguishing information availability from evidence credibility.

CIRCUIT-5 operationalizes this distinction through numerical completeness, validity, and reconciliation checks. All seven controlled evidence-defect tests passed, whereas complete source records generated no evidence-triggered screening changes. Lagasio [6] and Gorovaia and Makrominas [7] investigate broader greenwashing indicators; the present study addresses the narrower problem of computational input consistency.

### C. Practical and Policy Significance

For industrial analysts, spatial Pareto frontiers provide transparent comparisons between processing-cost minimization and emissions reduction. Han et al. [24] demonstrate the importance of recycling-network considerations, while Aminullah et al. [21] examine the financial implications of circular practices among SMEs. CIRCUIT-5 offers a preliminary screening approach, although actual facility selection requires transportation, capacity, and feedstock assessments. For financial institutions, carbon-valuation thresholds can clarify the sensitivity of preliminary rankings to environmental assumptions. Rikhardsson and Holm [26] investigate the role of environmental information in investment allocation, while McDonald and Siegel [30] establish the significance of uncertainty in investment timing. Nevertheless, screening indicators cannot substitute for project-level cash-flow analysis.

The framework also offers a mechanism for documenting numerical evidence. IFRS S1 [34] addresses sustainability-related financial disclosures, and IFRS S2 [35] concerns climate-related information. The GRI Standards [39] provide complementary sustainability-reporting guidance. Numerical reconciliation may support reporting processes but does not independently establish compliance. For sustainable finance, the Green Bond Principles [43] and Green Loan Principles [45] illustrate financing-specific documentation expectations. The EU Taxonomy Regulation [31] establishes distinct environmental classification requirements. CIRCUIT-5 may assist preliminary assessment without determining eligibility or regulatory alignment.

### D. Comparison With Existing Research

Woeste et al. [23] examine process-level battery-recycling economics, whereas Li et al. [49] provide the geographically disaggregated cost–GHG panel used in this study. CIRCUIT-5 applies comparative screening, Pareto analysis, carbon-valuation thresholds, and robustness evaluation to that published numerical evidence. The supplementary environmental benchmark reproduces selected calculations from Machala et al. [50]. Its industrial LCA results remain separate from the Chinese model because the underlying processes and functional units differ. The evidence-governance component also differs from corporate sustainability-disclosure studies. Luu et al. [8] investigate mandatory GHG reporting and greenwashing. Battisti et al. [9] examine certification and sustainability disclosure, while Wang et al. [15] investigate investment inefficiency associated with greenwashing. CIRCUIT-5 evaluates numerical screening behaviour rather than corporate misconduct or observed investment consequences. The study therefore contributes a decision-screening perspective complementary to process-based TEA–LCA and sustainability-assurance research.

### E. Study Limitations

The principal dataset contains model-generated estimates and projections, not independently observed facility outcomes [49]. Arithmetic reconciliation establishes numerical consistency without validating the underlying engineering assumptions. Spatial comparisons exclude

transportation, processing capacity, feedstock availability, and regulatory constraints. Han et al. [24] demonstrate why such network considerations matter for operational decisions. The economic assessment uses processing-cost indicators rather than complete discounted cash flows. Consequently, full project NPV, realized profitability, and investment-decision accuracy remain outside the study's scope.

Robustness experiments employ researcher-defined perturbations rather than empirically calibrated uncertainty distributions. Heijungs [28] discusses requirements for probabilistic environmental assessment, while Strong et al. [29] demonstrate a more advanced information-value methodology not implemented here. Evidence-gate tests use deliberately introduced numerical deficiencies. Their success establishes software consistency rather than independent assurance effectiveness. Sakchuenyos et al. [5] demonstrate that institutional oversight and external assurance involve additional considerations. Finally, selected industrial LCA totals were reproduced from Machala et al. [50] without independent reconstruction of proprietary facility measurements. Differences in assessment boundaries prevent pooling with the Chinese cost–GHG dataset. These limitations establish CIRCUIT-5 as a reproducible preliminary screening framework and identify the additional evidence needed for operational and investment validation.

## VI. CONCLUSION

This study developed and evaluated CIRCUIT-5, a reproducible computational framework integrating techno-economic and environmental assessment, cost–GHG trade-off analysis, decision robustness, and evidence-governed screening. Using 18,198 published model-derived battery-recycling records from Li et al. [49], four screening configurations were evaluated across 3,033 city–year choice sets, followed by spatial comparisons across 54 chemistry–year groups. Three principal findings emerged. First, cost-only and integrated cost–GHG screening produced identical chemistry selections, demonstrating that environmental integration does not necessarily change decisions when economic and environmental objectives align. Second, minimum-cost and minimum-emission cities differed across all spatial groups. Selecting the minimum-emission endpoint involved a median processing-cost premium of 18.33% and a corresponding median GHG reduction of 35.38%. Third, carbon valuation materially influenced spatial rankings, with 44 of 54 groups changing their preferred alternative at USD 100/$tCO_2e$. Assumption-based perturbations further revealed substantial ranking sensitivity.

The evidence-governance component passed seven controlled numerical-defect tests, while the separate industrial LCA assessment reproduced 12 published environmental totals from Machala et al. [50]. These findings establish computational consistency and demonstrate the importance of distinguishing environmental preferences, decision stability, and evidence eligibility. CIRCUIT-5 contributes a transparent approach to preliminary circular-investment screening by integrating economic–environmental trade-offs with robustness and numerical evidence controls. Future research should incorporate project-level cash flows, operationally feasible recycling networks, empirically calibrated uncertainty, and independently observed investment outcomes. Such extensions would strengthen external validation and support practical financial decision-making.

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