



Research article

Sustainable network design for waste mobile phone closed-loop supply chains: A multi-objective robust optimization approach under multi-source uncertainties

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Abstract: Driven by shortened mobile phone lifecycles, waste mobile phones have become a major e-waste stream and a valuable urban mine for resource recovery. In this study, we developed a multi-objective robust optimization framework for a sustainable closed-loop supply chain (CLSC) network under heterogeneous, multi-source uncertainty. Five uncertainty sources, namely recovery volume, recovery quality, market demand, second-hand prices, and material values, were modeled via a differentiated uncertainty set scheme integrating budgeted, box, and polyhedral sets to capture heterogeneous fluctuations and correlations. The model maximized profitability and customer satisfaction while minimizing carbon emissions and was reformulated as a linear robust counterpart via duality. As the recovery-volume disturbance coefficient increased from 0 to 0.5, total profit decreased by up to 25.1%, customer satisfaction declined by more than 50.5%, and carbon emissions decreased by 19.4%. Simulation and regional case studies indicated that the proposed robust framework improves solution feasibility under the considered multi-source uncertainty scenarios and yields implementable network layouts and capacity plans. The findings provide a basis for decision-makers to calibrate robust control parameters according to decision preferences and to determine resource allocation strategies under different decision scenarios by adjusting the relative weights of the three objectives. Overall, the proposed approach provides practical decision support for resilient and low-carbon CLSC planning, thereby advancing circular-economy implementation for end-of-life mobile phones.

Keywords: closed-loop supply chain; multi-objective robust optimization; multi-source uncertainties; circular economy

Mathematics Subject Classification: 90B06, 90C11, 90C29, 90C30

1. Introduction

With the rapid development of the digital economy and electronic communication technology, smartphones have become one of the fastest-growing and most widely used consumer electronic products worldwide [1]. By 2025, the proportion of global mobile phone users among the global population exceeded 91% [2]. Taking China as an example, the total number of discarded and idle mobile phones exceeded 6 billion from 2021 to 2025 [3]. Waste mobile phones are often regarded as a rich urban mine due to their high concentration of valuable metals such as gold, silver, copper, and palladium [4,5]. Particularly, since the surge in global precious metal prices (especially gold), the intrinsic economic value of these accumulated waste devices has been significantly amplified [6]. Therefore, to effectively translate the resource potential of waste mobile phones into recoverable economic and environmental benefits, it is imperative to establish a systematic recycling network and a well-coordinated reuse mechanism.

Closed-loop supply chains (CLSCs) have received increasing attention due to their capacity to integrate resource recovery, environmental governance, and value recirculation within a unified supply chain system [7,8]. Structurally, a CLSC network consists of a forward supply chain (FSC) and a reverse supply chain (RSC). The former covers activities from raw materials to the final products, while the latter involves the collection, processing, and reuse of recycled products [9]. With the advancement of the “Zero Waste City” initiative and growing environmental awareness among consumers, pure economic rationality alone is no longer sufficient to underpin sustainable development strategies for modern enterprises [10,11]. Strict limits on total carbon emissions and waste disposal compliance requirements necessitate the integration of environmental performance into the core considerations of supply chain decisions [12–14]. Nevertheless, only approximately 10% of waste mobile phones are processed through formal channels, such as professional recycling and trade-in programs, while over 54% of devices remained idle for prolonged periods due to pricing discrepancies, procedural barriers, and information security risks [15]. This paradox of high inventory and low recycling not only results in a significant waste of scarce precious metal resources but also poses serious environmental risks, including heavy metal leakage [16]. Given the highly personalized and privacy-sensitive nature of mobile phones, consumer trust and secondary-market acceptance depend not only on the convenience of reverse recycling, but also on the transparency of data security processing and the perceived quality of remanufactured products [17–19]. According to a survey, approximately 71% of consumers are unwilling to participate in recycling programs due to concerns about information leakage [20]. Unilaterally prioritizing cost reduction at the expense of service experience can trigger a consumer trust crisis, thereby creating bottlenecks at the recovery stage and destabilizing the closed-loop system [21]. Therefore, balancing the trade-offs among economic costs, environmental performance, and customer satisfaction remains a critical challenge in improving CLSC efficiency.

Moreover, the optimization practice of the CLSC for waste mobile phones is affected by multiple sources of uncertainty, which directly limit the robustness and resource allocation efficiency of the system [22]. On the supply and demand side, the recovery volume and market demand exhibit distinct

discrete uncertainties influenced by factors such as consumer preferences, macroeconomic fluctuations, and policy changes [23,24]. These uncertainties readily lead to resource misallocation and supply-demand imbalances in aspects like node layout, recycling radius, and transport capacity allocation [25]. On the operational side, the quality of recycled mobile phones exhibits interval-type uncertainty driven by consumer sorting awareness, product lifespan, and privacy concerns [26], which may lead to increased inspection and repair rates, decreased reuse rates, and weakened logistics timeliness [27]. On the value realization side, the prices of second-hand goods and the value of disassembled materials exhibit multidimensional interrelated uncertainty influenced by external factors such as market conditions, metal price fluctuations, and advancements in remanufacturing technology [28–30]. This form directly compromises network profitability and the optimal decision-making for recycling enterprises. In addition, the fluctuation patterns of uncertain factors across stages differ significantly, and the interaction and superposition further intensify the overall operational risks of the system.

In addressing uncertainty in recycling network design, researchers have employed several approaches, including stochastic programming, fuzzy programming, and robust optimization [31]. Stochastic programming requires precise probability distributions [32,33], whereas fuzzy programming often relies heavily on subjective expert judgment [34,35]. In addition, robust optimization provides stronger guarantees of solution feasibility under multiple uncertain perturbations [36]. Therefore, the robust optimization model has been widely used in fields such as furniture [37], food [38], and automobiles [12]. By leveraging box, budgeted, and polyhedral uncertainty sets, this approach effectively characterizes parameter perturbations [39,40]. However, the uncertain factors arising at different stages of the CLSC exhibit substantial heterogeneity in terms of information sources, fluctuation characteristics, and impact mechanisms [22]. Representing heterogeneous uncertain parameters with a single uncertainty set type within a robust optimization framework severely weakens the capacity of the model to characterize real-world risks, thereby precipitating biased or excessively conservative decisions in complex environments [41]. However, studies generally apply a uniform uncertainty set across different stages of CLSCs, while giving comparatively limited explicit attention to the heterogeneity of their disturbance structures.

In response to the above considerations, we address the following questions:

- How to construct an entire-process CLSC network based on the practical characteristics of the recycling of waste mobile phones?
- How to systematically identify the fluctuation characteristics and correlation of multidimensional uncertain factors in supply and demand, operations, and value realization?
- To enhance the decision robustness and practical adaptability of CLSC networks, how to develop a differentiated robust optimization model that matches the disturbance properties of various uncertain factors?
- Within a multi-objective framework covering economic, social, and environmental dimensions, how can the trade-off of comprehensive profits of CLSC networks be realized under multidimensional uncertainty, and what properties do optimal strategies exhibit under distinct decision-making preferences?

Grounded in product life-cycle theory and cleaner production principles, we design a sustainable CLSC network for waste mobile phones that integrates collection, testing, repair, disassembly, remanufacturing, waste treatment, and circulation in the second-hand market. The proposed network aims to maximize economic performance and customer satisfaction while minimizing carbon emissions. Additionally, it explicitly embeds consumer-related concerns, notably privacy protection,

into sustainable supply chain decision-making. To capture heterogeneous and interdependent uncertainties in practical recycling operations, we develop a multi-objective robust optimization model that explicitly accounts for recovery volume, inspection quality, market demand, second-hand product prices, and material recovery values. Specifically, budgeted, box, and polyhedral uncertainty sets are employed to match the distinct fluctuation patterns and correlation structures of different uncertain parameters. Numerical simulations and a regional case study validate the stability, robustness, and practical applicability of the model. Consequently, the findings provide theoretical support and managerial insights for e-waste resource utilization, multi-agent collaborative governance, and the development of “Zero Waste Cities”.

2. Literature review

2.1. CLSC design for waste mobile phones

In the field of CLSC for waste mobile phones, scholars have systematically explored network structure design, functional node allocation, and value recovery paths. For instance, Asefi et al. [42] developed a three-echelon urban logistics recycling network covering waste collection, intermediate transfer, and terminal disposal to address the collaborative optimization of waste management facilities. Song et al. [43] proposed a structure encompassing collection points, recycling centers, preprocessing centers, testing and reprocessing centers, and disposal centers, thereby providing an effective pathway for remanufacturing and maintenance. With an emphasis on data security and traceability, Dasaklis et al. [44] developed a waste mobile phone supply chain that integrates collection, grading, remanufacturing, and dismantling, thereby enhancing resource utilization and supporting an industrial closed-loop mechanism under information security constraints. Kumar Singh et al. [45] developed a reverse logistics model for end-of-life electronic products, integrating inspection, sorting, disassembly, repair, and recycling processes to facilitate resource recovery and minimize costs. Moreover, Singh et al. [46] integrated automated quality inspection with reverse logistics to support sustainable life-cycle management of electronic products through repair and resource recovery. Additionally, Guo [5] established a supply chain network model for waste mobile phones that spans collection, inspection, refurbishment, and disposal, revealing the value flows and reuse mechanisms among the network nodes. Although researchers have established a basic framework for CLSCs for waste mobile phones, the differentiated resource flows, and value realization mechanisms associated with recovered products of different quality grades remain insufficiently explored.

2.2. Uncertainty factors in CLSCs

In CLSC network design, fluctuations in uncertain factors directly affect network configuration and operational performance. Several researchers typically focus on a specific type of disturbance source. For example, Yan et al. [28] constructed a pricing decision model for recycling and remanufacturing to maximize expected corporate profits, specifically addressing quality uncertainty in recycled electronic products. Harijani and Mansour [47] accounted for the inherent uncertainty in municipal solid waste generation and developed a two-stage stochastic mixed-integer linear programming model to address the collaborative optimization problem of location, allocation, and transportation for sustainable municipal solid waste recycling networks. Dong et al. [48] developed a

two-stage stochastic optimization model from a fourth-party logistics (4PL) innovation perspective, aiming to minimize operational costs under demand uncertainty. Given that single-dimensional uncertainty is insufficient for CLSC operational reality, several researchers have increasingly shifted toward multi-stage uncertainty modeling. Ayvaz et al. [49] considered multiple uncertain factors, such as recycling quantity, quality, and transportation costs, and constructed a two-stage stochastic programming framework based on maximizing company interests. Shahparvari et al. [50] explored the dual-objective impact of uncertainty in recovery amount and recovery rate on cost and carbon emissions within an optimization framework that combines opportunity constraints and robustness. In addition, Abbas and Tamara [51] proposed a two-stage stochastic mixed integer quadratic programming model for multi-objective trade-offs involving economic, environmental, and social dimensions. Shahrabifarahani et al. [52] developed a multi-period, multi-objective robust possibilistic programming model to address epistemic data uncertainty in circular supply chains for smartphones. Notably, market prices at the downstream value realization stage act as critical variables in logistics operational strategies [53], yet their volatility remains underexplored [54]. Such factors compound with upstream and midstream uncertainties, thereby amplifying the intricacies of resource allocation. However, researchers fail to sufficiently embed lifecycle-wide uncertainties into CLSC design frameworks to investigate their synergistic effects.

2.3. Methodological approaches to uncertainty treatment

To address uncertainty in CLSC network design, researchers have predominantly relied on stochastic optimization, robust optimization, and fuzzy programming [55]. Nevertheless, these approaches exhibit several limitations. Yu and Sun [56] noted that stochastic programming is heavily dependent on the availability of historical data, implying that sparse samples could undermine decision reliability. Liu et al. [57] pointed out that fuzzy optimization is primarily suited to epistemic uncertainty, potentially undermining the reproducibility of the results. In contrast, robust optimization obviates the need for precise probability distribution assumptions, guaranteeing solution feasibility and operational stability through optimizing against worst-case scenarios within predefined uncertainty sets [58]. For example, Sarkar et al. [59] proposed a robust possibilistic chance-constrained programming model that incorporates data uncertainty and disruption risks into biodiesel supply chain optimization to enhance decision robustness under disruptive scenarios. Regarding the characterization of specific uncertainties, box uncertainty sets are designed to capture independent parameter fluctuations within strictly defined bounds [60]. Cuellar-Usaquén et al. [61] employed the box uncertainty set to characterize quality-level uncertainties in waste product recovery systems. Additionally, Jalilvand-Nejad et al. [62] employed an exclusively polyhedral uncertainty set to characterize uncertainties in processing time and market prices. Almaraj and Trafalis [63] demonstrated that the polyhedral uncertainty set is suitable for modeling linear correlations among uncertain variables. Yan et al. [28] further employed such sets to characterize the intrinsic linkage between price fluctuations and dismantled material value variations. In the context of discrete parameter fluctuations, the budgeted uncertainty set accommodates concurrent deviations of multiple parameters from their nominal values, effectively modulating the level of conservatism [39]. Cheng et al. [24] employed the strategy of a budgeted uncertainty set to quantify scenarios characterized by distinct or abrupt variations. However, the single-uncertainty-set approach fails to account for the variability and correlations of uncertain factors across stages [64].

2.4. Research gaps and contributions

To sum up, although researchers have incorporated multiple functional stages of CLSCs, the coordinated optimization of differentiated product flows and resource allocation across quality grades remains insufficiently explored. In the realm of uncertainty characterization, most studies restrict their scope to single or limited-dimensional perturbations, failing to account for the cumulative effects and intercorrelations of multi-dimensional factors. Moreover, insufficient differentiation regarding volatility characteristics and correlation structures leads to the indiscriminate employment of generic robust optimization methods. Such a single-set modeling approach fails to adequately capture the dynamic complexity and practical operating conditions of CLSC systems. Furthermore, robust optimization applications in mobile phone CLSCs typically focus on isolated objective performance, overlooking the holistic integration of economic, environmental, and social objectives.

The main contributions and innovations of this study are as follows:

- Construct a quality-grading-based CLSC network framework. From a life-cycle value perspective, a three-tier quality grading mechanism is introduced to achieve differentiated resource flows and a closed-loop operation mechanism for value recovery.
- A heterogeneous uncertainty characterization framework is developed by matching uncertainty-set structures to parameter-specific disturbance patterns.
- Construction of a multi-objective decision optimization system. Beyond the consideration of economic (e.g., cost) and environmental (e.g., carbon emissions) metrics, we incorporate customer satisfaction regarding price expectations, stock shortages, and privacy risks as a social dimension, thereby achieving a unified multi-objective optimization framework.

3. Model construction

3.1. Network architecture design

To address the multi-objective needs of resource recycling, economic efficiency, and the synergistic improvement of social and environmental benefits, we construct a full-process CLSC network for waste mobile phones, as shown in Figure 1.

The proposed network features a tailored design that maps product life-cycle stages to differentiate recovery routes, enabling life-cycle-aligned decision-making across collection, repair, disassembly, and end-of-life disposal processes. First, within the CLSC workflow, collection centers are tasked with retrieving discarded mobile phones from individual consumers and bulk waste devices from enterprise clients. The collected products are then transferred to testing facilities and sorted into three tiers via standardized inspection protocols: (1) repairable units (i.e., devices that can be returned to service after refurbishment); (2) non-repairable but dismantlable products (i.e., devices with severe hardware damage that renders them functionally irreparable, yet retain high-value internal components); and (3) non-recoverable residues (i.e., waste streams with complete functional failure and negligible recyclable value, rendering any further processing or reuse economically unfeasible).

Repairable units are forwarded to repair facilities for functional restoration through standardized procedures, including circuit board replacement, component replacement, and firmware refurbishment. The refurbished devices are subsequently reintroduced into the secondary market. Non-repairable products are transferred to disassembly centers for systematic deconstruction via mechanical crushing

and sorting, manual precision disassembly, and hydrometallurgical or pyrometallurgical treatment. This process separates recoverable components and materials, including copper, aluminum, stainless steel, plastic enclosures, and circuit boards bearing rare and precious metals such as gold, palladium, and silver. Recyclable materials are delivered to electronics manufacturing facilities, undergoing a sequence of cleaning, purification, smelting, and reprocessing to be reintegrated into the supply chain as raw materials for new product manufacturing. Non-recoverable fractions arising from inspection and disassembly operations, including contaminated low-grade plastics and toxic particulates, are directed to specialized facilities for end-of-pipe disposal. Treatment methods encompass incineration, solidification, sanitary landfilling, or harmless plasma treatment. The overarching workflow is designed to minimize ecological pollution while delivering the objectives of economic value recovery.

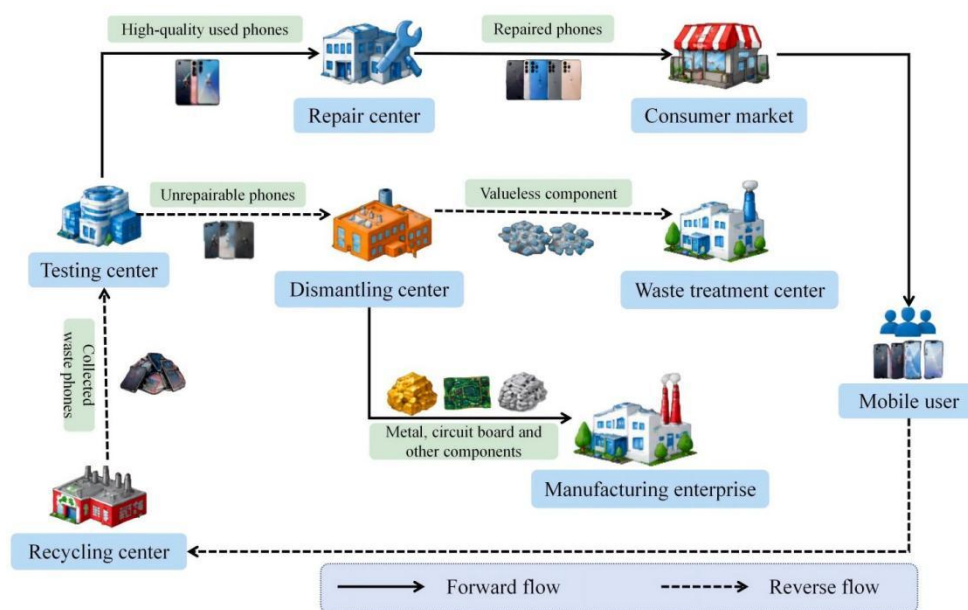


Figure 1. Schematic of the CLSC network structure for waste mobile phones.

3.2. Symbol definitions

The sets, parameters, and decision variables involved in the model are shown in Table 1, where the superscript “~” represents uncertain parameters.

Table 1. Symbols and meanings of sets, parameters, and decision variables.

	Symbol	Symbol description	Symbol	Symbol description	Symbol	Symbol description	Symbol	Symbol description
Assemble	J	Recycling center	M	Repair center	P	Disassembly center	G	Waste disposal center
	K	Testing center	N	Secondhand market	W	Remanufacturing center		
Parameter	f_j	Fixed cost at J	h_j	storage cost	W_t	Unit weight of product	R	Any larger constant
	f_k	Fixed cost at K	L_u	Residual price	W_k	Carbon emissions at point K	$\tilde{q}_j$	Daily recovery volume
	L_n	New product price	L_0	Satisfaction with benchmark price	W_p	Carbon emissions at P	$\tilde{r}$	High-quality recycling rate
	V	Total operating period days	γ	Sensitivity coefficient of price	UC_j	Maximum capacity of J	$\tilde{y}_{mn}$	Market demand quantity
	T	Storage cycle	β	Shortage penalty coefficient	UC_k	Maximum capacity of k	$\tilde{L}_{mn}$	Fix product market prices
	e	Shortage penalty cost	d_{jk}	Average distance from J to K	α	finished product conversion rate	$\tilde{V}_n$	Material evaluation value
	b_k	Unit testing cost	b_m	Unit repair cost	b_p	Unit dismantling cost	b_g	Unit waste disposal cost
	Ω	Privacy risk coefficient	c_n	Privacy protection coefficient	π_1	Data processing security factor	π_2	Qualification coefficient of J
	π_3	Privacy traceability coefficient	r_w	part remanufacturing ratio				
Decision variable	X_j	Establish a recycling center at J	Z_{jk}	The product is allocated from J to K	Q_{jk}	The quantity allocated from J to K	S_j	Product inventory at J
	D_{mn}	Market shortage quantity	X_k	Establish testing center at K				

3.3. Methodology

3.3.1. Main objective: Total economic profit model

The total economic profit model function of the CLSC network is specified in Eq. (1).

$$\begin{aligned}
 \max_{\substack{\tilde{q} \in U_q, \tilde{r} \in U_r \\ \tilde{V} \in U_V, \tilde{L} \in U_L}} \min TP = & -\sum_{j \in J} X_j f_j - \sum_{k \in K} Z_{jk} f_k - v \sum_{j \in J} \frac{31}{2} \tilde{q}_j h_j X_j - \frac{v}{T} \sum_{k \in K} b_k Q_{jk} \\
 & - \sum_{k \in K} \frac{v}{T} \left\{ \sum_{m \in M} \tilde{r} b_m Q_{jk} + \sum_{p \in P} (1 - \tilde{r}) b_p Q_{jk} + \sum_{g \in G} (1 - \tilde{r})(1 - r_w) b_g Q_{jk} \right\} - \sum_{n \in N} e \frac{v}{T} D_{mn} \\
 & + \frac{v}{T} \sum_{p \in P} \sum_{w \in W} r_w (1 - \tilde{r}) Q_{jk} \tilde{V}_n + \frac{v}{T} \sum_{m \in M} \sum_{n \in N} \tilde{r} Q_{jk} \alpha \tilde{L}_{mn} + \frac{v}{T} \left\{ \sum_{j \in J} s_j + \sum_{m \in M} \tilde{r} (1 - \alpha) Q_{jk} \right\} L_u
 \end{aligned} \quad (1)$$

The outer maximization determines facility-location, flow-allocation, inventory, and shortage decisions, whereas the inner minimization represents the most adverse realizations of uncertain parameters within the prescribed uncertainty sets. The profit structure incorporates fixed facility investment, inventory holding costs, processing costs for testing, repair, dismantling, and waste treatment, as well as shortage penalties. Revenue is generated through the sale of repaired products, recovered materials, and residual inventories. The inventory level represents the ending inventory at the end of each storage cycle.

S.T

$$\sum_{k \in K} Z_{jk} = 1 (\forall j \in J) \quad (2)$$

$$\sum_{j \in J} \tilde{q}_j T_j Z_{jk} = \sum_{j \in J} Q_{jk} + s_j (\forall j \in J, \tilde{q}_j \in U_q) \quad (3)$$

$$D_{mn} + \frac{v}{T} \sum_{m \in M} \tilde{r} \alpha Q_{jk} \geq \sum_{y \in Y} \tilde{Y}_{mn} (\forall m \in M, \forall \tilde{Y}_{mn} \in U_Y) \quad (4)$$

$$\sum_{j \in J} Z_{jk} \leq R X_j (\forall j \in J) \quad (5)$$

$$\sum_{j \in J} Z_{jk} \leq R X_k (\forall k \in K) \quad (6)$$

$$\tilde{L}_n + \tilde{V}_w \leq L_n \quad (7)$$

$$X_j, Z_j \in (0, 1) \quad (8)$$

$$Q_{jk}, D_{mn}, s_j \geq 0 (\forall j \in J, \forall k \in K) \quad (9)$$

$$\sum_{j \in J} \tilde{q}_j T \leq \sum_{j \in J} U C_j X_j (\forall j \in J, \forall \tilde{q}_j \in U_q) \quad (10)$$

$$\sum_{j \in J} Q_{jk} X_j Z_{jk} \leq \sum_{k \in K} U C_k (\forall j \in J, \forall \tilde{q}_j \in U_q) \quad (11)$$

In terms of constraint conditions, Eq. (2) specifies that all products from each waste mobile phone recycling center must be allocated to a single testing center. Eq. (3) represents the product flow balance constraint at each recycling center, ensuring that the total quantity of waste mobile phones collected within one storage cycle equals the sum of outbound shipments to testing centers and remaining inventory. Eq. (4) defines the product flow balance constraint for the second-hand market. Eq. (5) states that no waste mobile phones can be allocated from an unopened recycling center. Eq. (6) stipulates that an unopened testing center cannot receive waste mobile phones. Eq. (7) requires that the combined residual value and resale price of a given type of recycled mobile phones must not exceed the market price of new devices. Eq. (8) ensures that decision variables X_j and Z_{ij} are binary variables ranging from 0 to 1. Eq. (9) guarantees the non-negativity of decision variables Q_{jk} , D_{mn} , and S_j . Eqs. (10) and (11) govern inventory constraints across waste mobile phone recycling centers, testing centers, and repair centers.

Within the primary objective function, supplementary variables ε , φ , and ϕ are incorporated into the second, eighth, and ninth components, as detailed in equations (12) to (14), respectively.

$$\varepsilon \geq v \sum_{j \in J} \frac{1}{2} \tilde{q}_j h X_j \quad (12)$$

$$\varphi \leq \sum_{p \in P} \sum_{w \in W} \frac{2}{3} (1 - \tilde{r}) Q_{jk} \tilde{V}_n \quad (13)$$

$$\phi \leq \sum_{m \in M} \sum_{n \in N} \tilde{r} Q_{jk} \alpha \tilde{L}_{mn} \quad (14)$$

3.3.2. Auxiliary objective 1: Customer satisfaction model

To quantify the social profits of the closed-loop supply chain (CLSC) network, we build upon the Kano-based customer satisfaction framework proposed by Yao et al. [65] for second-hand apparel platforms, as well as the customer satisfaction modeling approach for products in closed-loop supply chains developed by Shambayati et al. [66]. The proposed model retains the dynamic mechanism underlying customer satisfaction responses while incorporating the specific characteristics of second-hand mobile phone transactions, particularly those related to data privacy and information security. Market performance for waste mobile phones is driven by three interrelated factors: (1) Price fluctuations directly shaping willingness to pay and perceived value; (2) stockout severity adversely affecting customer expectations and service experience; and (3) privacy risks undermining user trust and perceived privacy protection [67]. Together, these three factors shape consumer willingness to pay, expectation formation, and overall satisfaction. Consequently, the model is specified under two distinct decision scenarios that capture supply and demand volatility, specifically integrating mobile phone price fluctuations and consumer privacy risk perceptions, as presented in Eq. (15).

$$\max TE = \begin{cases} \sum_{n \in N} (1 - \gamma \frac{|\tilde{L}_n - L_0|}{L_0}) - (1 - C_n) \Omega & \tilde{y}_{mn} \leq Q_{mn} \\ \sum_{n \in N} (1 - \gamma \frac{|\tilde{L}_n - L_0|}{L_0}) - \beta \frac{D_{mn}}{\tilde{y}_{mn}} - (1 - C_n) \Omega & \tilde{y}_{mn} > Q_{mn} \end{cases} \quad (15)$$

S.T

$$C_n = \pi_1 \pi_2 \pi_3 \quad (16)$$

$$\begin{cases} L_0 \leq \tilde{L}_n \\ D_{mn} \leq \tilde{Y}_{mn} \end{cases} \quad (17)$$

Under the full demand satisfaction scenario, the price sensitivity coefficient (γ) is introduced together with the privacy risk coefficient (Ω) and privacy protection coefficient (C_n) to quantify the effects of privacy protection and traceability. C_n integrates the effects of the data processing security factor (π_1), the qualification factor of the recycling entity (π_2), and the privacy traceability factor (π_3), as shown in Eq. (16). For scenarios with unmet demand, a stockout penalty coefficient (β) is introduced to mitigate the impact of stockout risk on customer satisfaction. Constraint (17) indicates that the benchmark price for customer satisfaction in the market must remain within the fluctuation range of second-hand mobile phone prices, while the market shortage must remain within total market demand.

3.3.3. Auxiliary objective 2: Carbon emission model

Based on the life cycle assessment framework defined in ISO 14040 and ISO 14044 [68,69], the Chinese greenhouse gas accounting methodology for waste electrical and electronic product recycling and treatment (T/CACE 035-2021), and existing life cycle assessment studies on waste mobile phone recycling [70], we develop a carbon-emission quantification model for the CLSC network of waste mobile phones.

$$\min TS = \frac{V}{T} \left[\sum_{j \in J} \sum_{k \in K} W_k Q_{jk} + \sum_{k \in K} \sum_{p \in P} W_p (1 - \tilde{r}) Q_{jk} + \sum_{k \in K} \sum_{p \in P} \sum_{g \in G} W_g (1 - r_w)(1 - \tilde{r}) Q_{jk} \right] \quad (18)$$

S.T

$$W_k = \frac{0.2361 d_{jk}}{Q_{jk}} \quad (19)$$

The environmental impact of CLSC networks is characterized using a carbon-emission quantification model. Carbon emissions mainly arise from three sources. First, mobile phones are transported from recycling centers to testing centers, generating primary emissions through vehicle fuel consumption. Using a fuel consumption rate of approximately 10 L/100 km and a gasoline emission factor of 2.361 kg CO₂-eq/L, transportation emissions are calculated as $(d_{ik}/100) \times 10 \times 2.361 / Q_{jk} = 0.2361(d_{ik}/Q_{jk})$ [71]. Second, energy consumption and emissions occur during the dismantling stage, with the carbon-emission factor per dismantled product established as $W_p = 0.2$ kg CO₂-eq based on energy-consumption data from WEEE dismantling enterprises and relevant industry studies [72]. Third, emissions arise from transportation to and treatment at e-waste treatment centers. The unit treatment carbon-emission factor is set to 0.5 kg CO₂-eq, namely $W_g = 0.5$ kg CO₂-eq, to reflect the volume, weight, and composition of organic or combustible fractions in recovered smart WEEE, alongside emission estimates for landfilling and incineration [73].

4. Robust counterpart formulation under heterogeneous uncertainties

To address the heterogeneous uncertainty associated with recovery volume, recovery quality, market demand, second-hand product price, and dismantled material value, we develop a differentiated robust optimization strategy that matches uncertainty-set structures with parameter-specific fluctuation patterns.

4.1. Budget uncertainty set for recovery volume

Influenced by discrete events such as consumer behavior and policy shifts, the recovery volume of waste mobile phones exhibits significant discrete temporal volatility and unpredictability [69]. By constraining the deviation range of uncertain parameters through a perturbation budget, the budgeted robust optimization approach can effectively match the fluctuation characteristics of such uncertainties [39]. In this study, we introduce a robust control parameter Γ_i and a perturbation ratio $\chi_j \in [0, 1]$ to control the overall uncertainty budget of recovery volume and the maximum relative deviation of each recovery-volume parameter, respectively. Specifically, $\bar{q}_j$ denotes the nominal recovery volume,

while $\hat{q}_j = \chi_j \bar{q}_j$ represents the maximum absolute deviation. When $\chi_j = 0$, the recovery volume remains at its nominal value; when $\chi_j = 1$, the deviation is allowed to reach its prescribed maximum relative magnitude. The budget parameter Γ_l constrains the aggregate deviations of multiple recovery-volume parameters, thereby regulating the degree of robust protection under different uncertainty levels [53]. Since the constraints (3), (10), and (12) of the objective model (TP) are included in the recovery quantity parameter $\tilde{q}_j$, Eq. (3) is selected for detailed illustration as a representative case.

First, Eq. (3) is relaxed without altering the optimal value, resulting in the inequality constraints presented in Eq. (20):

$$\sum_{j \in J} \tilde{q}_j TZ_{jk} \geq \sum_{j \in J} Q_{jk} + s_j (\forall j \in J, \tilde{q}_j \in U_q) \quad (20)$$

Following relaxation of the original formulation, the budgeted robust control parameters are introduced, as shown in Eq. (21).

$$\sum_{j \in J} \bar{q}_j TZ_{jk} - \max_{\{s \cup \{t\} | s \in J, |s| = \lceil \Gamma_l \rceil, t \in J \setminus s\}} \left\{ \sum_{i \in s} \hat{q}_i TZ_{jk} + (\Gamma_l - \lceil \Gamma_l \rceil) \hat{q}_t TZ_{jk} \right\} \geq \sum_{j \in J} Q_{jk} + s_j (\forall j \in J) \quad (21)$$

Eq. (21) introduces a fully deviating subset (s), which selects parameters $|s|$ to construct the worst-case scenario under the robustness budget Γ_l . The index (t) denotes a single partially deviating parameter, namely an element selected from the remaining set $J \setminus s$ after s is excluded from J . This construction is used to address the case in which Γ_l takes a non-integer value.

To formulate the worst-case impact of recovery-volume uncertainty, a protection function is introduced to represent the maximum deviation induced by all admissible realizations within the budgeted uncertainty set, as shown in Eq. (22):

$$\xi(\beta, \Gamma_l) = \max_{\{s \cup \{t\} | s \in J, |s| = \lceil \Gamma_l \rceil, t \in J \setminus s\}} \left\{ \sum_{i \in s} \hat{q}_i TZ_{jk} + (\Gamma_l - \lceil \Gamma_l \rceil) \hat{q}_t TZ_{jk} \right\} \quad (22)$$

The integration of Eqs. (20) and (21) can be expressed as Eq. (23):

$$\sum_{j \in J} \bar{q}_j TZ_{jk} - \xi(\beta, \Gamma_l) \geq \sum_{j \in J} Q_{jk} + S_j (\forall j \in J) \quad (23)$$

The worst-case protection problem can be equivalently reformulated as a linear programming problem without changing its optimal value, as presented in Eq. (24):

$$\begin{cases} \max \sum_{j \in J_1} \hat{q}_j \chi_j Z_{jk} T \\ \text{s.t.} \sum_{j \in J_1} \chi_j \leq \Gamma_l, 0 \leq \chi_j \leq 1 \end{cases} \quad (24)$$

The dual problem corresponding to Eq. (24) is formulated as Eq. (25), where the nonnegative dual variables ς_j and δ_{jk} correspond to the uncertainty budget constraint and the upper-bound constraints on the deviation variables, respectively.

$$\begin{cases} \min \varsigma_j \Gamma_1 + \sum_{j \in I_1} \delta_{jk} \\ \text{s.t. } \varsigma_j + \delta_{jk} \geq \hat{q}_j TZ_{jk}, \forall j \in J_1 \\ \varsigma_j \geq 0, \delta_{jk} \geq 0, \forall j \in J_1 \end{cases} \quad (25)$$

For any fixed outer decision vector, the protection problem in Eq. (24) is a continuous linear programming problem. Since $0 \leq \Gamma_1 \leq |J_1|$ and $0 \leq \chi_j \leq 1$, the primal problem is feasible and has a finite optimal objective value, satisfying the conditions for strong duality. According to the strong duality theorem, the primal and dual problems achieve the same optimal objective value. Finally, substituting the objective function and all constraints into the protection function yields the equivalent linear model given in Eq. (26), along with constraints (27) and (28).

$$\sum_{j \in J} \bar{q}_j TZ_{jk} - \varsigma_j \Gamma_1 - \sum_{j \in J} \delta_{jk} \geq \sum_{k \in K} Q_{jk} + s_j (\forall j \in J) \quad (26)$$

$$\varsigma_j + \delta_{jk} \geq \hat{q}_j TZ_{jk} (\forall j \in I_1, j \in J) \quad (27)$$

$$\varsigma_j \geq 0, \delta_{jk} \geq 0 (\forall j \in I_1, j \in J) \quad (28)$$

4.2. Budget uncertainty set for market demand

Influenced by economic conditions, consumption trends, and the competitive landscape, secondary market demand for mobile phones exhibits regional discrete volatility and unpredictability [25]. Accordingly, we adopt a budgeted uncertainty set to model market-demand perturbations. Γ_2 is defined as a robust control parameter for market demand to limit permissible deviations from the nominal value, while χ_y represents the disturbance ratio characterizing the degree of fluctuation. Taking the constraint condition Eq. (4) of the main objective model as an example, we define $\bar{Y}_{mn}$ and $\hat{Y}_{mn}$ as the average and maximum deviation values of the product market demand, respectively. Therefore, the robust equivalent form of Eq. (4) is expressed as follows:

$$D_{mn} + \frac{\nu}{T} \sum_{m \in M} \tilde{r} \alpha Q_{jk} \geq \sum_{y \in Y} \bar{Y}_{mn} + \frac{\Gamma_2}{|Y|} \hat{Y}_{mn} (\forall y \in Y_1) \quad (29)$$

4.3. Box uncertainty set for quality grading

Owing to fluctuations in equipment operational conditions, the recovery quality rate presents continuous interval-type variations [74]. A box uncertainty set is adopted for this parameter, as historical inspection data enable its upper and lower bounds to be reliably quantified [75]. The model restricts the recovery quality rate within the interval $\{\tilde{r} | \underline{r} \leq \tilde{r} \leq \bar{r}\}$ via a set of inequality constraints, where $\bar{r}$ and $\underline{r}$ represent the upper and lower bounds of the quality rate, respectively. By applying a box uncertainty set to characterize the interval range of uncertain recovery quality parameters, we

derive the corresponding constraint formulations with embedded quality uncertainty, as presented in Eq. (30):

$$\sum_{k \in K} \left\{ \sum_{m \in M} \tilde{r} Q_{jk} + \sum_{p \in P} (1 - \tilde{r}) Q_{jk} + \sum_{g \in G} (1 - r_w)(1 - \tilde{r}) Q_{jk} \right\} \leq \sum_{k \in K} UC_k \quad (30)$$

To mitigate the risks associated with recovery quality uncertainty, the left-hand side expression is maximized using a box uncertainty set. The resulting constraint is presented in Eq. (31):

$$\sum_{k \in K} \left\{ \sum_{m \in M} \bar{r} Q_{jk} + \sum_{p \in P} (1 - \bar{r}) Q_{jk} + \sum_{g \in G} (1 - r_w)(1 - \bar{r}) Q_{jk} \right\} \leq \sum_{k \in K} UC_k \quad (31)$$

4.4. Polyhedral uncertainty set for price and value correlations

The Global E-waste Monitor 2024 [76] shows that the economic value of recoverable materials in e-waste varies with movements in secondary raw-material prices. Empirical evidence further suggests that reuse value and material-recovery value may co-vary through related value-realization channels [77,78]. Polyhedral uncertainty sets are therefore particularly appropriate for this setting, as they use linear constraints to represent interdependencies among uncertain parameters and to define the admissible range of joint fluctuations in prices and material values [63]. The model defines $(\bar{V}_n, \bar{L}_{mn})$ and $(\hat{V}_n, \hat{L}_{mn})$ as the nominal values and maximum deviations for the manufacturing value of disassembled materials and the market price of mobile phones, respectively. Subsequently, linear constraints are employed to bound the fluctuations of these prices and values. By employing a data-driven dynamic weighting mechanism (i.e., risk adjustment coefficients λ_1, λ_2), the model quantifies uncertainties in prices and values, as formulated in Eqs. (32) and (33). In alignment with market conditions, Eq. (34) constrains the combined value of second-hand and disassembled products to remain below new product benchmarks (L_n). Additionally, the objective is reformulated into a dynamic affinity form as shown in Eq. (35), which strengthens the model adaptability amidst market complexity.

$$\varphi = \min_{\tilde{V}_n \in U_V} \sum_{p \in P} \sum_{w \in W} (1 - r_w)(1 - \tilde{r}) Q_{jk} (\bar{V}_n - \lambda_1 \hat{V}_n) \quad (32)$$

$$\phi = \min_{\tilde{V}_n \in U_V} \sum_{m \in M} \sum_{n \in N} \tilde{r} Q_{jk} \alpha (\bar{L}_{mn} - \lambda_2 \hat{L}_{mn}) \quad (33)$$

S.T.

$$(\tilde{V}_n + \hat{V}_n) + (\tilde{L}_{mn} + \hat{L}_{mn}) \leq L_n \quad (34)$$

$$\varphi + \phi \leq \sum_{p \in P} \sum_{w \in W} (1 - \tilde{r}) r_w Q_{jk} (\tilde{V}_n - \hat{V}_n) + \sum_{m \in M} \sum_{n \in N} \tilde{r} \alpha Q_{jk} (\tilde{L}_{mn} - \hat{L}_{mn}) \quad (35)$$

5. Model verification and performance analysis

5.1. Multi-scale monte carlo validation

Monte Carlo simulations generate stochastic CLSC network instances of varying scales to validate the solution quality and robustness of the proposed model. The ranges of uncertain parameters

are determined based on historical statistical data from the waste mobile phone recycling industry. Given that robust optimization primarily evaluates system performance under worst-case scenarios within predefined uncertainty sets and does not rely on specific probability distributions, the daily recovery volume of recycling centers is selected as the primary uncertain parameter. The remaining uncertain parameters are assumed to follow uniform distributions within their predefined perturbation intervals, thereby ensuring comprehensive coverage of diverse fluctuation scenarios. Deterministic parameters are configured according to established standards, ensuring uniform settings across instances of identical scale. All simulations are implemented in Python, with the Gurobi 9.1.x solver invoked to solve the robust optimization models. It should be noted that the Monte Carlo simulation is primarily intended to compare the decision performance of different optimization models under identical uncertainty scenarios rather than to perform statistical inference on population parameters. Accordingly, model performance is evaluated primarily based on average performance and constraint violations, without conducting additional conventional significance tests.

We investigate the fluctuation trends of recovery volumes by varying the perturbation ratio (χ_j). Additionally, the following parameters are set as $\Gamma_2 = 0$, $\chi_y = 0$, and $\lambda_1 = \lambda_2 = 0$. For each combination of robust control parameters and perturbation coefficients, Monte Carlo simulations were performed to randomly generate realizations of uncertain parameters within the specified perturbation intervals. A preliminary convergence analysis based on pilot simulations demonstrated that the variation in the sample means of key performance indicators, such as total profit, remains below 1% when the number of replications reached 270, suggesting that the simulation results achieves sufficient stability. Increasing the number of replications further yielded marginal improvements in result accuracy while substantially increasing the computational burden associated with solving the mixed-integer programming model. Therefore, considering statistical reliability and computational efficiency, we adopt 270 replications as the Monte Carlo simulation scale. Table 2 compares the simulation outcomes of the deterministic and robust models regarding the main objective function across parameter combinations. The instance of $|J| \times |K| \times |Y|$ denotes the number of recycling centers, testing centers, and second-hand markets for electronic products, respectively.

Comparative simulation results across scales indicate that the robust optimization model yields lower total profit than the deterministic model under both nominal and simulated scenarios. This reduction stems from the conservative strategies adopted to hedge against uncertainty, thus representing the inherent cost of risk aversion. Under uniform perturbations of other parameters, the deterministic models exhibit severe constraint violations, while the robust model exhibits strong constraint-satisfaction capability and keeps constraint violations at a minimal level. When the parameters are set to $\Gamma_2 = 5$ and $\chi_j = 0.1$, the deterministic model with a scale of $25 \times 9 \times 9$ yields 160 violations, corresponding to a violation rate of nearly 59%. In contrast, the robust model incurs only 101 violations. With the increase in Γ_1 and χ_j , the number of constraint violations gradually decreases to zero; however, excessive uncertainty protection also substantially compresses the economic benefits. Overall, the model optimizes the trade-off between feasibility and cost-effectiveness. Flexible parameter adjustment enables decision-makers to tailor strategies according to their risk appetites, thereby ensuring robust planning for waste mobile-phone CLSC networks.

Table 2. Comparison results of deterministic and robust model solutions for the main objective function at different scales.

J × K × Y	Γ_I	χ_j	Under nominal data total		Under nominal data		Simulated data			
			profit (10 ⁴ CNY)		solution time/second		Violation count		Total profit (10 ⁴ CNY)	
			D	R	D	R	D	R	D	R
10 × 4 × 4	5	0.1		14226.73	0.03	0.03	33	12	11921.60	11440.06
		0.3	15059.50	12561.28	0.03	0.03	40	0	12046.94	10086.33
		0.5		10895.83	0.03	0.03	35	0	11834.63	8769.55
	10	0.1		13394.00	0.03	0.03	39	4	11944.52	10652.99
		0.3	15059.50	10063.10	0.04	0.04	40	0	11988.11	8206.52
		0.5		6732.20	0.03	0.04	43	0	11930.94	5480.12
	15	0.1		13394.00	0.04	0.04	42	3	12040.04	10831.85
		0.3	15059.50	10063.10	0.04	0.04	34	0	11998.09	8070.80
		0.5		6732.20	0.04	0.04	40	0	12044.41	5430.92
15 × 6 × 7	5	0.1		21456.45	0.04	0.04	34	8	17920.60	17048.94
		0.3	22289.17	19791.00	0.04	0.04	24	0	17885.72	16032.15
		0.5		18125.55	0.04	0.04	28	0	17866.91	14612.01
	10	0.1		20623.73	0.04	0.04	27	2	17800.70	16594.57
		0.3	22289.17	17292.83	0.04	0.04	23	0	17857.50	14001.86
		0.5		13961.93	0.04	0.04	32	0	18047.24	11309.41
	15	0.1		19791.00	0.04	0.04	31	0	17930.73	15952.11
		0.3	22289.17	14794.65	0.04	0.04	23	0	17716.57	11976.40
		0.5		9798.30	0.04	0.04	23	0	17800.18	7979.53
25 × 9 × 9	5	0.1		33975.10	0.04	0.04	160	101	29663.90	29345.88
		0.3	33828.63	34268.05	0.06	0.06	144	53	29565.54	28369.71
		0.5		33793.00	0.09	0.09	153	13	29690.74	27108.09
	10	0.1		34121.58	0.08	0.07	145	83	29609.95	28939.35
		0.3	33828.63	32960.28	0.07	0.08	161	2	29642.65	26196.75
		0.5		29629.38	0.06	0.06	153	0	29673.04	23853.86
	15	0.1		34268.05	0.06	0.06	134	37	29524.76	28203.48
		0.3	33828.63	30462.10	0.07	0.07	141	0	29545.93	24442.86
		0.5		25465.75	0.07	0.08	150	0	29597.53	20469.87

Note: D is the deterministic model, R is the robust model.

5.2. Comparative performance under multi-source uncertainties

To evaluate the decision quality and risk resilience of the proposed robust optimization model under multidimensional uncertainty, five experimental scenarios are designed to incorporate distinct uncertain factors, with the corresponding results reported in Table 3. The proposed robust optimization (RO) model is benchmarked against the deterministic linear programming (DLP) model and the stochastic programming (SP) model. To ensure a fair comparison, the three models adopt the same underlying CLSC network structure, baseline input data, objective functions, and weight settings, differing only in their treatment of uncertain parameters. The simulation is based on the infrastructure planning of the study area, with 25 recycling centers, 8 testing centers, and 9 second-hand markets incorporated into the network configuration. All three models are implemented in Python and solved using Gurobi 9.1.x. Furthermore, Monte Carlo simulation is employed to generate 270 datasets by sampling uncertain parameters within predefined perturbation intervals, ensuring that model performance is evaluated under consistent conditions. Finally, three performance indicators, namely total profit, the frequency of constraint violations, and opportunity-risk loss, are used to

comprehensively assess the economic performance and risk resilience of different optimization approaches under multidimensional uncertainty.

In Table 3, SP_{worst} and SP_{average} represent the total network profits of the stochastic programming model under the worst-case and average scenarios, respectively. Similarly, RO_{worst} and RO_{average} represent the corresponding total network profits of the RO model. The worst-case scenario denotes the total network profit associated with the optimal decision under the probability distribution within the ambiguity set that minimizes the objective value. By contrast, the average scenario is defined as the mean total operating profit computed over multiple simulated uncertainty realizations. In addition, the opportunity risk loss metrics for Robust Optimization (ORL_{RO}) and Stochastic Programming (ORL_{SP}) are introduced to quantify missed optimal opportunities and the potential risk losses induced by uncertainty, respectively.

Table 3. Comparison of model solving performance under different number of uncertain factors.

Num ber	Uncertain environmental settings		Deterministic model		Stochastic Programming model			Robust Optimization model				
	Factor combinat ion	Scenario setting	Total profit (10 ⁴ CNY)	Violation count	SP _{worst} (10 ⁴ CNY)	SP _{average} (10 ⁴ CNY)	ORL _{SP} (10 ⁴ CNY)	Violati on count	RO _{worst} (10 ⁴ CNY)	RO _{average} (10 ⁴ CNY)	ORL _{RO} (10 ⁴ CNY)	Violati on count
1	$\tilde{q}_j$	$\chi_j = 0.1$	29663.90	160	18755.25	26846.78	10116.31	59	20030.55	28607.36	8355.73	37
		$\chi_j = 0.3$	29565.54	144	13850.25	20074.50	13631.31	14	17676.15	25356.87	8348.94	20
		$\chi_j = 0.5$	29690.74	153	8945.25	13302.23	16178.62	48	15321.75	22106.18	7374.67	6
2	$\tilde{q}_j + \tilde{y}_{mn}$	$\chi_j = 0.1, \chi_y = 0.5$	29542.18	142	8766.63	12155.98	13122.19	37	14903.19	19898.45	5379.72	19
		$\chi_j = 0.2, \chi_y = 0.3$	29589.65	158	15285.51	20161.05	10328.66	45	18486.63	24305.98	6183.73	6
		$\chi_j = 0.5, \chi_y = 0.1$	29558.72	175	9727.35	14271.05	13646.88	21	15483.75	22268.18	5649.75	16
3	$\tilde{q}_j + \tilde{r} + \tilde{y}_{mn}$	$\chi_j = 0.1, \chi_y = 0.5$	29531.47	143	8546.24	12317.79	13146.41	33	14670.65	20069.18	5395.02	11
		$\chi_j = 0.2, \chi_y = 0.3$	29592.89	179	14893.36	20089.06	10312.49	14	18045.86	24225.07	6176.48	3
		$\chi_j = 0.5, \chi_y = 0.1$	29567.33	156	11092.27	15036.24	14261.63	38	17521.78	23410.72	5887.15	8
4	$\tilde{q}_j + \tilde{r} + \tilde{y}_{mn} + \tilde{v}_w$	$\chi_j = 0.1, \chi_y = 0.5, \lambda_l = 0.2$	29518.23	142	8575.63	12220.63	13011.03	9	14701.66	19966.66	5265.00	0
		$\chi_j = 0.2, \chi_y = 0.3, \lambda_l = 0.6$	29536.71	138	15037.13	20140.13	10217.34	1	18207.47	24282.47	6075.00	0
		$\chi_j = 0.1, \chi_y = 0.5, \lambda_l = 0.8$	29589.42	185	10510.28	14233.28	13537.5	7	16652.78	22211.78	5559.00	0
5	$\tilde{q}_j + \tilde{r} + \tilde{y}_{mn} + \tilde{v}_w + \tilde{z}_{mn}$	$\chi_j = 0.1, \chi_y = 0.5, \lambda_l = 0.2, \lambda_2 = 0.2$	29507.89	141	13981.55	14833.71	8741.52	2	22676.09	23125.66	449.57	0
		$\chi_j = 0.2, \chi_y = 0.3, \lambda_l = 0.6, \lambda_2 = 0.6$	29529.64	177	18766.58	19119.53	4344.64	0	22670.78	23067.47	396.70	0
		$\chi_j = 0.5, \chi_y = 0.1, \lambda_l = 0.8, \lambda_2 = 0.8$	29576.31	144	11161.80	12837.15	7290.00	3	17625.60	18876.38	1250.77	0

As shown in Table 3, the deterministic model achieves a relatively high total profit, but its minimum constraint-violation rate still exceeds 51.1%, which may substantially limit operational feasibility. As uncertainty intensifies, total profit in the waste mobile phone CLSC network decreases due to the increased cost associated with risk-averse decisions, whereas constraint violations in the RO and SP models progressively decrease. Notably, the RO model achieves a zero constraint-violation rate when accounting for four or five uncertain factors, indicating that the incorporation of multiple sources of uncertainty enhances network feasibility and stability under dynamic conditions.

When all five sources of uncertainty are simultaneously considered, the RO model exhibits superior profitability stability and risk mitigation capability compared with the SP model. Across different parameter combinations, RO_{average} consistently exceeds SP_{average} , with improvements ranging from approximately 39.48 to 82.92 million CNY. This indicates that the robust optimization framework

can maintain higher average economic returns under multi-source uncertain environments. Further comparisons under worst-case scenarios reveal that RO_{worst} also consistently outperforms SP_{worst} , achieving an advantage of approximately 39.04 – 86.95 million CNY, demonstrating that the RO model effectively alleviates the adverse impacts of uncertainty-induced perturbations on network economic performance. Moreover, the opportunity risk loss of the SP model remains within the range of 43.45 – 87.42 million CNY, whereas that of the RO model is reduced to approximately 3.97 – 12.51 million CNY. These results demonstrate that the robust optimization framework achieves a more effective trade-off between risk protection and profit preservation by sacrificing a limited portion of potential opportunity gains in exchange for enhanced adaptability to uncertain conditions.

6. Case study

6.1. Study area and case description

Given the economic trajectory and demographic structure of China, the national mobile phone stock is projected to reach 1.70284 billion units by 2030, alongside annual sales of 977.25 million units [79]. Driven by shortened replacement cycles, the number of waste mobile phones generated in the same year is expected to exceed 972.13 million units [80]. Against this background, the Guangxi Zhuang Autonomous Region, China, is selected as the empirical case area for the waste mobile phone CLSC network. Figure 2 illustrates the spatial planning scheme of the proposed network.

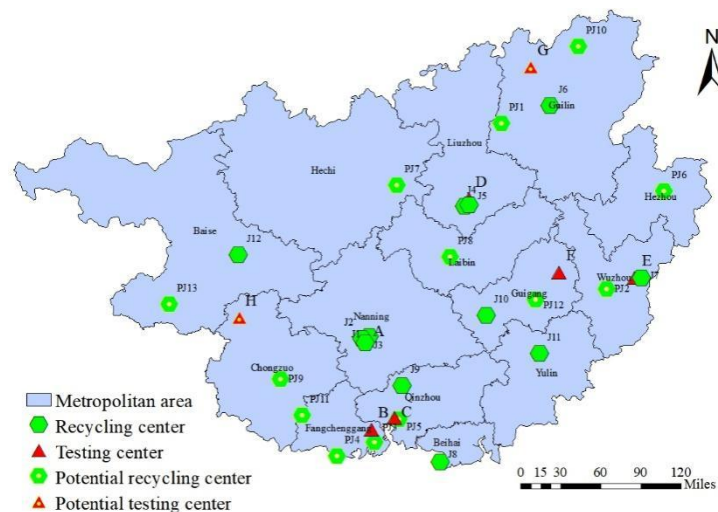


Figure 2. Spatial layout and network configuration for the waste mobile phone CLSC.

In view of regional practices, the provincial CLSC for waste mobile phones is underdeveloped, with an existing infrastructure limited to recycling centers and six testing centers. Since the existing disassembly, refurbishment, and waste treatment centers possess sufficient capacity to accommodate this new stream alongside current operations, they are not excluded from the network design. To foster industrial development and accommodate projected market demand, the Guangxi Zhuang Autonomous Region has planned the establishment of thirteen new recycling centers and two new testing centers. Consequently, the waste mobile phone CLSC network comprises twenty-five recycling centers, eight testing centers, and nine second-hand markets. Functioning as the core data support for the ensuing

case study, this network architecture provides a realistic context for the comprehensive analysis of CLSC network planning and optimization. The data on existing recycling and testing centers, as well as candidate locations for new centers across the province, are provided in Supplementary Tables S1–S3.

6.2. Parameter settings and data sources

Based on historical data and relevant industry technical specifications, we systematically define the key parameters for each node in the provincial waste mobile phone CLSC network, including operating costs, market response, and environmental constraints. The parameter settings are reported in Table S4 (Supplementary Material). Based on statistical analyses and fluctuation-pattern mining of historical data from the waste mobile-phone recycling industry, Table S5 (Supplementary Material) summarizes the quantitative characterization of multidimensional uncertainty parameters.

6.3. Network design and spatial layout optimization

6.3.1. Spatial layout and coverage analysis of service scope

Given the spatially dispersed layout of collection and testing centers, distinct transportation service areas are delineated across the study region, as shown in Figure 2. The Haversine formula is used to calculate the distance between each waste electronic products collection center and testing center. Specifically, the great-circle distance is calculated based on differences in latitude and longitude coordinates, the Earth curvature, and trigonometric transformations, as formulated in Eq. (38):

$$d=2R*\arcsin(\sqrt{\sin^2(\Delta N^\circ/2)+\cos N_1^\circ\cos N_2^\circ\sin^2(\Delta E^\circ/2)}) \quad (38)$$

In formula (38), R represents the Earth's radius (6,371 km), while ΔN° and ΔE° denote the differences in latitude and longitude, respectively. Spatial calculations indicate that the maximum service radius for each testing center is approximately 100 km. To assess the spatial efficiency of the distribution of centers, we employ the Thiessen (Voronoi) polygon method to delineate service areas (Figure 3).

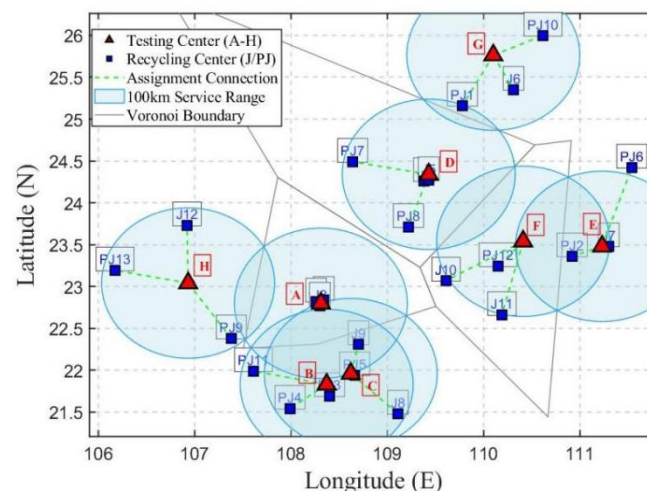


Figure 3. Optimization of service scope and spatial coverage of recycling centers.

6.3.2. Capacity and resource allocation of critical facility centers

In accordance with the spatial layout of collection and testing centers illustrated in Figure 3, Table 4 presents the specific variations in waste electronic product supply volumes for each testing center under uncertainties.

Table 4. Location of testing centers and average daily recycling volume.

Testing center	Recycling center	Number	Minimum processing capacity requirement	Maximum capacity limit	Shipping quantity ($\chi_j = 0.2$)		
					$\Gamma_I = 3$	$\Gamma_I = 1$	$\Gamma_I = 0$
A	J1, J2, J3	3	3600	5200	3786	4368	4770
B	PJ3, PJ4, PJ11	3	3350	4700	3450	4050	4350
C	J8, J9, PJ5	3	3400	5000	3522	4128	4440
D	J4, J5, Jq7, PJ8	4	4000	5800	4120	4954	5200
E	J7, Jq2, JP6	3	3500	5100	3618	4218	4560
F	J10, Jq11, Jq12	3	3300	4800	3450	4170	4350
G	J6, Jq1, Jq10	3	3250	4600	3402	4002	4290
H	J12, Jq9, Jq13	3	3550	4900	3618	4218	4560

When the robust control parameter $\Gamma_I = 0$ (i.e., the deterministic model), the actual throughput of all testing centers remains below their maximum capacity. Conversely, when Γ_I is set to 3 (the high robustness scenario), the supply of waste mobile phones consistently satisfies the minimum inspection volume requirements. Evidently, the network possesses a certain degree of resilience against variations in the robust control parameter. However, to ensure stability amid extreme fluctuations in recovery volume, individual network nodes must employ strategies such as spatial coverage optimization, elastic capacity design, and risk-adaptive adjustment.

6.3.3. Supply-demand balance analysis

Figure 4 shows variations in market demand and supply adaptability after the CLSC network planning for discarded mobile phones. The results demonstrate that across all robust intervals, second-hand products sufficiently cover market demand fluctuations under different scenarios. Therefore, by regulating design capacity and allocating resources rationally, decision-makers can effectively buffer the network against external uncertainty shocks. This strategy stabilizes reverse logistics flow, minimizes resource wastage, and maximizes overall system profits.

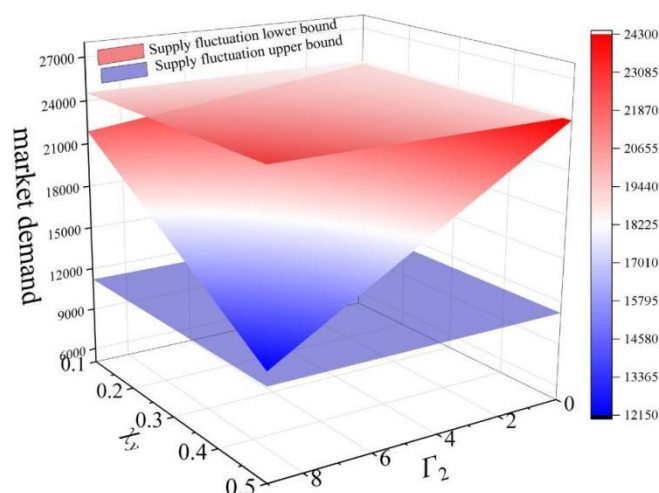
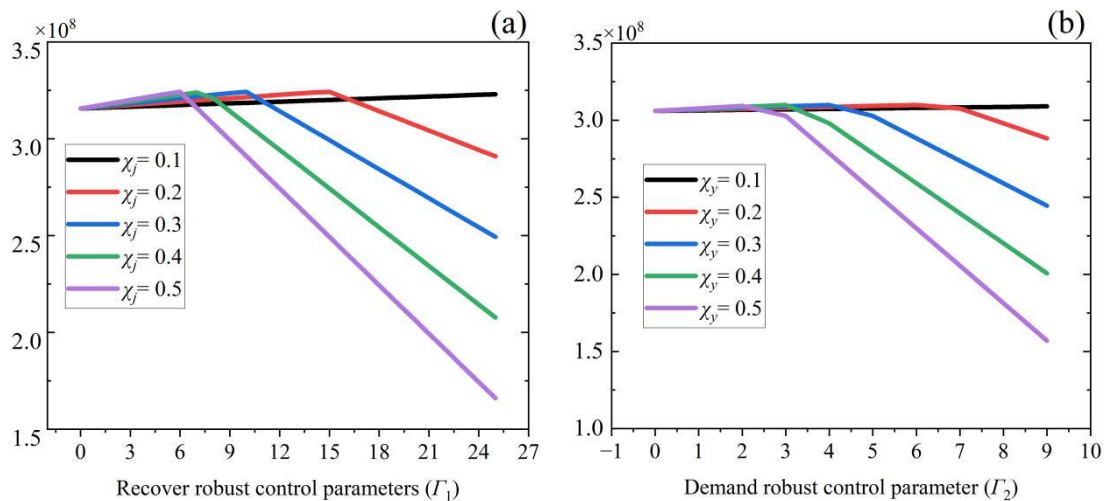


Figure 4. Market demand fluctuation range and supply adaptability.

6.4. Sensitivity analysis of supply and demand uncertainty

Based on historical fluctuations in regional waste mobile phone recovery and market demand, a sensitivity analysis is performed on the perturbation ratios of the variables (e.g., recovery volume and market demand). Figure 5(a) shows that total profit exhibits a clear boundary threshold under the uncertainty of the recycling amount. In the low robustness interval ($0 < \Gamma_1 < 6$), all perturbation ratio curves exhibit a slight upward trend as Γ_1 increases. Beyond this range, total profit continues to exhibit slight growth at $\chi_j = 0.1$ but declines rapidly once this threshold is exceeded. Specifically, a higher disturbance ratio corresponds to a lower threshold for robust control parameters and a more rapid rate of decrease.

Figure 5(b) illustrates that total profit remains relatively stable within the low robustness interval ($0 < \Gamma_2 < 2$), exhibiting a distinct threshold effect; profit remains essentially constant in the moderate robustness interval ($\chi_y = 0.1$) and declines slightly in the high robustness interval ($\chi_y = 0.2$). However, once the threshold is surpassed ($\chi_y > 0.2$), the curve exhibits a near-linear downward trend declining more sharply as the perturbation ratio increases. Thus, high values of Γ_1 and Γ_2 render total profit highly sensitive to volatility in recovery and demand. To optimize decisions under uncertainties, decision-makers should align robust control parameters with their risk appetites, thereby balancing economic, environmental, and social outcomes.



a. The trend of total profit changing with Γ_1 b. The trend of total profit changing with Γ_2

Figure 5. Trend of total profit of the recycling network with robust control parameters.

Table 5 details the results of a further multi-objective analysis. With the robust control parameter for recovery volume fixed at $\Gamma_1 = 12$, raising χ_j from 0.1 to 0.5 leads to a 25.1% drop in total profit, an over 67% reduction in customer satisfaction, and a 19.4% reduction in carbon emissions. The results indicate that increasing recovery volume uncertainty is associated with reductions in total profit, customer satisfaction, and carbon emissions. Consequently, Γ_1 should be dynamically adjusted to strike a balance between total profit and carbon emissions.

Table 5. Impact of the recycling disturbance ratio on system performance metrics.

Disturbance ratio (χ_i)	Total profit (10^4 CNY)	Customer satisfaction	Carbon emissions (kgCO ₂ -eq)
0	37076.63	0.8000	32095.50
0.1	35750.09	0.7389	30853.50
0.2	33751.55	0.6532	29611.50
0.3	31753.01	0.5676	28369.50
0.4	29754.47	0.4820	27127.50
0.5	27755.93	0.3963	25885.50

6.5. Synergistic effects of multidimensional uncertainties on objectives

6.5.1. Impact on total profit

Figure 6 depicts the synergistic effect of robust control parameters and the disturbance ratio on the total profit of the CLSC network. Specifically, Figure 6(a) depicts the response of the total network profit to changes in the recovery robust control parameter Γ_1 (0 – 25) and the recovery disturbance ratio χ_i (0 – 50%). Figure 6(b) shows the total profit response as a function of the market demand robust control parameter Γ_2 (0 – 9) and the second-hand market demand disturbance ratio χ_y (0 – 50%).

Total profit decreases as the robust control parameters and the perturbation ratio increase. Recovery volume uncertainty plays a more prominent role in the low robustness range ($\Gamma_1 < 5$), while market demand emerges as the dominant factor in the high robustness regime ($\Gamma_2 > 4$). Therefore, decision-makers should adjust Γ_1 and Γ_2 according to their risk preferences to optimize the trade-off between risk and profit.

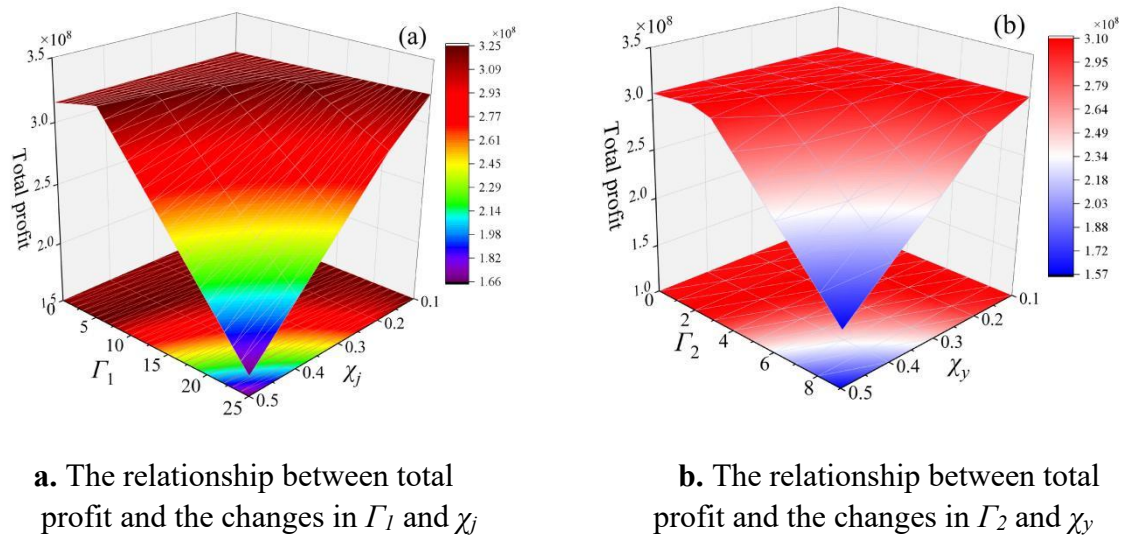


Figure 6. The trend of total profit in a CLSC network as a function of robust control parameters and disturbance ratios.

6.5.2. Impact on customer satisfaction

In this study, we investigate the influences of multiple factors on the dynamic quantification model for customer satisfaction, namely the robust control parameter for market demand (Γ_2), the price risk adjustment coefficient (λ_1), and the privacy protection coefficient (C_n). The detailed results are presented in Figure 7.

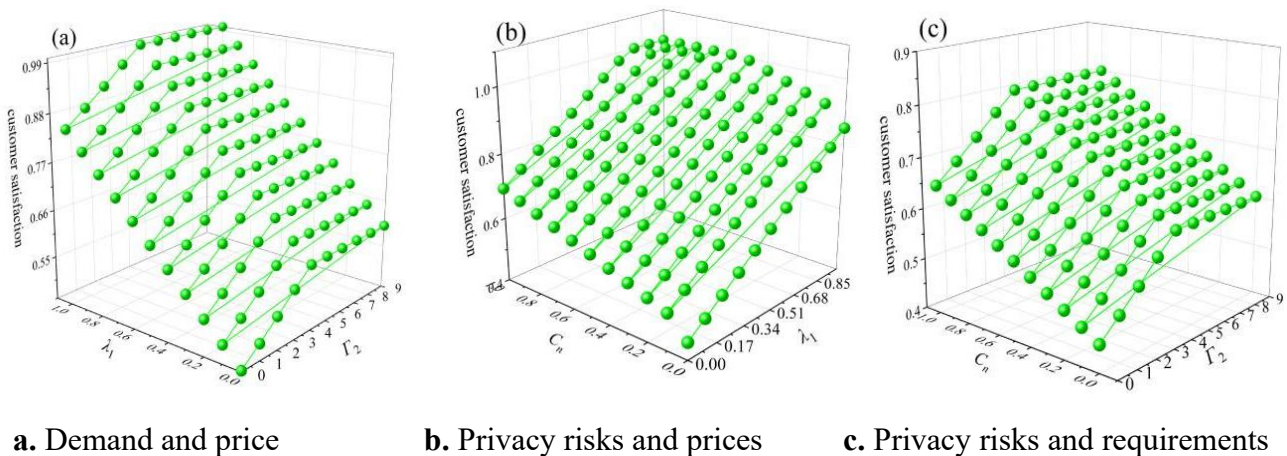


Figure 7. Trend factors influencing customer satisfaction.

Figure 7(a) illustrates the interaction between Γ_2 and λ_I in relation to customer satisfaction. In the high robustness interval ($\Gamma_2 \geq 4$), customer satisfaction exhibits a stepwise increase as λ_I increases, consistently remaining above 0.6. Notably, under an ideal price state ($\lambda_I = 1$), satisfaction approaches saturation. In the low-robustness range ($\Gamma_2 \leq 4$), customer satisfaction declines markedly as Γ_2 and λ_I decline, falling below 0.5 under unfavorable demand-robustness and price-adjustment conditions. Therefore, demand uncertainty is prone to causing stockouts and price rigidity, which hinder the mitigation of customer experience losses arising from supply-demand mismatches.

Figure 7(b) reveals the synergistic effects of C_n and λ_I on customer satisfaction. Price risk exerts a significantly more pronounced influence on customer satisfaction than privacy risk. Increasing C_n from 0 to 1 increases customer satisfaction by a maximum of 0.2, whereas increasing λ_I from 0 to 1 yields a 0.4 increase. The results indicate that, under conditions of privacy assurance, price risk adaptability becomes a critical supplementary factor in determining customer satisfaction.

Figure 7(c) illustrates the interaction effect of C_n and Γ_2 on customer satisfaction. Within the low-to-medium robustness range ($\Gamma_2 \leq 4$), C_n exerts a significant marginal effect on customer satisfaction. As C_n increases from 0.2 to 0.8, customer satisfaction rises by 0.11. In the high robustness interval ($\Gamma_2 > 4$), customer satisfaction remains relatively stable, fluctuating within the range of 0.6 to 0.8. In this interval, increasing the privacy protection coefficient exerts a progressively diminishing effect on satisfaction. In addition, privacy protection serves as a buffer against demand volatility. By enhancing customer trust, comprehensive privacy protection mechanisms (e.g., thorough data erasure, entity authentication, and traceability systems) can partially offset the adverse effects of supply-demand imbalances.

Therefore, enterprises should prioritize the advancement of privacy protection technologies and management systems. On this basis, they should optimize pricing strategies for second-hand products to accommodate market fluctuations and moderately control the conservatism of demand robustness strategies, thereby achieving the synergistic optimization of trust building, price alignment, and risk mitigation.

6.5.3. Impact on carbon emissions

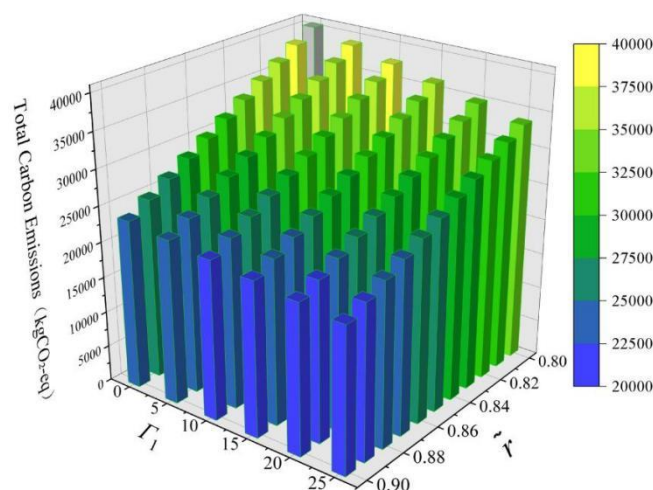


Figure 8. Impact of recovery robustness and quality rate on total carbon emissions.

In this study, we establish a carbon emission quantification model anchored in the dual uncertainties of recovery volume and quality. Specifically, the analysis simultaneously examines the impacts of the recovery robust control parameter (Γ_l) and fluctuations in recovery product quality ($\tilde{r}$) on carbon emissions, as shown in Figure 8.

6.5.4. Sensitivity analysis of uncertain parameters in multi-objective models

Figure 9 depicts the sensitivity of the economic, social, and environmental objectives under various uncertain factors. Specifically, while all other parameters are held at their baseline values, each uncertain parameter is varied within its perturbation range, and its influence is quantified by the resulting change in the objective function value. As shown in Figure 9, the left side lists the uncertain factors, including disassembly material value ($\tilde{V}_n$), product price ($\tilde{L}_{mn}$), market demand ($\tilde{y}_{mn}$), recovery volume ($\tilde{q}_j$), and high-quality recycling rate ($\tilde{r}$). The right side (Figure 9) presents the optimization objectives, comprising total profit, customer satisfaction, and total carbon emissions. The central region displays values ranging from 0% to 100%, representing the degree of influence of various uncertain factors on different optimization objectives.

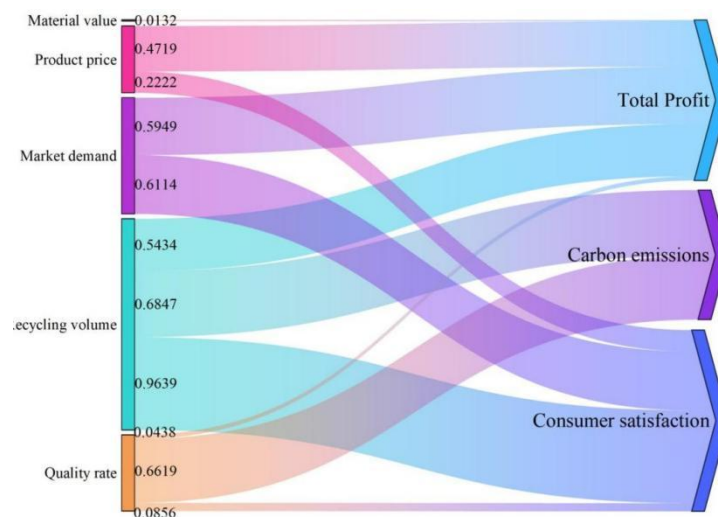


Figure 9. The impact of different uncertainty factors on multi-objective sensitivity.

Among the five uncertain parameters, $\tilde{q}_j$ exhibits the largest relative sensitivity across the three optimization objectives. Within its perturbation range, variations in $\tilde{q}_j$ result in maximum relative changes of 96.39%, 68.47%, and more than 54.34% in customer satisfaction, carbon emissions, and total profit, respectively. $\tilde{y}_{mn}$ exhibits relatively high sensitivity to the economic and social objectives, with maximum relative changes of 59.49% in total profit and 61.14% in customer satisfaction, respectively. In contrast, the $\tilde{r}$ shows a more pronounced sensitivity to the environmental objective, with a maximum relative change of 66.19% in carbon emissions. These results indicate that different uncertain parameters exhibit heterogeneous sensitivities across the three optimization objectives. The $\tilde{V}_n$ and $\tilde{L}_{mn}$ primarily drive economic objectives, exhibiting complementary behavior in response to changes in the market environment. In conclusion, recovery quantity acts as the pivotal parameter for all three objectives. Market demand plays a critical role in economic and social dimensions, whereas

the high-quality recovery rate, material value, and second-hand product price significantly influence specific objectives.

6.6. Multi-objective optimization and robust parameter configuration

In this study, we employ the decomposition-based multi-objective evolutionary algorithm (MOEA/D) to solve the multi-objective robust optimization problem of the waste mobile phone CLSC network and obtain an approximate Pareto-optimal solution set. Specifically, MOEA/D serves as a decomposition-based search framework that transforms the original multi-objective formulation into a series of scalarized subproblems by assigning distinct weight vectors to the three conflicting objectives. Within this framework, MOEA/D is primarily responsible for decomposing the multi-objective problem, managing the weight vectors, and updating the solution set, whereas the scalarized subproblems are solved exactly by Gurobi. Specifically, Gurobi serves as the inner exact optimization solver and returns the optimal solutions to MOEA/D for population evolution. Subsequently, candidate solutions generated under different weight vectors are subjected to non-dominated sorting and selection, resulting in an approximate Pareto frontier that characterizes the trade-offs among economic performance, customer satisfaction, and carbon emission mitigation.

In computational experiments, the population size of MOEA/D is set to 80, with a maximum of 200 iterations. An approximate Pareto-optimal solution set is obtained through decomposition based on multiple weight vectors and iterative search, as shown in Figure 10. To quantitatively assess the convergence and diversity of the approximate Pareto front, the hypervolume (HV) indicator is calculated after normalizing the values of the three objectives. Using (1.1, 1.1, 1.1) as the reference point in the normalized objective space, the approximate Pareto solution set yields an HV value of approximately 0.82.

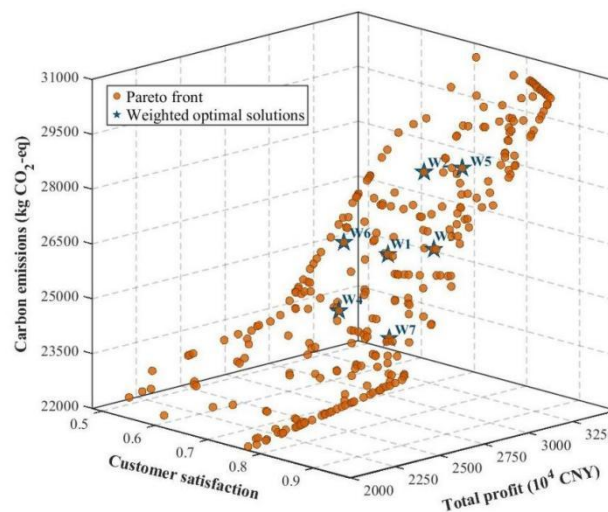


Figure 10. Approximate Pareto front for the three objectives.

Subsequently, seven representative solutions corresponding to distinct decision-making preferences are selected from this set to illustrate the trade-offs among economic, social, and environmental objectives, as presented in Table 6.

The objective weights are specified based on decision preferences, with due consideration of industry development, prior studies, and relevant policy guidelines, and are then used to select

representative solutions from the approximate Pareto set [68]. As summarized in Table 6, we define three preference structures for the weight vector: i) A balanced preference, where we assign equal weights (0.333, 0.333, 0.333); ii) a single-objective dominance, where the prioritized objective receives a weight of 0.5 and the remaining two objectives receive 0.25 each (e.g., a profit-oriented setting uses (0.5, 0.25, 0.25)); and iii) a dual-objective preference, where the two prioritized objectives are weighted at 0.4 each and the remaining objective at 0.2 (e.g., prioritizing profit and satisfaction uses (0.4, 0.4, 0.2)). As a result, the total profit is positively correlated with carbon emissions, indicating that higher returns come at the cost of increased emissions. In contrast, customer satisfaction shows a negative correlation with profits across most instances.

Table 6. Representative solutions under different decision preferences.

NO.	Preference situation	Objective weight			Total profit (10 ⁴ CNY)	Customer satisfaction	Carbon emission (kgCO ₂ -eq)	Robust control parameters (Γ_1, Γ_2)
		economy	environment	society				
W1	balance	0.333	0.333	0.333	3196.85	0.9026	28895.97	(9, 6)
W2	economy	0.500	0.250	0.250	3460.06	0.8463	29736.80	(7, 3)
W3	society	0.250	0.500	0.250	3102.54	0.9465	30173.42	(6, 3)
W4	environment	0.250	0.250	0.500	2228.47	0.5732	22443.88	(25, 9)
W5	economy, society	0.400	0.400	0.200	3281.90	0.816	28977.37	(9, 4)
W6	economy, environment	0.400	0.200	0.400	2024.33	0.4937	22943.79	(23, 8)
W7	society, environment	0.200	0.400	0.400	2575.64	0.7332	28335.38	(8, 8)

Further analysis underscores the clear practical utility of robust control parameters in relation to stakeholder preferences. Specifically, lower settings (e.g., $\Gamma_1 = 7$, $\Gamma_2 = 3$) in economically oriented scenarios imply a risk-tolerant stance towards volume and demand volatility to maximize profitability. Conversely, a preference for environmental performance results in elevated parameter levels (e.g., $\Gamma_1 = 25$, $\Gamma_2 = 9$), indicating a conservative strategy. Here, carbon emission reduction is realized through higher recovery safety margins and stringent transfer controls, inevitably trading off profitability and satisfaction. In the balanced configuration, the parameters are set to moderate values (e.g., $\Gamma_1 = 9$, $\Gamma_2 = 6$), indicating a strategy of moderate defense that balances fluctuation risks and multi-objective performance. In dual-objective scenarios like the economic and social preference, lower values (e.g., $\Gamma_1 = 9$, $\Gamma_2 = 4$) imply a synergy between economic and social objectives with less emphasis on risk defense. Conversely, scenarios combining economic-environmental or social-environmental objectives are characterized by elevated parameter values (e.g., $\Gamma_1 = 23$, $\Gamma_2 = 8$). This indicates that achieving environmental goals necessitates greater redundancy in recovery and processing to ensure system robustness. In conclusion, low parameter values indicate a profit-centric aggressive strategy, while high values signify a conservative configuration limited by environmental and social constraints.

7. Conclusion

Designing a sustainable network for the waste mobile phone CLSC is a complex challenge characterized by multi-source uncertainties. Drawing on a regional case study, in this study, we develop a comprehensive CLSC network for waste mobile phones by integrating a three-tier quality-grading mechanism with a differentiated multi-objective robust optimization approach. The findings

reveal pronounced threshold effects associated with uncertainty in recovery volumes and market demand. Once the corresponding thresholds are exceeded, total profit shows an approximately linear decline as the level of robustness increases. Among sensitivity factors, price compatibility exerts the most significant positive marginal effect on customer satisfaction. Conversely, stockouts exert the strongest adverse effect on customer satisfaction, yet enhanced privacy protection substantially attenuates satisfaction losses under high demand uncertainty. Fluctuations in recovery quality are a key driver of system-wide carbon emissions. Appropriate calibration of robust control parameters can limit the inflow of low-quality waste mobile phones into the CLSC, thereby reducing carbon emissions. In addition, variations in the calibrated robust-control parameters across preference settings underscore distinct strategic orientations. In this study, we provide a systematic methodological framework for the sustainable planning of CLSC networks for waste mobile phones under multi-source uncertainty and offer actionable decision-making guidance for the coordinated optimization of economic, social, and environmental performance.

Nevertheless, the study is subject to several limitations. First, the model assumes product homogeneity and does not fully account for differences in material composition and recovery value across brands and models, potentially affecting the accuracy of resource flow estimates and evaluations of economic and environmental performance. Second, the model primarily represents uncertainty within the recycling network as exogenous parameter perturbations and does not explicitly account for endogenous behavioral interactions among stakeholders. Third, the customer satisfaction function developed in this study has been theoretically adapted to the context of waste mobile phone recycling but has not been empirically validated using independent consumer survey data, thereby limiting its ability to capture the actual subjective perceptions of consumers. Consequently, its ability to characterize the dynamic transmission mechanisms linking key variables remains limited. In future studies, researchers could relax the homogeneity assumption by introducing more refined product classification criteria and developing a multi-product material flow optimization model. Furthermore, integrating agent-based modeling with dynamic robust optimization could facilitate the examination of how policy incentives influence consumer recycling behavior and network operational decisions, thereby enhancing the explanatory power and practical applicability of the model in real-world closed-loop supply chains.

Author contributions

Shuming Liu: Conceptualization, Methodology, Data curation, Writing - original draft. Xiang Liu: Data curation, Writing - review & editing, Supervision. Xianghua Liu: Methodology, Visualization, Investigation, Writing - review & editing. Ziquan Li: Software, Formal analysis, Resources. Qiuzhi He: Conceptualization, Validation, Supervision.

Use of Generative-AI tools declaration

In the preparation of this work, the authors used Generative AI tools such as ChatGPT to assist in improving the clarity of the language. All AI-assisted content was carefully reviewed and revised by the authors, who take full responsibility for the final version of the manuscript.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

References

1. X. Mu, M. Zhang, X. Chu, L. Li, F. Yin, Exploration of driving factors for smartphone abandonment and recycling in China, *J. Mater. Cycles Waste Manag.*, **27** (2025), 4499–4515. <https://doi.org/10.1007/s10163-025-02380-8>
2. S. Ramirez, Mobile phone usage statistics 2026: What the latest data reveals, *SQ Magazine*, 2025. Available from: <https://sqmagazine.co.uk/mobile-phone-usage-statistics/>.
3. F. Zhang, M. Wang, Y. Wang, Circular utilization: Turning waste mobile phones into treasures through recycling, *The People's Daily*, 2024. <http://paper.people.com.cn/rmrb/images/2024-06/03/01/rmrb2024060301.pdf>.
4. D. Teng, J. Wu, Q. Ma, W. Wang, G. Zhou, G. Fan, et al., Advances in the recovery of critical rare dispersed metals (gallium, germanium, indium) from urban mineral resources, *ACS Omega*, **10** (2024), 76–92. <https://doi.org/10.1021/acsomega.4c08689>
5. Y. Guo, Circular economy of waste electronic products based on gompertz model, *Proc. Integr. Optim.*, **9** (2025), 667–79. <https://doi.org/10.1007/s41660-024-00477-5>
6. Global commodities outlook 2025: Gold prices and market drivers, *J.P. Morgan Chase & Co*; 2025. Available from: <https://www.jpmorgan.com/insights/global-research/commodities/gold-prices>.
7. M. Fattahi, K. Govindan, Integrated forward/reverse logistics network design under uncertainty with pricing for collection of used products, *Ann. Oper. Res.*, **253** (2017), 193–225. <https://doi.org/10.1007/s10479-016-2347-5>
8. S. Beheshti, J. Heydari, Z. Sazvar, Food waste recycling closed loop supply chain optimization through renting waste recycling facilities, *Sustain. Cities Soc.*, **78** (2022), 103644. <https://doi.org/10.1016/j.scs.2021.103644>
9. T. Abdallah, A. Farhat, A. Diabat, S. Kennedy, Green supply chains with carbon trading and environmental sourcing: Formulation and life cycle assessment, *Appl. Math. Model.*, **36** (2012), 4271–4285. <https://doi.org/10.1016/j.apm.2011.11.056>
10. A. Bal, S. I. Satoglu, A goal programming model for sustainable reverse logistics operations planning and an application, *J. Clean. Prod.*, **201** (2018), 1081–1091. <https://doi.org/10.1016/j.jclepro.2018.08.104>
11. Y. Xu, X. Wu, M. Tang, C.-H. Yeh, L. Zhang, Developing effective intervention strategies to improve public participation in household waste recycling program: A data-driven agent-based behavior analysis approach, *Sustain. Cities Soc.*, **127** (2025), 106447. <https://doi.org/10.1016/j.scs.2025.106447>

12. I. I. Almaraj, T. B. Trafalis, A robust optimization approach in a multi-objective closed-loop supply chain model under imperfect quality production, *Ann. Oper. Res.*, **319** (2022), 1479–1505. <https://doi.org/10.1007/s10479-021-04286-8>
13. J. Ba, Y. Wang, D. Wang, X. An, M. Zhang, Carbon footprint accounting of E-waste dismantling process in China: field-based research, *Carbon Res.*, **5** (2026), 1. <https://doi.org/10.1007/s44246-025-00238-0>
14. M. Mohsenizadeh, M. K. Tural, E. Kentel, Municipal solid waste management with cost minimization and emission control objectives: A case study of Ankara, *Sustain. Cities Soc.*, **52** (2020), 101807. <https://doi.org/10.1016/j.scs.2019.101807>
15. Unblocking “the green cycle” of waste mobile phone recycling, *National Development and Reform Commission*, 2025. Available from: https://www.ndrc.gov.cn/fggz/hjyzy/zyzhlyhjhj/202506/t20250611_1398381_ext.html.
16. F. Gu, P. A. Summers, P. Hall, Recovering materials from waste mobile phones: Recent technological developments, *J. Clean. Prod.*, **237** (2019), 117657. <https://doi.org/10.1016/j.jclepro.2019.117657>
17. W. Sun, J. M. Price, The impact of environmental uncertainty on increasing customer satisfaction through corporate social responsibility, *Eur. J. Mark.*, **50** (2016), 1209–1238. <https://doi.org/10.1108/EJM-02-2015-0077>
18. M. Wilhelm, M. Hutchins, C. Mars, C. Benoit-Norris, An overview of social impacts and their corresponding improvement implications: a mobile phone case study, *J. Clean. Prod.*, **102** (2015), 302–315. <https://doi.org/10.1016/j.jclepro.2015.04.025>
19. B. Yang, C. Lee, I. W. K. Suryawan, Resilient socio-technical systems for adaptive consumer e-waste management, *Sustain. Cities Soc.*, **118** (2025), 106026. <https://doi.org/10.1016/j.scs.2024.106026>
20. A. Li, B. Li, X. Liu, Y. Zhang, H. Zhang, X. Lei, et al., Characteristics and dynamics of university students’ awareness of retired mobile phones in China, *Sustainability*, **14** (2022), 10587. <https://doi.org/10.3390/su141710587>
21. T. B. Yahya, N. M. Jamal, B. Sundarakani, S. Z. Omain, The effects of data security and perceived benefits on mobile phone recycling behaviour and the recycling intention mediation role, *Recycling*, **8** (2023), 27. <https://doi.org/10.3390/recycling8010027>
22. S. J. H. Dehshiri, M. Amiri, Considering the circular economy for designing closed-loop supply chain under hybrid uncertainty: A robust scenario-based possibilistic-stochastic programming, *Expert Syst. Appl.*, **238** (2024), 121745. <https://doi.org/10.1016/j.eswa.2023.121745>
23. Y. Du, Y. Zhou, D. Jia, X. Li, The end-of-life power battery recycling & remanufacturing center location-adjustment problem considering battery capacity and quantity uncertainty, *J. Environ. Manag.*, **357** (2024), 14. <https://doi.org/10.1016/j.jenvman.2024.120774>
24. H. Cheng, C. Yu, Y. Shi, C. Wang, C. Liu, Z. Jin, Collaborative medical triage under uncertainty: A multi-agent dynamic matching approach, 2021. <https://doi.org/10.48550/arXiv.2507.22504>
25. Q. Zhang, Z. Wang, M. Huang, H. Wang, X. Wang, S.-C. Fang, Collaborative supply chain network design under demand uncertainty: A robust optimization approach, *Int. J. Prod. Econ.*, **279** (2025), 109465. <https://doi.org/10.1016/j.ijpe.2024.109465>
26. H. S. Kilic, U. Cebeci, M. B. Ayhan, Reverse logistics system design for the waste of electrical and electronic equipment (WEEE) in Turkey, *Resour. Conserv. Recycl.*, **95** (2015), 120–132. <https://doi.org/10.1016/j.resconrec.2014.12.010>

27. M.-L. Bentaha, P. Marangé, A. Voisin, N. Moalla, End-of-Life product quality management for efficient design of disassembly lines under uncertainty, *Int. J. Prod. Res.*, **61** (2023), 1146–1167. <https://doi.org/10.1080/00207543.2022.2028199>
28. G. Yan, Y. Ni, X. Yang, Optimal pricing in recycling and remanufacturing in uncertain environments, *Sustainability*, **12** (2020), 3199. <https://doi.org/10.3390/su12083199>
29. J. Lin, X. Li, Y. Zhao, W. Chen, M. Wang, Design a reverse logistics network for end-of-life power batteries: A case study of Chengdu in China, *Sustain. Cities Soc.*, **98** (2023), 104807. <https://doi.org/10.1016/j.scs.2023.104807>
30. J. Morell, D. Ribas, I. Tristany, X. Guimerà, A. D. Dorado, Metal recovery in mobile phone waste: Characterization of metal composition and economic assessment through shredding and screening processes, *Waste Manage.*, **196** (2025), 93–105. <https://doi.org/10.1016/j.wasman.2025.02.014>
31. L. Chen, T. Dong, J. Peng, D. Ralescu, Uncertainty analysis and optimization modeling with application to supply chain management: A systematic review, *Mathematics*, **11** (2023), 2530. <https://doi.org/10.3390/math11112530>
32. S. Mohseni, M. S. Pishvaei, Data-driven robust optimization for wastewater sludge-to-biodiesel supply chain design, *Comput. Ind. Eng.*, **139** (2020), 105944. <https://doi.org/10.1016/j.cie.2019.07.001>
33. M. Kiani-Moghaddam, M. N. Soltani, P. D. Weinsier, A. Arabkoohsar, A bi-level, many-objective stochastic optimization model for handling simultaneous uncertainties in the operation of multi-carrier integrated energy systems: A hospital case study, *Sustain. Cities Soc.*, **127** (2025), 106430. <https://doi.org/10.1016/j.scs.2025.106430>
34. P. He, S. Geng, F. T. Chan, C. Pang, H. Tang, Joint decisions of pricing and inventory of a dual-channel supply chain with demand ambiguity considering free-riding behavior under sales effort: based on a fuzzy optimization method, *Expert Syst. Appl.*, (2026), 131182. <https://doi.org/10.1016/j.eswa.2026.131182>
35. N. Mirzaei, A. Mahmoodirad, S. Niroomand, R. Nowzari, A sustainable intuitionistic fuzzy Z-number multi-objective model for optimizing electric vehicle charging infrastructure in the European side of Istanbul, *Sustain. Cities Soc.*, 2026, 107391. <https://doi.org/10.1016/j.scs.2026.107391>
36. S. Rosenberg, S. Huster, A. Rudi, F. Schultmann, Assessing economic uncertainty in dynamic reverse logistics networks—A stochastic modeling approach for planning circular battery treatment, *Comput. Ind. Eng.*, **201** (2025), 110900. <https://doi.org/10.1016/j.cie.2025.110900>
37. P. Surya, K. Sameer, S. Gunjan, J. Vipul, R. A. P. Singh, Closed-loop supply chain network design and modelling under risks and demand uncertainty: an integrated robust optimization approach, *Ann. Oper. Res.*, 2018. <https://doi.org/10.1007/s10479-018-2902-3>
38. A. Hasani, S. H. Zegordi, E. Nikbakhsh, Robust closed-loop supply chain network design for perishable goods in agile manufacturing under uncertainty, *Int. J. Prod. Res.*, **50** (2012), 4649–4669. <https://doi.org/10.1080/00207543.2011.625051>
39. D. Bertsimas, M. Sim, Robust discrete optimization and network flows, *Math. Program.*, **98** (2003), 49–71. <https://doi.org/10.1007/s10107-003-0396-4>
40. K. Govindan, M. Fattahi, E. Keyvanshokoo, Supply chain network design under uncertainty: A comprehensive review and future research directions, *Eur. J. Oper. Res.*, **263** (2017), 108–141. <https://doi.org/10.1016/j.ejor.2017.04.009>

41. C. Johnstone, B. Cox, Conformal uncertainty sets for robust optimization, *Conformal and probabilistic prediction and applications*, 2021. <https://doi.org/10.48550/arXiv.2105.14957>
42. H. Asefi, S. Shahparvari, P. Chhetri, Integrated Municipal Solid Waste Management under uncertainty: A tri-echelon city logistics and transportation context, *Sustain. Cities Soc.*, **50** (2019), 101606. <https://doi.org/10.1016/j.scs.2019.101606>
43. Z. Song, H. Sun, X. Liu, M. Wang, Optimal design of reverse supply chain network for waste mobile phones under uncertainty, *Proc. 2020 IEEE Int. Conf. Artif. Intell. Comput. Appl. (ICAICA)*, 2020, 898–908. <https://doi.org/10.1109/ICAICA50127.2020.9181931>
44. T. K. Dasaklis, F. Casino, C. Patsakis, A traceability and auditing framework for electronic equipment reverse logistics based on blockchain: The case of mobile phones, *Proc. 2020 11th Int. Conf. Inf., Intell., Syst. Appl. (IISA)*, 2020, 1–7. <https://doi.org/10.1109/IISA50023.2020.9284394>
45. S. Kumar Singh, A. Chauhan, B. Sarkar, Supply chain management of e-waste for end-of-life electronic products with reverse logistics, *Mathematics*, **11** (2022), 124. <https://doi.org/10.3390/math11010124>
46. A. Singh, A. Goel, A. Chauhan, S. K. Singh, Sustainability of electronic product manufacturing through e-waste management and reverse logistics, *Sustain. Futures*, **9** (2025), 100490. <https://doi.org/10.1016/j.sfr.2025.100490>
47. A. M. Harijani, S. Mansour, Municipal solid waste recycling network with sustainability and supply uncertainty considerations, *Sustain. Cities Soc.*, **81** (2022), 103857. <https://doi.org/10.1016/j.scs.2022.103857>
48. D. Dong, Z. Bai, M. Yin, S. Li, L. Xiao, Optimizing e-waste recycling networks under uncertain environment: a fourth-party logistics perspective, *5th International Conference on Internet of Things and Smart City (2025)*, **13739** (2025), 144–151. <https://doi.org/10.1117/12.3072630>
49. B. Ayvaz, B. Bolat, N. Aydın, Stochastic reverse logistics network design for waste of electrical and electronic equipment, *Resour. Conserv. Recy.*, **104** (2015), 391–404. <https://doi.org/10.1016/j.resconrec.2015.07.006>
50. S. Shahparvari, H. Soleimani, K. Govindan, B. Bodaghi, M. T. Fard, H. Jafari, Closing the loop: Redesigning sustainable reverse logistics network in uncertain supply chains, *Comput. Ind. Eng.*, **157** (2021), 107093. <https://doi.org/10.1016/J.CIE.2020.107093>
51. A. R. Abbas, K. Tamara, Optimization of sustainable reverse logistics network with multi-objectives under uncertainty, *J. Remanuf.*, (2023), <https://doi.org/10.1007/s13243-022-00118-5>
52. S. Shahrabifarahani, S. A. Torabi, M. Rahiminia, Circular sustainable supply chain network design for electronic devices, *Environ. Dev. Sustain.*, (2025), 1–34. <https://doi.org/10.1007/s10668-025-06068-9>
53. F. Yang, Y. Wang, J. Pei, J. Li, Electronic markets selection in supply chain with uncertain demand and uncertain price, *Math. Probl. Eng.*, **2015** (2015), 939284. <https://doi.org/10.1155/2015/939284>
54. J. Xiao, K. Huang, S. Terzi, R. Bandinelli, Towards uncertainty of End-of-Use product recycling: a general screw connection-oriented disassembly analysis, *Int. J. Prod. Res.*, (2025), 1–24. <https://doi.org/10.1080/00207543.2025.2507111>
55. Y. Zhao, M. R. Ghiasvand, B. M. Tosarkani, Balanced uncertainty sets for Closed-Loop supply chain Design: A Data-Driven robust optimization framework with Fairness considerations, *Expert Syst. Appl.*, **276** (2025), 127170. <https://doi.org/10.1016/j.eswa.2025.127170>

56. H. Yu, X. Sun, Uncertain remanufacturing reverse logistics network design in industry 5.0: Opportunities and challenges of digitalization, *Eng. Appl. Artif. Intell.*, **133** (2024), 108578. <https://doi.org/10.1016/j.engappai.2024.108578>
57. Y. Liu, L. Ma, Y. Liu, A novel robust fuzzy mean-UPM model for green closed-loop supply chain network design under distribution ambiguity, *Appl. Math. Model.*, **92** (2021), 99–135. <https://doi.org/10.1016/j.apm.2020.10.042>
58. D. Bertsimas, D. B. Brown, C. Caramanis, Theory and applications of robust optimization, *SIAM Rev.*, **53** (2011), 464–501. <https://doi.org/10.1137/080734510>
59. B. Sarkar, S. K. Singh, A. Chauhan, An advanced robust possibilistic chance-constrained programming model for the animal fat-based biodiesel supply chain network, *J. Ind. Inf. Integr.*, **47** (2025), 100884. <https://doi.org/10.1016/j.jii.2025.100884>
60. A. Dehnokhalaji, S. Khezri, A. Emrouznejad, A box-uncertainty in DEA: A robust performance measurement framework, *Expert Syst. Appl.*, **187** (2022), 115855. <https://doi.org/10.1016/j.eswa.2021.115855>
61. D. Cuellar-Usaquén, M. W. Ulmer, O. Antons, J. C. Arlinghaus, Dynamic multi-period recycling collection routing with uncertain material quality, *OR Spectrum*, **47** (2025), 699–742. <https://doi.org/10.1007/s00291-025-00808-z>
62. A. Jalilvand-Nejad, R. Shafaei, H. Shahriari, Robust optimization under correlated polyhedral uncertainty set, *Comput. Ind. Eng.*, **92** (2016), 82–94. <https://doi.org/10.1016/j.cie.2015.12.006>
63. I. I. Almaraj, T. B. Trafalis, A robust optimization approach in a multi-objective closed-loop supply chain model under imperfect quality production, *Ann. Oper. Res.*, **319** (2022), 1479–1505. <https://doi.org/10.1007/s10479-021-04286-8>
64. S. Leyffer, M. Menickelly, T. Munson, C. Vanaret, S. M. Wild, A survey of nonlinear robust optimization, *INFOR Inf. Syst. Oper. Res.*, **58** (2020), 342–373. <https://doi.org/10.1080/03155986.2020.1730676>
65. Y. Yao, H. Xu, H.-Y. Song, Exploring the key factors affecting customer satisfaction in China's sustainable second-hand clothing market: A mixed methods approach, *Sustainability*, **17** (2025), 1694. <https://doi.org/10.3390/su17041694>
66. H. Shambayati, M. S. Nikabadi, M. Rahmanimanesh, Customer satisfaction optimisation in a dynamic closed-loop supply chain under uncertainty, *Int. J. Ind. Syst. Eng.*, **49** (2025), 18–56. <https://doi.org/10.1504/IJISE.2023.10059290>
67. C. L. Miltgen, J. Henseler, C. Gelhard, A. Popovič, Introducing new products that affect consumer privacy: A mediation model, *J. Bus. Res.*, **69** (2016), 4659–4666. <https://doi.org/10.1016/j.jbusres.2016.04.015>
68. M. Mottaghi, S. Mansour, A multi-objective robust optimization model to sustainable closed-loop lithium-ion battery supply chain network design under uncertainties, *Comput. Chem. Eng.*, **195** (2025), 109008. <https://doi.org/10.1016/j.compchemeng.2025.109008>
69. O. Polat, O. Capraz, A. Gungor, Modelling of WEEE recycling operation planning under uncertainty, *J. Clean. Prod.*, **180** (2018), 769–779. <https://doi.org/10.1016/j.jclepro.2018.01.187>
70. L. Yao, T. Liu, X. Chen, M. Mahdi, J. Ni, An integrated method of life-cycle assessment and system dynamics for waste mobile phone management and recycling in China, *J. Clean. Prod.*, **187** (2018), 852–862. <https://doi.org/10.1016/j.jclepro.2018.03.195>

71. L. Kauhanen, Towards a carbon-neutral waste management: an assessment of the potential CO₂ emissions reductions from waste transport optimization, 2024. <https://urn.fi/URN:NBN:fi:amk-2024121937507>
72. W. Pan, K. Li, Y. Teng, Rethinking system boundaries of the life cycle carbon emissions of buildings, *Renw. Sust. Energ. Rev.*, **90** (2018), 379–390. <https://doi.org/10.1016/j.rser.2018.03.057>
73. E. Sahle-Demessie, B. Mezgebe, J. Dietrich, Y. Shan, S. Harmon, C. C. Lee, Material recovery from electronic waste using pyrolysis: Emissions measurements and risk assessment, *J. Environ. Chem. Eng.*, **9** (2021), 104943. <https://doi.org/10.1016/j.jece.2020.104943>
74. Y. Gao, Y. Feng, Q. Wang, H. Zheng, J. Tan, A multi-objective decision making approach for dealing with uncertainty in EOL product recovery, *J. Clean. Prod.*, 2018. <https://doi.org/10.1016/j.jclepro.2018.09.080>
75. H. Lu, B. Sturt, On the sparsity of optimal linear decision rules for a class of robust optimization problems with box uncertainty sets, *Oper. Res.*, 2025. <https://doi.org/10.1287/opre.2023.0603>
76. C. P. Baldé, R. Kuehr, T. Yamamoto, R. McDonald, E. D'Angelo, S. Althaf, et al., *Global e-waste monitor 2024*, 2024. Available from: <https://ewastemonitor.info>.
77. S.-Y. Youn, J. Hwang, N. Ju, Blockchain transparency in reducing second-hand luxury shopping uncertainty and the role of price consciousness, *Fash. Text.*, **12** (2025), 10. <https://doi.org/10.1186/s40691-025-00420-3>
78. M. Hayati, S. M. S. A. Ganji, S. H. Shahcheraghi, R. R. Khabir, Optimization of copper recovery from electronic waste using response surface methodology and Monte Carlo simulation under uncertainty, *J. Mater. Cycles Waste Manag.*, **25** (2023), 211–220. <https://doi.org/10.1007/s10163-022-01526-2>
79. China National Resources Recycling Association, Development report of China waste electrical and electronic products recycling and treatment industry 2023: *China National Resources Recycling Association*, 2023. Available from: <https://gfcl.hbzhan.com/news/169775.html>.
80. X. Guo, K. Yan, J. Zhang, G. Huang, Q. Tian, Exploitation potentiality analysis of metal resources in typical electronic waste, *Chin. J. Nonferrous Met*, **28** (2018), 365–376. <https://doi.org/10.19476/j.ysxb.1004.0609.2018.02.19>



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