

# TECHNO-ECONOMIC ASSESSMENT OF ARTIFICIAL INTELLIGENCE-ENABLED SORTING FOR SCALABLE RECYCLING OF SPENT CONSUMER BATTERIES IN THE UNITED STATES

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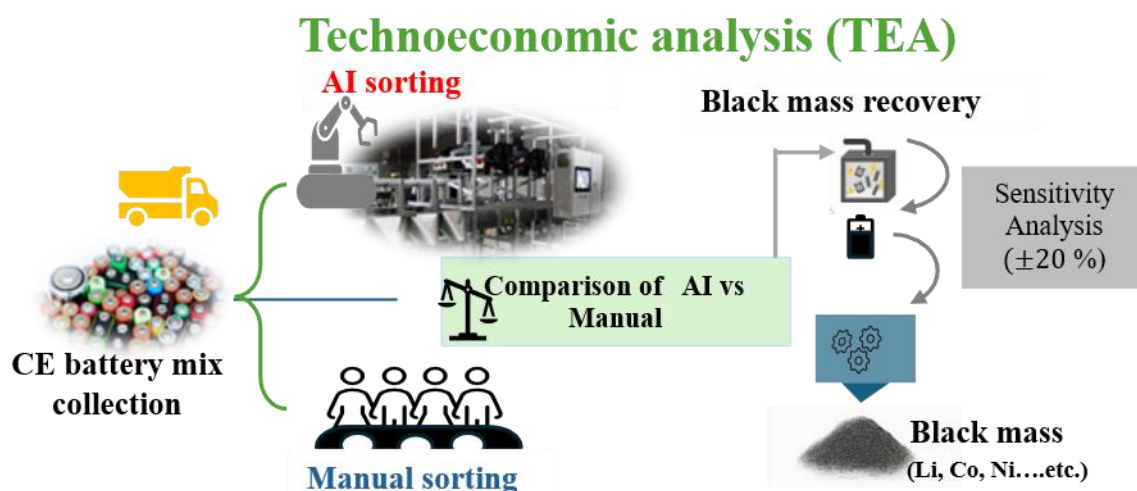
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## Graphical Abstract



## Abstract

The growing stream of spent consumer electronic batteries (e.g., alkaline, lithium-ion, NiMH, NiCd, small-sealed lead-acid) in the U.S. poses environmental risks like groundwater contamination and fire hazards, alongside economic challenges from rising battery demand and raw material supply risks. Effective end-of-life management is essential to recover critical materials. While automotive battery recycling (e.g., lead-acid) is well-established, consumer battery recycling is underexplored despite its hazardous waste impact and resource potential. Conventional recycling relies on inefficient, costly manual sorting due to diverse chemistries. Integrating AI for sorting could revolutionize recycling by improving efficiency, accuracy, and scalability, reducing costs and environmental impacts. This study presents a preliminary techno-economic analysis of an AI-enabled sorting system developed by UHV Technologies for mixed consumer electronic batteries in the United States, benchmarked against manual sorting. The facility was modelled at 4,000 tons per year and assessed across three battery mix scenarios: SC1 (pessimistic), dominated by low-value primary chemistries; SC2 (base case), reflecting current U.S. collection data; and SC3 (optimistic), simulating a future stream rich in high-value Li-ion batteries. Revenues were derived from black mass containing Co, Ni, Li, and Mn, while expenses included transportation, capital costs, and operating costs, all scaled with throughput. Sorting efficiencies of 50–100 % were tested across the three scenarios, with revenues, expenses, and net profits recalculated for each case. At 90 % efficiency, AI-enabled sorting consistently outperformed manual methods by reducing OPEX and improving scalability. A multi-variable sensitivity analysis, performed in Python, evaluated uncertainties in black mass price ( $\pm 20\%$ ), throughput ( $\pm 20\%$ ), transport distance (1,250–3,750 miles), and sorting efficiency (50–100 %). Results confirm the economic viability of AI-enabled sorting, with black mass price and annual throughput as the

largest cost drivers. To our knowledge, this is the first U.S.-focused TEA comparing AI-enabled and manual sorting of mixed consumer batteries, providing a data-driven foundation to advance sustainable recycling infrastructure and support national critical material recovery goals.

**Keywords:** End-of-life treatment; Artificial intelligence; Black mass recovery; Techno-economic analysis; Sorting; Consumer electronic batteries

## 1.0 Introduction and Motivation

Consumer electronic (CE) batteries are ubiquitous and produce significant U.S. waste streams. Inappropriate disposal leads to fires and other environmental issues<sup>1</sup>. These batteries span multiple chemistries (Li-ion, alkaline, nickel-metal hydride (NiMH), etc)- thus, proper end-of-life management is required to reclaim valuable components and reduce supply-chain vulnerability. However, while leading U.S. collection programs like Call2Recycle collected ~4,000 t yr<sup>-1</sup> of CE batteries<sup>3</sup>, over 3 billion CE battery units (180,000 t yr<sup>-1</sup>, with more than 95 % being single-use alkaline) are disposed of by Americans every year<sup>1,4</sup>. This large disparity indicates a great opportunity to scale up the recycling capacity of spent CE batteries to recover critical materials and reduce environmental and fire hazards. Good recycling depends especially on precise sorting since direct-recycling techniques call for single-chemistry inputs to yield high-purity cathode materials<sup>2</sup>.

Manual sorting, the current and most predominant strategy, is labor-intensive, error-prone, and unscalable, leading to cross-contamination, reduced black mass purity, and recycling rates as low as 15 % for mobile phone batteries<sup>5,6</sup>. Even human-assisted direct recycling, which relies on manual cathode-chemistry identification during pretreatment, fails to achieve financial viability at scale due to persistent labor costs and throughput bottlenecks<sup>7</sup>. The diverse chemistries (alkaline, Li-ion, NiMH, NiCd, SSLA), form factors, and residual charge levels complicate downstream processing, while automotive battery recycling is mature, with lead acid recycling reaching 99 % in USA<sup>8</sup>, consumer electronic battery streams remain underexplored<sup>1</sup>.

This study fills a key gap in CE battery recycling by evaluating AI sorting and pre-treatment, as an explicit economic driver in techno-economic analysis, an aspect that remains underexamined in prior TEA studies that largely focus on EV batteries or assume pre-sorted feedstocks. We develop a full discounted-cash-flow model for an AI-enabled sorting system at 4,000 t yr<sup>-1</sup> and benchmark it against manual sorting across pessimistic, base, and optimistic U.S. waste-stream scenarios. Using industry data (UHV Technologies) and 2024 Call2Recycle compositions, we assess profitability, scalability, and risk, providing a data-driven foundation for modular and scalable U.S. sorting infrastructure aligned with national resource-security goals.

## 2.0 Review of Related Work

Prior research has demonstrated the potential of AI-enabled sorting systems using machine vision and machine learning to classify battery chemistries with >90 % accuracy. Several works have evaluated direct-recycling pathways and the role of economies of scale in lowering per-ton processing costs, but these studies have largely focused on EV batteries<sup>6,8-10</sup>. Existing TEA analyses typically assume pre-sorted, single-chemistry feedstocks and do not assess the economic implications of automated versus manual sorting for mixed consumer battery waste. To date, no U.S.-focused TEA has quantified how sorting accuracy influences black-mass value or the overall financial viability of small- and medium-scale recycling operations. This study addresses this gap by comparing AI-enabled sorting with manual sorting under realistic consumer electronic waste-stream conditions. By explicitly treating sorting efficiency as a variable economic driver rather than a fixed preprocessing assumption, this work provides new insights into how upstream sorting efficiency propagate through black-mass valuation and overall profitability, scalability, and financial risk in consumer electronic battery recycling systems.

## 3.0 Technology Approach

### 3.1 System Boundary and Scope

This study presents a techno-economic analysis (TEA) to evaluate the viability of AI-enabled sorting (AIS) for recycling mixed end-of-life (EoL) consumer electronic batteries (CEB) in the United States, benchmarked against manual sorting (MS). The model strictly adheres to the computational framework defined in our coded structure, integrating capital expenditure (CAPEX), operational expenditure (OPEX), revenue streams, and discounted cash flow (DCF) analysis to compare the two sorting technologies. The analysis follows a gate-to-gate system boundary,

encompassing all operations from collection and transport of mixed EoL batteries to sorting (either AI-enabled ultra-high vision or manual) and subsequent on-site black mass (BM) recovery (discharge, disassembly, mechanical size reduction, and separation). The AIS conducts real-time identification and classification of batteries by chemistry on a conveyORIZED feed and uses a series of two-axis actuators to direct each battery into its corresponding output stream, as illustrated in Fig. 1. The BM facility produces black mass sold at market prices. Upstream stages (battery manufacture and use) and downstream metal refining and cathode remanufacturing are excluded from the boundary. All metrics are normalized to 1 metric ton (t) of EoL CEB processed, with costs/revenues in constant 2024 US dollars. Analyses assume a 10-year project lifespan and utilization ramp-up. The model was implemented in Python 3.12 (NumPy, Pandas, Matplotlib) for reproducibility.

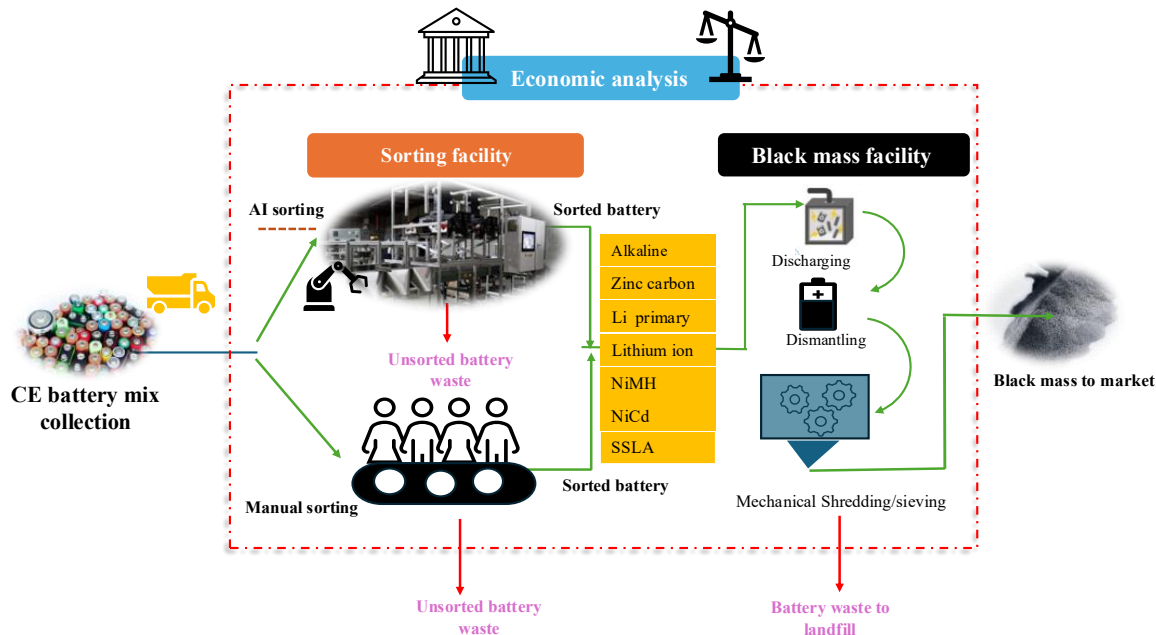


Fig. 1. System boundary and process flow used in this study for AI-enabled and manual sorting coupled with black-mass recovery of end-of-life consumer electronic batteries.

Two systems were assessed. Thus, a manual-sorting system (MS+BM) with 80–90 % efficiency and an AI-enabled sorting system (AIS+BM), which uses machine vision and machine learning for chemistry recognition at 90 % accuracy. Both provide a shared black-mass recovery process generating a Co/Ni/Li/Mn-rich concentrate.

### 3.2 CEB Feedstock Characterization and Scenarios

Based on 2024 Call2Recycle collection data, it was projected that mixed consumer electronic batteries (CEBs) in U.S. would have a baseline throughput of 4,000 t yr<sup>-1</sup><sup>3</sup>. The collected consumer electronic batteries (CEBs) include zinc–carbon, lithium primary, and lithium-ion (Li-ion) types lithium cobalt oxide (LCO), nickel manganese cobalt oxide (NMC), nickel cobalt aluminum oxide (NCA), lithium iron phosphate (LFP), lithium manganese oxide (LMO), and lithium titanate (LTO), as well as nickel–metal hydride (NiMH), nickel–cadmium (NiCd), and sealed lead–acid (SSLA) batteries. Three waste-stream scenarios were modeled (Table 1): a legacy-dominated pessimistic mix (SC1), a representative U.S. composition from 2024 collections (SC2), and a Li-ion-rich future stream enabled by improved sorting and policy support (SC3).

Table 1. Battery waste stream composition across three U.S. collection scenarios.

Battery Chemistry	SC1 – Pessimistic (%)	SC2 – Base (%)	SC3 – Optimistic (%)
Alkaline	62.1	29.7	10.0
Zinc Carbon	2.5	1.2	0.5
Lithium Primary	0.5	0.2	0.1

Other Primary	2.0	1.0	0.3
Li-ion*	12.5	40.7	70.0
LCO	5.0	16.3	28.0
NMC	4.4	14.2	24.5
NCA	1.3	4.1	7.0
LFP	1.3	4.1	7.0
LMO	0.3	1.0	1.8
LTO	0.3	1.0	1.8
Ni-MH	1.5	1.2	2.5
Ni-Cd	1.3	11.1	5.0
SSLA / Pb	17.7	14.8	11.6
<b>Total Battery</b>	<b>100.0</b>	<b>100.0</b>	<b>100.0</b>

\*Li-ion = LCO + NMC + NCA + LFP + LMO + LTO.

### 3.3 Black Mass Valuation

Black-mass value was computed using metal mass fractions for each chemistry and 2025 USGS metal prices<sup>11</sup>, applying standard payable coefficients (60–75 %) <sup>12</sup> to reflect refining losses. These chemistry-specific values were aggregated using the scenario waste-stream fractions to obtain the per-ton revenue used in the TEA model. The spot value of black mass (\$/t) was therefore determined as the sum of recoverable metal contributions, adjusted for chemistry-specific payables<sup>12</sup>:

$$BM_k = \sum_{i=1}^M w_{i,k} p_i \phi_i \quad (1)$$

where,  $BM_k$  is the value of the black mass from battery chemistry  $k$  (\$ t<sup>-1</sup>),  $w_{i,k}$  is the mass fraction of metal  $i$  in chemistry  $k$  (wt %),  $p_i$  is the corresponding metal price (\$ t<sup>-1</sup>), and  $\phi_i$  is the payable fraction (typically 0.6–0.75), reflecting refining losses and process inefficiencies.

### 3.4 Technoeconomic Analysis Model Inputs and Assumptions

#### 3.4.1 Sorting Facilities

Bill of materials and economic parameters for AI-assisted sorting operations were supplied by industry collaborator UHV AI Sorting Technologies. For this analysis, capital expenditures (CAPEX) were scaled down to a 4,000-t yr<sup>-1</sup> capacity to capture a representative baseline scenario for smaller-scale deployments. We adopted the six-tenths rule<sup>13</sup> (n=0.6), positing capital costs<sup>14</sup> rise with capacity to the power of 0.6. The scaling equation is:

$$\frac{C_2}{C_1} = \left(\frac{Q_2}{Q_1}\right)^N \quad (2)$$

where  $C_1$  refers to the known investment for capacity  $Q_1$ ;  $C_2$  refers to the investment desired for capacity  $Q_2$ ; and  $N$  is the investment-capacity factor. AIS operating costs were derived from labor, maintenance, and throughput-dependent expenses, with OPEX scaling sub-linearly<sup>15</sup> with capacity ( $Q^{0.9}$ ). Baseline CAPEX for a 4,000-t yr<sup>-1</sup> facility included site preparation, utilities, and equipment for automated vision-based sorting. Manual sorting CAPEX was estimated at 0.62× AIS (reflecting lower automation needs, e.g., fewer sensors/robots), and OPEX at 2.27× AIS per ton. These ratios are benchmarked from U.S. LIB recycling studies<sup>6</sup>. Logistics costs encompassed transportation (\$0.156 per ton-mile × 2,500 miles average U.S.<sup>15</sup>, end-of-life collection/handling (\$400/t at drop-off points like Home Depot), and tipping fees for unsorted residuals (\$60/t to landfills/incinerated)<sup>16</sup>. Maintenance requirements for the AI-enabled sorting system include routine sensor calibration, mechanical servicing of conveyors and handling equipment, and periodic software and model updates. These activities were incorporated into annual operating expenditures (OPEX).

#### 3.4.2 Black Mass Recovery Step

We conducted the analysis on a standardized black mass recovery process encompassing discharge, semi-automated disassembly, and mechanical pretreatment integrated with either AIS+BM or manual sorting (MS+BM) for direct comparison. Economic parameters for the black mass recovery step were sourced from a prior battery recycling

investment report<sup>17</sup>. This reference specifies a capital cost of \$9.94 million and a fixed operating cost of \$1.2 million per year at a capacity of 10,000 t yr<sup>-1</sup>.

### 3.5 Economic Analysis and Calculations

The annual revenue (Eq. 3) generated from the recycling process was estimated by summing the contributions from all battery chemistries, accounting for their respective fractions in the feed, sorting efficiencies, and yields.

$$R_{\text{annual}} = Q\eta Y \sum_{k=1}^K f_k \text{BM}_k \quad (3)$$

where,  $R_{\text{annual}}$  is the annual revenue (\$ y<sup>-1</sup>),  $Q$  is the throughput (t y<sup>-1</sup>),  $\eta$  is the sorting efficiency,  $Y$  is the black-mass yield (t BM t<sup>-1</sup> feed),  $f_k$  denotes the mass fraction of chemistry  $k$  in the feed,  $K$  is the total number of chemistries present, and  $\text{BM}_k$  is the value of black mass from chemistry  $k$ . Eq. (2) thus scales the feed-weighted valuation to annual economic output, capturing the combined effects of feed composition, recovery efficiency, and throughput. For baseline simulations,  $\eta$  and  $Y$  were assumed constant across chemistries, while  $f_k$  reflected measured waste-stream compositions. The corresponding annual profit ( $P_{\text{annual}}$ ) was determined by introducing all relevant cost components. The equation is given by:

$$P_{\text{annual}} = Q\eta Y \sum_{k=1}^K f_k \text{BM}_k - Q(1 - \eta)c_{\text{tip}} - Q(c_{\text{coll}} + c_{\text{tr,base}}) - \text{CRF } C_{\text{cap}} - F_o - V_o \quad (4)$$

where,  $P_{\text{annual}}$  is the annual profit (\$ y<sup>-1</sup>),  $Q$  is the annual throughput (t y<sup>-1</sup>),  $f_k$  is the mass fraction of chemistry  $k$ ,  $V_o$  is the variable operating cost (\$),  $c_{\text{tip}}$  is the tipping fee per ton of waste material (\$ t<sup>-1</sup>),  $c_{\text{coll}}$  is the collection costs per ton (\$ t<sup>-1</sup>),  $C_{\text{cap}}$  is the total nominal capital investment (\$), and  $F_o$  is the fixed annual OPEX (\$ y<sup>-1</sup>). CRF is the capital-recovery factor<sup>18</sup>.

Discounted-cash-flow (DCF) analysis was used to evaluate economic performance over a 10-year project life, computing net present value (NPV), internal rate of return (IRR), and payback. Annual operating profit was derived from throughput, sorting efficiency, black-mass yield, and fixed/variable OPEX and CAPEX terms, using standard accounting without double-counting capital recovery. After-tax cash flow was calculated using straight-line depreciation (10 years), a 25 % corporate tax rate, and a discount rate of 8 %. Start-up behavior was represented with utilization (0.6, 0.8, 1.0) and OPEX multipliers (1.2, 1.1, 1.0) for Years 1–3, respectively, converging to steady-state thereafter. NPV, IRR, and payback were obtained from the annual cash-flow series. All techno-economic computations were performed in Python; underlying scripts and datasets can be made available upon reasonable request.

Uniform sorting efficiency and black-mass yield were assumed across battery chemistries at a given efficiency level to isolate the system-level economic impact of sorting accuracy and enable a consistent comparison between AI-enabled and manual sorting configurations. In practice, chemistry-dependent sorting performance may vary depending on sensor configuration and classifier training; however, these effects are abstracted here into a single system-level efficiency parameter. The overall sorting efficiency ( $\eta$ ) was therefore treated as a variable and systematically varied from 50–100% in subsequent analyses to quantify its influence on revenue, profitability, and discounted cash-flow metrics

### 3.6 Sensitivity Analysis

Under the baseline SC2 scenario (4,000 t yr<sup>-1</sup>), sensitivity analysis was carried out to assess how important variables affect annual profit for both AIS+BM and MS+BM configurations. To evaluate how black-mass price, throughput, logistics expenses, tipping fees, and collection charges affect total economic performance, a deterministic  $\pm 20$  % tornado study was run.

The TEA formulation also highlights the main factors that contribute to AIS economic performance, namely throughput capacity, sorting accuracy (informed by sensor and algorithm improvements), and the scalability of the system architecture, such as adding additional sorting lanes or actuators. These factors frame the economic drivers explored in the following results.

## 4.0 Discussion

### 4.1 Techno-Economic Baseline (SC2, 90 % efficiency)

A representative techno-economic baseline for the AIS+BM system was established using three collection-mix scenarios spanning realistic end-of-life battery chemistry (Table 2).

Table 2. Baseline (SC2, 90 % sorting efficiency)

Scenario	Revenue/ ton (\$)	Total expense /ton (\$)	Profit (\$/y)	NPV (\$)	IRR (%)	Payback
SC1	1,124.3	1,535.5	-1,644,836	-12,937,632	n/a	n/a
SC2	1,908.5	1,535.5	1,491,770	3,942,307	17.7	5
SC3	2,521.0	1,535.5	3,941,780	15,386,150	40.7	3

The SC2 configuration represents a balanced and financially viable operating regime, delivering positive cash flow and moderate investment returns under realistic feed conditions. In this study, increasing Li-ion from 41 % to 70 % while reducing alkaline from 30 % to 15 % and Pb from 15 % to about 5 % raises IRR from 17.7 % (SC2) to 40.7 % (SC3), an average increase of 8 % per 10 percentage point increase in Li-ion. This finding aligns with downstream hydrometallurgical models, which report IRR gains of 5.5–10.6 % for every 10 % shift toward high-value cathodes<sup>15</sup>. It confirms that upstream AI sorting achieves comparable economic leverage—even in heterogeneous waste streams<sup>15,19</sup>. These findings position the SC2 case as a robust economic midpoint, forming the reference basis for subsequent analyses of sensitivity. Additionally, this indicates that systems targeting Li-ion–dominant streams (as in SC3) can achieve markedly higher capital productivity.

### 4.2 Impact of Sorting Efficiency on Economic Performance

Sorting efficiency ( $\eta$ ) exerts a decisive influence on the techno-economic viability of battery-recycling systems. This influence has been widely reported in prior techno-economic assessments of lithium-ion battery recycling processes<sup>20–22</sup>. Across the 50–100 % range (Fig. 2 a,b), both (AIS + BM) and (MS + BM) configurations exhibit sharp improvements in profitability with increasing sorting accuracy. At low efficiencies (< 70 %), revenue from recovered black mass remains insufficient to offset operating and capital costs, resulting in negative margins. As  $\eta$  increases, revenue per ton rises almost linearly with the fraction of correctly identified material. In contrast, total expenditure increases only marginally. This behavior arises because fixed capital costs and maintenance dominate operating expenses, limiting cost sensitivity to sorting accuracy.

Accounting analyses (Fig. 2b) show that AI sorting system achieves profitability at  $\eta$  of 72.9 %, compared with 75.4 % for MS, owing to lower labor and handling, consistent with prior modelling of battery recycling systems<sup>21</sup>. Beyond these thresholds, the AI sorting profit curve steepens rapidly, reflecting its 56 % lower specific OPEX and greater throughput stability. Once the AI system surpasses its break-even point, each incremental percentage improvement in precision increases marginal returns, underscoring the economic leverage of AI-driven classification where fixed costs are already sunk.

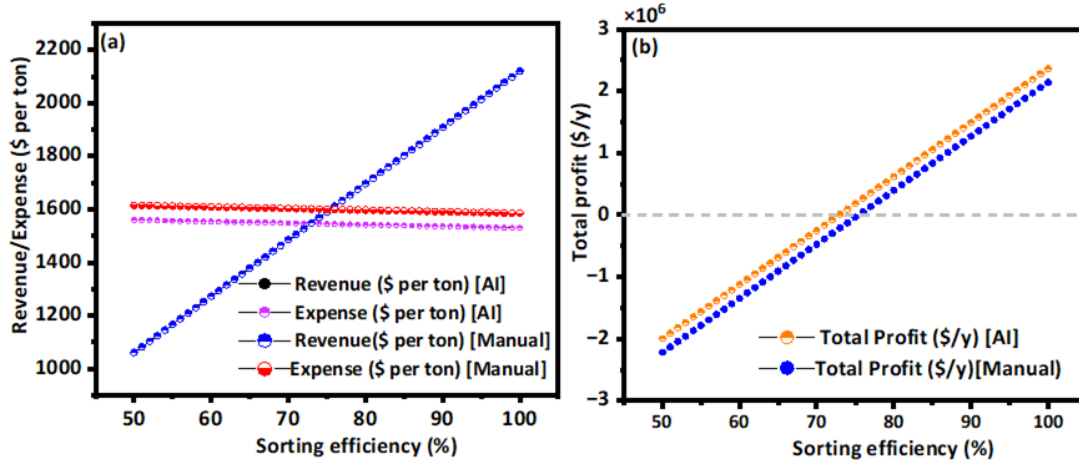


Fig. 2 Effects of sorting efficiency on (a) revenue, total expense, and (b) annual profit ( $\eta = 50\text{--}100\%$ ). Note: Revenue per ton is identical for AI-assisted and manual sorting; therefore, the data points overlap in panel (Fig 2a).

Discounted-cash-flow analysis further reinforces this trend under an 8 % discount rate and a 25 % corporate tax rate (Fig. 3a–c). As sorting efficiency increases, both systems transition from negative to positive net present value (NPV; Fig. 3a). The AI-assisted system crosses the zero-NPV threshold earlier, at approximately 73 %, compared with about 76 % for MS. At the baseline 90 % efficiency, AIS delivers roughly  $2.5 \times$  greater discounted net value, combining lower OPEX with faster capital recovery. The curvature of the NPV– $\eta$  relationship indicates that small efficiency gains near the break-even threshold produce steep improvements in long-term project value. This behavior highlights the sensitivity of financial resilience to classification accuracy, particularly under volatile black-mass pricing conditions commonly observed in lithium-ion battery recycling markets.<sup>15</sup>

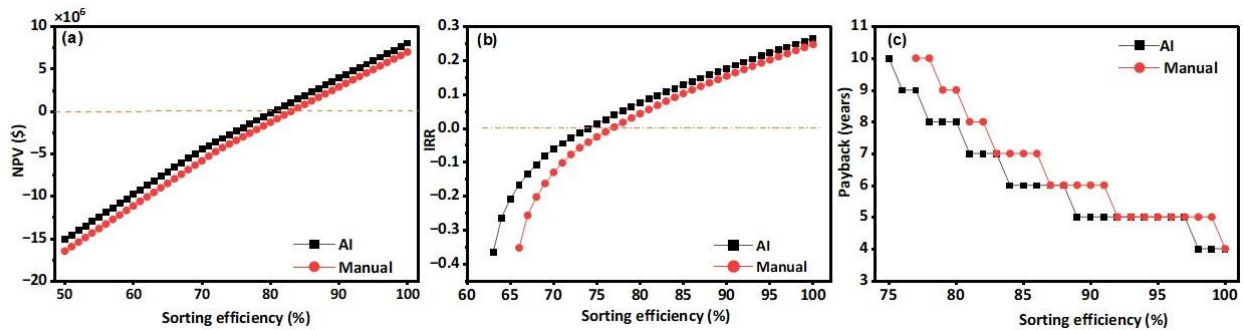


Fig. 3. Discounted-cash-flow (DCF) performance (a) NPV, (b) IRR, and (c) Payback vs Sorting Efficiency ( $\eta = 50\text{--}100\%$ , SC2).

The internal rate of return (IRR, Fig. 3b) exhibits a similar trend. Both systems exceed the 8 % investment hurdle near their respective break-even efficiencies, but AIS achieves double-digit IRRs ( $>20\%$ ) once  $\eta > 85\%$ , whereas MS remains below this level even at 90 %. The divergence reflects the compounded advantage of automation: lower marginal costs and steadier yield increase after-tax cash flows across the project lifetime. In investment terms, the AI-enabled system remains profitable even under moderate market conditions, whereas manual operations quickly lose financial viability without external support or high-grade feedstock. Payback analysis (Fig. 3c) further quantifies this efficiency leverage. The payback period of the AIS declines from 10 years at 75 % efficiency to 5 years at 90 %, while MS remains at 6 years across comparable efficiencies. The shorter payback horizon directly reduces financial exposure and accelerates reinvestment potential, a key criterion for early commercial deployment. Overall, sorting efficiency is the dominant economic lever that links process accuracy to profitability, investment resilience, and risk profile.

### 4.3 Sensitivity

The tornado analysis (Fig. 4) shows that black-mass price dominates annual profit variability, with a  $\pm 20\%$  shift producing nearly  $\pm \$1.53$  million  $y^{-1}$  in both configurations. Throughput scaling emerges as the next-largest contributor ( $\pm \$0.63$  million  $y^{-1}$  for AIS and  $\pm \$0.60$  million  $y^{-1}$  for manual sorting), followed by process operating cost, which adds  $\pm \$0.41$ – $0.46$  million  $y^{-1}$  in leverage at steady state. By contrast, variations in tipping fee, collection cost, and transport distance exert smaller and largely symmetric effects, reflecting the dominance of material-value recovery over logistics in overall profitability.

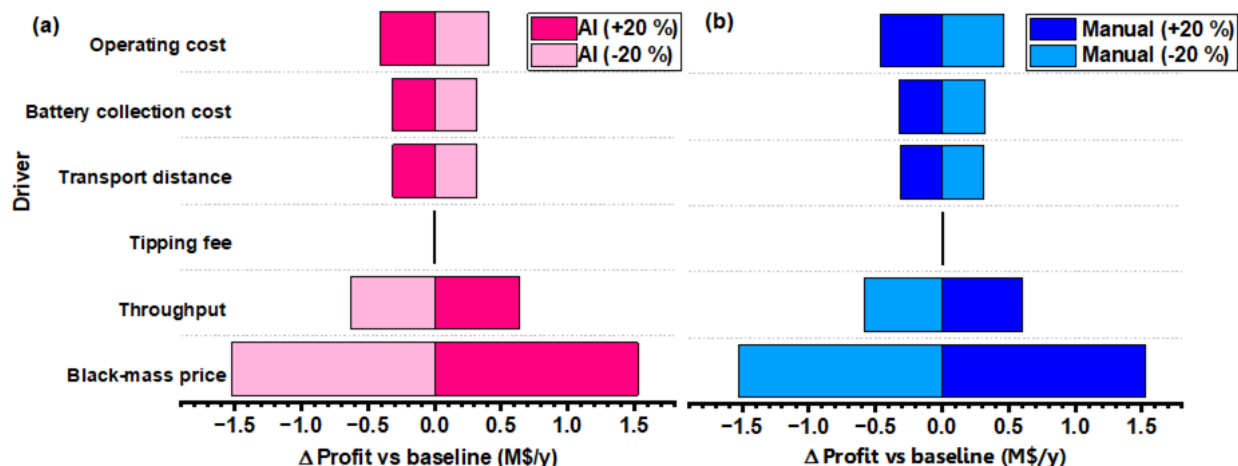


Fig. 4. Tornado analysis showing annual-profit variation ( $\pm 20\%$ ) for key parameters.

The sensitivity ranking shows black-mass price  $>$  throughput  $>$  operating cost  $>$  collection  $\approx$  transport  $>$  tipping fee aligns with evidence from prior techno-economic analyses of black-mass production and recycling<sup>23</sup>. Further, automation of sorting and high-volume processing reinforces that when sorting throughput and product value dominate margin, logistics and disposal costs become comparatively minor, even if OPEX increases by 20%<sup>24</sup>, whereas manual sorting approaches breakeven under similar perturbations.

In practical deployment, AI-enabled battery sorting systems may be influenced by factors such as feedstock heterogeneity, sensor fouling, conveyor downtime, and the need for periodic retraining of classification models as battery chemistries evolve. Pilot-scale evaluation of the sorting system is currently ongoing and will be reported in future work. In the present study, these real-world considerations are implicitly reflected through conservative sorting-efficiency ranges (50–100%) and operating-cost sensitivity analysis, enabling evaluation of economic robustness under realistic operational variability. A further limitation of the present analysis is that changes in battery chemistry over time may affect sorting efficiency and classifier performance; these effects are abstracted here into a system-level efficiency parameter and represent an important area for future investigation.

### 5.0 Conclusion and Recommendations

For U.S. consumer electronic battery recycling, this research shows that AI-enabled sorting yields better and more consistent economic performance than manual sorting. Driven by reduced operating costs, increased sorting efficiency, and improved black-mass recovery, the AI system achieves favorable net present value (NPV) and an internal rate of return (IRR) of around 18% at a 4,000  $ty^{-1}$  baseline. The economic advantage of AIS arises from its higher sorting accuracy and substantially lower labor dependence, which together produce more stable throughput and higher-value black-mass output. Here, the developed TEA framework gives a solid foundation for planning modular, scalable American recycling plants. The TEA framework developed here provides a practical basis for designing scalable, modular U.S. recycling facilities. Future work may extend this framework to assess alternative AIS architectures, including robotic-arm sorters, XRF-assisted sensing, and hybrid multi-sensor systems while integrating environmental life-cycle metrics such as avoided emissions and material savings to complement accuracy–cost trade-off analysis and provide a more holistic system assessment.

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