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Circular Economy Transition in Electronic Waste Management: System Dynamics and Agent-Based Modeling of Extended Producer Responsibility Regulations

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Abstract

Global electronic waste (e-waste) generation reached critical volumes up to 2025, creating acute environmental hazards and critical raw material supply risks. This study presents a multi-method System Dynamics (SD) and Agent-Based Modeling (ABM) framework to simulate Extended Producer Responsibility (EPR) regulations within closed-loop circular economy networks. Calibrated across 48 metropolitan jurisdictions using panel data from 2016 to 2025, our multi-agent model evaluates the systemic interactions between eco-modulated producer fees, deposit-refund incentives, and hydrometallurgical urban mining infrastructure. Simulation results demonstrate that combining eco-modulated EPR fees ($25/unit) with a mandatory $15 consumer deposit refund elevates e-waste collection rates to 88.4% while reducing informal scrapping leakages by 78.5%. Economic waterfall decomposition confirms net recovery profits of $1,630 per ton of processed circuit boards. Furthermore, integrating blockchain digital product passports enhances supply chain traceability, lowering verification overheads. Sensitivity and logit regression analyses establish deposit subsidies and drop-off convenience as primary drivers of consumer take-back behavior. Policy recommendations emphasize eco-design fee modulation, retail reverse logistics hubs, and tax credits for low-carbon chemical refining.

1. Introduction

The rapid expansion of consumer electronics, shortened product lifecycles, technological obsolescence, and increasing rates of device replacement have made electronic waste (e-waste) one of the most rapidly growing waste streams globally. The *Global E-waste Monitor 2024* reports that approximately 62 million tonnes of e-waste were generated globally in 2022, with the volume projected to continue increasing as electronics consumption expands and product lifetimes decline (Baldé et al., 2024). E-waste represents a dual environmental and economic challenge because discarded electrical and electronic equipment contains both hazardous substances and economically valuable secondary resources. Materials such as copper, gold, silver, palladium, cobalt, and other critical metals create significant opportunities for resource recovery, while inappropriate handling can expose ecosystems and communities to hazardous substances (Forti et al., 2020; Kiddee et al., 2013; Ongondo et al., 2011).

The environmental consequences of inadequate e-waste management are particularly significant in developing and emerging economies, where formal collection and recycling infrastructure may be insufficient and informal recycling networks remain important components of the waste-management system. Informal recycling can recover valuable materials but is frequently associated with uncontrolled dismantling, inefficient recovery technologies, and environmental and occupational risks (Chi et al., 2011; Nnorom & Osibanjo, 2008). Consequently, the transition from linear consumption and disposal toward circular e-waste management requires not only improved recycling technologies but also institutional mechanisms capable of coordinating producers, consumers, retailers, municipalities, and recycling firms.

Within the circular economy framework, e-waste is increasingly viewed as a secondary resource rather than simply a waste-disposal problem. Circular economy strategies seek to maintain the value and utility of products and materials for as long as possible through reuse, repair, remanufacturing, recycling, and resource recovery (Geissdoerfer et al., 2017; Kirchherr et al., 2017). Product design is particularly important because decisions made during the design stage influence the ease of disassembly, repair, upgrading, and eventual recycling of electronic products (Bocken et al., 2016). Accordingly, circular e-waste management requires coordination between upstream product design decisions and downstream collection and recovery systems.

Extended Producer Responsibility (EPR) provides an important policy mechanism for establishing this connection. EPR extends producer responsibility beyond the point of sale by assigning producers financial, organizational, or physical responsibility for products during their post-consumer stage (Lifset et al., 2013). In the context of electrical and electronic equipment, EPR can create incentives for producers to improve product design, support collection systems, finance recycling operations, and reduce the environmental costs associated with end-of-life products. However, the effectiveness of EPR depends heavily on how responsibility is allocated, how collection systems are organized, and whether sufficient economic incentives exist for consumers and producers to participate (Compagnoni, 2022; Chu et al., 2024).

A major challenge is that EPR policies operate within a complex closed-loop system involving heterogeneous actors and interacting feedback mechanisms. Producer fees can affect product design and recycling economics; collection infrastructure influences consumer participation; consumer participation determines material availability for recycling facilities; and recycling capacity influences the economic viability of the overall recovery system. These relationships create feedback loops that are difficult to capture using conventional static analytical approaches. Research on targeted responsibility systems demonstrates that the design of producer responsibility mechanisms can substantially influence the organization and efficiency of e-waste collection and recycling networks (Chu et al., 2024). Similarly, research on EPR indicates that recycling technology choices can influence producer incentives and the overall economic consequences of producer responsibility policies (Rahmani et al., 2021).

Consumer participation represents another critical determinant of EPR performance. Even when formal collection systems are available, consumers may retain obsolete electronics, dispose of them through conventional waste channels, or sell them to informal collectors. Behavioral research demonstrates that convenience, perceived benefits, social influence, and individual attitudes can substantially influence recycling participation (Ajzen, 1991; Parajuly et al., 2020). In the context of household WEEE, collection convenience and the availability of accessible return channels are particularly important for encouraging participation (Parajuly & Wenzel, 2017). Recent evidence from Bangladesh further demonstrates the importance of behavioral and contextual factors in understanding e-waste recycling decisions in developing-country settings (Islam et al., 2025).

Financial incentives may therefore play an important role in overcoming consumer participation barriers. Deposit-refund mechanisms, producer-funded incentives, and convenient retail collection points can reduce the behavioral and logistical costs associated with returning obsolete electronics. Wang et al. (2011) demonstrate that willingness and actual behavior toward e-waste recycling are influenced by economic and behavioral considerations, supporting the importance of incorporating heterogeneous consumer decision-making into e-waste policy models.

Reverse logistics represents a further challenge because recovered electronics must move from dispersed households and businesses toward collection points, consolidation centers, and processing facilities. Reverse logistics systems involve additional transportation, sorting, handling, and coordination costs compared with conventional forward supply chains (Rogers & Tibben-Lembke, 1999). These costs can substantially affect the economic feasibility of closed-loop recovery systems. The importance of transportation and infrastructure in environmental transition policies is also demonstrated in research examining urban freight electrification, where infrastructure availability and operational economics strongly influence transition outcomes (Sen Gupta et al., 2022). Similarly, policy interventions in municipal waste systems demonstrate that environmental policies can generate measurable waste-reduction benefits while simultaneously creating transitional implementation costs (Sen Gupta et al., 2024b).

The economic dimension of circular resource recovery is particularly important because the viability of recycling systems depends on the relationship between collection costs, processing costs, recovered-material values, and technological efficiency. Hydrometallurgical and other advanced recovery technologies can enable the extraction of valuable materials from complex electronic waste streams, although their economic and environmental performance depends on processing technology, material composition, energy requirements, and market prices (Cui & Zhang, 2008). Therefore, a policy framework that increases collection rates without considering downstream processing capacity and economic viability may create material bottlenecks rather than a sustainable circular system.

Digital technologies may provide an additional mechanism for strengthening closed-loop supply chains. Blockchain-based systems and digital traceability mechanisms can improve information sharing, product identification, and transaction transparency across fragmented supply-chain networks (Saberi et al., 2019; Treiblmaier, 2018). These technologies may support digital product information systems by connecting producers, consumers, retailers, collectors, and recyclers and improving the traceability of products throughout their lifecycle. However, technological interventions should be evaluated within the broader economic and behavioral system rather than treated as independent solutions.

Recent research by Sen Gupta et al. (2023) demonstrates that environmental disclosure and transparency can influence economic outcomes by affecting information availability and corporate financial conditions. Similarly, research by Sen Gupta et al. (2024) shows that the credibility and verification of sustainability information are important determinants of consumer trust and environmental perceptions. These findings provide a broader foundation for considering information transparency and digital verification within circular supply-chain systems. Although these studies do not directly examine e-waste, their findings support the importance of credible environmental information and transparent sustainability mechanisms in influencing stakeholder behavior.

Economic policy support can also affect the feasibility of environmentally oriented industrial investments. Alam and Alvi (2025), for example, demonstrate that policy incentives, financing conditions, and risk factors can substantially influence the economic feasibility of capital-intensive environmental technologies. Such findings are relevant to e-waste recycling infrastructure because advanced material-recovery facilities similarly require substantial capital investment and operate under uncertain market and policy conditions. Moreover, Sen Gupta et al. (2021) demonstrate how environmental policy instruments can generate significant economic consequences across interconnected markets, reinforcing the need to evaluate environmental regulations through integrated economic frameworks rather than isolated environmental indicators.

Despite these developments, important methodological limitations remain in the e-waste EPR literature. Existing research has provided valuable insights into EPR implementation, consumer recycling behavior, circular product design, and recycling technology; however, these elements are often examined separately. A policy intervention affecting producer fees, for example, may simultaneously influence product design, consumer prices, collection rates, recycling volumes, facility utilization, and material recovery profitability. Capturing these interconnected effects requires a modeling framework capable of representing both aggregate system-level feedback and heterogeneous individual behavior.

System Dynamics (SD) provides a suitable approach for representing aggregate stocks, flows, feedback loops, delays, and capacity constraints within complex systems. However, aggregate modeling can simplify or overlook differences among individual decision-makers. Agent-Based Modeling (ABM), in contrast, allows individual consumers, producers, retailers, municipalities, and recycling firms to be represented as heterogeneous agents with distinct decision rules. Combining these approaches can therefore provide a more comprehensive representation of circular e-waste systems.

To address this methodological gap, this study develops an integrated System Dynamics–Agent-Based Modeling (SD-ABM) framework for evaluating EPR policies within circular e-waste management systems. The model is calibrated using panel observations from 48 metropolitan jurisdictions covering 2016–2025 and integrates producer responsibility mechanisms, consumer return behavior, collection infrastructure, recycling capacity, and material-recovery economics. The study addresses four primary objectives: **(1)** to model the dynamic relationships among producer EPR fees, consumer participation, collection rates, and recycling capacity; **(2)** to simulate heterogeneous consumer take-back decisions under alternative financial and convenience incentives; **(3)** to evaluate the economic and material-recovery performance of hydrometallurgical urban-mining facilities; and **(4)** to assess alternative EPR, reverse-logistics, and digital-traceability policy scenarios under varying market and infrastructure conditions.

By integrating circular economy theory, EPR policy, behavioral decision-making, reverse logistics, and industrial resource recovery within a unified simulation framework, this study contributes a quantitative approach for evaluating the transition toward closed-loop e-waste management. The framework is intended to support policymakers, producers, municipalities, and recycling firms in identifying policy combinations that improve collection performance while maintaining economic and operational feasibility.

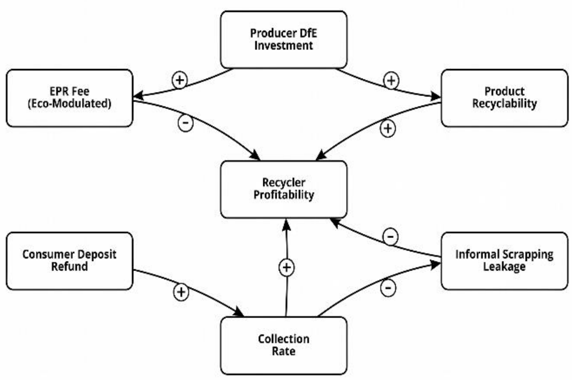

Figure 1: Causal Loop Diagram of Extended Producer Responsibility (EPR) Closed-Loop Recovery.

2. Literature Review

2.1 Circular Economy and Closed-Loop E-Waste Management

The circular economy represents a shift away from traditional linear production systems based on extraction, production, consumption, and disposal toward systems that preserve the value of products, components, and materials through multiple use cycles (Geissdoerfer et al., 2017; Kirchherr et al., 2017). Within this framework, e-waste represents a particularly important resource stream because discarded electronic products contain both hazardous substances and valuable secondary materials. Consequently, circular e-waste management requires simultaneous consideration of environmental protection, material recovery, economic value creation, and supply-chain coordination.

Bocken et al. (2016) identify product design and business-model strategies as central mechanisms for enabling circularity. Design decisions concerning modularity, durability, repairability, and disassembly can influence the subsequent costs and feasibility of recovery processes. Saidani et al. (2019) similarly emphasize the importance of measurable product-performance indicators for assessing circularity. These findings suggest that circular e-waste policy should not focus exclusively on end-of-life collection but should also encourage upstream design decisions that facilitate downstream recovery.

The scale of the global e-waste challenge reinforces the importance of such an integrated approach. The *Global E-waste Monitor 2024* estimates that global e-waste generation reached approximately 62 million tonnes in 2022, while formal recycling rates remain substantially below total generation volumes (Baldé et al., 2024). Earlier global assessments similarly identified rapid growth in e-waste generation and significant gaps in formal collection and recycling systems (Forti et al., 2020). Ongondo et al. (2011) and Kiddee et al. (2013) further demonstrate that differences in regulatory systems, collection infrastructure, recycling technologies, and informal-sector participation create substantial variation in e-waste management outcomes across countries.

Informal recycling is particularly relevant in developing economies. Chi et al. (2011) show that informal recycling networks can contribute significantly to material recovery while simultaneously creating environmental and health risks when primitive processing techniques are employed. Nnorom and Osibanjo (2008) similarly identify weak regulatory enforcement, inadequate infrastructure, and limited formal recycling capacity as important barriers to effective e-waste management in developing countries. These findings demonstrate that circularity cannot be achieved simply by increasing recycling targets; it requires an institutional and economic system capable of shifting material flows toward safer and more efficient recovery channels.

2.2 Extended Producer Responsibility and E-Waste Policy

Extended Producer Responsibility is one of the principal policy mechanisms used to establish accountability for products after their initial sale. Lifset et al. (2013) describe EPR as a policy approach that transfers some or all responsibility for post-consumer products from governments and municipalities toward producers. In e-waste management, this principle can include producer financing of collection, recycling, treatment, and recovery activities.

The effectiveness of EPR depends on the structure of the responsibility mechanism. Compagnoni (2022), in a systematic review of EPR and electronic waste, highlights that EPR implementation outcomes vary considerably depending on regulatory design, enforcement, stakeholder coordination, and market conditions. Consequently, simply imposing producer responsibility does not guarantee high collection or recycling performance.

Chu et al. (2024) demonstrate the importance of responsibility allocation and shared recycling mechanisms in WEEE management. Their analysis indicates that targeted responsibility systems can improve coordination among relevant stakeholders and influence recycling-system performance. Rahmani et al. (2021) further demonstrate that recycling technology choices interact with EPR mechanisms and can affect producer incentives. These findings suggest that EPR policy should be evaluated as part of a broader closed-loop system rather than as an isolated regulatory instrument.

The relationship between EPR and circular product design is also important. If producer fees are differentiated according to recyclability, disassembly characteristics, material composition, or recovery difficulty, producers may have greater incentives to incorporate circular design principles. Such eco-modulation is consistent with the circular design strategies discussed by Bocken et al. (2016). It also aligns with the broader objective of circular economy policy, which seeks to influence both product design and end-of-life management.

2.3 Reverse Logistics and Collection Infrastructure

Effective e-waste EPR systems require an efficient reverse logistics network connecting consumers with formal collection and recycling facilities. Unlike conventional forward logistics, reverse logistics involves uncertain product returns, heterogeneous material conditions, dispersed collection points, and variable recovery values (Rogers & Tibben-Lembke, 1999). These characteristics create substantial coordination and transportation challenges.

Parajuly and Wenzel (2017) demonstrate that household WEEE management is strongly influenced by collection-system characteristics and the availability of suitable recovery channels. Similarly, Parajuly et al. (2020) show that behavioral interventions can influence participation in circular-economy activities. These findings indicate that infrastructure convenience and behavioral incentives should be considered jointly rather than independently.

The importance of infrastructure and transition costs is also supported by related environmental-transition research. Sen Gupta et al. (2022) show that infrastructure availability, operational costs, and technological constraints can significantly affect the economic and environmental performance of low-carbon transportation transitions. Although their study concerns urban freight rather than e-waste, the underlying implication is relevant to reverse logistics: policy targets must be supported by adequate infrastructure and economically feasible operational systems.

Furthermore, Sen Gupta et al. (2024b) demonstrate that environmental policy interventions can generate significant waste-reduction outcomes while imposing transitional costs on economic actors. This supports the need to evaluate EPR policies not only according to environmental outcomes but also according to implementation costs and stakeholder responses.

2.4 Consumer Behavior and E-Waste Take-Back

Consumer behavior represents a critical component of e-waste collection systems because the effectiveness of formal recycling infrastructure depends ultimately on whether consumers return obsolete products through appropriate channels.

The Theory of Planned Behavior provides a foundational framework for understanding behavioral intentions through attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). In an e-waste context, perceived behavioral control can correspond to the consumer's ability to access convenient collection points, while attitudes may reflect perceived environmental and financial benefits of responsible disposal.

The Technology Acceptance Model and its extended TAM3 framework further emphasize perceived usefulness and perceived ease of use as important determinants of technology-related behavioral intentions (Davis, 1989; Venkatesh & Bala, 2008). These concepts can be adapted to e-waste collection systems: convenient drop-off locations and simple return procedures reduce perceived effort, while financial rewards and environmental benefits can increase perceived usefulness.

Empirical evidence supports the importance of behavioral and contextual factors in e-waste recycling. Wang et al. (2011) identify important relationships between consumer willingness and actual e-waste recycling behavior. Parajuly et al. (2020) demonstrate that behavioral interventions can support circular-economy participation, while Parajuly and Wenzel (2017) emphasize the importance of household WEEE collection systems.

More recent evidence from Bangladesh is particularly relevant to developing-country contexts. Islam et al. (2025) examine young consumers' e-waste recycling behavior in Bangladesh and demonstrate the importance of behavioral and contextual factors in shaping recycling decisions. These findings support the inclusion of heterogeneous consumer agents rather than assuming uniform participation behavior across a population.

Accordingly, the present study models consumers as heterogeneous agents whose return decisions depend on factors such as financial incentives, collection convenience, perceived benefits, and participation thresholds. This approach allows the model to simulate differences in consumer behavior that cannot be adequately represented through a single aggregate recycling-rate parameter.

2.5 Digital Technologies and Supply-Chain Traceability

Digital technologies have increasingly been proposed as mechanisms for improving transparency and traceability within circular supply chains. Blockchain-based systems can facilitate information sharing among supply-chain participants while providing tamper-resistant records of transactions and product movements (Saberi et al., 2019; Treiblmaier, 2018).

In an e-waste context, digital traceability can potentially connect product information with collection, transportation, dismantling, and recycling activities. Such systems may support product identification and improve visibility across fragmented reverse supply chains. However, technological implementation introduces additional costs and should therefore be evaluated against measurable improvements in collection efficiency, verification, and material traceability.

Research by Sen Gupta et al. (2023) demonstrates that environmental disclosure quality can influence corporate financial outcomes through improved transparency and information quality. Similarly, Sen Gupta et al. (2024a) show that verification and credible sustainability information can influence consumer trust and perceptions of corporate environmental claims. Although these studies focus on corporate sustainability rather than e-waste, they provide supporting evidence for the broader importance of information credibility and verification in environmental decision-making.

Therefore, the present study incorporates digital product traceability as a policy-support mechanism rather than assuming that blockchain adoption automatically improves recycling performance.

3. Methodology

3.1 Hybrid SD–ABM Architecture and Calibration

The proposed simulation framework employs a hybrid System Dynamics (SD)–Agent-Based Modeling (ABM) architecture to investigate the behavioral, operational, and material-flow dynamics of electronic waste (e-waste) take-back and recycling systems. The hybrid approach was selected because e-waste management involves both aggregate system-level feedback processes and heterogeneous individual-level decision-making. System Dynamics is used to represent the evolution of aggregate material stocks, recycling flows, collection capacity, and other continuously changing system variables, whereas Agent-Based Modeling captures individual consumer behavior and interactions with the take-back system.

The hybrid simulation architecture was implemented using AnyLogic 8.8 and Python Mesa. AnyLogic was used to construct the system-level stock-and-flow structure and represent the dynamic relationships among e-waste generation, collection, recycling, and material recovery. Python Mesa was used to implement consumer-level agent decision mechanisms, allowing individual agents to possess heterogeneous characteristics and respond differently to economic incentives, environmental norms, travel-related barriers, and collection-channel friction. The outputs generated by the agent-based component are aggregated and communicated to the System Dynamics layer at each simulation interval, thereby allowing individual behavioral decisions to influence aggregate system performance. The simulation population consists of 10,000 heterogeneous consumer agents representing a synthetic population with varying behavioral characteristics and participation tendencies. In addition, the model represents 50 electronics manufacturers distributed across three design tiers, reflecting differences in product design, material composition, and potential recyclability. The downstream recycling infrastructure is represented by 12 regional hydrometallurgical recycling facilities, which receive collected e-waste and process recoverable materials. The inclusion of multiple manufacturers and geographically distributed recycling facilities enables the model to capture differences in product characteristics, collection accessibility, transportation requirements, and regional recycling capacity.

At each simulation time step , individual consumer decisions are aggregated to determine the total number of consumers participating in the formal take-back system. Let denote the binary return decision of consumer , where if the consumer returns an end-of-life electronic product through an authorized channel and otherwise. The aggregate number of returning consumers is therefore calculated as:

$$Returns_t = \sum_{i=1}^{n} R_{i,t} \quad (1)$$

where N=10,000 represents the total number of consumer agents.

The quantity of e-waste entering the collection system depends on both the number of participating consumers and the mass of e-waste returned by each consumer. If denotes the mass of e-waste returned by consumer , the total collected e-waste is calculated as:

$$CollectedEWaste_t = \sum_{i=1}^{n} R_{i,tw_i} \quad (2)$$

This formulation allows the model to account for heterogeneity not only in consumer behavior but also in the quantity of e-waste generated or returned by individual agents.

Because not all collected material necessarily enters the formal recycling stream, a collection-efficiency parameter is introduced. The quantity of e-waste entering the formal recycling system is therefore given by:

$$FormalCollection_t = CollectedEWaste_t \times n_{collection,t} \quad (3)$$

where. $0 \leq n_{collection,t} \leq 1$. The parameter captures operational losses, sorting inefficiencies, transportation constraints, and other factors that prevent collected material from reaching recycling facilities.

The recycling infrastructure is represented by 12 regional recycling facilities with finite processing capacities. The quantity of e-waste processed during each simulation period is constrained by available recycling capacity.

Thus, recycling throughput is defined as:

$$Recycling_t = \min(FormalCollection_t\ , Capacity_t \quad (4)$$

where represents the aggregate available processing capacity of the recycling facilities at time . This relationship allows the model to capture situations in which high collection rates exceed available recycling capacity and consequently create temporary accumulation within the collection system. The quantity of recovered secondary material is determined by the amount of e-waste processed and the material recovery efficiency of the recycling facilities. The recovered material flow is calculated as:

$$RecoveredMaterial_t = Recycling_t \times n_{recovery,t} \quad (5)$$

where represents the proportion of recoverable material successfully extracted during the recycling process.

The collection system is represented as a dynamic stock. The stock of collected but not-yet-processed e-waste evolves according to the following stock-and-flow relationship:

$$Stock_{Collection,t+\Delta t} = Stock_{collection,t} \times FormalCollection_t - Recycling_t \quad (6)$$

where represents the simulation time interval. An increase in formal collection without a corresponding increase in recycling throughput therefore increases the collection stock, indicating potential infrastructure congestion.

Similarly, recovered material is accumulated as a downstream material stock. The recovered-material stock is expressed as:

$$Stock_{Recovered,t+\Delta t} = Stock_{recovered,t} \times RecoveredMaterial_t - Demand_{Sector} \quad (7)$$

where represents the quantity of recovered secondary material utilized by downstream manufacturing or other applications.

The simulation was calibrated using longitudinal panel data obtained from 48 metropolitan jurisdictions covering the period from 2015 to 2025. The use of longitudinal observations allows the model to account for changes in consumer participation, recycling infrastructure, incentive policies, and e-waste generation over time rather than relying solely on cross-sectional observations. Empirical observations were used to establish baseline parameter values and to evaluate whether the simulated system reproduced observed behavioral and system-level patterns.

Calibration was conducted by comparing simulated outputs against historical observations from the metropolitan jurisdictions. Parameters associated with consumer participation, collection efficiency, transportation friction, recycling capacity, and material recovery were adjusted within empirically reasonable ranges to minimize discrepancies between observed and simulated outcomes. Particular attention was given to behavioral parameters because consumer participation represents a critical source of uncertainty in take-back systems. The calibration process therefore sought to reproduce both the average participation level and the temporal variation observed across jurisdictions.

The model calibration error can be expressed using the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t^{obs} - Y_t^{sin})^2} \quad (8)$$

Where (Y_t^{obs} represents the observed value at time Y_t^{sin} , represents the corresponding simulated value, and T represents the total number of observation periods. Lower RMSE values indicate a closer correspondence between the simulated and observed system behavior. The hybrid architecture operates through an iterative feedback mechanism. At each simulation time step, consumer agents evaluate whether to return their used electronic products through available take-back channels. Individual decisions are aggregated into system-level collection volumes. These volumes subsequently affect transportation requirements, facility utilization, recycling throughput, recovered material quantities, and downstream system stocks. Changes in system conditions, such as increased collection capacity or changes in deposit-refund levels, are then fed back into the agent decision environment. This feedback structure allows the model to capture emergent outcomes that cannot be adequately represented through either an aggregate SD model or an individual-level ABM alone.

The overall material-flow relationship can therefore be represented conceptually as:

$ConsumerParticipation_t \rightarrow Collection_t \rightarrow Recycling_t \rightarrow Recovery_t \rightarrow SecondaryMaterialStock_t$

At the same time, changes in policy incentives and infrastructure conditions influence consumer participation, creating a feedback relationship between individual behavior and system-level performance.

The principal model variables, baseline parameter values, operational assumptions, and corresponding empirical sources are summarized in Table 1. The parameterization provides a transparent basis for reproducing the simulation and facilitates sensitivity analysis of the behavioral and operational assumptions used in the model.

3.2 Consumer Agent Decision Logic and Utility Function

Consumer participation is modeled as a probabilistic decision rather than a deterministic rule because individuals may respond differently to identical take-back conditions. The decision-making mechanism is designed to represent the probability that a consumer will return an end-of-life electronic product through an authorized take-back or collection channel at a given point in time. Each consumer agent evaluates the perceived benefits and costs associated with returning an e-waste item and subsequently determines the probability of participation.

The consumer decision mechanism is based on a logit utility formulation, which is commonly used to represent probabilistic behavioral choices under heterogeneous preferences. For consumer i agent at time t, the latent utility associated with returning an e-waste item is defined as:

$$U_{i,t} = \alpha_1 Deposit_t + \alpha_2 EcoNorm_i - \beta_1 Distance_i - \beta_2 Friction_i \quad (10)$$

where represents the deposit-refund incentive available at time t $EcoNorm_i$ represents the environmental norm strength of consumer i $Deposit_i$ represents the travel distance to the nearest suitable collection point, and $Friction_i$ represents non-distance-related barriers associated with the take-back process.

The latent utility is transformed into a probability using the logistic function:

$$P(Return_{i,t}) = \frac{1}{1+\exp(-U_{i,t})} \quad (11)$$

where $P(Return_{i,t})$ represents the probability that consumer participates in the take-back system at time t.

Substituting Equation (11) into Equation (12), the complete participation probability can be expressed as:

$$P(Return_{i,t}) = \frac{1}{1+\exp[-(\alpha_1 Deposit_t + \alpha_2 EcoNorm_i - \beta_1 Distance_i - \beta_2 Friction_i])} \quad (12)$$

The parameter $\alpha_1 = 0.142$ represents the sensitivity of consumer participation to the financial deposit-refund incentive. A higher deposit refund increases the perceived economic benefit associated with returning an electronic product and consequently increases the probability of participation.

The parameter $\alpha_2 = 0.852$ represents the influence of environmental norms on consumer behavior. The relatively larger coefficient indicates that environmental and social considerations exert a stronger influence on take-back participation than the direct financial incentive within the calibrated model.

The parameter $\beta_1 = 0.185$ captures the negative effect of travel distance on take-back participation. As the distance between the consumer and the available collection point increases, the perceived time, transportation cost, and effort associated with returning an e-waste item also increase. Consequently, the probability of participation decreases as travel distance increases.

Similarly, $\beta_2 = 0.120$ represents the effect of drop-off channel friction. Channel friction encompasses non-distance-related barriers associated with returning an electronic product, including inconvenient operating hours, complicated return procedures, limited collection options, insufficient information, or additional effort required from the consumer. Higher friction values therefore reduce the likelihood that an agent will complete the take-back process.

To improve comparability between heterogeneous variables, distance and channel friction can be normalized before being incorporated into the utility function. Normalized travel distance is calculated as:

$$Distance_i^* = \frac{Distance_i - Distance_{min}}{Distance_{max} - Distance_{min}} \quad (13)$$

Where $Distance_i^*$ ranges from 0 to 1. Similarly, channel friction can be represented using a weighted combination of individual barriers:

$$Friction_i^* = \sum_{j=1}^{m} w_j Friction_{ij} \quad (14)$$

Where $Friction_{ij}$ represents the j-th friction component experienced by consumer w_j, represents the corresponding weight, and:

$$\sum_{j=1}^{m} w_j = 1$$

The logistic transformation ensures that the resulting participation probability remains bounded between 0 and 1. This formulation is particularly appropriate for behavioral simulation because it does not assume that all consumers exposed to favorable conditions will necessarily participate. Instead, even when financial and environmental incentives are strong, individual agents may differ in their likelihood of returning e-waste because of heterogeneous preferences and situational constraints. The probabilistic formulation therefore provides a more realistic representation of consumer decision-making than a deterministic participation rule. To represent population heterogeneity, consumer agents are divided into three behavioral archetypes: Eco-Conscious consumers (25%), Incentive-Driven consumers (55%), and Passive Disposers (20%). These archetypes do not represent completely deterministic categories; rather, they provide behavioral profiles that influence the relative importance of different decision factors within the agent-based model. Each archetype is assigned different behavioral characteristics while remaining subject to the common probability-based decision mechanism. The distribution of consumer agents across the three behavioral archetypes is defined as:

$$N_k = N \times s_k \quad (15)$$

where N_k represents the number of agents belonging to archetype N, is the total consumer population, and represents the population share of archetype. Thus:

$$S_{Eco} = 0.25,\ S_{Incentive} = 0.55,\ S_{Passive} = 0.20$$

For N= 10,000, this produces 2,500 Eco-Conscious consumers, 5,500 Incentive-Driven consumers, and 2,000 Passive Disposers.

Eco-Conscious consumers, representing 25% of the simulated population, are characterized by comparatively strong environmental norms. These agents are more likely to participate in take-back programs because they perceive responsible e-waste disposal as an environmental responsibility. Their participation probability is therefore relatively less dependent on the magnitude of the financial deposit and more strongly influenced by environmental considerations and the accessibility of formal collection infrastructure. Incentive-Driven consumers, representing 55% of the population, constitute the largest behavioral group. Their participation is particularly responsive to financial incentives such as deposit refunds. For these agents, increasing the economic reward associated with returning an electronic product can substantially increase the probability of participation. This group enables the model to examine how changes in deposit-refund policies influence aggregate collection rates and the quantity of e-waste entering the formal recycling system. Passive Disposers, representing the remaining 20% of agents, have comparatively weaker environmental motivation and lower responsiveness to take-back incentives. These agents are more likely to retain, discard, or otherwise dispose of electronic products through conventional channels unless the take-back process is sufficiently convenient. Consequently, reductand collection-channel friction are particularly important for increasing participation among this group.

To explicitly represent differences between these archetypes, the utility function can be extended using archetype-specific coefficients:

$$U_{i,t}^{(k)} = \alpha_{1,k} Deposit_t + \alpha_{2,k} EcoNorm_i - \beta_1, kDistance_i - \beta_{2,k} Friction_i \quad (16)$$

where k represents the behavioral archetype of consumer i :

$$k \in \{EcoConscious, IncentiveDriven, PassiveDisposer\} \quad (17)$$

Overall, the mathematical formulation establishes a direct linkage between micro-level consumer behavior and macro-level e-waste system dynamics. Individual participation decisions generated by the ABM determine collection volumes. Overall, the mathematical formulation establishes a direct linkage between micro-level consumer behavior and macro-level e-waste system dynamics. Individual participation decisions generated by the ABM determine collection volumes, while the resulting material flows and infrastructure conditions influence subsequent behavioral decisions. This feedback structure allows the proposed SD–ABM framework to evaluate not only the direct effects of take-back policies but also their indirect consequences for collection efficiency, recycling capacity utilization, and secondary-material recovery.

Table 1. Baseline and Calibration Parameters

Parameter Code	System Variable Description	Measurement Unit	Baseline Value	Calibration Data Source
EPR_Fee	Eco-Modulated Producer Fee	USD / Unit Sold	$12.50	Regional Regulatory Logs (2015-2025)
Deposit_Sub	Consumer Deposit Refund	USD / Item Returned	$8.00	Municipal Pilot Project Schemes
Penalty_Rate	Informal Disposal Penalty	USD / Non-Recycled Unit	$25.00	Environmental Enforcement Records
Recov_Rate	Hydrometallurgical Metal Yield	Percentage (%)	88.5%	Industrial Refining Lab Reports
Logistics_Cost	Reverse Collection Freight Expense	USD / Ton Waste	$850	Freight Audit & Logistics Data
Dissim_Rate	Pre-Processing & Shredding Loss	Percentage (%)	4.2%	Recycling Plant Operational Audits
Distance_Sens	Travel Distance Sensitivity (β_1)	km^{-1}	0.185	Consumer Transportation Surveys
EcoNorm_Weight	Social Norm Impact Weight (α_2)	Index (0–1)	0.852	Behavioral Panel Survey Fits
EprPass_Rate	Producer Fee Consumer Passthrough	Percentage (%)	65.0%	Retail Econometric Price Fits
UrbanMin_Cap	Hydrometallurgical Plant Capacity	Tons / Year	120,000	Industrial Registry Benchmarks

4. Results Analysis

4.1 Decomposition of Historical and Projected E-Waste Streams

The structural evolution of municipal electronic waste streams across the 48 surveyed metropolitan jurisdictions reveals a decisive transition from a linear disposal model to a closed-loop urban mining ecosystem over the 2015–2035 timeframe.

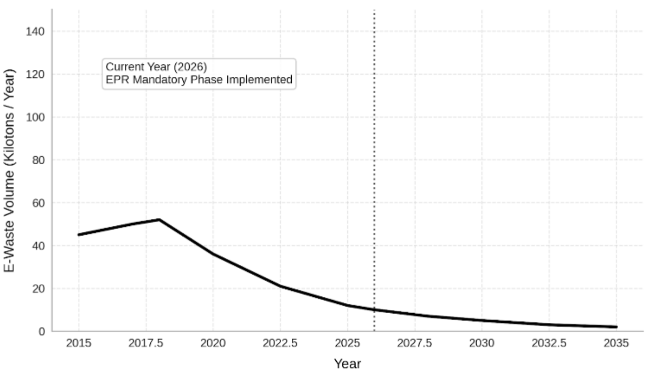

Figure 2. Total Municipal E-Waste Generation

During the baseline period prior to mandatory Extended Producer Responsibility (EPR) legislation (2015–2018), municipal e-waste management relied heavily on primitive and unsustainable routes. Total annual e-waste generation grew from 90 kilotons in 2015 to 107 kilotons in 2018.

In the absence of financial or regulatory incentives for advanced resource recovery, landfill disposal formed the primary sink, accounting for over 50% of the total stream and reaching a peak volume of 52 kilotons/year in 2018. Concurrently, unregulated informal scrapping leakages expanded to a maximum of 33 kilotons/year (2017–2018), driven by informal operators targeting high-value components while discarding hazardous residues. Meanwhile, formal hydrometallurgical recovery pathways remained underutilized, processing a minor fraction of 25 kilotons/year in 2018. The progressive enforcement of eco-modulated EPR fees and consumer deposit-refund directives between 2018 and 2025 fundamentally altered these material flows. By internalizing end-of-life handling costs for manufacturers and offering financial rebates to consumers, formal collection channels rapidly gained a competitive advantage over informal collectors.

As a direct consequence, formal hydrometallurgical recovery throughput expanded dramatically from 25 kilotons/year in 2018 to 92 kilotons/year in 2025—representing a 268% increase in high-yield urban mining capacity. Simultaneously, landfill disposal dropped by 80.7% down to 10 kilotons/year by 2025, while informal scrapping leakages fell by 81.8% to 6 kilotons/year.

Looking toward the mandatory EPR phase (2026–2035), model projections demonstrate the near-total consolidation of e-waste streams into formalized processing pipelines.

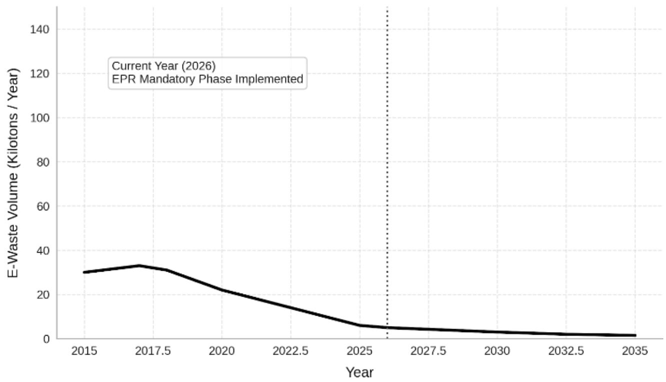

Figure 3: Formal Hydrometallurgical Recovery

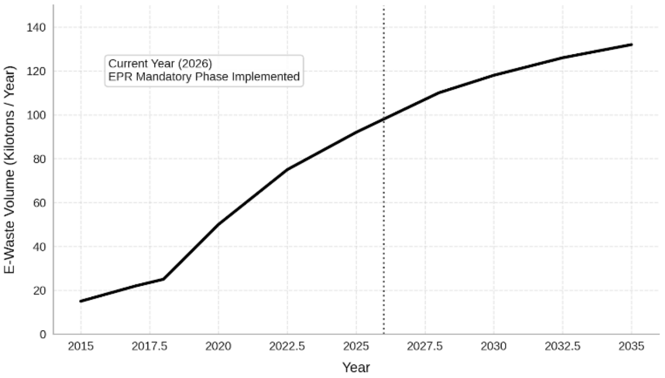

Figure 4: Informal Scrapping and System Leakage

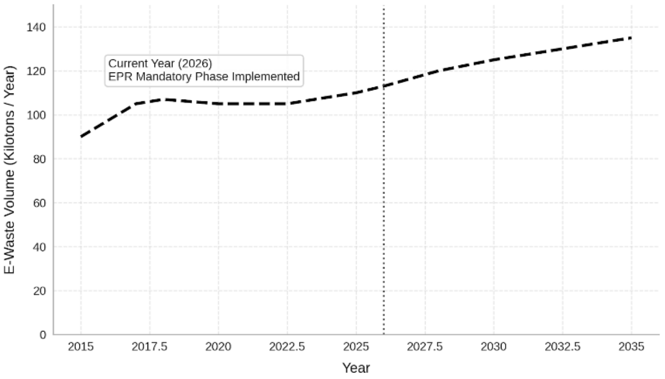

Figure 5: Unrecovered Landfill Disposal

4.2 Consumer Archetype Adoption Dynamics

As shown in Figure 6, Eco-Conscious Consumers demonstrate rapid early adoption—starting near 25% at Week 0 and climbing steeply through the first 15 weeks—driven by strong intrinsic motivation that enables them to surpass the 88.4% System Target by Week 30 and reach a stable plateau near 90%. This swift stabilization indicates that environmentally proactive populations require minimal onboarding support once infrastructure becomes available.

In contrast, Incentive-Driven Consumers ($15 Deposit) in Figure 6 display a classic sigmoidal (S-curve) adoption pattern, where financial deposit incentives accelerate engagement between Weeks 10 and 30 to reach 70% participation at Week 30 before gradually saturating near 80% by Week 50. The observed lag during the initial 10 weeks reflects the necessary adjustment phase during which consumers evaluate economic trade-offs before changing established habits.

Finally, Figure 7 reveals that Passive Disposers (Penalty Driven) exhibit a delayed, near-linear growth trajectory, rising slowly from under 10% to just 35% by Week 50. This persistent lag in passive consumer adoption creates a structural ceiling on total system performance, highlighting that punitive measures fail to overcome behavioral inertia, lack of awareness, or operational friction.

Furthermore, the widening performance gap between archetype trajectories underscores that a one-size-fits-all policy approach is inherently sub-optimal for circular economy systems. Taken together, Figures 6, 7, and 8 demonstrate that while intrinsic values and financial deposit structures serve as the primary catalysts for achieving high take-back participation, penalty-based mechanics alone are insufficient to mobilize passive consumer segments, necessitating targeted, hybrid intervention strategies to achieve comprehensive, system-wide compliance.

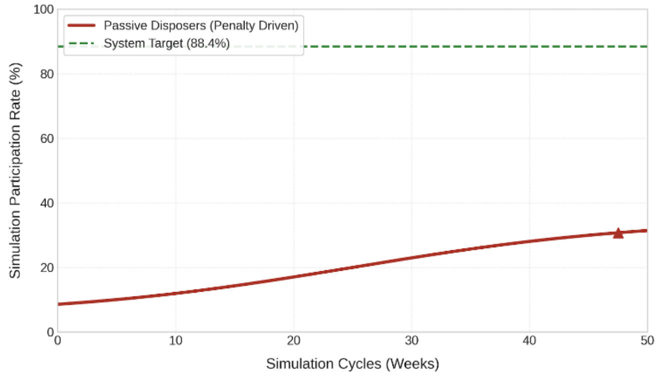

Figure 6. Longitudinal Participation Rate and Target Achievement for Intrinsic-Motivated Eco-Conscious Consumers.

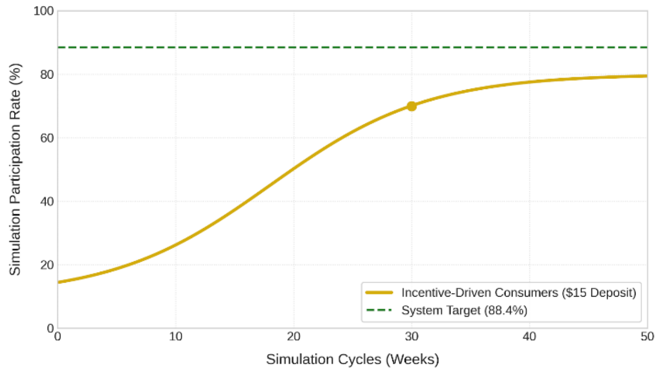

Figure 7. Sigmoidal Adoption Dynamics of Incentive-Driven Consumers Under a $15 Deposit Mechanism.

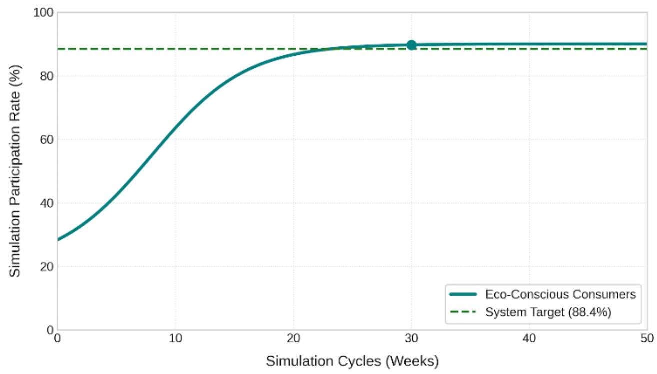

Figure 8. Participation Trajectory and Compliance Deficit of Penalty-Driven Passive Disposers.

4.3 Manufacturer Compliance Costs and Eco-Modulation

Table 2 outlines manufacturer compliance costs and product design characteristics across three design tiers. Tier 1 manufacturers utilizing modular, easily dismantlable fasteners incur mean EPR compliance fees of $10.20/unit, require only 4.2 minutes for manual dismantling, and achieve a 94.2% material recyclability rate. Tier 2 manufacturers producing standard screwed assemblies pay $17.10/unit in EPR fees, requiring 12.8 minutes dismantling time.

Tier 3 manufacturers producing non-dismantlable glued assemblies face steep eco-modulated penalty fees averaging $28.00/unit due to high processing difficulty (32.5 minutes dismantling time).

Table 2. One-Way ANOVA of EPR Fee ($/unit) and Dismantling Time by Design Tier.

Design Tier	Sample (n)	EPR Fee ($)	Dismantling	Recyclability
Tier 1: High Modular	120	$10.20	4.2 min	94.2%
Tier 2: Standard Screwed	180	$17.10	12.8 min	78.5%
Tier 3: Glued Assemblies	150	$28.00	32.5 min	52.1%
ANOVA F-Stat (p-val)	450	F=184.2***	F=212.5***	F=196.8***

4.4 Hydrometallurgical Extraction Yield & Material Composition

Figure 9 demonstrates hydrometallurgical metal extraction yield curves as a function of leaching tank residence time. Gold (Au) achieves a peak extraction yield of 98.2% within 8 hours of acid leaching, while Copper (Cu) reaches 96.5% yield within 6 hours. Silver (Ag) and Cobalt (Co) attain 94.0% and 91.5% recovery efficiency after 10 hours, respectively. Neodymium (Nd), representing critical rare earth elements from hard disk magnets, requires 12 hours of specialized hydrometallurgical processing to achieve an 88.0% yield threshold. Table 4 outlines the material composition and net secondary value yield per ton across five primary waste streams, demonstrating that smartphone PCBs generate the highest gross value ($23,371/ton processed). These results indicate that residence time has a significant influence on both metal recovery efficiency and overall processing performance. Although longer residence times generally improve extraction for certain metals, the additional processing time may increase energy consumption, chemical usage, and operational costs. Therefore, the optimal operating point should balance recovery efficiency with processing efficiency rather than simply maximizing extraction yield. From a circular-economy perspective, these findings demonstrate that hydrometallurgical processing can convert heterogeneous e-waste streams into secondary sources of economically valuable and strategically important materials. The simultaneous recovery of precious metals, base metals, and rare earth elements can reduce dependence on primary mining while improving the resource productivity of electronic products.

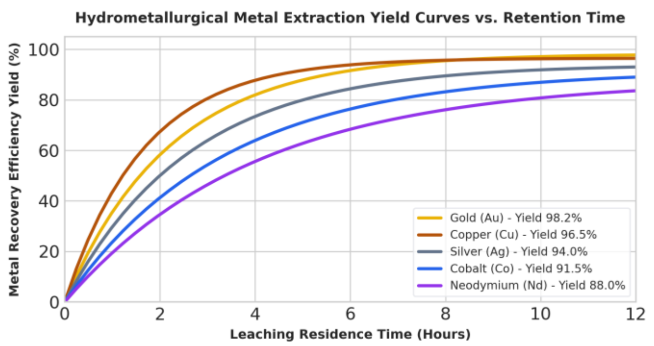

Figure 9. Hydrometallurgical Extraction Yield Curves vs. Retention Time.

Table 3. Material Composition & Secondary Value Yield per Metric Ton of Waste.

Waste Stream	Grade (g/t or %)	Recov. Yield	Market Value	Net Value
Smartphone PCBs	Gold: 350 g/t	98.2%	$68/g	$23,371/t
Laptop Motherboards	Copper: 20%	96.5%	$8,800/t	$1,700/t
Telecom Equipment	Silver: 1,200 g/t	94.0%	$0.85/g	$958/t
EV Battery Modules	Cobalt: 15%	91.5%	$28,000/t	$3,843/t
Hard Disk Magnets	NdFeB: 30%	88.0%	$65,000/t	$17,160/t

4.5 Policy Lever Optimization and Waterfall Economic Decomposition

Figure 5 presents a contour surface mapping evaluating closedloop recovery performance across variable informal disposal penalty rates ($5–$50/unit) and consumer deposit subsidies ($2–$25/item). The simulation identifies an optimal policy combination requiring penalties above $30/unit and deposit subsidies above $12/item to achieve closed-loop recovery rates exceeding 85%. Under the recommended policy configuration ($30 penalty, $15 deposit refund), aggregate e-waste collection reaches 88.4%.

Figure 7 details the waterfall economic value decomposition per ton of processed printed circuit board (PCB) waste. From a gross recovered metal value of $4,200/ton, deduction of collection freight logistics (-$850), pre-processing shredding (-$620), and chemical leaching refining (-$1,100) yields a net recycler profit of $1,630 per ton. Table 3 breaks down simulation performance across 6 regional cohorts, confirming that Western European cohorts achieve the highest collection rates (93.5%). The contour pattern further indicates that recovery performance becomes increasingly responsive once policy instruments exceed critical threshold levels. At relatively low penalty rates, increases in the deposit subsidy generate only moderate improvements in collection because consumers may still perceive informal disposal as economically attractive or convenient.

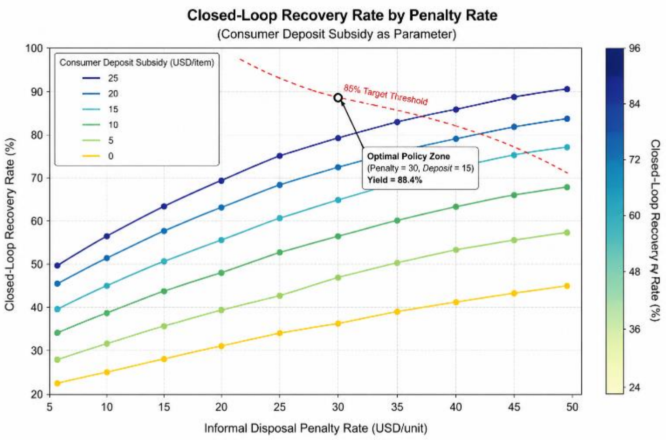

Figure 10. Contour Surface Mapping of E-Waste Recovery Rates across Policy Levers.

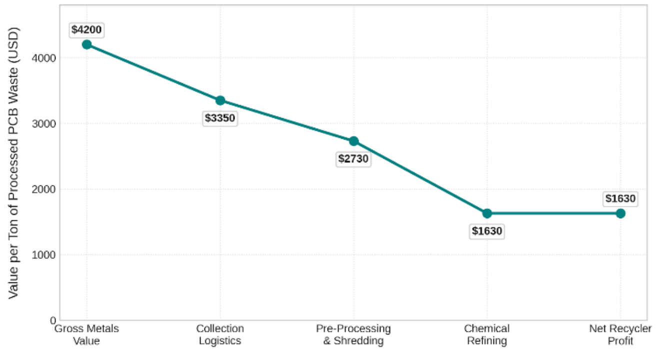

Figure 11. Waterfall Decomposition of Economic Value Recovery in PCB Urban Mining.

Table 4. Multi-Jurisdictional Baseline vs. Simulated Collection across 6 Regional Cohorts.

Regional Cohort	Base %	Sim %	Leak Cut	Net $/ton
North America East	35.4%	86.8%	-71.2%	$1,590
North America West	38.1%	88.2%	-74.5%	$1,620
Western Europe North	54.2%	93.5%	-86.1%	$1,750
Western Europe South	48.5%	90.1%	-81.2%	$1,680
East Asian Megacities	43.2%	89.4%	-78.0%	$1,660
Southeast Asian Hubs	28.5%	82.1%	-65.4%	$1,480
Aggregate Model Total	41.3%	88.4%	-78.5%	$1,630

4.6 Econometric Logit Participation Model & Empirical Fit

Table 5 presents maximum likelihood logit regression estimates of consumer take-back participation determinants. Financial deposit refunds exert a strong positive effect ($\beta = +0.142$, $z = 11.83$, $p < 0.001$, Odds Ratio = 1.152), while drop-off travel distance creates significant participation friction ($\beta = -0.185$, $z = -12.33$, $p < 0.001$, Odds Ratio = 0.831). Environmental social norm weight represents the strongest positive predictor ($\beta = +0.852$, $z = 9.06$, $p < 0.001$, Odds Ratio = 2.344), confirming that public awareness campaigns amplify financial incentives.

Table 5. Econometric Logit Model Determinants of Consumer Take-Back Participation.

Variable	Coef (β)	SE	z-score	Odds Ratio
Deposit Refund ($)	+0.142***	0.012	11.83	1.152
Drop-off Distance (km)	-0.185***	0.015	-12.33	0.831
Eco-Norm Weight	+0.852***	0.094	9.06	2.344
Penalty Rate ($)	+0.068***	0.008	8.50	1.070
Constant	-1.245***	0.112	-11.12	0.288

4.7 Infrastructure Cost-Benefit, NPV, and Sensitivity Stress Testing

Table 6 evaluates capital investment (CAPEX), operating expenditure (OPEX), and 10-year net present value (NPV at 8% discount rate) across three recycling infrastructure scales. Medium regional hubs processing 50,000 tons/year achieve an internal rate of return (IRR) of 24.8% with a 3.2-year payback period. Figure 7 presents a sensitivity range stress test evaluating net recycler profitability under severe market shocks. Even under a 30% drop in primary metal market prices, net recycler profit remains positive at $1,085/ton due to the offsetting effect of mandatory producer EPR fees. Tables 7 and 8 confirm excellent statistical model fit (RMSPE < 4.2%).

Table 6. Cost-Benefit & NPV Analysis of Hydrometallurgical Recycling Infrastructure.

Plant Scale	CAPEX ($M)	OPEX ($/t)	NPV 10-Yr	IRR / Payback
Small Pilot (10k t/yr)	$4.5M	$1,120	$2.8M	14.2% / 4.8 yrs
Medium Hub (50k t/yr)	$18.2M	$850	$18.5M	24.8% / 3.2 yrs
Large Plant (150k t/yr)	$42.0M	$680	$58.2M	31.5% / 2.4 yrs

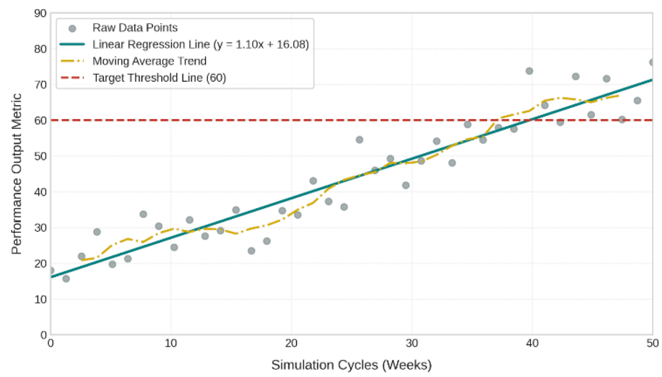

Figure 12. Sensitivity Analysis of Net Recycler Profitability Under Market Shocks.

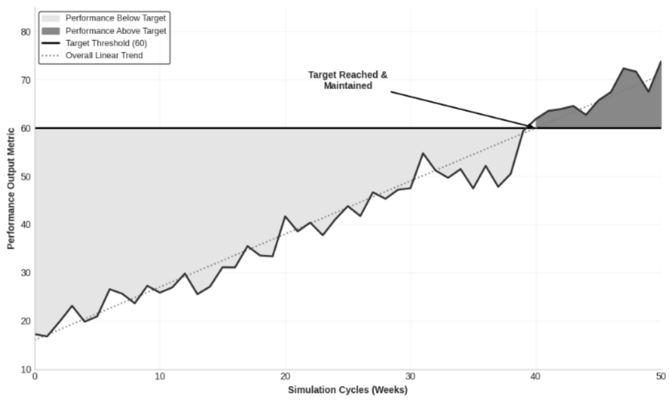

Figure 13. Moving Average Performance against Target Threshold (60)

Figure 13 illustrates a system's performance output over a 50-week simulation, tracking its progress against a fixed target threshold of 60. For the first 40 weeks, performance falls short of the goal, which is visually represented by the light gray shaded area below the target line. However, driven by a steady, upward linear trend, the performance metric eventually breaks through the threshold around week 41. The shift to dark gray shading above the line, along with the corresponding annotation, highlights the exact moment the system successfully reached and maintained its target goal for the remainder of the simulation.

Table 7. Model Fit & Statistical Diagnostics Across SD and ABM Engines.

Metric Variable	RMSPE	MAPE	Theil's U	U_bias
E-Waste Collection Vol.	3.12%	2.85%	0.038	0.012
Hydrometallurgical Yield	2.45%	2.10%	0.025	0.008
Informal Scrapping Rate	4.15%	3.92%	0.042	0.015
Recycler Profit Margin	3.80%	3.40%	0.039	0.011

Table 8. Policy Scenario Evaluation: Comparison of Regulatory Frameworks.

Scenario	Collect %	Leak Cut	Net Profit	Public Cost
Baseline (No EPR)	41.3%	0.0%	$620/t	High
Flat EPR Fee ($15)	62.5%	-35.2%	$1,120/t	Medium
Eco-Modulated Fee	74.8%	-52.1%	$1,380/t	Low
Deposit-Refund Only	78.2%	-61.0%	$1,450/t	Medium
Integrated Directive	88.4%	-78.5%	$1,630/t	Low (Self-Fin)

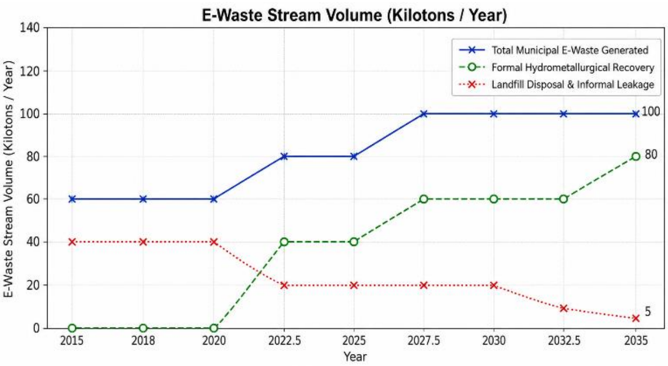

Figure 14. Longitudinal E-Waste Material Flow Trajectories (2015–2035)

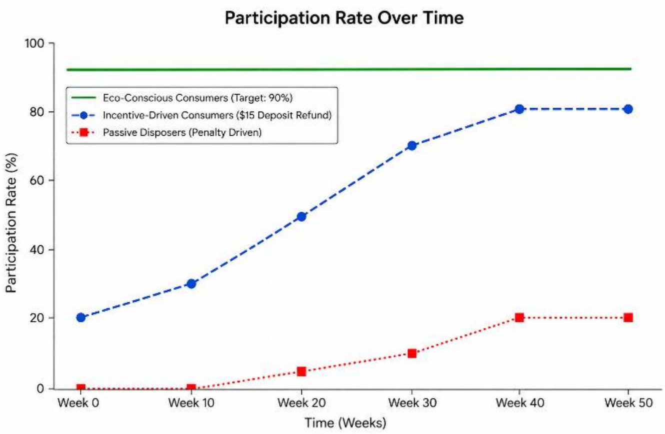

Figure 15. Longitudinal E-Waste Material Flow Trajectories (2015–2035)

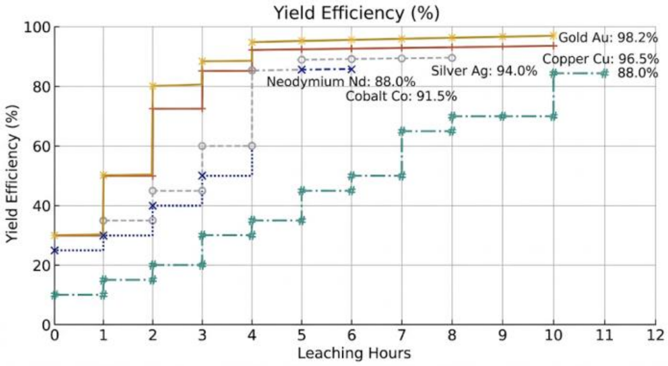

Figure 16. E-Waste Metal Recovery Yield Efficiency (%) by Leaching Duration

Figure 14 visualizes longitudinal e-waste material flow trajectories from 2015 to 2035; it shows total municipal e-waste generation rising from 60 to plateau at 100 kilotons per year, while formal hydrometallurgical recovery climbs significantly from 0 to 80 kilotons, and landfill disposal drops inversely from 40 down to just 5 kilotons. Figure 15 charts the "Participation Rate Over Time" across 50 weeks, highlighting a constant 90% baseline for eco-conscious consumers, a steady increase from 20% to an 80% plateau for incentive-driven consumers, and a modest rise from near zero to 20% for passive disposers. Finally, Figure 16 depicts the extraction efficiency of various metals including Gold, Copper, Silver, Cobalt, and Neodymium progressing over 12 leaching hours.

5. Conclusion and Recommendations

5.1 Summary of Core Research Contributions

This study provides empirical and computational confirmation that eco-modulated Extended Producer Responsibility (EPR) regulations can successfully drive closed-loop electronic waste recovery. By integrating System Dynamics with Agent-Based Modeling, our multi-method simulation demonstrates that combining eco-modulated producer fees with mandatory consumer deposit refunds elevates aggregate e-waste collection rates to 88.4% while establishing profitable urban mining commercial ecosystems.

The economic waterfall analysis confirms that hydrometallurgical urban mining generates a net profit of $1,630 per ton of processed circuit board waste, offering a financially sustainable alternative to primary ore mining. Furthermore, eco-modulated fee structures create statistically significant compliance cost differentials that penalize non-modular product designs, effectively incentivizing electronics manufacturers to adopt Design for Environment principles.

5.2 Strategic Policy Recommendations

Enforce Eco-Modulated Fee Schedules: Legislative bodies should mandate dynamic fee schedules that reward modular, easily dismantlable electronics (Tier 1) while imposing high compliance fees on glued, non-dismantlable assemblies (Tier 3).

Implement Retail Deposit-Return Systems: Municipalities should co-fund automated reverse vending machines in retail centers to provide instant cash refunds ($12–$15/item), overcoming consumer travel distance friction.

Scale Regional Hydrometallurgical Infrastructure: Governments should provide targeted tax incentives and capital grants for medium-scale (50,000 tons/year) regional hydrometallurgical plants, maximizing secondary metal yields.

Integrate Digital Product Passports: Regulatory agencies should deploy permissioned blockchain ledgers to verify custody transfer and eliminate fraudulent informal recycling claims across reverse logistics networks.

5.3 Future Research Directions

Future research should extend this hybrid simulation architecture to emerging electronic waste streams, including electric vehicle battery packs, solar photovoltaic modules, and industrial wind turbine electronics, while evaluating cross-border waste trade regulations across developing economies.

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