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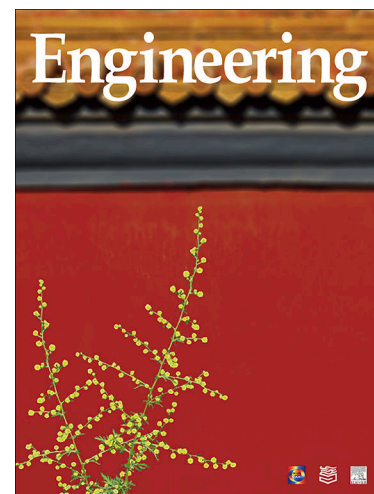
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AI-Enhanced Assessment Framework for City-Scale Management of Municipal Living Plastic Waste Towards Zero-Waste Cities

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Abstract

Managing municipal living plastic waste (MLPW) entails complex system-level challenges across collection, recycling, and treatment, necessitating simultaneous optimization of resource, environmental, and economic objectives. However, robust assessment is frequently impeded by data scarcity and measurement inaccuracies, which undermine the transferability of evaluation models. To address these limitations, an artificial intelligence (AI)-enhanced evaluation framework is proposed. Baseline material flows were derived directly from field measurements, while machine learning algorithms were employed for independent validation and data imputation, thereby enhancing the credibility of environmental and economic assessments. The framework was applied in a megacity as the case study. Results indicated that MLPW management should focus on upgrading recycling and advancing the substitution of biodegradable plastics while rigorously enforcing source reduction. The recycling/treatment yields a 96.3% reduction in annual emissions by 2060 relative to the baseline. Cumulatively, this optimal trajectory achieves a reduction of 22.22 Mt CO₂-eq between 2020 and 2060, generating economic benefits of approximately 197.7 billion CNY. Given the current technological conditions, mechanical recycling is identified as the priority pathway, offering superior mitigation potential (emission intensity of about 108 kg CO₂-eq·t⁻¹) and cost-effectiveness (economic return of around 613.9 CNY·t⁻¹). By leveraging AI to ensure evaluation completeness and credibility even under data-constrained conditions, this framework offers a transferable tool for providing quantitative evidence to support policy prioritization in zero-waste city initiatives globally.

Keywords: Waste Plastic Disposal, Artificial Intelligence, Life Cycle Assessment, Carbon Emission Reduction, Cost–benefit Analysis

1. Introduction

Plastics are integral to the modern economy, yet the prevailing linear take–make–dispose model sustains resource use, greenhouse-gas (GHG) emissions, and environmental burdens [1,2]. In 2019, global plastic waste generation totaled 353 million tonnes (Mt). Only 9% was recycled, 19% was incinerated, nearly half was landfilled, and a substantial share remained outside formal management, leaking into the environment [3]. Plastic consumption intensity, waste generation, and treatment profiles differ markedly among economies. These differences, coupled with uneven institutions and infrastructure, amplify transnational and interregional pollution disparities [4,5].

Disparities at the city scale are pronounced. The near-linear scaling of waste generation with city size suggests that plastic pressures are jointly driven by population, economic activity, governance capacity, and resource endowments [6–8]. Governance practices vary widely, from incineration-dominated systems with low recycling rates to schemes featuring government–community co-led sorting and pay-as-you-throw programs. In many cities, informal sectors play a role in the recovery chain. These institutional and infrastructural configurations shape spatial heterogeneity in management performance [9–12]. Accordingly, transitioning to a circular plastics economy requires the identification of city-scale constraints and advantages, as well as the implementation of intervention portfolios tailored to local conditions.

City-scale plastic management research has advanced along two strands. The one quantifies environmental performance and mitigation potential using material flow analysis (MFA) and life-cycle assessment [13–15]. Topics include dynamic MFA of polyvinyl chloride (PVC) [16], circularity feasibility in developing countries [17], plastic packaging flows [18] and life-cycle comparisons for plastics in waste electrical and electronic equipment (WEEE) [19]. The other examines fiscal feasibility and optimization-based decision-making [20–23]. Studies compared incineration and recycling using cost–benefit and mathematical programming models and solve for optimal sorting and recycling strategies [24,25]. Multi-city scenario assessments set recycling-rate targets, yielding a reusable comparative framework [26].

Previous studies have assessed environmental and economic outcomes within unified frameworks, often projecting national or global scenarios. For example, Pottinger et al. [27] developed multi-scenario models extending to 2050, integrating plastic demand, product lifetimes, collection coverage, recycling quality, and policy portfolios. Basuhi et al. [28] combined life-cycle assessment with process-based cost analysis for US post-consumer plastics, comparing mechanical, energy, and fuel recovery, as well as estimating capital requirements. However, many analyses were based on data with limited accuracy and accessibility, failing to account for city-level differences in institutions, infrastructure, and market conditions. As a result, the

Artificial intelligence (AI) has the potential to mitigate these constraints. AI models leveraged multi-source socioeconomic and spatial covariates to generate short-term forecasts of waste generation and composition, improving small-area estimations [32]. AI-enabled computer vision and near-infrared hyperspectral imaging assisted in waste identification and process monitoring. These tools enhance data accuracy and resolution [33]. Integrating AI with process systems engineering facilitated assessment and optimization frameworks that explicitly couple life-cycle assessment and cost–benefit analysis, enabling robust screening of management pathways [34].

Inspired by this, we initially employed AI to address data gaps and validate foundational city-level plastic data. This study proposes an AI-driven framework that establishes a robust, quality-controlled data foundation and subsequently conducts an integrated environmental and economic assessment within a unified system boundary. We conducted systematic field measurements to reconstruct household-source plastic material flows, and then applied machine learning for independent validation and propagated uncertainty to the baseline. Within a unified system boundary, we aligned life-cycle carbon emissions with process-based cost–benefit models. We derived indicators such as annual and cumulative abatement, abatement cost per unit, and net benefits to evaluate management pathways robust in both environmental and fiscal outcomes. The AI-integrated approach enhances data robustness with minimized data requirements. It has the potential to transfer across cities and extend to other waste subsystems, including paper, metals, glass, and food waste. The framework provides quantitative evidence for pathway prioritization, facility location, and budget planning.

2. Materials and methods

2.1 Framework of the theory

Fig. 1 shows the study framework. A city served as the unit of analysis, and the workflow followed a data–scenario–assessment–decision chain. Within this framework, three interconnected analyses supported the overarching objective:

(1) Material flow analysis quantified scale, composition, and destinations of plastic waste. It parameterized interventions through category shares, recycling rates, and substitution rates, ultimately producing scenario trajectories. To address data gaps at the city scale, we conducted systematic field surveys to quantify municipal living plastic waste (MLPW) generation, composition, and end-of-life destinations. Machine learning (ML)-based checks and missing-data imputation-controlled sampling error, thereby improving consistency. We combined annual re-audits with multi-source covariates to establish traceable error bounds, explicitly propagating uncertainty into subsequent environmental and economic accounts. Validated data were used to develop low-carbon scenarios encompassing source reduction, bio-based substitution, and enhanced sorting and recycling capacity. City-level plastic flows and end-of-life structures were updated over time.

(2) In the environmental impact analysis, carbon-emission models converted flows into a greenhouse-gas inventory and intensity metrics. This process identified emission hotspots and attainable mitigation potential. ML-derived error bounds were propagated into interval estimates. Life-cycle accounting encompassed the collection, transport, and treatment stages. Avoided emissions from recycled-material substitution for virgin production and from energy recovery were accounted for. At the economical side, cost–benefit analysis, conducted under a consistent system boundary and data framework, quantified capital and operations and maintenance (O&M) expenditures, revenues from energy and secondary materials, and the unit abatement cost. Sensitivity analyses were performed on key price and efficiency parameters.

(3) To obtain optimal pathways, the two assessment streams were compared on a unified platform to derive indicators such as annual and cumulative abatement, abatement cost per unit, net benefits, and break-even points. ML-derived error bounds were expressed as intervals or probabilities to identify pathways robust in both environmental and fiscal dimensions, supporting the identification of feasible pathways under budgetary or compliance constraints. The methods are illustrated through the following case study in Section 2.2.

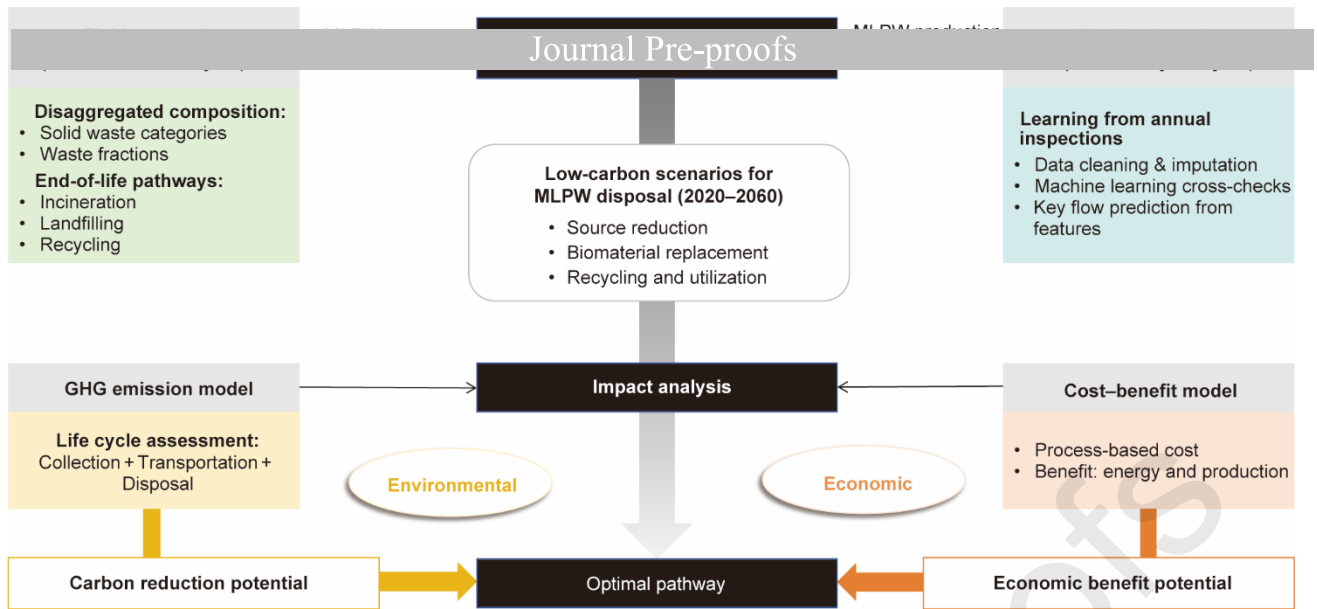


Fig. 1. Flowchart of the assessment framework. MSW: municipal solid waste; MLPW: municipal living plastic waste; GHG: greenhouse gas.

2.2 Case study

Nanjing was selected as the sample city for the urban analysis. It has a resident population of approximately 9.31 million, classified as a megacity under the State Council's 2014 urban size criteria [35]. It was broadly representative in terms of economic scale, population density, and infrastructure, making it an appropriate case for analyzing plastic management issues in municipal solid waste and conducting scenario assessments for Chinese megacities. We selected 2020 as the reference year. In that year, extended home stays and increased online consumption led to a significant rise in the use of single-use packaging, plastic containers, and delivery materials [36,37]. Packaging accounted for 40% of total plastic use [3]. This highlights the growing pressure on urban plastic waste management, especially in megacities like Nanjing.

2.2.1 MLPW material flow analysis

2.2.1.1 Field study To obtain quantifiable and traceable data on plastics in municipal solid waste for 2020, we conducted comprehensive field surveys and weighing campaigns. We then mapped the surveyed entities and their spatial distribution, as shown in Fig. S1 in Appendix A. Yellow stars represent curbside recycling points, red building icons denote city transfer stations, blue-green circles indicate digital transfer hubs outside the city, and brown icons represent waste-to-energy incineration plants. Red arcs trace the primary transport routes of household plastics from communities to transfer facilities and final treatment plants.

Sampling locations and site deployments were selected following the Nanjing Municipal Environmental Sanitation Facilities Master Plan (2017–2035), covering community collection stations, transfer stations, sorting facilities, and end-of-life treatment plants. At each facility, we conducted direct weighing and recorded the origin of incoming loads, vehicle trips, and weighbridge tickets. We also obtained detailed composition samples through on-site sampling. Under this protocol, we measured the plastic mass fraction in municipal solid waste at both the community and transfer stages and compiled the polymer subclass composition within MLPW. The resulting data on totals, composition, and end-of-life destinations served as foundational inputs for the subsequent material flow analysis.

After the implementation of the Nanjing Municipal Solid Waste Management Regulation in 2020, the city's plastics recovery system underwent structural changes. Few integrated green sorting centers were operational, and a significant share of recovery was conducted by unregistered sole operators in outlying districts. To ensure verifiability and reproducibility, Fig. S1 displayed only government-partnered digital transfer hubs and their corresponding service points. These service points corresponded to pilot residential communities within an approximate 10 km service radius. They encompassed diverse residential types and service catchments, enabling cross-district comparisons and extrapolations.

To ensure data quality and reliable extrapolation, several controls were implemented. We calibrated and inspected weighing equipment, repeating measurements on the same routes and facilities at different times to mitigate variability between shifts and across days. Global Positioning System (GPS) coordinates, vehicle logs, and weighbridge tickets were cross-matched to create a closed-loop record from community collection to end-of-life facilities. For recovery points that were difficult to access, indirect verification reconciled transfer manifests and settlement documents with upstream digital hubs, and uncertainty was quantified as error bounds in the material flow balance. Due to the dispersion of sampling sites, the system was fragmented, and compliant operators were limited, making the acquisition of verifiable data challenging. The field team worked across districts and coordinated with multiple agencies to ensure comprehensive coverage of different subareas and service models.

The field campaign yielded three key categories of outputs. First, the baseline-year plastics proportion and total quantity, which supported scenario design and the evaluation of recovery pathways. Third, the spatial structure of end-of-life destinations and primary transport routes, which underpinned subsequent accounting of transport emissions and database development. These outputs corresponded to the network shown in the figure and provided a unified data foundation for subsequent material-flow, carbon-emissions, and cost–benefit analyses.

2.2.1.2 Differential scanning calorimetry (DSC) DSC is a widely used thermal analysis technique in materials science, commonly employed to study polymer behavior. Under a controlled heating program, DSC records enthalpy-related heat flow and identifies key parameters, such as the glass-transition temperature (T_g), onset of melting, melting peak temperature (T_m), and melting enthalpy (ΔH). Melting enthalpy is used to calculate crystallinity, and the distinct features of the thermogram act as a polymer “fingerprint.” Therefore, in plastic pollution studies, DSC is an effective method for characterizing the composition of plastic fragments [38].

To establish a unified classification protocol and an operational on-site identification framework, this study conducted DSC (TA DSC25) tests on multiple MLPW categories. Based on predefined composition profiles, a field classification scheme was developed to clarify the correspondence between polymers and end uses and specify classification boundaries (Fig. S2 in Appendix A). The experiments were conducted under a nitrogen atmosphere with a heating rate of $10\text{ }^{\circ}\text{C}\cdot\text{min}^{-1}$, ranging from 30 to $300\text{ }^{\circ}\text{C}$. The test set included common MLPW types, such as plastic films, woven products, rigid plastic containers, rigid foams, and plastic building materials.

2.2.1.3 Machine learning Previous studies have demonstrated that machine learning is effective for data validation and uncertainty analysis [32]. In this study, machine learning was employed to independently validate survey-based estimates and derive error bounds for subsequent analyses. The data collection stage included plastics-related statistical indicators and socio-demographic attributes to enhance the model’s accuracy in characterizing plastic generation, as detailed in Table S1 in Appendix A. Given the established correlations between plastic waste generation and social factors, these variables were included in the feature set [4,39,40]. We prioritized these structural determinants to balance model accuracy with cross-city transferability, with a detailed theoretical justification provided in Section S2 in Appendix A.

After data cleaning, we developed a regression model based on an artificial neural network (ANN). ANN was chosen for its proven efficacy in modeling complex non-linear relationships, significantly outperforming traditional linear methods in waste management context [41,42]. Preliminary tests confirmed its adaptability to our dataset, validating its suitability for the specific reconstruction tasks in this study. We conducted a systematic evaluation of diverse model architectures, comparing combinations of hidden-layer sizes with Tanh, Sigmoid, and Rectified Linear Unit (ReLU) activation functions. For validation, the dataset was divided into 80% training and 20% testing subsets, with robustness further verified through repeated random resampling. All analyses were executed using Python 3.10. To quantitatively evaluate the model performance, we employed three statistical metrics: Nash–Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), and the ratio of root mean square error to the standard deviation (RSR). NSE assesses the predictive power relative to the observed variance; PBIAS measures the average tendency of the simulated data to be larger or smaller than observations; and RSR standardizes the root mean square error. The detailed calculation formulas for these metrics are provided in the Section S2.

As shown in Fig. S3 in Appendix A, a single hidden layer with ReLU activation yielded the best fit. Model outputs were compared to field-survey values to identify systematic bias and outliers. Prediction intervals and uncertainty ranges were subsequently derived. SHapley Additive exPlanations (SHAP)-value analysis was also applied to quantify each feature’s contribution to local predictions (Fig. S4 in Appendix A). This workflow was designed to independently validate survey data and explicitly propagate uncertainty into subsequent material flow, carbon emissions, and cost–benefit assessments.

2.2.1.4 MLPW material flow analysis The calculation was carried out in two steps. Step 1 uses the baseline-year municipal solid waste total and the plastics proportion to compute the total MLPW. Step 2 allocates this total to each subcategory based on the composition proportions within MLPW, yielding the quantity for each subcategory. Detailed breakdown of the material flow variables is given in Section S3 in Appendix A.

2.2.2 Scenario setting

The 14th Five-Year Plan for Plastic Pollution Control and the Carbon Peaking Action Plan (collectively referred to as the Action Plans) outlined strategies for plastic pollution control and established targets for municipal solid-waste recycling rates. Within this policy framework, we utilized Nanjing’s forty-year waste growth projections to develop a growth-trajectory model for plastic waste. The scenario design focused on three key interventions—source reduction, bio-based substitution, and recycling and recovery—designed to provide an evidence base for effective plastic waste management.

In the scenarios, source reduction and reuse were considered first-order principles and common preconditions for all pathways. The incremental effects of improving recycling efficiency and substituting materials were assessed. To effectively reduce plastic pollution and related emissions, unnecessary plastic consumption must first be reduced, followed by expanded reuse and improvements in collection and recycling [43]. The pathways involved improving recovery rates for mechanical and chemical recycling, along with suppressing plastic waste generation at the source to reduce greenhouse gas emissions. Specifically, mechanical recycling is defined as the physical reprocessing of plastic waste into secondary granular materials

without altering the polymer's primary chemical structure. In contrast, chemical recycling utilizes thermochemical processes to decompose polymers into their constituent monomers or smaller molecules. Under the baseline scenario assumptions, recovery rates for mechanical recycling reached 55% by 2030 and 70% by 2060, while for chemical recycling, they were 25% and 55%, respectively. Based on this, three composite scenarios were constructed, with S representing source reduction, R representing material substitution, and U representing recycling and recovery. To assess the pivotal role of source reduction in composite scenarios, an S3 scenario was introduced to examine the incremental effect of S, with R and U at their respective optima. Scenario settings and parameters are provided in Table 1, with detailed definitions in Table S4.

Table 1
Low-carbon emission scenarios for MLPW disposal (base year: 2020)

Optimization measure	Details	Scenario	Target
S: Source reduction	According to "Nanjing Master Plan for Environmental Sanitation Facilities (2017–2035)," the growth rate of plastic waste treatment volume is set at 1.5% by 2035	S0: Baseline scenario	Annual growth rate of MLPW (2035–2060): 1.5%
		S1: Mild reduction	Annual growth rate of MLPW (2035–2060): 1%
		S2: Severe reduction	Annual growth rate of MLPW (2035–2060): 0
		S3: Substantial increase	Annual growth rate of MLPW (2035–2060): 3%
R: Biomaterial replacement	Replacing traditional petroleum based plastics with biodegradable plastics (increasing year by year to the target value of 2060)	R0	Substitution rate in 2060: 0
		R25	Substitution rate in 2060: 25%
		R50	Substitution rate in 2060: 50%
U: Recycle and utilization	According to "Action Plan," total recycling rate is expected to reach 65% and 100% by 2030 and 2060; then set two scenarios considering different development levels of chemical recycling technology	Ubase: Business as usual	By 2030: Incineration: 62.5%; Mechanical recycling: 37.5%; Chemical recycling: 0 By 2060: Incineration: 62.5%; Mechanical: 37.5%; Chemical: 0%
		Um: Mechanical recycling dominates	By 2030: Incineration: 35%; Mechanical recycling: 55%; Chemical recycling: 10% By 2060: Incineration: 0; Mechanical recycling: 70%; Chemical recycling: 30%
		Uc: Develop chemical recycling	By 2030: Incineration: 35%; Mechanical recycling: 40%; Chemical recycling: 25% By 2060: Incineration: 0; Mechanical recycling: 45%; Chemical recycling: 55%

2.2.3 Impact analysis

2.2.3.1 Carbon emission assessment. We applied life-cycle assessment to integrate analysis across all stages of MLPW treatment, systematically evaluating environmental impacts and material and energy flows throughout the entire life cycle [19,44,45]. Using this method, we quantified and visualized environmental impacts under alternative treatment scenarios

$$GHG_{\text{emission}} = GHG_{\text{collection}} + GHG_{\text{transportation}} + GHG_{\text{disposal}} \quad (1)$$

where GHG_{emission} (t CO₂-eq) denotes the total CO₂ emissions of municipal living plastic waste, and $GHG_{\text{collection}}$, $GHG_{\text{transportation}}$, and GHG_{disposal} (t CO₂-eq) denote the total emissions from the collection, transportation, and treatment stages, respectively.

2.2.3.2 Cost-benefit analysis Building on Basuhi et al. [28], we modeled the economic costs of MLPW treatment to assess cost-benefit trade-offs across alternative technologies. We employed a process-based cost modeling tool (PBCM) for forecasting [46–48]. The PBCM required two categories of inputs: Operational inputs included throughput, wages, utilities, working hours, and equipment maintenance. Process-specific inputs included process throughput, equipment costs, required energy and materials, and labor costs and overhead. Scenario net benefit was defined as the total revenues from collection and each treatment stage, minus total costs. Total costs were decomposed into cost elements, with calculation relationships provided in Eq. (2) and parameter definitions in Section S3.

$$C_p = C_p^{\text{energy}} + C_p^{\text{raw-materials}} + C_p^{\text{labor}} + C_p^{\text{feedstock}} + \text{annualized}(C_p^{\text{equipment}} + C_p^{\text{building}}) + C_p^{\text{maintenance}} + C_p^{\text{overhead}} \quad (2)$$

where C_p denotes the total cost (CNY). Energy, materials, labor, raw materials, and landfill (feedstock) fees were categorized as variable costs. Equipment, infrastructure (building), maintenance, and administrative (overhead) expenses were treated as annualized fixed costs. A 12% annual interest rate was applied to the annualized valuation of equipment procurement and construction expenditures, amortized construction costs over 20 years, and computed revenues from power generation and secondary materials. The composition of total revenue is outlined in Eq. (3).

$$B_p = B_p^{\text{Incineration}} + B_p^{\text{Mechanical recycling}} + B_p^{\text{Chem recycling}} \quad (3)$$

B_p (CNY) denotes total revenue, $B_p^{\text{Incineration}}$, $B_p^{\text{Mechanical recycling}}$, and $B_p^{\text{Chem recycling}}$ (CNY) denote the revenues from incineration, mechanical recycling, and chemical recycling, respectively. Electricity revenue was calculated using the utility's real-time tariff. Revenue from recycled plastics was estimated from surveys of plastic recycling enterprises. Revenues from monomers and by-products in chemical recycling were obtained from prior studies. Detailed breakdown of cost and benefits variables is given in Section S3.

2.2.4 Optimal pathway

We defined an optimal pathway as a portfolio of scenarios that met both environmental targets and baseline economic feasibility within a unified system boundary. On the environmental side, we used two indicators: total GHG abatement and target-year GHG abatement. On the economic side, we used two indicators: life-cycle net benefits and abatement cost per unit. We adopted a two-step approach, consisting of hierarchical screening followed by ranking.

When selecting scenarios, we prioritized those with better environmental performance to avoid the appearance of “more production, more profit.” Step one established environmental thresholds with uncertainty propagation. Scenarios were required to meet both cumulative and annual abatement targets within their uncertainty intervals to be included in the candidate set. Step two ranked candidates based on economic performance and robustness. We first required life-cycle net benefits to be as high as possible, followed by prioritizing lower unit abatement costs. Robustness was assessed through compliance pass rates under parameter perturbations and maximum regret.

Given the heterogeneous allocation of costs and benefits across stakeholders, the preferred solution was a system-wide, long-term sustainable compromise, rather than maximizing profit for a single actor. Total cost was used as a tiebreaker and terminal constraint to avoid anomalous investment levels and to express a preference when abatement and net benefits were comparable.

3. Results

3.1 Characteristics of MLPW in Nanjing

Using 2020 as the baseline year, field surveys and direct weighing estimated total MLPW at approximately 386.6 kt. Fig. 2 presents a Sankey diagram that illustrates material composition and end-to-end destinations. Plastic films totaled about 130.22 kt and, together with textiles, rigid containers, and rigid foams, were classified as packaging. Packaging-related plastics accounted for approximately 89.4% of MLPW; because plastic packaging typically has a service life of less than one year and is predominantly single-use, this high share is expected [49]. By polymer type, the stream was dominated by polyethylene (PE), polypropylene (PP), polystyrene (PS), and polyethylene terephthalate (PET), with PE at ~48.1%, PP at ~10.7%, PET at ~10.7%, PS at ~8.0%, and PLA at ~3.2% [50,51]. In terms of treatment outcomes, packaging plastics totaled ~313.2 kt, of which only 27.8% was effectively recycled, while most of the remainder was sent to incineration [52]. Among non-packaging plastics, construction-related items included PE, polyvinyl chloride (PVC), acrylonitrile butadiene styrene plastic (ABS), and

to material recycling. Incineration recovers electricity but entails significant fossil carbon emissions and energy losses, thereby exerting additional climate pressure. By contrast, improving sorting and recycling yields superior environmental performance. Chemical and mechanical recycling are broadly comparable in climate impacts and energy use, but chemical recycling is constrained by greater engineering complexity and higher costs [52].

The ML model demonstrated strong performance, with NSE = 0.99, PBIAS = -2.21, and RSR = 0.09. The training and test fit curves were closely aligned, indicating stable model fitting and good out-of-sample generalization (Fig. S3). The model estimated the total 2020 MLPW at approximately 451.6 kt, about 65.0 kt above the measured value, corresponding to a bias of roughly 16.8%. The primary source of this bias was the use of national-scale data for training, which tends to scale totals upward along macro drivers for megacities. Nevertheless, structural indicators, such as polymer composition and packaging share, were consistent with measurements, and the directions of flows and relative importance were aligned. SHAP attribution (Fig. S4) indicated that plastic-use intensity was the dominant driver, with the share of Nanjing's population aged 15–64 also contributing to the overestimation.

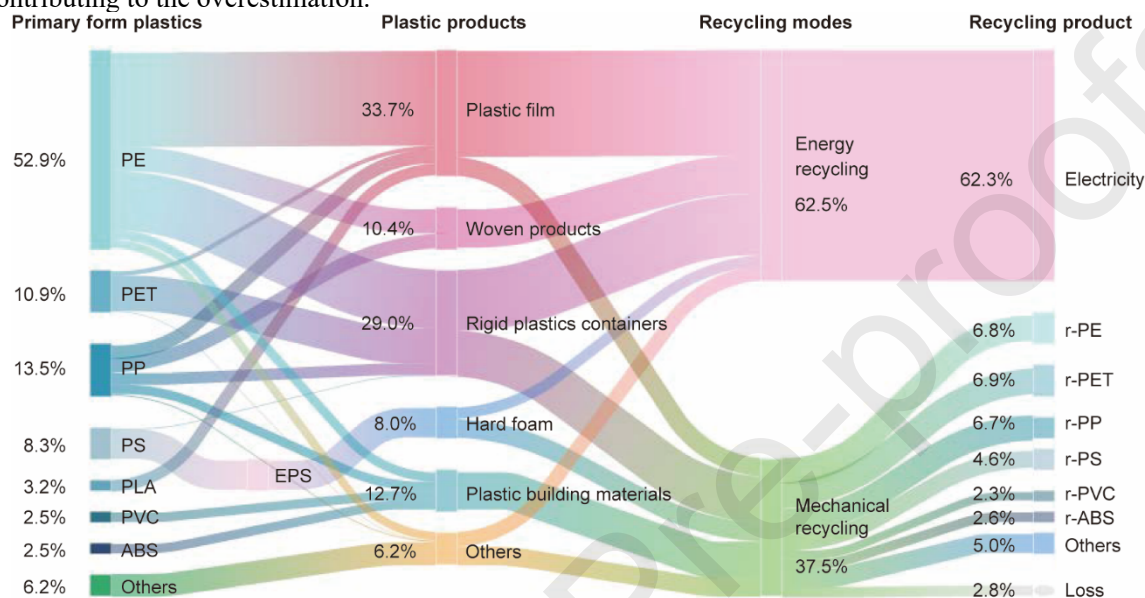


Fig. 2. Material flow of MLPW generation and recycling in Nanjing. Colors represent polymer types on the left, while right-side flows indicate treatment pathways (Pink: Incineration; Green: Mechanical recycling). The prefix r represents recycled.

3.2 Carbon reduction potentials in MLPW disposal

As shown in Fig. 3, GHG emissions from the treatment of municipal living plastic waste in 2020 totaled approximately 5.86 million tonnes of carbon dioxide equivalent (CO₂-eq). The baseline scenario S0 assumed an annual MLPW growth rate of 1.5% through 2035, resulting in an emissions trajectory without additional interventions, which served as the reference for low-carbon scenarios.

In earlier stages, when mechanical and chemical recycling technologies and related infrastructure were not fully mature, adopting source reduction and bio-based substitution resulted in short-term emissions abatement. Compared with S0, S1 and S2 reduced emissions by 1.23 and 3.30 Mt in 2060, corresponding to reductions of 11.6% and 31.1%, respectively. Over the cumulative period from 2020 to 2060, the two scenarios achieved abatement of 1.45 and 4.04 Mt, respectively. Compared with S1, S2 achieved an additional 2.58 Mt CO₂-eq in reductions over the forty-year period, indicating that stronger source-reduction assumptions markedly expanded mitigation potential.

Building on source reduction, advancing material substitution also provided net benefits. With bio-based material substitution, an additional 0.15–0.39 Mt CO₂-eq reduction was achieved by 2060, beyond the corresponding source-reduction scenarios, equivalent to a further 14.2%–36.4% decrease. Compared with source reduction alone, the inclusion of bio-based substitution significantly lowered carbon emissions. Replacing conventional plastics with biodegradable materials and pairing them with appropriate end-of-use treatments substantially reduced GHG emissions. This result was consistent with the literature on the GHG advantages of biodegradable materials under suitable treatment pathways [54]. Based on the multi-scenario simulation results presented in Fig. 3, we quantified the independent abatement contribution of each core intervention relative to the baseline scenario (S0). Standalone implementation of source reduction achieved an emission reduction of 4.4%–12.3%, bio-based substitution yielded a marginal abatement contribution of 10.6%–21.2%, while recycling and recovery exerted the dominant mitigation effect, with an abatement range of 47.9%–54.9%.

Deep decarbonization relied on sustained improvements in recovery and utilization capacity. When mechanical and chemical recycling were incorporated into the pathway, emissions decreased significantly. In the composite scenarios S2R50Um and S2R50Uc, emissions in 2060 decreased by 10.24 and 10.18 Mt CO₂-eq, corresponding to reductions of 96.3% and 95.8%, respectively. Compared to the current situation, the two scenarios delivered cumulative reductions of 22.22 and 22.03 Mt over forty years, respectively. Compared to implementing only source reduction and material substitution, adding

recycling and recovery resulted in an additional 16.90 Mt CO₂-eq of abatement. The two recycling pathways exhibited similar performance. It should be noted that chemical recycling still faces substantial challenges in process complexity and engineering implementation. Therefore, in the near term, it is advisable to prioritize improvements in mechanical recycling efficiency, continue research and demonstrations for chemical recycling, and ensure steady progress in source reduction and material substitution.

To examine how changes in total waste generation affect the optimal composite pathway, we defined scenario S3R50Um. This scenario retained R50 + Um as the optimal combination but allowed S to increase substantially, assuming a 3% annual growth in total waste generation from 2035 onward. The results showed cumulative abatement of 20.92 Mt CO₂-eq over 2020–2060, lower than the 22.22 Mt CO₂-eq achieved in S2R50Um, while the annual reduction by 2060 still reached 91.3%. This indicated that, when recycling and substitution were already at their optima, expanding the total waste quantity increased the recoverable material stream and boosted annual revenues but diluted cumulative climate performance. In comparison, cumulative abatement in S3R50Um fell between S1R50Um and S2R50Um, implying that, when recycling and utilization were already optimal, stronger source reduction helped control total waste quantities but also reduced the recoverable material flow, thereby diminishing the mitigation benefits from circular substitution.

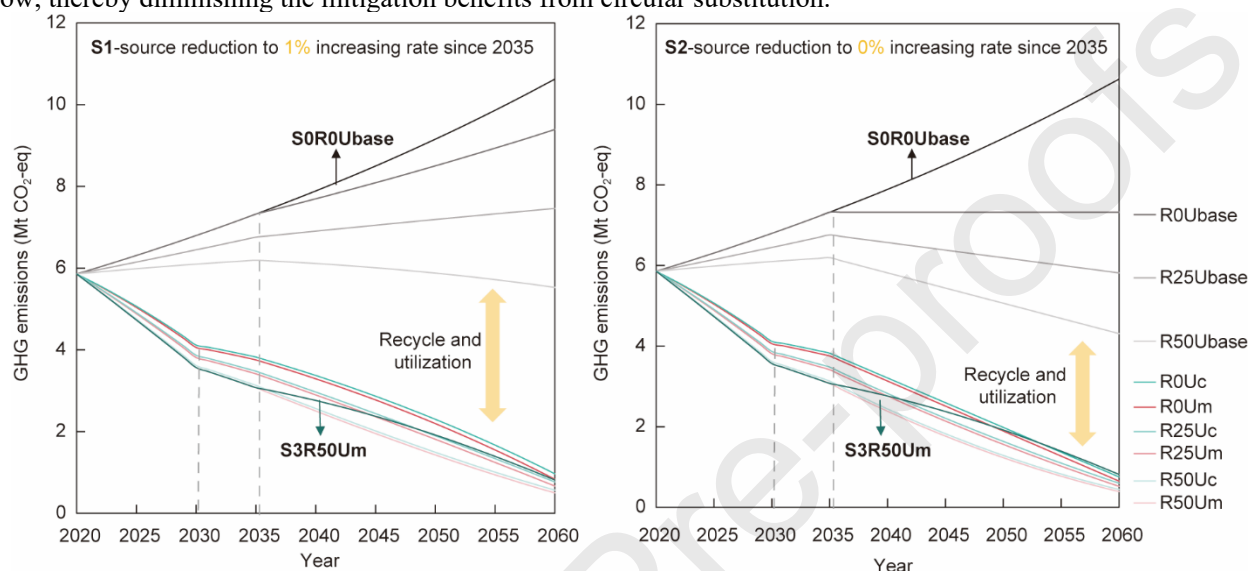


Fig. 3. Predicted carbon emissions from MLPW disposal under different scenarios from 2020 to 2060. The S0 scenario represents continuing a growth rate of 1.5% in MLPW as 2035 (black lines). S1 (left) and S2 (right) scenarios represents a growth rate of 1% and 0% in MLPW since 2035, combined with measures in biomaterial replacement (R) and recycling and utilization (U).

Overall, source reduction and material substitution provided robust near- to mid-term emissions reductions, while capacity building in recycling and recovery determined the feasibility of achieving net-zero targets. Phased combinations of these measures achieved a better balance between environmental performance and engineering feasibility.

3.3 Economic benefits of optimal MLPW disposal pathways

Economic outcomes associated with MLPW are presented in Fig. 4. In scenario S1, the most profitable pathway was S1R50Um, which became profitable in waste-plastics management from 2024 onward. Cumulative profit was projected to reach 243 million CNY by 2060, with total profit over forty years amounting to 4.99 billion CNY. Under S1R50Um, costs were mainly driven by expenditures for incineration, mechanical recycling, and chemical recycling. Specifically, over forty years, incineration costs amounted to 2.72 billion CNY, mechanical recycling costs amounted to 9.79 billion CNY, and combined chemical-recycling costs for petro-based and bio-based plastics totaled 4.13 billion CNY. Revenues were dominated by mechanical recycling, with expected revenue of 15.17 billion CNY over forty years and total revenue reaching 21.64 billion CNY. In scenario S2, the highest-revenue pathway was S2R50Um, with projected revenue of 4.41 billion CNY over forty years, primarily sourced from mechanical recycling of petro-based plastics and chemical recycling of bio-based plastics. To evaluate the economic effect of source reduction under the optimal composite pathway, we defined the scenario S3R50Um. The results showed that by 2060, the annual net benefit reached 397 million CNY, significantly higher than that of other pathways in the same figure (Fig. 4). Combined with the comparable climate findings, cumulative abatement for S3R50Um over 2020–2060 was 20.92 Mt CO₂-eq, lower than the 22.22 Mt CO₂-eq for S2R50Um, suggesting that higher annual economic returns did not necessarily translate into greater cumulative mitigation.

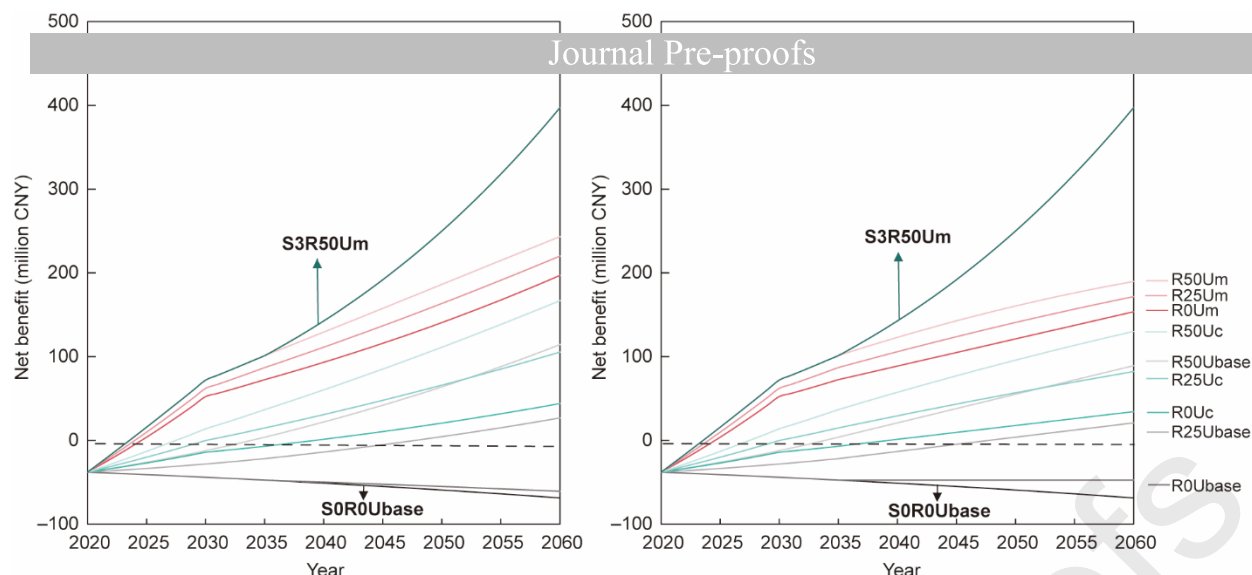


Fig. 4. Life-cycle net economic benefits of MLPW management under different scenarios from 2020 to 2060. The S0 scenario represents continuing a growth rate of 1.5% in MLPW as 2035 (black lines). S1 (left) and S2 (right) scenarios represents a growth rate of 1% and 0% in MLPW since 2035, combined with measures in biomaterial replacement (R) and recycling and utilization (U).

The sustained implementation of source reduction, bio-based substitution, and recycling strategies generated positive net economic returns. The combined low-carbon strategies could achieve a cumulative economic benefit of up to 197.7 billion CNY. In full alignment with the national Action Plans defined in this study, the integrated implementation of the three core management pathways (source reduction, bio-based substitution, and recycling) achieves a minimum cumulative emission abatement of 20.39 Mt CO₂-eq over the 2020–2060 study period (in the S1R25Uc scenario), and a minimum cumulative net economic benefit of 170.6 billion CNY (in the S2R50Uc scenario). At the unit level, mechanical recycling had a life-cycle emission intensity of ~108 kg CO₂-eq · t⁻¹, and a net economic return of ~613.90 CNY · t⁻¹, outperforming other treatment pathways. Fig. 5 illustrates that as recycling and recovery intensity increased, net benefits and carbon abatement rose in tandem. However, the bubble color scale deepened, indicating simultaneous increases in cost inputs. Taking S3R50Um as an example, the forty-year cost structure was dominated by mechanical recycling, comprising about one-third of the total cost, followed by chemical recycling at roughly one-quarter, incineration at about one-fifth, transport-related costs at about one-eighth, and a very small share for composting. On the revenue side, mechanical recycling accounted for the largest share, contributing over seventy percent of total revenue, chemical recycling contributed just over twenty percent, and incineration accounted for the smallest share. This structure explained why scenarios that aggressively expanded mechanical recycling outperformed other pathways economically; mechanical recycling had lower unit costs, more stable product values, and could be monetized at scale. Chemical recycling also generated substantial revenue, but its net benefit remained below that of mechanical recycling under current technology due to the process costs for additives, solvents, and catalysts. The gap is likely to narrow with advances in high recycling rates, high process yields, and closed-loop solvent systems. Incineration persisted due to its procedural simplicity, but it was costlier and yielded limited revenue, primarily from power generation. As recycling technologies advanced and costs declined, its long-term share was displaced by higher-quality recovery pathways offering superior environmental and economic performance. Overall, mechanical recycling served as the near-term economic lever, while targeted demonstration projects and cost-reduction research for chemical recycling proceeded in parallel, coordinated with source reduction and bio-based substitution. This approach ensured that net benefits and carbon abatement rose together, without unduly inflating system costs.

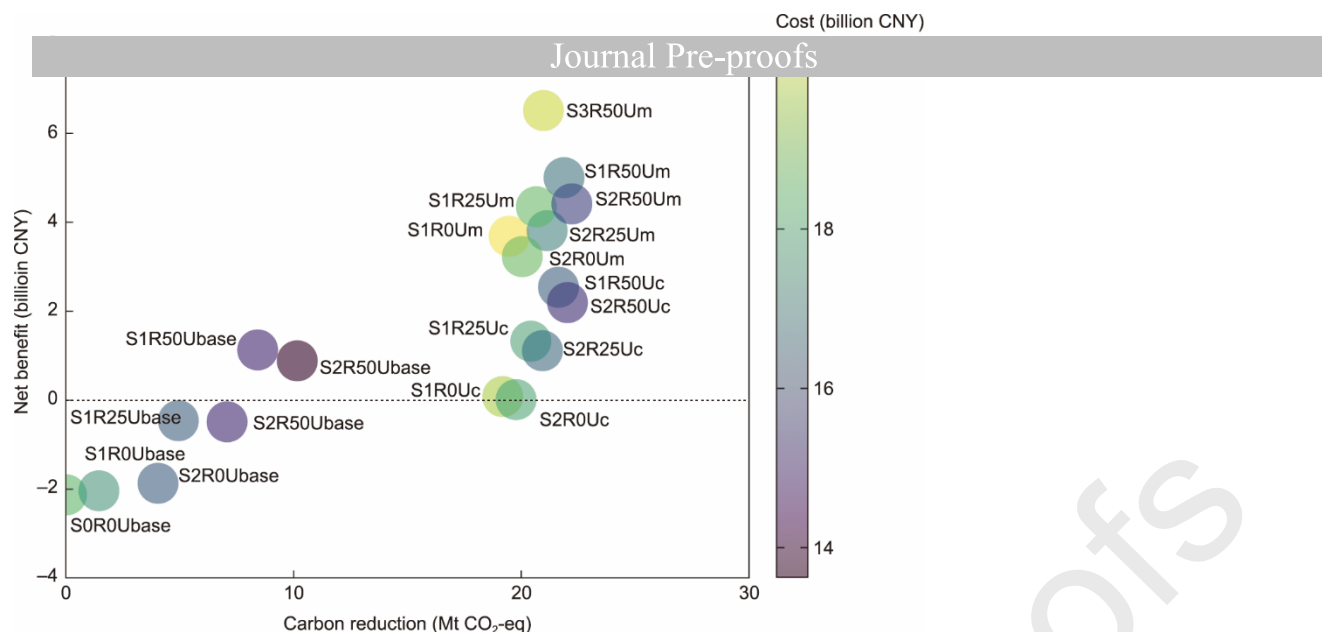


Fig. 5. Cost–benefit analysis of MLPW management. The economic costs and benefits of each scenario along with their potentials in emission reductions.

In terms of economic feasibility, most waste-plastic treatment pathways achieved sector-level self-sufficiency and no longer depended on government fiscal subsidies. Specifically, under the shared premise of high recycling and high substitution in R50 + Um, the choice of S determined the direction of the economic-climate trade-off. If the goal prioritized long-term mitigation and system robustness, S2R50Um would be preferable. If the emphasis was on maximizing returns and the market could continue to absorb secondary materials, S3R50Um would be superior financially. However, attention was needed to upstream environmental burdens and potential lock-in effects associated with scale expansion, while S1R50Um fell between the two. Regardless of the chosen S, the color scale in Fig. 5 indicated that stronger recycling increased cost inputs. However, with a structure dominated by high-quality mechanical recycling, revenues increased faster, and net benefits shifted upward. Therefore, policy should continue to treat source reduction and design for circularity as long-term constraints, use high-quality mechanical recycling as the near-term lever, and advance chemical recycling through targeted demonstration projects, avoiding path dependence on the "more production-more recycling" model under the S3 scenario.

4. Discussion

The results indicated that the combined strategies of source reduction, bio-based substitution, and recycling and recovery simultaneously delivered significant environmental and economic gains. Implementing source reduction alone resulted in emissions reductions of 4.4%–12.3%. The marginal contribution of bio-based substitution ranged from 10.6%–21.2%. Recycling and recovery contributed the most, with reductions reaching 47.9%–54.9%. When implemented together, at least 20.39 Mt CO₂-eq was avoided, and economic benefits of 170.6 billion CNY were realized. Taking scenario S2R50Um as an example, incineration-related emissions decreased by 71.2% over a 40-year period, primarily due to substitution with bio-based materials and the displacement of conventional incineration by mechanical and chemical recycling.

Within recovery and utilization pathways, mechanical recycling was prioritized due to its superior performance. Figs. 3 and 4 illustrates that mechanical recycling outperformed alternatives in both environmental and economic terms. After mechanical recycling, emissions amounted to approximately 108 kg CO₂-eq per tonne of plastic, with an economic return of approximately 613.90 CNY per tonne. Due to low pollution burdens, modest capital and operating requirements, and operational stability, mechanical recycling was widely adopted and remains the primary route for waste-plastic treatment in China [56,57]. These advantages were based on mature processes; industrial-scale mechanical recycling has been developed over many years, with relatively stable technical and economic performance [58]. Chemical recycling, a promising technology, still has room for improvement and is expected to deliver better environmental and economic performance as technologies advance and deployment scales up [25]. Taken together, policy should treat source reduction and material substitution as near- to mid-term levers, prioritize mechanical recycling with chemical recycling as an incremental complement, steadily reduce incineration, and work toward higher recycling rates and lower emissions.

When recycling, utilization, and material substitution were near their optima, we further assessed whether source reduction should remain a constraint. Although S3R50Um yielded higher annual net benefits, approaching 100% recycling did not mean that upstream output control could be eased. Achieving 100% recycling was inherently difficult due to technical bottlenecks such as contamination, impurities, material aging, and mixing. Challenges also arise from long-tail dispersed sites and residual handling. These issues are further compounded by behavioral and institutional limits, including household participation, sorting compliance, and reverse logistics coverage. As the recycling rate approached its ceiling, marginal costs for collection and sorting increased, and losses mounted. The market absorption of secondary materials depended on quality and stability, and expanding output could depress prices, weakening net benefits. From a life-cycle perspective, new production still

investment was largely borne by municipalities and facilities, with ongoing operating costs for collection and sorting incurred. Revenues from secondary materials were concentrated among recyclers and mid-stream firms, while rising marginal costs affected informal collectors and transfer units with limited revenue elasticity, and price volatility amplified uncertainty in cash-based buyback operations. Taken together, these factors implied that the more robust choice frequently combined high-quality recycling with strengthened source reduction and material substitution. This reduced the need for long-tail collection and deep sorting, shortened payback periods, and reduced revenue risk from falling secondary-material prices. Meanwhile, cumulative abatement for S3R50Um over 2020–2060 was lower than for S2R50Um, further indicating that reliance on high recycling alone could not guarantee long-term climate performance. Guided by the waste-management hierarchy, source reduction and design for circularity were treated as long-term constraints. High-quality recycling was viewed as necessary but not sufficient, and quality standards, market instruments, and extended producer responsibility were employed to form a coordinated strategy of reduction, substitution, and high-quality recycling.

Methodologically, this study developed a transferable research framework for urban solid-waste governance. Its core was to establish a material-flow baseline through field measurements, conduct independent validation with machine learning, propagate uncertainty, and align environmental and economic assessments within a unified system boundary and common data foundation. With only a minimal dataset that included sampled information on generation, composition, and end-of-life destinations, along with unit-process emission factors and cost parameters, the framework could be extended to subsystems such as paper, metals, glass, and food waste, and updated regularly across cities and time periods. The resulting quantitative evidence directly informed pathway screening, facility siting, and budget planning, supporting robust decision-making under concurrent mitigation goals and fiscal constraints.

This study has several limitations. The analysis primarily focused on greenhouse-gas emissions as the key environmental metric. Landfill-closure timelines varied across cities, and from a greenhouse-gas perspective, landfills may have outperformed energy recovery in certain cases. Constrained by insufficient city-scale data and the complexity of fieldwork, the study focused on household-source plastic waste, while urban plastic sources were more diverse. Official data on plastic production, use, and end-of-life management remained incomplete, limiting the accuracy of material-flow analysis. Further work is needed to address inconsistencies between product and waste classifications, data gaps, conflicts, and unclear records [59]. Future efforts should involve conducting in-depth surveys in more cities and developing MLPW management programs tailored to local conditions, thereby improving managerial effectiveness and environmental performance.

5. Conclusions

This study developed and validated an AI-driven, transferable city-scale assessment framework for municipal living plastic waste. The framework reconstructed material flows from field measurements. Machine learning was applied for independent validation, missing-data imputation, and uncertainty propagation. By aligning life-cycle environmental accounting with process-based costs and benefits within a unified boundary, the approach provides robust support for forecasting and elastic dispatch. Using Nanjing as an example, the synergy of source reduction, bio-based substitution, and high-quality recycling resulted in a 96.3% reduction in annual emissions relative to baseline by 2060. Scenario S2R50Um achieved cumulative abatement of 22.22 Mt CO₂-eq over 2020–2060, along with substantial net benefits. Scenario S3R50Um delivered higher annual returns but achieved 20.92 Mt CO₂-eq in cumulative abatement, suggesting that reliance on high recycling alone could dilute long-term performance. Policy recommendations included treating source reduction and design for circularity as long-term constraints, prioritizing improvements in mechanical recycling, advancing chemical recycling steadily, and strengthening quality standards and market instruments to stabilize the demand for secondary materials. The AI-driven framework has modest data needs and could transfer across cities, be adapted to other solid waste subsystems, and support zero-waste city initiatives as well as sustainable, low-carbon governance and investment prioritization.

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Declaration of Interest Statement

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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