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Published in:
Journal of Cleaner Production

DOI:
10.1016/j.jclepro.2023.136396

Published: 01/04/2023

Document Version
Publisher's PDF, also known as Version of record

Journal of Cleaner Production 395 (2023) 136396

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Finding high-impact intervention points for plastic recycling using an exploratory stock-flow model

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ARTICLE INFO

Handling Editor: Govindan Kannan

Keywords:
Circular economy
Plastic recycling
Stock-flow modeling
Recycling systems

ABSTRACT

With the growing impetus to increase the recycling of plastic waste, a more detailed understanding of the impact of different interventions on improving material circulation in the plastic value chain is needed. This paper uses an exploratory stock-flow modeling approach to analyze the impact potential of critical intervention points and their combinations for increasing circularity and reducing linearity in the Finnish plastic recycling system. The results show that interventions at all our selected intervention points—demand, collection, sorting, and processing—are needed to reach the best outcomes in terms of linear material flows. With uncertainty regarding international flows, collection- and sorting-targeting actions are most effective in avoiding the most pessimistic circularity outcomes, whereas demand- and capacity-targeting interventions have the potential to achieve the best optimistic circularity outcomes. The results contribute to previous research on plastic recycling by improving understanding of the critical bottlenecks and synergistic effects of supply- and demand-side interventions, as well as by supporting policy and industrial decision-making by drawing attention to effective combinations of interventions under uncertainty. The analysis also highlights how the coarse resolution structure of the material flow system governs the impact potential of intervention points, while many system parameters are less significant.

1. Introduction

In recent years, there has been increasing awareness of the environmental issues associated with growing greenhouse gas emissions from plastic production and the leakage of plastic waste into nature (e.g., Geyer et al., 2017; Jambeck et al., 2015; Worm et al., 2017; Zheng and Suh, 2019; see also EASAC, 2020). In response, regulatory and voluntary actions have emerged to increase the recycling of plastic waste, which is seen as a way forward to reducing the production of virgin plastics and the amount of plastic waste ending up in nature. In 2014, 18% of nonfiber plastic waste was recycled globally, with the highest recycling rates observed in the EU, at around 30% (Geyer et al., 2017). Thus, significant leaps are required to increase plastic recycling.

Previous research has identified several challenges in increasing the circulation of plastic waste that relate to different stages of the recycling value chain (Milios et al., 2018). For instance, increasing the separate collection of plastic waste calls for the development of the collection infrastructure (Gong et al., 2020; Hossain et al., 2022) and changes in user behavior (Allison et al., 2022). Furthermore, recycled plastics suffer from several quality-related problems, which call for improvements in product and packaging designs (Hahladakis and Iacovidou, 2018) and sorting and processing techniques (Paletta et al., 2019; Ragaert et al., 2017). Increasing plastic recycling also requires investments in new recycling capacity, which are challenged by the quality and availability of plastic waste streams, economic conundrums, and uncertainties linked to regulation (Bening et al., 2021; Siltaloppi and Jähi, 2021). Finally, increasing the use of recycled plastics requires upstream improvements in material supply, as well as the adaptation of product designs and production processes by converters and brand owners (Milios et al., 2018).

Creating an efficient and effective system for plastic recycling calls for a focus on the multiple distinct processes that make up the recycling value chain from collection to sorting, processing, and use. Previous studies have highlighted various challenges at different stages of the value chain and identified interactions between these stages (Bening et al., 2021; Milios et al., 2018; Siltaloppi and Jähi, 2021). However,

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https://doi.org/10.1016/j.jclepro.2023.136396
Received 26 August 2022; Received in revised form 3 February 2023; Accepted 8 February 2023
Available online 10 February 2023

there is a need for a fuller understanding of how improvements in different stages of the recycling value chain affect recycling outcomes and how improvements in specific stages are contingent on improvements elsewhere in the value chain. While these questions are partially addressed in simulation-based studies that assess the impact of interventions on the entire material flow system (e.g., Ghosh et al., 2023 Guzzo et al., 2022; Wang et al., 2020), these studies tend to narrow the scope of analysis to specific interventions and thus overlook the variety of potential interventions identified in qualitative studies. Hence, the purpose of this paper is to assess the plastic recycling material flow system at an aggregated scale to identify which stages, and combinations of stages, of the recycling value chain hold the greatest potential for improving recycling outcomes.

We approach this question with an exploratory stock-flow simulation model, which provides a complete (though coarse resolution) view of the recycling system. This approach draws on a systems-theoretical framework, which directs attention to the internal connectivity, boundaries, and openness of the material flow system. It is suited for analyzing possible outcomes following a wide variety of alternative interventions subject to many sources of uncertainty. Specifically, our case system is industrial and consumer packaging waste recycling in Finland. We simulate the effects of interventions at the four critical stages of the recycling value chain (collection, sorting, processing, and use/demand) on linear and circular flows. By varying uncertain parameters and testing extreme values at these key intervention points, the simulation results suggest that improvements at the four intervention points alone and in combination have different effects on linearity and circularity indicators. Uncertainties associated with import and export flows increase the variance of results, particularly with interventions targeting demand and processing capacity.

The findings contribute to research on plastic recycling by improving understanding of the critical bottlenecks in the plastic recycling system and the synergistic effects of supply- and demand-side interventions on reducing linear flows and increasing circular flows. The findings also enrich the understanding of how uncertainty affects the expected effectiveness of interventions. Methodologically, the results complement previous simulation studies by taking a coarse-resolution view of a broad system scope. We also show that many conclusions stem from the flow structure and openness of the material flow system rather than from specific parameter assumptions. The exploratory modeling approach provides a broad view of the impact potential of a large variety of potential interventions rather than specific interventions. In addition, this approach can generate knowledge about macroscale changes in recycling and other systemic contexts characterized by several uncertain parameters.

The remainder of this paper is structured as follows. Section 2 reviews the previous literature on plastic recycling. Section 3 presents our simulation approach and describes the model, its parameters, and test scenarios. Section 4 reports the results of the simulations and analyzes the key mechanisms that underpin the effects of alternative sets of interventions. Section 5 discusses the contributions and limitations of the study, and Section 6 provides a concluding summary.

2. Literature review

To address sustainability issues associated with the plastic value chain, improvements in the recycling of plastic waste are urgently needed. This need is reflected in several voluntary and policy-driven initiatives to increase plastic recycling (e.g., EASAC, 2020; Ellen MacArthur Foundation, 2016), such as the EU target to increase the recycling rate of plastics to 55% by 2030 (EU, 1994). From an operations standpoint, fulfilling these objectives calls for actions that increase the capacity of the entire recycling system so that a larger portion of the generated plastic waste can be processed into high-quality raw material. Ultimately, this can reduce the use of virgin plastics in manufacturing.

Four key stages can be identified in the plastic recycling value chain: collection, sorting, processing, and use. Each has distinct challenges in improving the quantity and quality of recycling material flows (e.g., Milios et al., 2018). First, the *collection* of plastic waste covers the activities needed to collect plastic waste from consumers and industry actors as a separate waste stream available for downstream processing. In the literature, the challenges of this stage are associated with user, particularly consumer, behavior in sorting plastic waste for separate collection (Allison et al., 2022; Ma et al., 2020). Other challenge areas include a lack of infrastructure for the separate collection of plastic waste (Gong et al., 2020; Hossain et al., 2022; Ma et al., 2020), operational challenges in waste logistics (Siltaloppi and Jähi, 2021), and missing economic incentives for waste management companies to develop effective collection systems (Milios et al., 2018).

Second, separately collected plastic waste moves to *sorting*, in which different polymers are sorted for downstream processing. At this stage, there are technical and cost limitations to technologies that identify and separate different polymers (Milios et al., 2018; Siltaloppi and Jähi, 2021). In addition, the lack of circular design principles in product and packaging design means that the waste stream consists of varied polymers that are challenging to separate. For instance, many waste items consist of multiple materials (e.g., laminated packaging), which prevent sorting and result in a higher number of rejects (Hahladakis and Iacovidou, 2018; Leal Filho et al., 2019).

Third, sorted waste streams are moved to *processing*, in which the plastic waste is turned into recycled plastic. Today, most plastic waste is processed using mechanical processing techniques, in which the plastic waste is washed, ground, and compounded into granulates. In addition, chemical processing techniques are emerging, in which plastic waste is processed into monomers or petrochemical feedstocks that can be used as raw material in plastic production (e.g., Kawashima et al., 2019; Ragaert et al., 2017). The challenges of mechanical processing are mainly related to the quality of recycled plastic, which is typically inferior to virgin plastics due to the color issues and contaminants present in the mixed plastic waste stream (Gong et al., 2020). Mechanical techniques cannot process certain fractions (Paletta et al., 2019). Furthermore, there is varying quality of plastic waste supply, high cost of processing, and uncertain demand for mechanically recycled plastics. In economic terms, these increase the risks of investing in technology development and new recycling capacity (Bening et al., 2021; Hossain et al., 2022; Milios et al., 2018; Siltaloppi and Jähi, 2021). Chemical recycling can solve quality issues but introduces higher energy demand and requires high volumes to achieve cost-effectiveness (Ragaert et al., 2017).

Finally, converters *use* recycled plastics for plastic procucts, parts and packaging. From a demand perspective, mechanically recycled plastics are typically inferior in quality than virgin plastics, but high processing costs mean that their price is close or equal to virgin plastics. Therefore, the use cases for recycled plastics are often limited (e.g., they cannot be used in food-safe packaging), and their business case relies on sustainability-related image benefits (Siltaloppi and Jähi, 2021). In addition, using recycled plastics requires investments in product design and more intensive collaboration with suppliers and downstream customers. This would secure both an adequate supply of raw materials and demand for products (Milios et al., 2018).

Overall, the literature focused on the qualitative assessment of development barriers reveals that recycling outcomes depend on improvements in multiple process stages. Each stage faces distinct challenges and can be influenced by various actions by the industry, government, and consumers. Moreover, dependencies exist between the process stages, calling for a systemic assessment of how actions by different stakeholders at different process stages interact to inhibit or enable desired changes (Bening et al., 2021; Siltaloppi and Jähi, 2021). For instance, increasing the collection rate of plastic waste may not generate more recycled plastics if available sorting techniques are inadequate or the processing capacity is not expanded (Dijkstra et al., 2020; Milios et al., 2018; Paletta et al., 2019; Siltaloppi and Jähi, 2021).

Simulation methods can represent such complex interconnections between the recycling process stages consistently and allow the conducting of tests on the impact of specific interventions. In previous studies, simulation methods have been utilized to assess accumulated material stocks (Ciacci et al., 2017; Jiang et al., 2020; Lee et al., 2015; Wang et al., 2018; Zhou et al., 2013) and to test the effects of specific interventions on parts of the plastic recycling system (e.g., Dhanshyam and Srivastava, 2021; Giannis et al., 2017; Kerdlap et al., 2022; Wang et al., 2018). A few studies have focused on the whole material flow system of plastic recycling. They simulate the sizes of different material flows, such as primary extraction and collection flows, and use these to estimate other indicators, such as life-cycle emissions and operational profits. For example, Wang et al. (2020) compared the effects of different policy interventions and identified a policy mix of industry subsidies, mandatory use of recycled materials in manufacturing, and deposit schemes as favorable to increasing the recycling of polyethylene terephthalate (PET) bottles. Similarly, Guzzo et al. (2022) compared collection-enhancing policy mixes, and Ghosh et al. (2023) provided evidence in support of combining collection interventions and chemical recycling.

While these studies provide evidence in favor of a combination of policy or industry interventions, they ultimately test a narrow selection of all reasonable options. As shown in our synthesis of qualitative studies, a very wide variety of intervention points and actions can have a significant impact on recycling material flows. Furthermore, impact assessment of specific actions relies strongly on validating the strength and form of causality between action and immediate effect. Such validation by questionnaires or statistics carries inherent uncertainty. Validation can be inaccurate due to sampling bias or, more subtly, inherently uncertain due to the unknown and assumed function forms used to describe causality (also known as model uncertainty; see, e.g., Pindyck, 2015). Breznau et al. (2022) report researchers arriving at opposite conclusions despite using the same data and hypotheses, highlighting that statistical validation does not remove uncertainty from policy impact assessment and other social research. While the social and behavioral aspects of recycling systems are uncertain, we point out that the sequence and direction of material flows in the system are more easily knowable. As illustrated later in this paper, the material flow structure can provide a sufficient basis for understanding the significance of each process stage to recycling outcomes.

We therefore argue that the literature has yet to take advantage of simulating the properties of a complete recycling material flow system. The significance of multiple process stages and the variety of potential interventions are highlighted in the qualitative literature. However, the simulation-based literature tends to opt for a narrower system scope or narrower sets of test cases. Studying the material flow system *as such* calls for a systems-theoretical framework, as opposed to a particular behavioral or institutional theory. Systems theory provides explanations based on *connectivity* rather than, for example, statistical tests or behavioral theory. We highlight three key claims of systems theory that frame our approach to studying recycling. First, a system is an abstract concept defined as a whole consisting of interacting elements that have some behavior over time (Meadows, 2008, p. 11). Second, how systems are identified in the real world and where system boundaries are set are a matter of interpretation and researcher perspective (Beer, 1966, pp. 241–243). Third, the analysis of systems can complement perspectives grounded in substance expertise (Mobus and Kalton, 2015, pp. 3–30). These premises allow us to identify a research object—the material flow system of plastic recycling—whose behavior is explained based on its internal interconnections rather than disciplinary frameworks (e.g., behavioral theories or engineering solutions concerning recycling).

3. Methods

3.1. Exploratory stock-flow modeling

To address the identified knowledge gaps, we modeled a case recycling system and investigated the potential of each process step to increase recycling by adopting an exploratory approach to stock-flow modeling. Exploratory modeling means using a variety of model assumptions to understand what could produce particular outcomes (Gelfert, 2016). This means that we model the material stocks and flows at a coarse resolution level, using relatively few variables to place more emphasis on exploring a wide variety of alternative interventions. This approach is particularly appropriate when there is no guiding theory to guide the selection of model assumptions and when significant uncertainties pertain to the model assumptions. Thus, the exploratory approach enables us to answer a “how-possibly” question (Massimi, 2019): *How* could the linearity/circularity of the plastic system *possibly* decline/increase, assuming improvements at different intervention points?

Exploratory modeling has been promoted as a response to uncertainty in the context of sustainability transition research (de Haan et al., 2016; Moallemi and Köhler, 2019; Moallemi et al., 2020). A particular source of uncertainty in sustainability transitions is that the decision-making rules of actors are complex and likely to change (Otto et al., 2020). In this paper, we do not adopt any particular assumptions regarding pro-recycling actions or their effects. Instead, we explore the potential effectiveness of interventions at critical stages in the recycling value chain and their combinations, as discussed in Section 2. The value chain stages are thus represented as intervention points, which capture the diverse array of policy and industry actions that can improve plastic recycling at a coarse resolution level.

3.2. Context of the model

Our model represents the plastic recycling system in Finland. Currently, a total of 330 kt of plastic waste is produced annually in Finland, of which approximately 150 kt is consumer and industrial packaging waste. However, only around 40 kt of the packaging waste is recycled as secondary material, and the rest is used in energy production. Thus, the current state is falling far short of EU policy targets to increase the recycling rate of plastic packaging waste to 50% by 2025 and 55% by 2030.

There are three partially overlapping systems for collecting and recycling packaging waste in Finland. First, PET beverage bottles are recycled within a deposit system run by the brewery industry’s Extended Producer Responsibility (EPR) organization. In this system, bottles are voluntarily collected at retail stores (incentivized by a deposit fee), transported and preprocessed by the contract partners of the EPR organization, and processed by different recycling operators in and outside Finland. Second, the recycling of industrial packaging waste is overseen by another EPR organization for companies that package goods or import packaged goods in different industries. In this system, the partner companies transport collected plastic waste separately to collection terminals, from where the material is moved to processing partners across the country. Third, the recycling of post-consumer plastic waste was previously organized under the second recycling system, with several hundred voluntary collection points set up across the country for consumers. Recently, however, the collection of post-consumer plastic waste has been integrated with municipal waste collection systems in several regions, in which plastic waste is collected separately from consumers and transported to processing operators. In all cases, the processing operators oversee the recycling operation and sell the recycled material to converters within and outside Finland.

3.3. Model scoping and data gathering

The model focuses on the recycling of *industrial and consumer plastic packaging waste* (systems two and three in Section 3.1) for three reasons. First, it is a key focus of current EU policy. Second, we excluded the separate collection of plastic bottles (system one) since its recycling rate is already above 90% and features relatively little potential for further improvement. This system is also entirely separate from the mixed packaging waste stream and implies different parametric conditions (e.g., demand for recycled PET is higher due to the high purity of clear, separately collected PET). Third, although improving the recycling of nonpackaging plastic waste (e.g., electronics components, construction materials) remains an important objective, it offers less intuitive generalizability for a macro-scale model than it is possible to represent for packaging waste. This is due to longer and varying life cycles, the use of specialized materials, and distinct processing steps needed in removal, collection, and recycling.

We also narrow the model scope to *monomaterial items*, that is, items of packaging that consist of one polymer type (e.g., low- or high-density polyethylene, polypropylene). Recycled monomaterial strains are suited to more diverse applications than multimaterial packaging items (e.g., laminated food packaging) and are economically more valuable. Furthermore, monomaterial items already make up a large share of packaging in use (based on the interviews, we used the assumption of 70–90%—see Table 1 and the Appendix). Thus, excluding multimaterial items narrows the scope of the model in a relatively minimal way while retaining focus on the more realistic material solutions. In the model, monomaterial products that are included in mixed strains notionally exit the system as rejects. This represents lost monomaterial potential and contributes to the bottleneck of recycled monomaterial supply.

We simulate the material flows as a single aggregated mass of monomaterial, although the interpretation needs to be that distinct material types would, in reality, be processed separately if they are to remain as monomaterials. Simulating a single material category across the material flow system allowed us to use just one set of uncertain parameters instead of as many multiples as there are different material categories (e.g., low- and high-density polyethylene, polypropylene, PET). This allowed us to focus on exploring alternative scenarios at the intervention point level as we performed simulations on all possible combinations of our four intervention points (see Section 3.4).

The model structure is based on previous literature describing the key stages of the plastic recycling value chain. In addition, we used information from 20 semi-structured interviews (see the Appendix) to contextualize the model to the Finnish context and the present challenges for recycling development at each stage of the value chain. The interviewees represented for-profit and nonprofit organizations involved in the recycling of plastic waste or the use of recycled plastics in products or packaging applications. The key parameters and parameter values in the model were based on publicly available quantitative data on plastic recycling in Finland. In addition, we conducted four follow-up interviews with informants who are experts in the Finnish recycling system to validate the model, key parameters, and parameter values.

Table 1
Model parameters.

Parameters	Units	Value	Directly affected flow (s)
Demand for recycled monoplastics at the start	kt/y	13	Ui_c
Collection rate at the start	% of end-of-life stream	30	Uo_l Uo_c
Sorting rate at the start	% of collected stream	35	Ci L
Processing capacity at the start	kt/y	52	Co Po_e
Total nondeposit monoplastic use	kt/y	116.5	Ui_l
Exported recycled plastics at the start	% of processing capacity	0	Po_e
Exported recycled plastic change	% points	0–50	Po_e
Imported collected plastics at the start	% of supply deficit	0	Pi_i
Imported collected plastic change	% points	0–50	Pi_i
Processor buffer size	Multiples of processor capacity per time step	2–6	Co

3.4. Model structure

The core mathematical elements of a stock-flow model are stock variables (accumulations of material; calculated as integrals; boxes in Fig. 1), flow variables that increase and decrease stocks at each time step (arrows connecting stocks in Fig. 1), and auxiliary variables that control how flows change as a function of other variables in the model (not visualized). We built the model using the system dynamics simulation software Vensim DSS 9.0.0.

The material flow structure and its notation are shown in Fig. 1. The model has three material stocks: plastics in use by consumers and industry (U), plastics in collection that are kept in high-purity monomaterial strains (C), and plastics in processing (P). Here, processing refers to the processing of plastic waste into recycled plastics to be used downstream in converting. The three stocks form a circular material flow loop. However, the material can also exit from and enter the system boundary (clouds in Fig. 1).

Primary plastic use represents a linear inflow (Ui_l —read "use inflow, linear"). Circular plastics (Ui_c) can be supplied by the domestic recycling system. The material that is not collected (Uo_c) is disposed of linearly (Uo_l)—in Finland, this is done predominantly by incineration. Sorting techniques may be used to create sorted strains of high-purity monomaterial supplies (Ci). Unsorted plastics do not, in reality, exit the logistics system; however, they notionally exit the continuous flow of monoplastic circulation (L). Collected materials flow to processing (Co) when domestic capacity permits. The collected material that cannot be absorbed by domestic processing capacity is exported (Co_e). Processors can also receive monomaterial supplies as imports (Pi_i) from outside the system. Besides providing circular plastics back to domestic use (Ui_c), processors can also export circular plastics (Po_e). Note that Ui_c can, in practice, represent the material that exits Finland for converting and reenters the country as plastic products. This flow is notionally internal to the system, as outputs from domestic processing return to domestic use.

We made three notable exclusions and assumptions in the material flow structure to allow for a meaningful analysis of the intervention points. An excluded material flow is the inflow of circular plastics to use U from outside the system. In other words, recycled plastics produced in other countries do not feature in tests, outcomes, or indicators. We also assumed that processors use domestic supplies C before resorting to imports Pi_i to fulfill processing capacity. However, processors first meet their export demand Po_e before supplying plastics for possible domestic demand Ui_c as supply permits. These choices allow the endogenous material bottlenecks that follow the continuous material flow stream to be revealed, as opposed to parametrically assuming an outcome (see Section 1 of the Appendix for further justification).

3.5. Parameters, scenarios, and indicators

Table 1 lists 10 key parameters in the model. Three parameters governing processor inflows and outflows are given ranges instead of a single value. In each scenario, including the baseline scenario, these ranges are sampled 200 times using Latin hypercube sampling. In other words, each of the 200 runs per scenario uses a unique combination of uncertain parameters. We further discuss how this method affects the

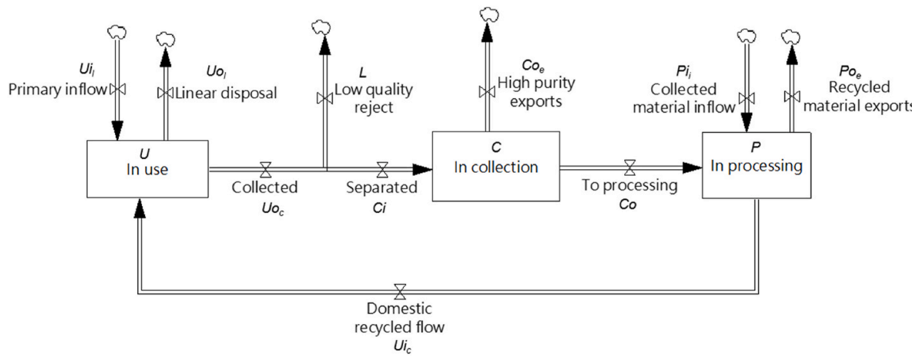

Fig. 1. Stock-flow model of the recycling of plastic packaging waste. Black arrows indicate the direction of flow.

interpretation of results in Section 3 of the Appendix. The sources and justifications for the parameter values are documented in Table A1 of the Appendix.

We based the test scenarios around the four critical intervention points that represented actions across the entire material flow system: "Demand," "Collection," "Sorting," and "Capacity." Our four single-intervention scenarios represented extreme or very large interventions at the intervention points (Table 2). In addition, we systematically explored all possible combinations of these intervention points. In total, we reported four single-intervention scenarios, six two-intervention scenarios, four three-intervention combinations, and one four-intervention scenario. Including the baseline, these amounted to 16 scenarios overall.

We also ran additional scenarios with uncertain starting state parameters and some modified parameters to prove the robustness of results and to better understand certain key mechanisms. These additional tests are reported in Section 7 of the Appendix.

All parameter changes in the scenarios were implemented as S-shaped increases (see Section 5 of the Appendix). The following is a list and interpretation of our baseline run and four single-intervention scenarios.

- **Baseline scenario**: No change over time in any of the four test parameters. However, the baseline includes changes due to (uncertain) changes in processor behavior. In other words, the baseline represents the possible outcomes of a do-nothing approach under the same (exogenous) uncertainties as other scenarios.
- **Demand scenario**: Demand for circular monoplastics increases significantly (e.g., converters/brand owners prioritize using recycled plastics for their monomaterial packaging). This can represent technical improvements in the quality of recycled plastics, the competitive price of recycled plastics, brand effects of recycled plastics, or regulatory requirements to use recycled plastics. The scenario sets a target for rate Ui_c, displacing Ui_l as much as supply P permits.
- **Collection scenario**: The collection rate increases to 100%. This would imply perfect collection behavior from packaging users and complete coverage of a collection and logistics infrastructure. It affects flows Uo_c and Uo_l.
- **Sorting scenario**: The sorting rate increases to 100%. This scenario can represent a combination of many types of changes: technical solutions to improve the sorting of plastic waste, disposal of plastic waste into separate collection bins by plastic types, or standardization of the variety of plastic types in circulation so that easily sorted plastics make up a larger share of collected plastics. It affects flows C_i and L.
- **Capacity scenario**: Processing capacity is increased by 50 kt annually, representing about a doubling of current and currently planned capacity. This intervention represents any actions that improve investment expectations for capacity expansion, such as improvements in the financial feasibility of recycling operations or available subsidies. It affects inflows to stock P, most directly Co and Po_e (exports are a fraction of capacity), and can indirectly affect Pi_i as a function of P.

Table 2
Scenario settings: the amounts of change applied to variables in each scenario.

Scenario name	Test parameter	Value	Notes
Demand	Domestic use of recycled monoplastics	+120 kt/y	Increase stops if the value reaches 131 kt/y, which is the maximum range of total plastic consumption
Collection	Collection rate	+70% points	Increase stops if the value reaches 100%
Sorting	Sorting rate	+70% points	Increase stops if the value reaches 100%
Capacity	Processing capacity	+50 kt/y	

We used three key indicators to compare the outcomes between scenarios (Table 3). The indicators seek to represent linearity and circularity separately since they are not symmetrical in an open system. Our system (Fig. 1) has two flows representing linearity: linear inflows (Ui_l) and linear outflows (Uo_l). We distinguish between the two since they serve as proxies for different environmentally problematic outcomes. Linear inflows represent the origin and dependency of plastics in the hydrocarbon industry, where ecological impacts are associated with the extraction and refinement of fossil raw materials for polymer production. Linear outflows represent emissions from incineration and lost opportunities to circulate materials. As our circularity indicator was circular flows, we selected the sum of high-purity secondary material inflows and outflows and the recycled materials flow to use Ui_c. These represent the closed-loop circulation of plastics in the value chain. In Section 4 of the Appendix, we discuss the reasoning for this indicator definition and explain how the time step values of variables are transformed to represent one-year flows for each indicator.

Note that for linear inflows and linear outflows, lower values are desirable. For circular flows, higher values are desirable. To make the comparison of results more intuitive, we used value-laden terms to

Table 3
Outcome indicators.

Indicator	Variable(s)	Notes
Linear inflows	Ui_l	Represents primary plastics flowing into the system
Linear outflows	Uo_l	Represents disposal in general waste, leading to incineration
Circular flows	Co_e+ Pi_i+ Po_e+ Ui_c	The sum of these variables represents "circularity" as resulting from the endogenous functions of the system; excludes low-quality circular plastics that are not sorted into monomaterial streams

reference the direction of change in results and the minima and maxima of the results. For instance, *reduction* in *minimum* linear outflow results would mean that the "optimistic" extreme of results "improves," or an *increase* in *minimum* circular flow results would mean that the "pessimistic" extreme of results "improves."

4. Results

Our results are variances and distributions following from a multitude of runs with a random sampling of uncertain parameters. The results are reported in Table 4 in terms of minimum and maximum values for each indicator at the end of each simulation. Since an increase in circular flows is desirable, while a decrease in both linearity indicators is desirable, we describe results in terms of "optimistic" and "pessimistic" extremes of results. We also present selected figures of scenarios that illustrate changes in indicators over time (more figures are provided in the Appendix). In these figures, the blue curve represents the result that follows when using the average value of the uncertain parameters. The colored area is the full variance, and the coloring provides information on distribution: 100% of results are within the gray area, 50% are within the blue area, and 10% are within the orange area. In Section 4.1, we first report some key system characteristics: baseline trends, how bottlenecks manifest in single-intervention scenarios, and how uncertainties affect these results. Section 4.2 identifies the synergistic outcomes of combined interventions. Section 4.3 discusses the robustness of the model.

4.1. Single-intervention scenarios

4.1.1. Baselines

Scenarios with interventions should be compared to the full variance of the baseline results. The baseline variance of results for circular flows increases over time, reaching 13–64 kt/y by the end of the simulation. The wide variance is due to uncertain import and export actions of processors, which make improvement in circular flows possible, even without our intervention scenarios. Linear inflows also show a small variance in baseline results. This is because, in a minority of runs, processor exports Po_e are so high that within-system recycled materials supply Ui_c cannot meet demand, and these materials are replaced by primary materials.

4.1.2. Maximizing demand for recycled plastics

Although we tested a recycled material demand increase of 120 kt and assumed direct displacement of linear inflows, the most optimistic reduction in linear inflows in the Demand scenario was ~40 kt. Furthermore, a rebounding trajectory can reverse all progress in linear inflow reduction (Fig. 2a). This occurs when processors momentarily deliver more materials domestically Ui_c than they can sustain in the long term, given the net effect of their material inflows and exports. Demand interventions are thus subject to a supply bottleneck in the system: the reduction in linear inflows is lower than our intervention size due to insufficient supplies. At worst, they are entirely ineffective at reducing national linear inflows, given uncertainties in the future export behavior of processors.

Technically, the duration for which the system can generate more recycled plastics domestically than it receives material supplies is governed by the size of the material stock P that processers target (controlled by parameter b; see Table 1). If outflows are higher than inflows, a rebound eventually occurs. Uncertainty regarding stock size, therefore, does not influence the existence of bottlenecks in the long term, but it could facilitate a shorter period of unbalanced processor flows without hitting a bottleneck.

Demand interventions can, in principle, improve circular flows by directing materials to domestic recycled use Ui_c. However, this effect is limited by processing capacity and the extent to which that capacity is already utilized, even before a demand intervention (Fig. 2b). Again, the key uncertainty is whether processors already operate at full capacity by importing and exporting materials across the system boundary.

4.1.3. Maximizing collection and sorting rates

A high collection or sorting rate supplies material downstream to the system, where it ends up in one of the possible circular flows. Both intervention points allow for improving pessimistic results substantially and narrowing the variance of the results. However, optimistic circular flow results counterintuitively decline in the Collection and Sorting scenarios compared to the baseline. This is because a more efficient collection and sorting system displaces two variables of the circular flow indicator: higher domestic collection C_o displaces collected plastics imports Pi_i and collected plastic exports Co_e. Collection is the only single-intervention scenario that affects linear outflows, and it does so directly without uncertain contingencies.

Table 4
End-of-simulation minimum and maximum results.

Scenario category	Scenario name	Linearity indicators				Circularity indicator	
		Linear outflows		Linear inflows		Circular flows	
		Min (optimistic)	Max (pessimistic)	Min (optimistic)	Max (pessimistic)	Min (pessimistic)	Max (optimistic)
Baseline	*Baseline*	81.6	81.6	103.5	110.2	12.9	63.7
Single-intervention scenarios	*Demand*	81.6	81.6	**65.0**	110.2	12.3	**93.0**
	Collection	**0.7**	**0.7**	103.5	103.5	**39.6**	40.4
	Sorting	81.6	81.6	103.5	103.5	**34.9**	41.3
	Capacity	81.6	81.6	103.5	110.0	13.6	**114.1**
Multi-intervention scenarios	*Demand–Collection*	**0.7**	**0.7**	64.7	**95.0***	39.9	67.0
	Demand–Sorting	81.6	81.6	64.7	**98.9***	35.0	70.9
	Demand–Capacity	81.6	81.6	**15.8^{A}**	110.4	12.3	**197.4^{C}**
	Collection–Capacity	**0.7**	**0.7**	103.5	103.5	19.8	87.5
	Collection–Sorting	**0.7**	**0.7**	103.5	103.5	**114.9^{B}**	115.1
	Sorting–Capacity	81.6	81.6	103.5	103.5	19.8	91.9
	Demand–Collection–Sorting	**0.7**	**0.7**	64.5	**90.3**	**114.9^{B}**	114.9
	Demand–Collection–Capacity	**0.7**	**0.7**	**15.8^{A}**	**96.2***	39.9	**175.4^{C}**
	Demand–Sorting–Capacity	81.6	81.6	**15.8^{A}**	**98.8***	34.9	**175.4^{C}**
	Collection–Sorting–Capacity	**0.7**	**0.7**	103.5	103.5	**113.2*^{B}**	114.9
	Demand–Collection–Sorting–Capacity	**0.7**	**0.7**	**15.0**	**65.2**	101.6*	114.9

Note: Bolded values are those we informally highlight as being among the best, comparing single-intervention and multi-intervention scenarios separately. If one result was best by a wide margin, we also bolded clusters of "runner up" results. Superscripted values are referred to in the text. Values with an asterisk are flagged in a robustness check (see Section 4.3).

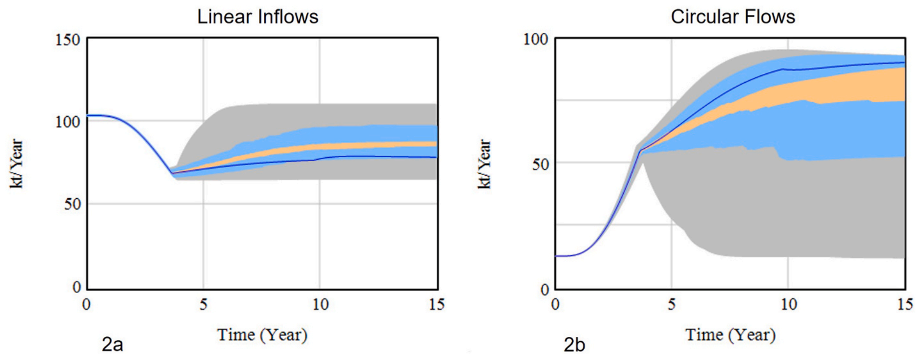

Fig. 2. Results for the Demand scenario.

4.1.4. *Increasing recycling capacity*

The Capacity scenario enables the best optimistic outcomes for circular flows out of all the single-intervention scenarios, while hardly improving pessimistic outcomes (Fig. 3). The Capacity scenario can improve circular flows substantially if either a) higher capacity is filled to a large degree with imports Pi_i and recycled plastics can be exported to foreign markets Po_e, or b) there is a simultaneous increase in the supply of domestic collected materials C. If, pessimistically, neither condition is met, capacity interventions make little difference to circular flows.

4.2. *Synergies in multi-intervention scenarios*

4.2.1. *Synergies for reducing linearity*

Optimistic results for the Demand–Capacity scenario are among the best we simulated (Fig. 4a). However, pessimistic results do not improve, given that the domestic supply of collected materials is not improved in this scenario, and net imports by processors are uncertain. We can demonstrate the significance of the import/export uncertainty by making an alternative assumption: imports always fill processing capacity if the domestic supply does not. In this case, the pessimistic results of the Demand–Capacity scenario improve substantially (Fig. 4b). Another way to improve the outcomes of the Demand-Capacity scenario would be to assume no exports: the 50% range in particular is restricted, implying a higher certainty of better outcomes (Fig. 4c).

Making all four interventions produces the best optimistic and pessimistic linear inflow results (Fig. 4d). Some three-intervention scenarios feature similar optimistic results (cells A, Table 4) but leave room to improve pessimistic results and feature the worst 50% ranges (see Appendix, Figs. A3 and A4). The Demand–Capacity scenarios with special import/export assumptions also achieve similar results to a four-intervention scenario (the variance in Fig. 4b is similar to Fig. 4d; the 50% and 10% ranges in Fig. 4c reach lower than in Fig. 4d).

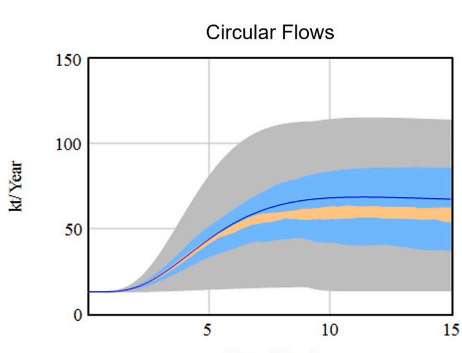

Fig. 3. Circular flow results for the Capacity scenario.

4.2.2. *Synergies for improving circularity*

Counterintuitively, combining all four pro-recycling interventions shows neither the best optimistic nor the best pessimistic circular flow outcome (Fig. 5a). The scenarios that include the Collection–Sorting combination show the best pessimistic results (cell B). The reason that pessimistic results in the four-intervention scenario are lower is that a demand or capacity bottleneck directs collected and sorted materials to circular uses anyway. If demand or capacity is increased, there will be higher use of collected materials Co (not accounted for in circular flows), which displaces collected material exports Co_e (accounted for in circular flows), while the import and export flows of processors (accounted for in circular flows) can remain low.

Scenarios that include the Demand–Capacity combination show the best optimistic results (cells C). These intervention points govern the upper limit of what is achievable (Fig. 5b). Making further supply interventions to increase domestic supply Co (not accounted for in circular flows) does not increase that upper limit but can instead retract from collected material exports Co_e and imports Pi_i (accounted for in circular flows). However, a Demand–Capacity combination leaves pessimistic results low.

4.3. *Sensitivity analysis*

We ran a sensitivity analysis on uncertain starting state parameters: domestic demand for recycled plastics, total demand for monomaterial plastic products, collection rate, sorting rate, and processing capacity. These results are reported in the Appendix. Using reasonable ranges of values did not change our assessment of the most effective (combinations of) intervention points (i.e., the bolded values in Table 4). In other words, the above model is robust against uncertainty regarding these state parameters. We do not need to know the exact current state of the system to identify high-impact intervention strategies.

That being said, different sizes of interventions would naturally affect the results. A special case of this issue is that since the effects of multiple interventions interact, we cannot be sure that high-effectiveness intervention combinations under our maximal test settings would remain so under more modest interventions. To test this, we reran all multi-intervention simulations while scaling down the interventions by 50%. These results are reported in the Appendix. In the minority of cases (6 out of 66 indicator values), our identification of highly effective scenarios changed (flagged in Table 4 with asterisks). The practical takeaway is that when case-specific policy targets or intervention strategies are known (e.g., targeting a specific collection rate: 50%), these should be factored into the analysis. The model remains valid for the purposes of this paper: to explore its *potential* effectiveness at different intervention points.

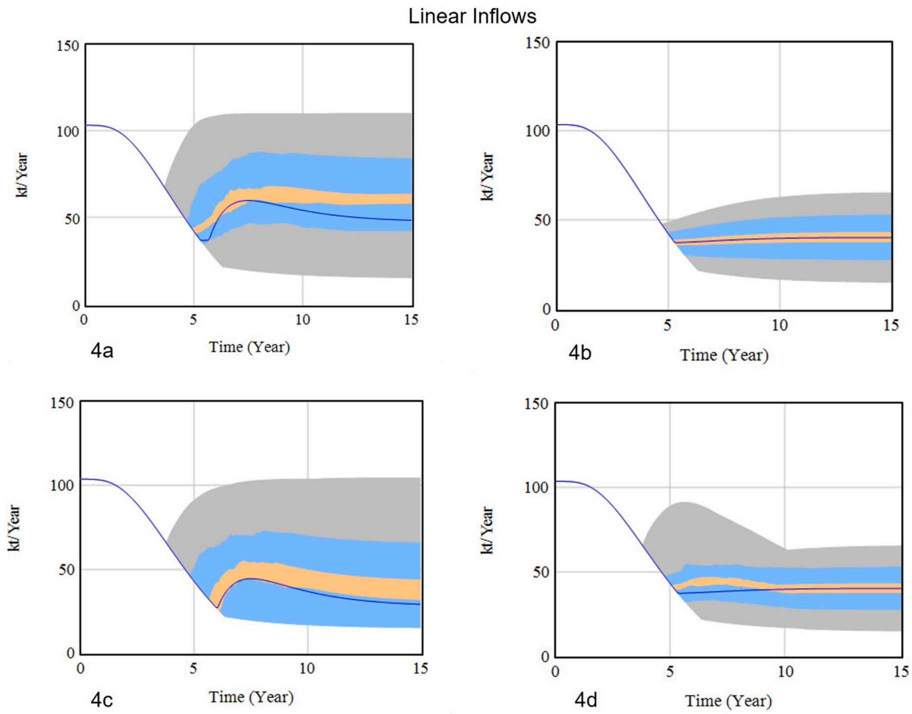

Fig. 4. Linear inflow results for three iterations of the Demand–Capacity scenario—standard assumptions (4a), maximum imports (4b), and no exports (4c)—and the four-intervention scenario (4d).

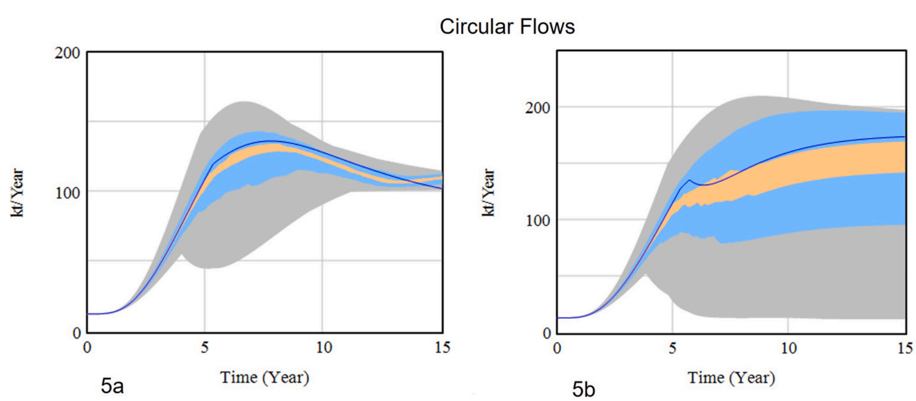

Fig. 5. Circular flow results for the four-intervention scenario (5a) and the Demand–Capacity scenario (5b).

5. Discussion

5.1. Contributions

These results provide substantive and methodological contributions to the existing research on plastic recycling. First, our simulation results draw attention to critical bottlenecks to increasing plastic recycling and emphasize the importance of simultaneous interventions at different stages of the value chain to achieve the best system-level outcomes. Thus, the findings substantiate previous research that calls for coordinated changes to the entire recycling value chain to achieve significant increases in the recycling of plastic waste (e.g., Milios et al., 2018; Siltaloppi and Jähi, 2021). Furthermore, we respond to the need to understand how challenges and interventions at multiple stages of the value chain interact in inhibiting or allowing increases in plastic recycling at the system level (Bening et al., 2021). Specifically, the findings draw attention to the synergies between supply- and demand-side interventions to achieve the best outcomes but also highlight differences in the effectiveness of different intervention combinations concerning different indicators. The highest reduction in primary plastic use was achieved by targeting all four intervention points. The best circularity results were achieved by combining either collection and sorting interventions or demand and capacity interventions, depending on how import/export flows develop. Uncertain starting state parameters had little effect on the conclusions.

Second, our findings complement previous simulation studies that tested the effects of specific interventions on recycling material flows (e.g., Ghosh et al., 2023; Guzzo et al., 2022; Wang et al., 2020). In particular, our intervention points approach provides a more holistic view of the effects of possible interventions in aggregate, rather than zooming in on the effects of specific actions. This improves the current understanding of the relative importance of different recycling value chain stages for increasing recycling without limiting conclusions to specific interventions. In addition, the findings draw attention to trade-offs between interventions, particularly concerning circularity. This suggests that there may not be one best strategy for improving “the whole recycling system,” as the assessment of different actions depends on the chosen performance indicators and uncertainties.

Third, our exploratory approach allowed us to bring forward some policy- and market-related uncertainties discussed in recent research (Bening et al., 2021; Leal Filho et al., 2019; Siltaloppi and Jähi, 2021). Overall, we considered uncertainties related to import and export flows, stock accumulation by processing operators, starting state parameters, and intervention sizes. The analyses show that exact starting state parameters did not influence the results, and the stock accumulation of processors influenced how indicators developed over time, but not whether a bottleneck dynamic exists. However, uncertainties in import and export flows had a significant impact on the range of results, particularly for demand- and capacity-targeting interventions, which were critical to achieving the best simulation results. Thus, the findings accentuate the importance of actions that reduce uncertainty at these key stages of the value chain. As discussed in recent literature, proactive efforts to alleviate uncertainties (e.g., in the availability of waste streams, market demand for recycled plastics, and policy conditions) can support industry actors in committing resources to technology development, new recycling capacity, and the use of recycled plastics (Bening et al., 2021; Milios et al., 2018; Siltaloppi and Jähi, 2021).

Finally, the findings demonstrate the value of the exploratory and coarse resolution modeling approach in offering a practical way to analyze complex systems characterized by several sources of uncertainty. This pertains not only to the analysis of plastic recycling systems but also to a wider array of management, policymaking, and sustainability transition contexts (Wiman et al., 2022). In this paper, using a small number of intervention points on an aggregated system instead of a large number of actions and product or user cases allowed for systematically exploring all possible combinations of intervention points. Since detail per se does not increase a model's predictive or explanatory power (Puy et al., 2021), the iterative search for "what matters" in a complex system can be more important than targeting the most detailed knowledge of mechanisms. Our results showed that it was possible to increase understanding of the properties of a recycling system based on a qualitative system structure, modest parametrization, and no assumptions regarding how actors might react to policy. Furthermore, we could show that starting state parameters matter little to conclusions.

5.2. Limitations and future research avenues

The limitations of this study relate to the selection of the system boundary and the treatment of all interventions as independent. Starting with the former, the national scope of the study meant that our circularity indicator could not account for the effects that stem from the interaction of national systems. For instance, the model did not have a mechanism for deciding whether exported recycled materials displace primary or recycled materials or add to materials used in other countries. We also could not include the import of recycled plastics (post-processing but pre-converting) as this would have fed an assumption directly to our results, specifically the linearity indicator.

Overcoming issues arising from import/export flows would likely require selecting a real-world material flow system in which (nearly) all circular flows are internal to the system. Future research could simulate the effects of different interventions with an international model scope, such as in the context of the EU, where developments are aligned with common EU directives. An international scope could also allow other research questions to be answered. These include how varying policies between countries influence import and export flows, how the clustering of plastic product manufacturing in different regions influences demand and thus the direction of import/export flows, and how imports/exports offer ways for national systems to exploit loopholes in regulations, thus impacting overall recycling rates at an international level.

In the simulation model, we treated all interventions as independent. While this allowed for the systematic exploration of different combinations of pro-recycling actions, it prevented us from considering the potential co-influence of interventions. For instance, demand-targeting interventions (such as mandatory recycled content) can address some of the obstacles to investing in new processing capacity. Similarly, demand- and capacity-related decisions can be influenced by the quantity and quality of available waste streams for processing. Quality, in turn, depends on the actions of a wide variety of stakeholders, such as product designers, waste management companies, and consumers. Without a specific theory of change, our approach was not to incorporate uncertain co-influences in the model. Future research is thus needed to explore realistic social and industrial dynamics that can generate (or inhibit) long-term increases in plastic recycling. Such research can benefit from our exploratory findings by selecting some of our promising material flow synergies (e.g., Demand–Capacity or the four-intervention scenario).

New forms of collaboration are needed to achieve significant increases in plastic recycling, both between industry actors (e.g., Milios et al., 2018; Paletta et al., 2019; Siltaloppi and Jähi, 2021) and between industry and policymakers (Bening et al., 2021; Leal Filho et al., 2019). The variances in our results resulting from specific uncertain parameters reinforce this observation, calling for future work to explore ways in which collaborative actions can be directed toward shared system-level objectives. For instance, the research could more deeply examine the influence of binding regulations and supportive policy tools, such as R&D funding, on joint innovation and business activities in plastic recycling and its value chains (Bening et al., 2021). In addition, future research could investigate different ecosystem arrangements as ways of orchestrating industry activities toward desired system-level circular economy objectives (Aarikka-Stenroos et al., 2021; Thomas and Autio, 2020).

6. Conclusion

With the growing concern about the negative environmental implications of plastics (Geyer et al., 2017), recycling is seen as an effective way to reduce the leakage of plastic waste into natural environments and decouple plastic production from fossil raw materials. Achieving significant increases in plastic recycling calls for solutions at all stages of the plastic recycling value chain. Previous literature has established a detailed understanding of challenges at each stage of the recycling value chain in isolation, identified interconnections between the stages, and simulated the effects of specific interventions on material flows. A more holistic view of the effectiveness of interventions across the value chain has been missing.

We applied an exploratory stock-flow modeling approach in the context of the plastic recycling system for industrial and post-consumer packaging waste in Finland. The findings of this paper enrich the existing literature by identifying how interventions at different stages of the recycling value chain can synergistically affect improvements in linear and circular material flows across the system, as well as on the sensitivity of such effects to variance in uncertain parameters. Furthermore, the findings demonstrate the value of exploratory modeling in accounting for various assumptions concerning the material flow system and enabling the analysis of a wide variety of potential interventions without making assumptions about the behavior of different stakeholders linked to specific interventions. Thus, besides improving the current understanding of the actions needed to increase plastic recycling, the findings also offer methodological insights that can benefit research on the circular economy more broadly. Future research can benefit particularly from understanding the import and export behaviors of national recycling systems and the co-influence of different stakeholders and institutions within recycling systems.

CRediT authorship contribution statement

Henri Wiman: Conceptualization, Investigation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Jaakko Siltaloppi:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Anna Leinonen:**

Conceptualization, Investigation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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.

Data availability

All data and functions used are documented in the appendix

Acknowledgments

This research was funded by the Strategic Research Council of the Academy of Finland, grant number 352439.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.136396.

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