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A System Dynamics–Optimization Framework for Sustainable Municipal Solid Waste Management: Integrating Behavioral Feedbacks, Technology Selection, and Circular Economy Pathway

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Abstract

Rapid urbanization and rising waste generation have intensified the environmental and economic challenges of municipal solid waste (MSW) management, particularly in systems that rely on landfills. This study develops a hybrid system dynamic–optimization framework to identify sustainable long-term MSW management pathways by integrating technological, economic, environmental, and behavioral feedback mechanisms. The framework couples a system dynamics model with a β-Hill Climbing optimization algorithm to evaluate waste treatment strategies, including recycling, composting, anaerobic digestion, incineration, pyrolysis, gasification, and landfilling, under alternative policy scenarios for 2027–2050. The proposed framework is applied to Alborz Province, Iran, to optimize technology portfolios while considering citizen participation, financial constraints, and environmental objectives. Results show that integrated policies substantially outperform single-technology approaches, reducing cumulative landfilled waste by 91–93% compared with the baseline scenario. Anaerobic digestion is the most effective option for organic waste management, while the optimal dry-waste treatment pathway depends on participation levels and economic conditions. Under limited participation, pyrolysis is preferred due to lower investment requirements, whereas enhanced participation supports a combination of incineration, pyrolysis, and gasification for improved resource recovery. The optimized strategies transform the MSW system from a net greenhouse gas emission source into a mitigation-oriented system, achieving cumulative reductions of 24.44–25.96 million tons of CO_2-equivalent. The results demonstrate that sustainable waste transitions require coordinated behavioral policies and technology planning rather than isolated technology selection. The proposed framework provides a decision-support tool for designing circular and low-carbon MSW management systems under dynamic socioeconomic conditions.

Keywords: Municipal solid waste; System dynamics; Optimization; β-Hill Climbing; Circular economy; Waste-to-resource

Highlights

- A novel closed-loop System Dynamics–Optimization framework is proposed for MSW management.
- Waste treatment technologies are dynamically optimized rather than predefined as scenarios.
- Behavioral participation and municipal financial feedback are explicitly integrated.
- The framework captures long-term interactions between policies, technologies, and sustainability outcomes.
- Adaptive waste management strategies are identified under uncertain socioeconomic conditions.

1. Introduction

The transition to a circular economy is changing the purpose of municipal solid waste (MSW) management from removing unwanted materials to retaining their environmental and economic value. Municipalities are increasingly expected to prevent waste, support reuse and source separation, recover materials and nutrients, generate low-carbon energy from appropriate residual streams, and minimize final disposal (Geissdoerfer et al., 2017; Kirchherr et al., 2017; Lenkiewicz et al., 2024). This transition is particularly important because decisions about waste infrastructure have long-term consequences: treatment facilities are capital-intensive, operate for many years,

and can lock municipalities into particular material-flow patterns. Sustainable MSW planning must therefore determine not only which technologies perform well today, but also which combinations remain appropriate as waste generation, public participation and financial conditions change.

This planning challenge is becoming more urgent as the volume and complexity of urban waste continue to increase. Population growth, urbanization, rising incomes and changing consumption patterns are placing growing pressure on collection services, treatment capacity, landfill space and municipal budgets (Kaza et al., 2018; Maçin, 2026). These pressures are particularly severe in developing and middle-income countries, where infrastructure expansion often fails to keep pace with waste generation and where landfilling, uncontrolled disposal and fragmented recycling remain common. At the same time, the waste sector contributes to climate change through landfill methane, fossil-derived emissions from treatment processes, and energy and material consumption across the management chain (Guivarch et al., 2023). Moving away from landfill-oriented systems is therefore necessary, but the appropriate pathway depends on how upstream prevention and separation policies interact with downstream treatment decisions.

MSW infrastructure cannot be planned independently of household behavior because changes in reuse and source separation reshape the material entering the formal waste system. Greater participation can reduce mixed-waste collection, improve the quality of recyclable and organic fractions, extend landfill life, and lower some municipal operating costs. It can also reduce the amount of feedstock available to material-recovery and energy-generation facilities, alter recycling revenues and change the capacity required from treatment technologies. These effects create an important but often overlooked planning risk: infrastructure designed around current mixed-waste volumes may become oversized or unsuitable if participation improves, while inadequate upstream separation can undermine the environmental and financial performance of advanced facilities.

Behavioral policy should therefore be understood as an infrastructure-planning variable rather than merely a public-awareness intervention.

Technology selection is further complicated because the environmental performance of a treatment option is inseparable from the characteristics of the waste stream and the wider system in which it operates. Life Cycle Assessment (LCA) studies have shown that recycling, composting, anaerobic digestion, thermal treatment and landfilling produce different combinations of direct emissions, avoided emissions, resource recovery and residual waste (Finnveden et al., 2009; Laurent et al., 2014). Their relative performance can change with waste composition, separation quality, energy-substitution assumptions and the boundaries adopted for avoided products and emissions. Recent work has consequently combined environmental assessment with economic and social indicators to provide a more balanced evaluation of MSW strategies (Nabavi-Pelesaraei & Hamidinasab, 2025; Torkayesh et al., 2022; Wang et al., 2025). Nevertheless, these assessments generally compare a limited number of predefined scenarios and provide only a static representation of systems that evolve over time.

The main limitation of static assessment is that it cannot fully represent the feedback mechanisms through which today's policies change tomorrow's waste system. Educational investment may improve participation after a delay; improved reuse and separation may reduce collection and disposal expenditure; financial savings may create additional capacity for environmental programs and infrastructure investment; and new treatment capacity may generate revenues that further alter municipal liquidity. Conversely, expensive technologies can weaken financial flexibility and limit future investment, even when they offer attractive environmental performance. Although LCA can quantify the consequences of a particular configuration, it is less suited to explaining how behavioral, financial and technological interactions generate different configurations over a long planning horizon (Fouquet et al., 2015; Yi et al., 2023). Capturing these interactions requires a

modeling approach that represents both physical waste flows and the feedback structures shaping their evolution.

System Dynamics (SD) is well suited to this task because it represents feedback loops, time delays, nonlinear relationships and the accumulation of stocks over time (Sterman, 2002). In MSW research, SD has been used to investigate waste generation, source separation, collection, recycling, treatment capacity, landfill use and policy interventions under changing demographic and socioeconomic conditions (Estay-Ossandon & Mena-Nieto, 2018; Pinha & Sagawa, 2020; Rafew & Rafizul, 2021). More recent regional models have extended this systems perspective to the long-term evolution of waste flows, resource recovery, and infrastructure performance (Ng & Yang, 2023). SD models therefore provide a valuable understanding of how waste systems behave, but most evaluate technology configurations or participation policies specified before the simulation rather than determining how these conditions should reshape investment decisions.

Optimization models address a different part of the planning problem by identifying technology mixes, capacities, waste allocations, and investment strategies that satisfy economic and environmental objectives. Linear programming, mixed-integer programming, and metaheuristic methods have been widely applied to MSW facility planning and technology selection (Hosseinalizadeh, Izadbakhsh, & Shakouri G, 2021; Moussavi et al., 2026). Hybrid simulation–optimization research has further demonstrated that connecting an SD model to an optimization procedure can improve long-term technology planning by allowing investment decisions to respond to simulated system conditions (Hosseinalizadeh et al., 2022). However, previous applications have largely concentrated on waste-to-energy capacity or treated public participation, formal and informal recovery, and municipal financial resources as predetermined inputs. The unresolved issue is therefore not whether SD and optimization can be combined, but whether their

integration can explain how upstream behavioral change reconfigures the downstream technology portfolio through evolving material and financial conditions.

Accordingly, this study develops a behavior-conditioned SD–optimization framework for long-term MSW planning and applies it to Alborz Province, Iran. The framework integrates waste generation, reuse, source separation, formal and informal recycling, collection, biological and thermal treatment, landfill management, greenhouse gas emissions, environmental damage costs and municipal financial flows. It connects the SD model to a β-Hill Climbing search procedure to identify treatment portfolios under contrasting levels of public participation. In this way, the analysis examines not simply which technology performs best, but how changes in upstream participation influence residual material flows, treatment requirements, municipal liquidity and the economically feasible portfolio of downstream technologies.

This study makes three principal contributions. First, it conceptualizes behavioral participation as a driver of infrastructure configuration by showing how reuse and source separation alter the quantity and composition of waste available to different treatment pathways. Second, it represents municipal liquidity as an endogenous transmission mechanism linking participation, collection and disposal costs, resource-recovery revenues and investment capacity. Third, it places formal and informal recovery, biological treatment, thermal treatment and residual disposal within a unified simulation–optimization framework, allowing the environmental and economic consequences of their interactions to be examined over time. Through this perspective, the study provides a basis for coordinating behavioral and technological policies and avoiding fixed infrastructure decisions that may become unsuitable as the waste system evolves.

2. Materials and methods

2.1. Overview of the hybrid modeling framework

Fig. 1 summarizes the hybrid SD–optimization framework. The SD model represents long-term interactions among waste generation, participation, formal and informal recycling, treatment capacity, environmental impacts, and municipal finance. Its outputs are passed to a β-Hill Climbing algorithm that searches investment allocations among composting, anaerobic digestion, incineration, pyrolysis, gasification, and sanitary landfilling.

The analysis proceeds in four steps: develop and validate the SD model, simulate individual technologies, optimize integrated portfolios, and compare environmental and economic outcomes. Population and economic conditions drive waste generation; participation determines the mixed-waste stream; and treatment costs, revenues, and avoided impacts affect municipal liquidity and future investment. These feedbacks allow the algorithm to identify portfolios that reduce landfill dependence and environmental impacts while remaining financially feasible over the planning horizon.

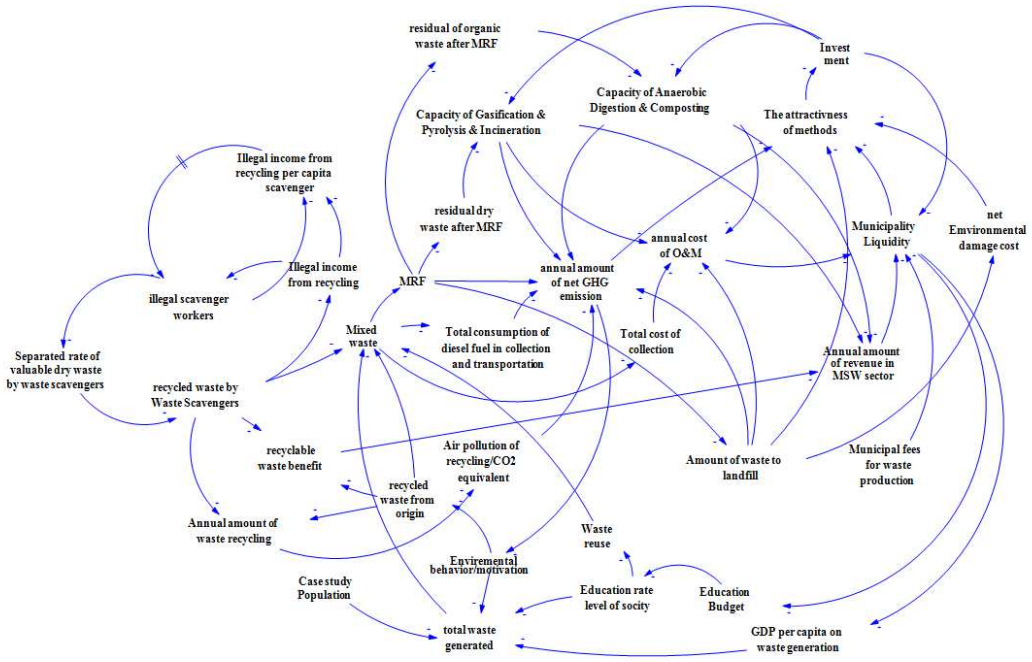


Fig. 1 Conceptual structure of SD model of municipal solid waste management

2.2. The SD model development

SD is a computational modeling approach for analyzing complex systems characterized by feedback loops, nonlinear relationships, delays, and time-dependent behavior (Sterman, 2002). Unlike static modeling approaches, SD enables the simultaneous representation of physical, economic, environmental, and behavioral processes, providing insights into how policy interventions influence system performance over extended time horizons.

The SD model was developed using data from the municipality of Alborz province in Iran, and consulting with experts there. Where local data were unavailable, parameter values were obtained from the literature and assessed through sensitivity analysis.

Model development proceeded through six stages. First, the system boundary and principal waste-management problem were defined for Alborz Province. Second, the main variables and causal relationships were identified from the collected data, technical reports, previous studies, and

consultations with local stakeholders. Third, these relationships were organized into causal-loop diagrams. Fourth, the causal structure was translated into a stock-and-flow model, including equations, initial values, delays, and feedback relationships. Fifth, the model was calibrated against historical observations. Finally, its structure, assumptions, and behavior were evaluated through expert review and the validation tests described in Supplementary material B.

The final model comprises five interconnected modules aligned with Sections 2.2.1–2.2.5: (1) waste generation, recycling, and collection; (2) waste treatment and environmental impacts; (3) behavioral feedback mechanisms; (4) informal recycling dynamics; and (5) investment attractiveness and technology adoption. Fig. 1 provides a module-level roadmap showing the material, environmental, behavioral, and financial connections among these modules, while Supplementary material A presents their detailed equations and stock-and-flow structures.

2.2.1. Waste generation, recycling, and collection module

The model links population and per-capita generation to seven waste fractions and subtracts reuse, source-separated recycling, and informal recovery to estimate mixed waste requiring collection. Formal and informal recovery, collection demand, transport emissions, and operating costs are calculated dynamically. The equations, parameters, and stock-and-flow diagrams are provided in Supplementary material A, Sections S1.1–S1.2 and Table S1.2.

2.2.2. Waste treatment and environmental impact module

The treatment module allocates waste among composting, anaerobic digestion, incineration, pyrolysis, gasification, and sanitary landfilling and calculates residual flows, recovered products and energy, costs, revenues, and GHG emissions. Biological pathways treat source-separated organics, whereas thermal pathways treat dry residual waste. Landfilling receives untreated waste

and process rejects. Net GHG emissions equal direct process and input-related emissions minus benefits from recovered materials and energy; negative values therefore indicate net avoided emissions. Environmental damage costs are estimated using the LIME method. The equations, conversion efficiencies, emission factors, and impact coefficients are provided in Supplementary material A, Sections S1.3–S1.4 (Shahbazi et al., 2023; Shahbazi et al., 2025).

2.2.3. Behavioral feedback mechanisms

Education affects awareness and reuse after a delay, while the resulting reduction in mixed-waste collection costs feeds back to municipal resources and service charges. The governing equations, assumptions, and feedback structure are reported in Supplementary material A, Section S1.5. The participation levels used in the policy cases are defined in Section 2.4.

2.2.4. Informal recycling dynamics

The model represents entry into informal recovery as a function of per-capita recycling income and competition for available recyclables. The governing equation and feedback structure are provided in Supplementary material A, Section S1.5.

2.2.5. Investment attractiveness and technology adoption module

Available municipal liquidity is allocated among technologies according to capacity gaps, capital requirements, and expected profitability. Attractiveness declines as installed capacity approaches demand and increases when a technology generates financial returns. The complete equations and stock-and-flow structure are provided in Supplementary material A, Section S1.6.

2.3. β-Hill Climbing optimization algorithm

Optimizing long-term MSW management requires identifying technology portfolios that simultaneously minimize environmental impacts and landfill dependency while maintaining economic viability. Because the proposed waste management system is characterized by nonlinear interactions, multiple decision variables, and dynamic feedback mechanisms, conventional optimization methods are often unable to efficiently explore the solution space or may become trapped in local optima (Hernando et al., 2018). To address this challenge, the SD model was integrated with the β-Hill Climbing optimization algorithm.

β-Hill Climbing searches continuous portfolio shares by repeatedly simulating neighboring allocations, accepting improvements, and occasionally accepting inferior solutions with probability β to escape local optima. Four independent variables determine composting, pyrolysis, incineration, and methane-collection efficiency, while complementary anaerobic-digestion and gasification shares enforce the portfolio constraints. Full initialization, step-size, penalty, and stopping rules, together with Algorithm S3.1, are provided in Supplementary material C, Section S3.1.

2.4. Scenario and policy formulation

To evaluate the long-term performance of alternative MSW management strategies, two complementary types of analyzes were conducted: technology-based scenarios and integrated policy optimization. The technology-based scenarios were designed to assess the individual performance of major waste treatment technologies, including composting, anaerobic digestion, incineration, pyrolysis, gasification, and the baseline landfill-oriented system. In each technology scenario, the allocation rate of the selected treatment method was fixed while the remaining

technologies were excluded, allowing the standalone environmental and economic performance of each option to be evaluated using the SD model without optimization.

In addition to the single-technology benchmarks, two integrated policy cases represented contrasting participation conditions rather than empirical forecasts. The pessimistic and optimistic policies impose maximum reuse and source-separation targets of 10% and 90%, respectively. Actual participation evolves dynamically toward these targets through the modeled education and behavioral feedback mechanisms. Within each case, the β-Hill Climbing algorithm determined treatment allocations and landfill methane-recovery efficiency endogenously to reduce environmental impacts and landfill dependence while improving long-term municipal financial performance.

2.5. Hybrid optimization framework, objective function, and model validation

The hybrid framework integrates the SD simulation model with the β-Hill Climbing optimization algorithm to identify long-term waste management strategies that simultaneously improve environmental and economic performance. The optimization seeks to minimize cumulative environmental damage costs (EDC), net GHG emissions, and landfilled waste (LW), while maximizing municipal liquidity (L), which represents the accumulated net financial balance of the waste management system. Accordingly, the optimization objective function is formulated as equation 6:

$$Min_Z = W_1 \times EDC + W_2 \times Net\,GHG + W_3 \times LW - W_4 \times L \qquad (6)$$

where (W_1)–(W_4) are weighting coefficients reflecting policy priorities, with greater emphasis assigned to environmental indicators to support sustainable waste management objectives. The four objectives are expressed in different units and were not subjected to a separate min–max

normalization procedure. Instead, their coefficients were selected to account jointly for differences in numerical magnitude and the relative importance assigned to each objective. Following the objective order, the coefficients were 0.6 for environmental damage costs, 0.1 for net GHG emissions, 0.3 for landfilled waste, and 0.0001 for municipal liquidity. Consequently, these coefficients serve as both policy-preference weights and scale-adjustment factors, and the resulting objective represents a composite policy score rather than a normalized, dimensionless measure.

The optimization framework was implemented by coupling the β-Hill Climbing algorithm with the SD model in the Python-based PySD environment. During each optimization iteration, the algorithm generated a candidate allocation of waste-treatment technologies, which was passed to the SD model as a set of input parameters. The SD model was then simulated over the complete planning horizon, and its resulting environmental and economic outputs, including environmental damage cost, net GHG emissions, landfilled waste, and municipal liquidity, were used to calculate the scalar objective value in Equation (6). This objective value was returned to the optimization algorithm to evaluate the candidate allocation and update the treatment rates for the next iteration. This iterative exchange continued until the specified iteration limit was reached, after which the best treatment allocation identified during the search was reported. The optimizer identifies a single treatment-allocation vector for each policy case over the planning horizon. Treatment shares remain fixed within each simulation, while waste flows, installed capacities, and municipal financial conditions evolve dynamically. The overall computational workflow is presented in Fig. 2.

The model was simulated over the period 2020–2050, following calibration using historical data from 2011–2020. Scenario-specific interventions and optimized technology allocations were activated from 2027 onward to represent the implementation of future waste management policies. All financial results are expressed in US dollars, with 2020 treated as the monetary base year.

Applicable costs, prices, and service fees are updated over the simulation period using the cumulative-inflation term reported in Table S1.2 in Supplementary material A. The annual and cumulative financial outputs are therefore presented in nominal, undiscounted US dollars.

Model credibility was assessed through structural review, dimensional consistency, extreme-condition, time-step, historical-behavior, and sensitivity tests. Population and total-waste MAPE values were 0.66% and 8.43%, respectively, and sensitivity tests changed output magnitudes without changing their trends. Full procedures and results are reported in Supplementary material B.

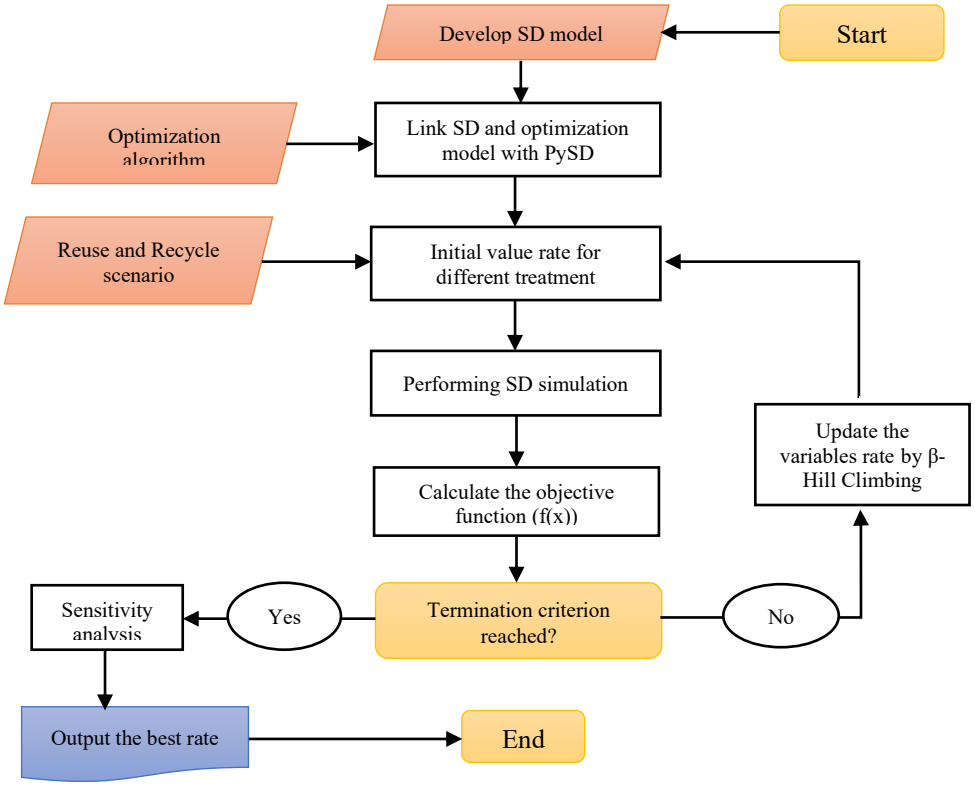


Fig. 2. Flowchart of the implementation steps of the dynamic-optimization model of the hybrid system.

3. Result and Discussion

3.1. System Dynamic Model

The baseline model represents the existing landfill-oriented MSW system in Alborz Province. It was calibrated using historical data for 2011–2020 and simulated over the period 2020–2050, with scenario-specific interventions and optimized technology allocations beginning in 2027. All technology scenarios and integrated policies described in Section 2.4 are compared with this same baseline.

3.1.1. Prediction of waste generation and its composition in Alborz Province

Waste generation in Alborz Province during the simulation period (2020–2050) increases from 698,835 tons to 744,718 tons (approximately a 7% growth), corresponding to an increase in daily waste generation from 1,900 to around 2,040 tons per day (Fig. 3a). The total waste generated over the entire simulation horizon is estimated at approximately 22 million tons. This increasing trend is justified by the province's high population density, commercial and industrial activities, and its high migration rate resulting from population spillover from Tehran Province (Hosseini et al., 2017). It is also consistent with the findings of Zanjani et al. (Zanjani et al., 2012), who found that waste generation in Tehran is highly correlated with population and per capita income. This trend is also reported in many other countries due to population growth, urbanization, and improvements in living standards (Abdelaal et al., 2019; Chen et al., 2020). This trend threatens the MSW infrastructure over the long-term planning horizon. Since the capacity of processing technologies, landfills, and requisite financial resources is a function of the input waste volume, even this relatively limited increase affects the economic and environmental performance of the waste management system. Therefore, this paper aims to accurately predict the amount of waste

generated over time, which provides the foundation for scenario analysis and ultimately for choosing the best combination of methods for MSW.

In terms of composition, organic matter constitutes the dominant share of the waste at 70.8%, followed by plastic (12.1%), paper (6.7%), others (6.9%), textiles (2.1%), metals (1.1%), and wood (0.3%) (Fig. 3b). These relative shares remain almost the same throughout the study period, and the increase in waste generation stems primarily from an increase in total generation volume rather than a change in its composition pattern. This is an important fact for long-term planning because it indicates that the technological needs in the study area over the study horizon are affected more by the required capacity increase for waste processing than by a change in the type of required technologies; therefore, infrastructure development planning must focus on increasing the capacity of existing systems, particularly in the organic waste management sector. The high share of organic waste aligns with the findings of other case studies in developed and developing countries (Bello et al., 2022) and makes the effective management of this fraction a central pillar in achieving sustainable waste management (Lohri et al., 2017). The dominance of organic matter in the waste composition, aside from emphasizing the importance of biological technologies, shows that the success of any waste management strategy in Alborz Province depends largely on how this component is managed. In other words, even using highly advanced technology to manage dry waste without effective management of the organic waste cannot lead to a significant decrease in landfilling, greenhouse gas emissions, and environmental damage costs. This structural characteristic reveals the distinct importance of organic waste management technologies in the scenario analysis of the subsequent sections.

a) b)

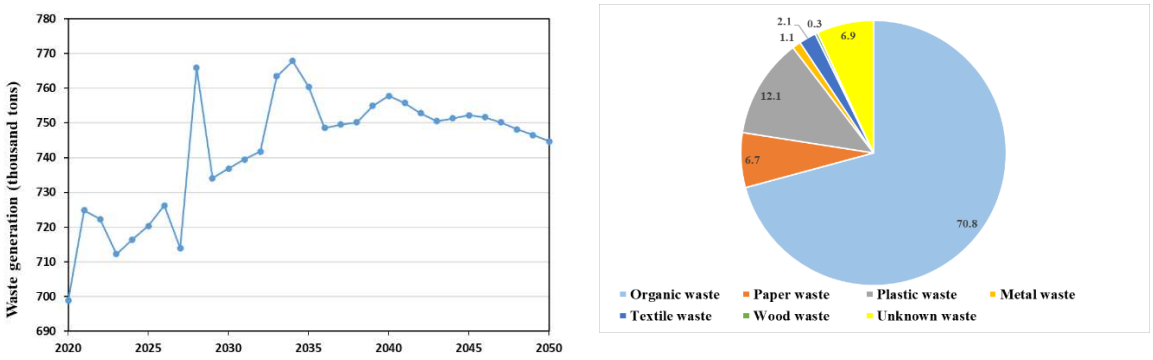


Fig. 3. Prediction of waste generation (a) and waste composition (b) during the simulation period in Alborz Province

3.1.2. Optimized technology portfolios under alternative behavioral policies

The hybrid system dynamics–optimization framework was applied to identify technology portfolios capable of improving long-term MSW management performance under different behavioral and socioeconomic conditions. Unlike conventional waste management studies that evaluate treatment technologies independently or assume fixed allocation rates, the proposed framework determines technology portfolios dynamically by considering interactions among waste composition, citizen participation, municipal liquidity, environmental objectives, and infrastructure requirements. Previous optimization-based studies have demonstrated that technology selection in MSW management is highly sensitive to economic constraints, investment requirements, and waste characteristics (Hosseinalizadeh, Izadbakhsh, Shakouri, et al., 2021; Moussavi et al., 2026). However, most existing approaches evaluate these factors under static assumptions and do not consider how behavioral policies and financial feedback mechanisms modify future technology choices. The results of the present study extend previous findings by demonstrating that the preferred technology pathway is not an inherent property of a treatment technology but an emergent outcome of the entire waste management system .

As summarized in Table 1, the optimized portfolios under both behavioral policies allocate 100% of the organic fraction to anaerobic digestion. This result is primarily explained by the high proportion of biodegradable waste in Alborz Province and the ability of AD to simultaneously reduce landfill demand, recover energy, and generate environmental benefits. Previous studies have also identified anaerobic digestion as an environmentally favorable option for organic waste management due to methane avoidance, renewable energy production, and nutrient recovery potential (Liu et al., 2021; Slorach et al., 2019). However, the present study provides an additional insight by demonstrating that the dominance of AD emerges not only from its environmental performance but also from its positive interaction with municipal financial dynamics through reduced disposal costs and energy recovery revenues.

Under the pessimistic policy, characterized by limited citizen participation (10% reuse and 10% source separation), the optimized portfolio selects pyrolysis as the dominant pathway for dry waste management. This result should not be interpreted as evidence that pyrolysis is universally superior to other thermal treatment technologies. Rather, it reflects the interaction between technological characteristics and financial limitations within the dynamic system.

Under limited behavioral participation, a larger fraction of mixed dry waste enters the treatment system, increasing the required investment demand. Since municipal liquidity is constrained under this condition, technologies with lower capital intensity become more attractive. Pyrolysis provides a comparatively lower investment requirement per unit of treatment capacity than incineration, allowing the system to expand treatment capacity under financial limitations. Therefore, the selection of pyrolysis represents a financially adaptive response of the system rather than a fixed technological preference .

This finding supports previous research highlighting the importance of capital constraints in shaping waste technology portfolios (Hosseinalizadeh et al., 2022). Recent comparative LCA reviews similarly indicate that the environmental ranking of biological and thermochemical technologies depends strongly on system boundaries and the integration of different treatment pathways (González-Mallén & Salhofer, 2026). However, unlike previous studies that typically treat financial parameters as external constraints, the present framework demonstrates that financial capacity itself evolves through feedback mechanisms involving waste reduction, recovery revenues, operational costs, and technology performance.

Under the optimistic policy, where reuse and source separation rates increase to 90%, the optimized dry waste pathway shifts toward a combination of incineration (74%), pyrolysis (21%), and gasification (5%). This transition represents one of the most important findings of the study because it demonstrates that improving behavioral participation can fundamentally modify technology selection.

The shift from pyrolysis toward incineration under higher participation conditions occurs through two interconnected mechanisms. First, increased reuse and source separation reduce the amount of residual dry waste requiring thermal treatment. Consequently, the total investment requirement decreases, partially alleviating the financial limitation that restricts expensive technologies under the pessimistic policy. Second, once the liquidity constraint becomes less restrictive, technologies with higher energy recovery efficiency become more competitive.

Incineration provides higher electricity recovery potential compared with pyrolysis, resulting in greater avoided emissions from conventional electricity production and improved environmental performance. Similar observations have been reported in studies comparing waste-to-energy alternatives, where the environmental performance of thermal treatment depends strongly on energy recovery efficiency, system boundaries, and displaced energy assumptions (Laurent et al.,

2014; Wang & You, 2021). Therefore, the optimized selection of incineration in this study reflects a system-level trade-off between economic feasibility and environmental efficiency rather than a general technological preference .

An important implication of these findings is that behavioral policies influence technology selection indirectly by modifying the physical and economic structure of the waste management system. Increasing public participation does not merely reduce waste quantities; it changes investment requirements, available revenues, technology attractiveness, and the long-term trajectory of infrastructure development. This result supports the argument that sustainable waste transitions require coordinated behavioral and technological interventions rather than isolated investment in treatment facilities (Estay-Ossandon & Mena-Nieto, 2018; Ng & Yang, 2023).

Overall, the optimization results demonstrate that there is no universally optimal MSW technology portfolio. Instead, optimal strategies are context-dependent solutions emerging from interactions among waste composition, behavioral conditions, financial resources, and environmental priorities. These finding challenges conventional approaches that rank technologies independently and highlight the importance of dynamic simulation–optimization frameworks for designing adaptive waste management pathways.

Table 1. Optimal allocation (%) of waste treatment technologies under different policy conditions

Policy condition	Reuse (%)	Source separation (%)	Organic waste treatment		Dry waste treatment			Final residue treatment	
			Composting (%)	Anaerobic digestion (%)	Incineration (%)	Pyrolysis (%)	Gasification (%)	Sanitary landfill (%)	Traditional landfill (%)
Pessimistic	10	10	0	100	0	100	0	100	0
Optimistic	90	90	0	100	74	21	5	100	0

3.1.3. Environmental and economic implications of optimized waste management pathways

3.1.3.1. Reduction of landfill dependency and transition toward resource recovery

Detailed single-technology benchmark results for landfill, thermal, and biological pathways are reported in Supplementary material D, Section S4.1. The integrated-policy results are retained here because they provide the primary comparison between the optimized pathways.

The greatest improvement is achieved under integrated behavioral policies. As shown in Fig. 4a, the optimistic and pessimistic policies reduce cumulative landfilled waste to approximately 1.2 and 1.4 million tons, corresponding to reductions of 93% and 91%, respectively, compared with the baseline scenario. Furthermore, the landfill capacity analysis presented in Fig. 4b demonstrates that these integrated policies prevent landfill exhaustion throughout the simulation horizon, whereas the baseline and sanitary landfill scenarios reach capacity limitations at the beginning of the planning period.

This result reveals that landfill sustainability is not primarily a function of disposal technology but an emergent outcome of coordinated behavioral and technological interventions. In other words, extending landfill lifetime requires reducing waste generation, increasing source separation, improving organic waste diversion, and optimizing residual treatment simultaneously. This finding extends previous SD-based waste studies (Estay-Ossandon & Mena-Nieto, 2018; Ng & Yang, 2023) by demonstrating quantitatively how behavioral feedbacks reshape long-term landfill trajectories.

a) b)

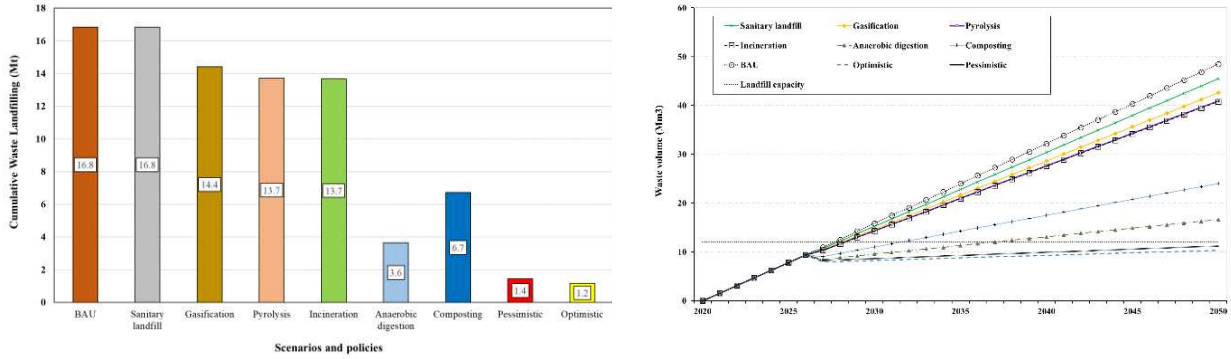


Fig. 4. Changes in cumulative landfilled waste (a) and the volume of landfilled waste (b) across scenarios and policies

3.1.3.2. Greenhouse gas mitigation potential

Annual trajectories and single-technology GHG comparisons are reported in Supplementary material D, Section S4.2. The principal cumulative and technology-contribution results are retained below.

The cumulative emission results in Fig. 5c further emphasize the long-term impact of integrated strategies. While the baseline scenario produces approximately 8.09 million tons of CO_2-equivalent emissions during the study period, the optimistic and pessimistic policies achieve cumulative reductions of 25.96 and 24.44 million tons of CO_2-equivalent, respectively (Fig. 5c). Therefore, the proposed waste management transition does not merely reduce emissions but changes the functional role of the waste sector from an emission source toward a mitigation-oriented system.

An important observation from Fig. 5b is that the technology with the largest capacity share is not necessarily the dominant contributor to emission reduction. For example, despite representing 74% of the dry waste treatment portfolio under the optimistic policy, incineration contributes only a limited proportion of total GHG reduction compared with anaerobic digestion. This finding

highlights the importance of evaluating technologies within the complete system boundary, including avoided landfill emissions, energy substitution, and behavioral changes.

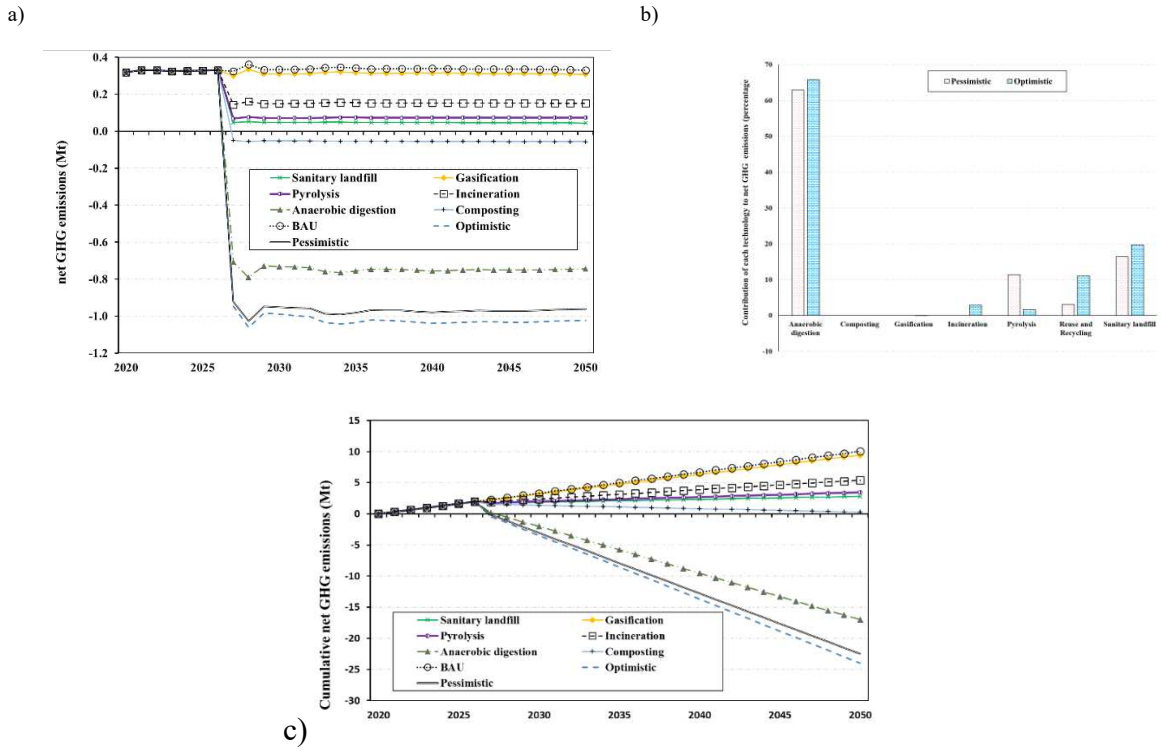


Fig. 5. Changes in the annual amount (a), the share of different methods (b), and the cumulative change trend (c) of net greenhouse gas emissions across scenarios and policies

3.1.3.3. Environmental damage costs and net environmental value

When avoided environmental benefits are considered, the ranking of management strategies changes substantially (Fig. 6b). The optimistic policy achieves the lowest net environmental damage cost (approximately −285 million USD), followed by the pessimistic policy and anaerobic digestion. These negative values indicate that the environmental benefits from resource recovery and renewable energy generation outweigh the environmental burdens of waste treatment. The normalized results (Fig. 6c) further demonstrate this improvement, with environmental damage costs decreasing from 25 USD in the baseline scenario to 6.6 USD, reaching −8.3 USD after

accounting for avoided impacts. Full direct and net environmental-damage-cost comparisons are reported in Supplementary material D, Section S4.3.

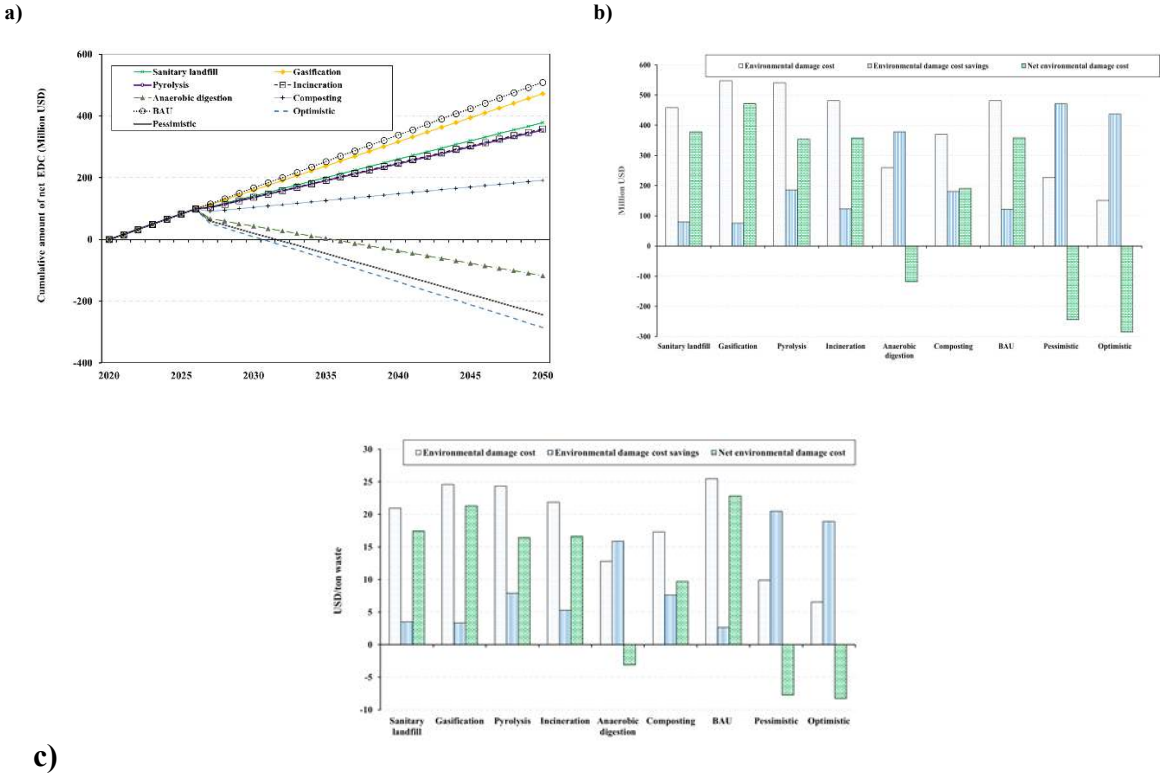


Fig. 6. Trends in cumulative environmental damage cost (a), cumulative net environmental damage cost (b), and environmental damage cost per ton of waste (c) across different scenarios and policies

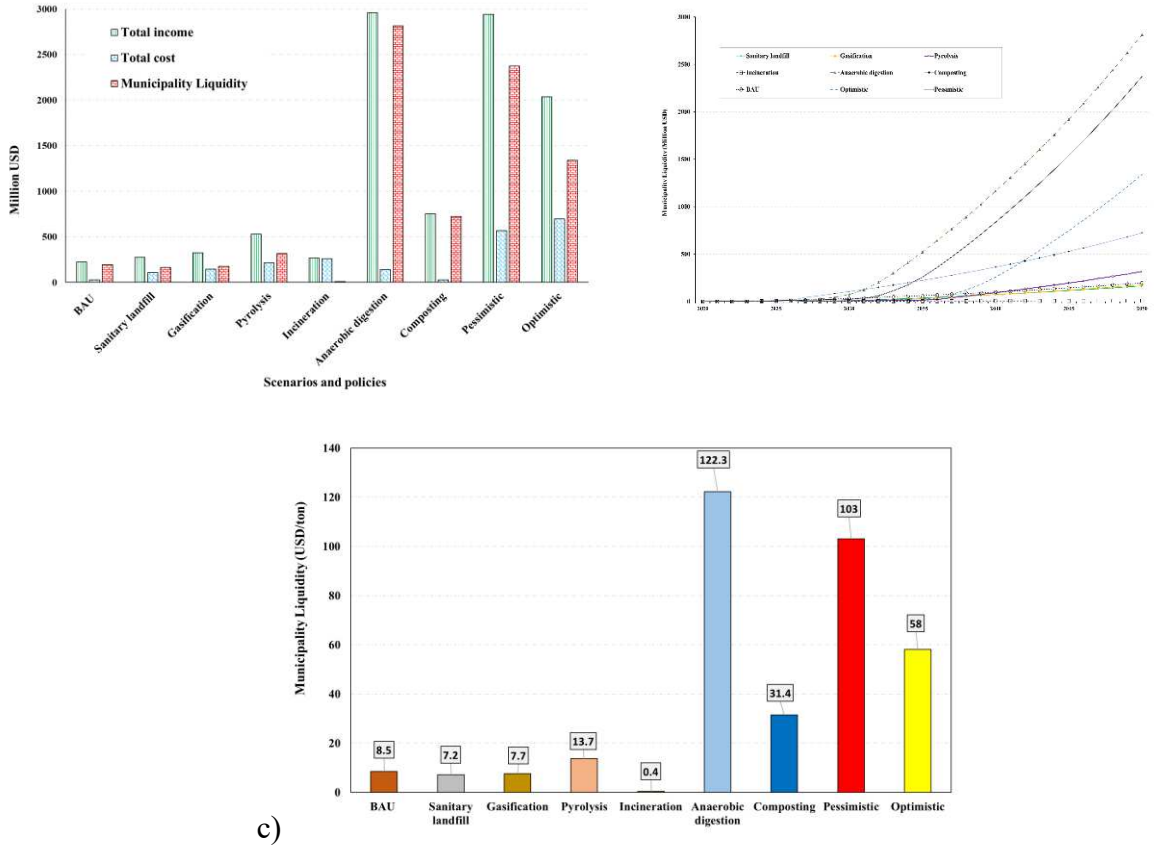
3.1.3.4. Dynamic economic performance and liquidity evolution

Full scenario-level cost, revenue, liquidity, and per-ton comparisons are reported in Supplementary material D, Section S4.4. Anaerobic digestion produced the highest cumulative liquidity, whereas incineration produced the lowest; the central policy trade-off is retained below.

As shown in Fig. 7a, despite its superior environmental performance, the optimistic policy produces lower cumulative liquidity ($1,339 million) than the pessimistic policy and the anaerobic digestion scenario. This reduction is attributable to two structural mechanisms within the model. First, increasing the reuse rate of dry waste reduces the recyclable base volume before calculating

recycling revenue; for this reason, despite a 90% separation rate in the optimistic policy, the volume of recycled waste and, consequently, the revenue generated from it are lower than in the pessimistic policy. Second, under the optimistic policy, three technologies are utilized simultaneously (incineration with a dominant share of 74%, pyrolysis, and gasification) for dry waste management, where incineration, as the most expensive technology, accounts for the largest share of investment and operational costs. The combination of these two factors, namely, the decrease in recycling revenues on the one hand and the increase in investment and operational costs on the other, results in a reduction in the net liquidity of this policy. This pattern indicates that maximizing environmental performance does not necessarily lead to maximizing economic performance, and selecting the optimal policy requires striking a balance between these two objectives. Therefore, the simultaneous evaluation of economic and environmental indicators is essential for decision-making regarding waste management systems. The cost of implementing educational programs for source separation and reuse during the simulation period for the pessimistic and optimistic policies amounts to $297 and $373 million, respectively, which explains part of the cost increase in these two policies. The corresponding cumulative liquidity trajectory and cash flow per ton are presented in Fig. 7b–c.

a) b)



c)

Fig. 7. Cumulative total revenue, total cost, and cash flow (a), the trend of cumulative cash flow (b), and cash flow per ton of waste (c) across different scenarios and policies

3.1.4. Role of behavioral and economic feedback mechanisms

Four interconnected feedback mechanisms explain the optimization outcomes. Behavioral feedback links environmental education to public participation in reuse and source separation. Participation increases over time, reaching approximately 10% under the pessimistic policy and 90% under the optimistic policy (Supplementary material E, Section S5.1). However, greater participation does not necessarily increase recycling revenue, as upstream reuse reduces the recyclable material stream from 0.34 to 0.28 million tones. This trade-off reflects the waste hierarchy, which prioritizes reuse over material recovery (Allwood, 2014).

Operational feedback arises as reduced mixed waste generation lowers collection and transportation costs, improving municipal financial capacity and expanding the scope for technology investment (Zare Mehrjerdi & Faramarzinejad, 2019). Meanwhile, formal–informal recycling interactions reveal that increased source separation reduces waste-picker collection and informal recycling revenue but does not proportionally increase formal recycling revenue, because reuse simultaneously reduces the available recyclable material stream (Supplementary material E, Section S5.3). Thus, improving formal recycling efficiency does not necessarily translate into higher revenues.

Finally, investment feedback and endogenous technology selection connect financial returns and capacity requirements to technology adoption. A balancing loop reduces investment attractiveness as installed capacity approaches projected demand, whereas a reinforcing loop increases attractiveness through energy and material recovery and avoided disposal costs (Supplementary material E, Section S5.4). Under pessimistic conditions, high waste flows and limited municipal liquidity favor pyrolysis because of its relatively lower capital requirements. Under optimistic conditions, improved financial flexibility enables a diversified portfolio dominated by incineration, complemented by pyrolysis and gasification.

Overall, these mechanisms demonstrate that optimized technology portfolios emerge from the dynamic interactions among behavioral policies, material flows, operational costs, financial constraints, and environmental objectives. Integrating these feedbacks into simulation–optimization frameworks therefore provides a more comprehensive basis for adaptive and financially feasible waste management planning.

4. Conclusion

This study developed a hybrid system dynamic–optimization framework to identify sustainable long-term pathways for MSW management by integrating technological decisions with behavioral, economic, and environmental feedback mechanisms. Unlike conventional waste management models that evaluate predefined technology scenarios under static assumptions, the proposed framework dynamically optimizes treatment portfolios while considering changes in waste generation, citizen participation, municipal financial capacity, and technology adoption over time. The results demonstrate that sustainable MSW transitions cannot be achieved through the selection of a single superior technology. Instead, optimal pathways emerge from the interaction among behavioral policies, waste composition, economic constraints, and treatment technologies. In the case study of Alborz Province, integrated strategies combining waste prevention, source separation, biological treatment, and optimized residual waste management substantially outperformed single-technology alternatives.

The optimization results revealed that anaerobic digestion represents the most effective strategy for managing the organic fraction due to the high proportion of biodegradable waste and its simultaneous environmental and economic benefits. For dry waste management, however, the optimal pathway was strongly dependent on behavioral participation and financial conditions. Under limited participation and constrained municipal liquidity, pyrolysis was selected because of its lower investment requirements, whereas enhanced participation improved financial flexibility and enabled the adoption of a combined thermal treatment portfolio dominated by incineration.

A key finding of this research is that technology selection is not an inherent characteristic of individual treatment options but an emergent outcome of system-level interactions. Behavioral interventions influence not only waste quantities but also material availability, recycling revenues,

operational costs, and investment capacity. Therefore, policies promoting reuse and source separation should be designed simultaneously with infrastructure planning rather than implemented independently.

The environmental assessment further demonstrated that integrated policies can transform MSW management from an emission-generating activity into a climate mitigation pathway. Compared with the baseline scenario, optimized strategies reduced cumulative landfilled waste by more than 90% and achieved substantial greenhouse gas mitigation over the planning horizon. These results confirm that combining upstream behavioral measures with appropriate treatment technologies provides greater sustainability benefits than relying solely on advanced processing technologies.

From a policy perspective, the findings highlight the importance of adaptive waste management planning. Municipalities should avoid fixed technology-selection approaches and instead adopt dynamic decision-support systems capable of updating strategies as waste generation, economic conditions, and public participation evolve. The proposed framework provides such a capability by linking behavioral policies, financial mechanisms, and technological decisions within a unified modeling environment.

Despite these contributions, several limitations should be acknowledged. The model parameters were calibrated based on the conditions of Alborz Province; therefore, application to other regions requires local data adaptation and model recalibration. Furthermore, uncertainties associated with future energy prices, recycled material markets, carbon pricing mechanisms, technological learning rates, and socioeconomic changes were not explicitly incorporated.

The findings have three principal implications. First, participation is an infrastructure-planning variable because reuse and source separation change residual-waste quantity, composition, collection costs, recovery revenue, and required treatment capacity. Second, municipal liquidity is an endogenous constraint linking these behavioral changes to the technologies that can be financed.

Third, environmental value and municipal cash flow may diverge because the wider social benefits are not necessarily captured by the municipality. Authorities should therefore evaluate facilities against alternative participation trajectories, prioritize technologies compatible with local waste composition, phase capital-intensive investments, preserve modular capacity, and integrate informal recyclers. External financial mechanisms and periodic portfolio review may be needed to align municipal incentives with environmental benefits. Extended theoretical discussion and policy recommendations are provided in Supplementary material F.

Future research can extend the proposed framework by integrating uncertainty analysis, stochastic optimization, machine learning-based parameter estimation, carbon market dynamics, and multi-objective decision-making approaches. Applying the framework across different geographical, economic, and institutional contexts would further improve its applicability as a decision-support tool for global circular economy transitions. Overall, this study demonstrates that sustainable MSW management is not simply a technological challenge but a dynamic socio-technical transition. Achieving circular and low-carbon waste systems requires coordinated design of behavioral policies, economic mechanisms, and technological pathways within an adaptive planning framework.

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Disclosure statement

No potential conflict of interest is reported by the authors.

Data availability

Data will be made available upon request from the corresponding author.

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