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METHODS ARTICLE

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Regional sensitivity analysis to assess critical parameters in circular economy interventions

An application to the dynamic MFA model

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Abstract

In evaluating a circular economy (CE), one needs to address the complexity arising from indicators with multiple objectives, multiple means of implementation with combinations of CE strategies, and the uncertainty inherent in resource cycle systems. Regional sensitivity analysis (RSA) is a version of global sensitivity analysis that can be used to determine whether the output variables of a mathematical model lie within a certain range. Although RSA has found application in a wide range of fields, no prior studies sought to apply the method to industrial ecology. In this study, RSA is applied to a dynamic material flow analysis (MFA) model to identify the essential factors and analyze the conditions under which two indicators, greenhouse gas emissions and total material requirement, are influenced, in the case studies for digital cameras and smartphones. To this end, RSA with 10,000 Monte Carlo simulations were performed. Two factors were found to be especially important: (1) controlling the collection channels of end-of-life products, and (2) encouraging consumers to use products over a longer period. It was also suggested that, for ambitious reductions in environmental impacts, the achievement of targets should be given priority over the speed of implementation of strategies. To avoid catastrophic environmental impacts, the first step should be to ensure higher recycling rates using well-developed collection routes. This study represents a major step forward from simply forecasting future cycles with the dynamic MFA model to the application of RSA to systematically consider parameter uncertainties with various possibilities of combined circular economy strategies.

KEYWORDS
circular economy, dynamic MFA, global sensitivity analysis, multiple objectives, parameter space, regional sensitivity analysis

1 | INTRODUCTION

In assessing a circular economy (CE), one must address the complexity that arises from indicators with multiple objectives, multiple means of implementation with combinations of CE strategies, and the inherent uncertainties that exist in resource circulation systems. The Ellen MacArthur Foundation (Ellen MacArthur Foundation, n.d.) identifies the challenges of CE as tackling climate change and other global issues while simultaneously addressing important social needs. From such observations, it is apparent that creating a CE is not an end in itself but rather represents a way of approaching diverse issues and objectives. Thus, when implementing CE strategies, it is necessary to focus not only on resource circularity but also on the environmental impacts of the strategy. The implementation of CE strategies does not necessarily mitigate environmental impacts harmoniously; rather, trade-offs may occur, involving, for example, the risk of backfire effects as identified by a recent systematic literature review of CE strategies (Koide et al., 2022). Various indicators have been proposed to measure circularity (Moraga et al., 2019), meaning progress toward CE. However, it has proven difficult to unify these indicators into a single indicator with a view toward a cross-sectional evaluation, largely due to the potential trade-offs among them.

An additional complexity arises from the variety of CE strategies available and the possibility of combining strategies. CE strategies include not only recycling and reuse but also remanufacturing, where parts of used products are reused to produce products equivalent to new ones. Long-life design, repair, and maintenance to extend the lifetime of products are also effective strategies, as are rental, leasing, and sharing whereby multiple consumers use but do not own a product (Lüdeke-Freund et al., 2019; Salvador et al., 2021). While a majority of existing studies assessing the environmental impacts of CE strategies have considered only individual CE strategies, ignoring the possibility of a parallel implementation of multiple strategies or the interactions among strategies (Cordella et al., 2021; Makov & Vivanco, 2018), such complexity needs to be explored. The aforementioned review pointed to the importance and potential of combining strategies through comparisons (e.g., rental vs. reuse) and a consideration of multiple strategy scenarios (e.g., combining rental and remanufacturing) (Koide et al., 2022).

Importantly, however, even if the complexities related to multiple objectives and strategies are addressed, identifying a suitable CE strategy requires a systematic consideration of uncertainties. The resource cycle is subject to various uncertainties, including fluctuations in demand, diverse user behaviors, an unstable supply of natural resources, and fluctuations in supply prices. To deal with these uncertainties, sensitivity analysis methods have been developed to analyze the contribution of the various input variables included in a mathematical model to the uncertainty of the output variables(Saltelli et al., 2004). Sensitivity analysis can deepen our understanding of the conditions underlying the output variables through a systematic exploration of the key input variables (European Commission, 2023). The objectives of sensitivity analysis in environmental models have been grouped into three categories: (i) screening, which identifies variables that have negligible effects on the results; (ii) ranking, which ranks variables according to their effects on the results; and (iii) mapping, which identifies the range of input variables that lead to significant or extreme results (Pianosi et al., 2016). When examining CE strategies to support decision-making that relates to their social implementation, a sensitivity analysis method for mapping can be used to quantitatively identify the conditions that lead to desirable results.

Among the various methods of sensitivity analysis, global sensitivity analysis (GSA) considers changes in multiple input variables simultaneously to account for discontinuities in the response of the output variables to the input variables, as well as the interactions between the input variables. In GSA, each input variable is given a distribution; the corresponding output variable distribution is then obtained by repeatedly running the model according to this distribution using Monte Carlo methods (Azzini et al., 2020). Several applications of global sensitivity analysis can be found in the field of material flow analysis (MFA) and life cycle assessment (LCA). For example, Qin and Suh (2021) identified Sobol's total effect approach as the most reliable method used in the existing literature for analyzing uncertainty in LCA. Džubur et al. (2017) identified several global sensitivity analysis methods for dynamic MFA, which similarly focus on the uncertainty of the output variable and its variance. As all these studies focus on improving the reliability of their results, sensitivity analysis focusing on variance has been adopted as the preferred method. However, to our knowledge, there has been no study that applies a non-variance-focused global sensitivity analysis in the field of MFA and MSA. Variance-focused methods such as Sobol's method quantify the extent to which input parameters explain the variances of the output indicators and thus identify only the relative explanatory importance of the input parameters. However, to support decision-making for the transition to a circular economy, we need to be concerned with whether the outputs are within a particular range; for example, do they satisfy a specific threshold of environmental impact or resource efficiency?

To overcome the limitations of the prevailing approach, this study uses regional sensitivity analysis (RSA), which is one of the few sensitivity methods for mapping that filters the output variables generated by the Monte Carlo method according to whether they are within or outside a given level and analyzes the contribution of the input variables to the difference between the two groups and the regions of the input variables corresponding to the two groups. Originally proposed for use in models related to environmental improvement (Spear & Hornberger, 1980; Young et al., 1978), the method can be used without relying on the structure of the model. Moreover, there are no restrictions on the sampling method employed and is easy to interpret. As a result, the method has been applied to a wide range of mathematical models in a variety of fields, from epidemiology to plant behavior and from explanatory models to stochastic models. However, the application of this method to the field of industrial ecology has yet to be explored.

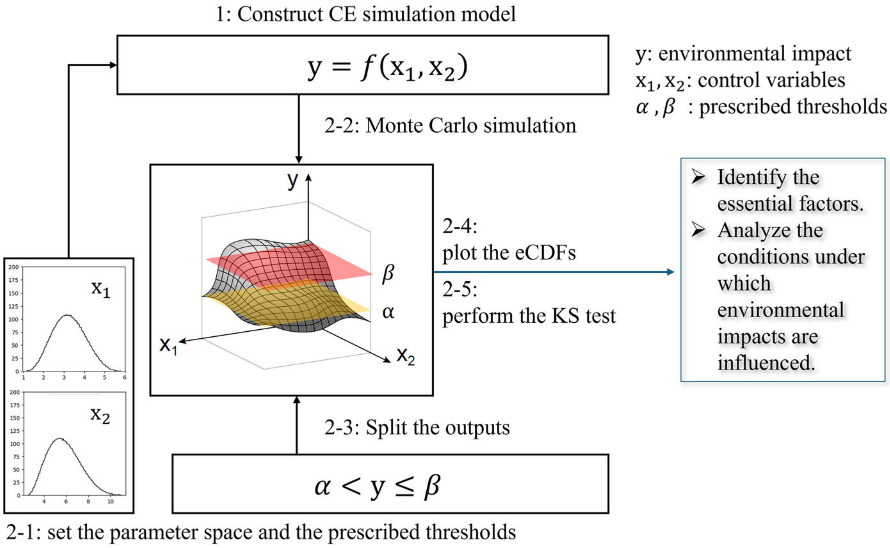

FIGURE 1 The procedures used in this study. Procedure 1 corresponds to Section 2.2, and procedures 2-1 through 2-5 correspond to steps 1 through 5 described in Section 2.3.

This study aims to apply the RSA method to support better decision-making in the implementation of a CE, taking into account multiple CE strategies and indicators. Specifically, we apply the RSA method to a dynamic MFA model in a case study involving consumer durables, focusing on two indicators: greenhouse gas (GHG) emissions and total material requirement (TMR). To demonstrate the usefulness and applicability of the RSA method to the dynamic MFA model for analyzing the benefits of introducing CE strategies, a case study featuring the reuse, rental, manufacturing, and recycling of two consumer durables in the Japanese market—digital cameras and smartphones—was used. By conducting Monte Carlo simulations on parameter spaces for the implementation of CE strategies and filtering outputs, we identify those factors that increase the impact of strategy implementation and analyze the conditions that these factors must satisfy. Finally, policy recommendations for promoting a better circulation of home electronics are derived to illustrate how an analysis based on the RSA method works.

2 | METHODS

2.1 | Overview of the procedure

Figure 1 describes the procedure followed in this study. First, a general dynamic MFA model that can be applied to the product of interest was constructed (see Section 2.2). Next, the range and distribution of the model's operating variables were assigned. RSA was then performed based on the model and operating variable settings for specific small household appliances (See Section 2.3). TMR, the residuals from processing, and GHG emissions were used as the outputs. As noted above, the devices featured in the case study were digital cameras and smartphones.

2.2 | Dynamic MFA model

Figure 2 gives an overview of the simulation model. Five CE strategies were selected for the model. The implementation rate for each CE strategy and other factors were input as the operating variables. The two evaluation indicators were calculated as the output. The data stored in the model, such as past shipments, the number of discharged units, and the duration of use (DoU) distribution, were also treated as input variables. The system boundaries were the domestic stock and flow of the product of interest, as shown in Figure S2 of Supporting Information S1. It was assumed that used products were never exported. Details of their setting in the model are described in Supporting Information S1 (section S1.1).

Figure 3 shows how the stock and flow of the product are modeled. The number of units in use and the number of units out of use for a given product in a year are obtained from the distribution of past shipments and DoUs using the population balance model (Himmelblau & Bischoff, 1968), a method for calculating the balance of material distribution in a space with external and internal coordinates. For the product DoU distribution, we utilized the Weibull distribution, a commonly used parametric function, estimated in Yamamoto et al. (2022).

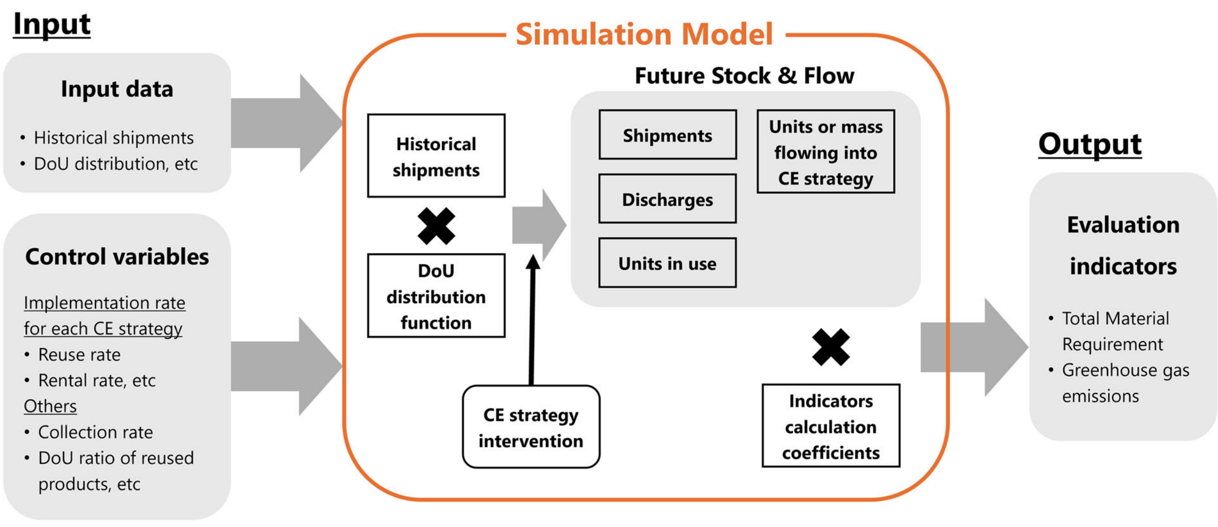

FIGURE 2 Overview of the simulation model.

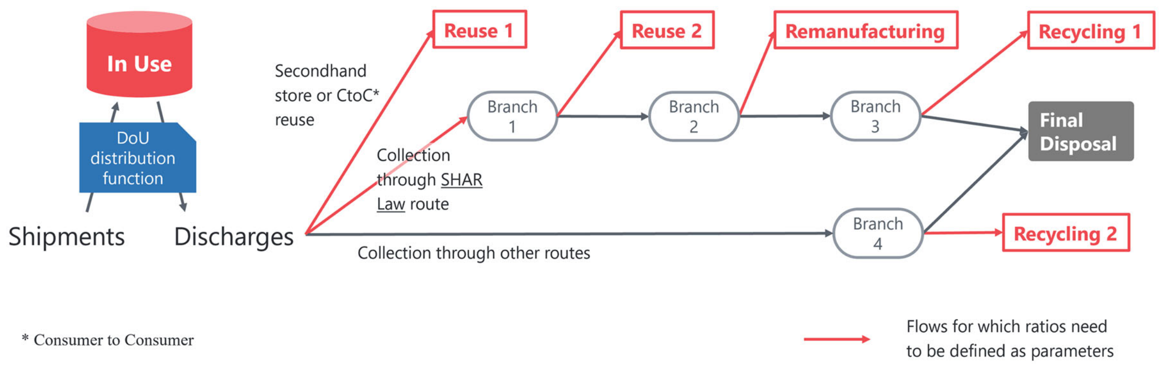

FIGURE 3 Overview of the product flow.

After use, the discharged products are divided into three categories: reuse, collection through routes that can be managed as a society (i.e., within the recycling laws and other schemes), and collection through other routes (i.e., those discharged without separation such as household general waste, which are not subsequently sorted or collected).

Products collected according to existing recycling laws were determined, on a stepwise basis, to be either reused, remanufactured, or recycled. Those not flowing into any of the three categories are passed to incineration or final disposal as residue. Products collected through other routes flow into either recycling or incineration/final disposal. Since there are two distinct routes to reuse and recycling, they are referred to as reuse1/reuse2 and recycle1/recycle2, respectively. The amount of flow into each category is determined by the control variables (collection rate, reuse rate 1, reuse rate 2, remanufacturing rate, recycling rate 1, and recycling rate 2), defined as the ratio of the flow to the previous treatment or event being considered. For example, the denominator in calculating the remanufacturing rate is not the number of units discarded or the number of units collected, but rather it is the number of units that were the subject of a remanufacturing decision. The DoU of reused products is derived using the Weibull distribution estimated in Yamamoto et al. (2022) with scaling parameters modified by the variable DoU ratio of reused products.

The model also considers DoU extension and rental as other CE strategies. DoU extension includes maintenance, repair, and extension of the product life through improved product design; the degree of extension was defined by the variable DoU extension ratio. Rental is described by the variables rental period, usage frequency ratio of rental products, and rental rate of new products in each year.

Each of the CE strategy adoption rates described above is assigned a target value by the end of the strategy implementation period, which is also a control variable in the model. That is, the implementation rate for each CE strategy is assumed to increase linearly from the first year of the simulation, reaching a specified maximum value in the final year of the CE implementation period, respectively.

In the case study, two small home appliances, digital cameras and smartphones, were targeted. These two consumer durables, both subject to the Act on the Promotion of Recycling for Small Waste Electrical and Electronic Equipment (hereinafter referred to as the SHAR Law), which allows flexibility in the design of collection and disposal schemes, were thought to be appropriate targets for the flexible exploration of circular strategies. In addition to having more complete data than other products, we believed that beneficial suggestions were likely to arise from a comparison of

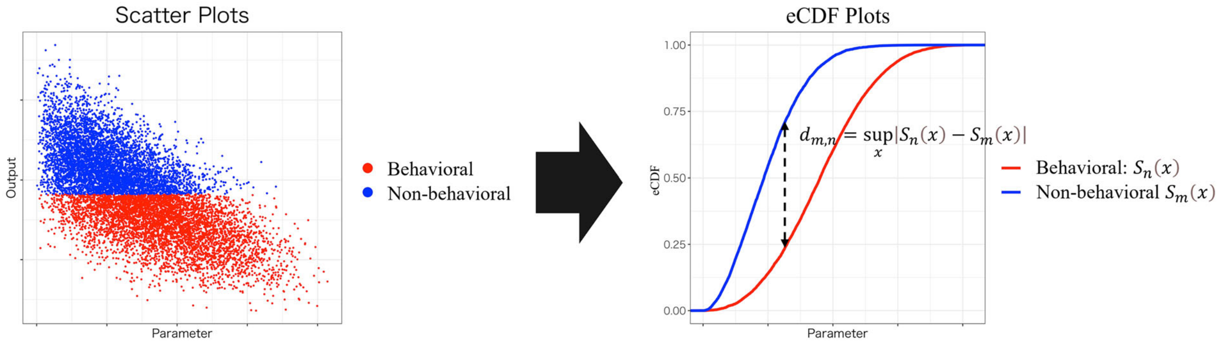

FIGURE 4 Empirical cumulative distribution function (eCDF) plots for the two groups. $S_n(x)$ denotes the eCDF for the behavioral group; $S_m(x)$ denotes the eCDF for the non-behavioral group. The test statistic $d_{m,n}$ is the maximum distance between $S_n(x)$ and $S_m(x)$; for example, in the case of the figure, $d_{m,n}$ is 0.47. If whether or not the parameter x exceeds a certain value determines whether the corresponding output belongs to the behavioral or non-behavioral group, then $d_{m,n}$ is 1.

results for two products having contrasting characteristics, which could include characteristics like product composition or trends in shipment levels. The period covered in the study is from 2021 to 2050. Table S2 of Supporting Information S1 summarizes the data that were used. Table S3 of Supporting Information S1 provides basic information on digital cameras and smartphones.

Various indicators are available to evaluate resource circulation. On the input side, we used TMR as our primary indicator. It consists of direct material input, which measures the total domestic input of natural resources and other inputs, plus any hidden domestic or international flows. Since hidden flows include the exposed soil and debris generated during resource extraction, TMR can be considered an approximate indicator of the scale of alterations to the Earth associated with system inputs. In addition, GHG emissions are used as a representative indicator of environmental impact to quantitatively evaluate the rebound effect identified in previous studies (Amasawa et al., 2020; Makov & Font Vivanco, 2018; Sai et al., 2023).

Cumulative totals for the simulation period were used to calculate the values of the evaluation indicators; that is, in the simulations performed for the period from 2021 to 2050, the cumulative totals calculated through each of the 30 years served as the indicator value. In the discussions that follow, the terms TMR and GHG emissions refer to these cumulative values unless otherwise noted.

In the TMR calculation, the quantity of natural resources altered by infrastructure development (factories, landfills, transportation, etc.), referred to as disturbed flows in the hidden material flows, are considered to be beyond the scope of this study. TMR does take into account ancillary flows, which are the quantities of materials that are the inevitable consequence of economic action, such as the rock and earth associated with the mining of ore. GHG emissions are calculated for each phase in the life cycle of two products with reference to Sai et al. (2023) and Cordella et al. (2021).

2.3 | Regional sensitivity analysis

RSA, a sensitivity method first proposed in the 1970s, can be used to identify the input variable conditions that produce the results of interest from the probability distributions of the variables (Saltelli et al., 2004). It can also be used in the ranking of parameters to measure the magnitude of each parameter's influence.

The basic RSA workflow consists of five steps (Song et al., 2015):

1. Establish a prior distribution of the parameters from which the results of Monte Carlo sampling will be drawn, together with the binary criteria that will be used to split the results into two groups.
2. Run the model with a set of parameters based on a Monte Carlo sampling design.
3. Split the results into two groups: the behavioral group and the non-behavioral group. The behavioral group satisfies the result of interest (e.g., meets a certain environmental threshold) and the non-behavioral group does not.
4. Plot the empirical cumulative distribution function (eCDF) for each group for each parameter value (Figure 4).
5. For each parameter, focus on the eCDFs and test whether there is a significant difference between them using the two-sample Kolmogorov–Smirnov (KS) test (Conover, 1980).

Using the analytical procedure described in Supporting Information S1 (section S1.2.1), the test statistic $d_{m,n}$ can be obtained for each input variable. These statistics represent the maximum gap exhibited in the eCDF for the parameters between the behavioral group and the non-behavioral group (Figure 4). For parameters that are found to be significant in the KS test, the statistics can be taken as "the magnitude of influence that a parameter has on the evaluation indicator." The positional relationship between the two eCDFs also enables us to establish the direction of the

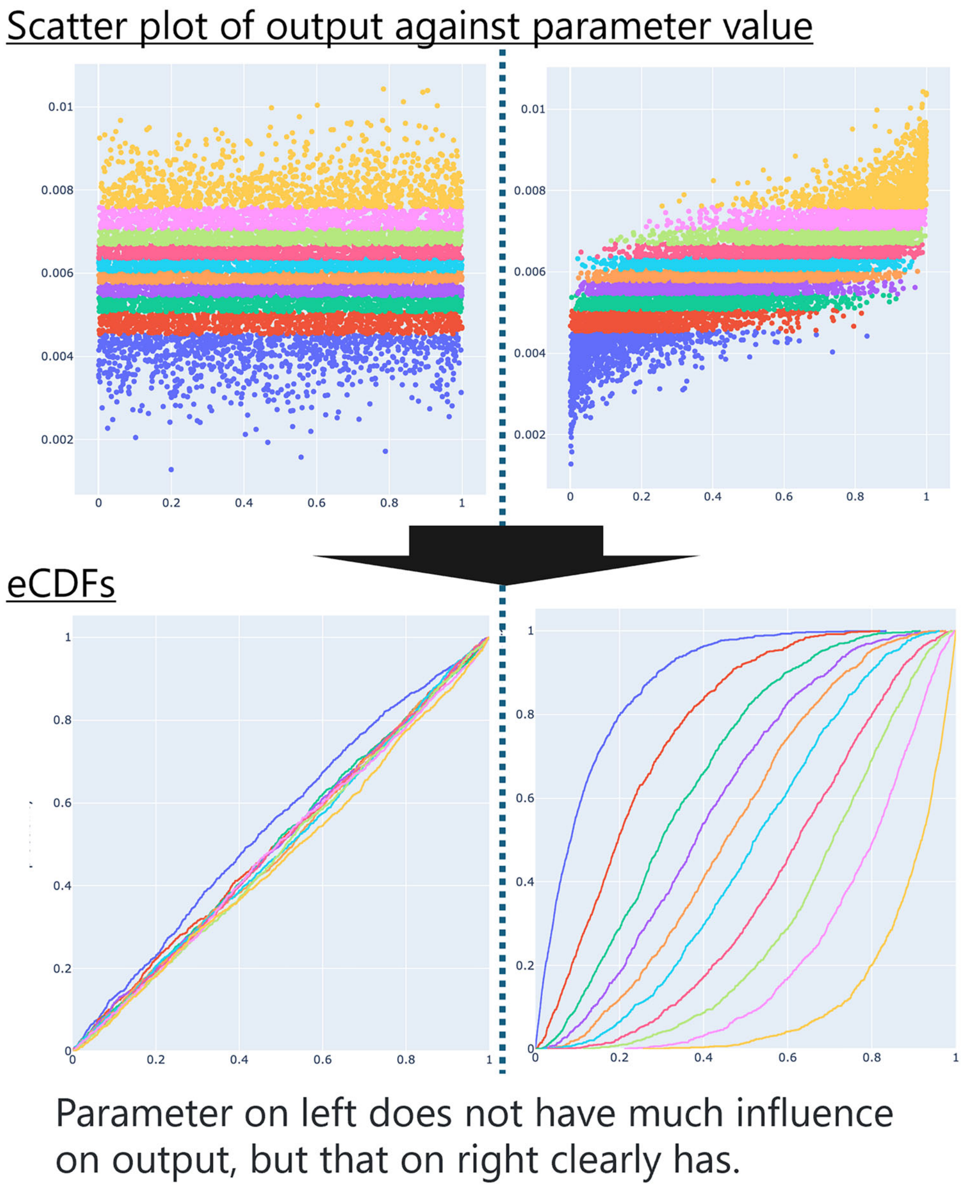

FIGURE 5 Formation of 10 groups based on ordered list, and comparison of empirical cumulative distribution functions (eCDFs).

influence of the parameters on the evaluation indicator. For example, if the eCDF for the behavioral group is located to the right of that of the non-behavioral group, a higher value of that parameter indicates that it tends to lead to the result of interest.

In RSA, the user decides what binary criteria will be used to separate the results to be focused on from other results. Understandably, such subjectivity has been identified as a potential problem (Song et al., 2015). One way to solve this problem is to sort the output values of interest, form groups based on an ordered list of the values, and compare the eCDFs for the identified groups (Wagener et al., 2001). Figure 5 shows an example using 10 groups.

It should also be noted that since RSA is unable to analyze higher-order interactions between variables, finding no significant difference between two distributions does not necessarily mean that the input variables are irrelevant to the results. This point should be kept in mind when interpreting the results of the KS test.

In this study, the prior distributions were determined using the mode, the maximum, and the minimum values for each variable, as shown in Table S4 of Supporting Information S1 (step 1). A total of 10,000 parameter sets were generated using Monte Carlo simulation (step 2). Before performing step 3 (and later), the eCDFs for 10 groups were plotted to establish whether a characteristic trend exists between the operating and output variables (Figure 5). Binary criteria were then used to divide the results into two groups—in this case, the top 10% and the bottom 10%—for each indicator and both of them (step 3 and later). Significant differences between the two groups for each operating variable were determined using the KS test.

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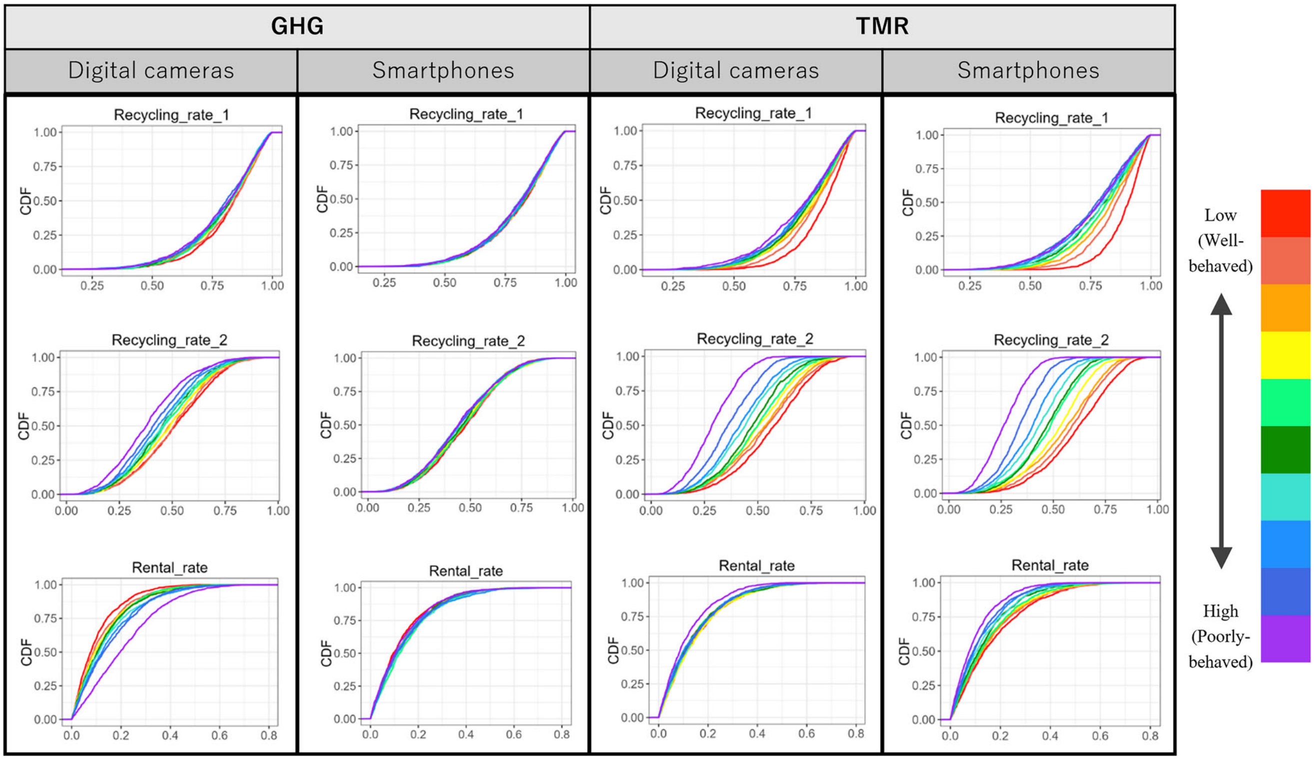

FIGURE 6 Selected empirical cumulative distribution functions (eCDFs). The underlying data for this figure are available in Supporting Information S2. GHG, greenhouse gas; TMR, total material requirement.

3 | RESULTS

For each evaluation indicator, the simulation results were arranged from lowest to highest value and divided into 10 groups. The eCDFs for nearly all parameters were found to be aligned according to the group order. However, a closer look at the eCDFs reveals that the gap between the groups for some parameters is quite small. Figure 6 shows the eCDFs for three of the operating variables for GHG emissions and TMR. For TMR, recycling rate 2 for both products shows a particularly large eCDF gap for the group with the worst results. In contrast, recycling rate 1 for TMR for both products, but especially for smartphones, shows the opposite trend, that is, the better the results are between the groups, the larger the gap between the eCDFs. However, these parameters have little impact on GHG emissions. For rental rate, the direction of the contribution for both indicators is reversed for digital cameras, while in all cases, a difference opens up when the load is large. The other variables that showed a gap between the eCDFs of certain groups for GHG emissions were strategy implementation period and reuse rate 1 for both devices and remanufacture rate for digital cameras. The collection rate shows a characteristic trend in TMR for smartphones (see Figure S3 to S6 of Supporting Information S1).

Table 1 shows the two-group KS test statistics using the top 10% and bottom 10% as binary criteria. The values shown provide a basis for discussing the impact of each of the variables quantitatively. In particular, for digital cameras, the collection rate and recycling rate 2 had a significant impact on TMR, while reuse rate 1 had the greatest impact on GHG emissions. For smartphones, the collection rate and recycling rate 2 were found to have a significant impact on TMR, similar to the results for digital cameras, while the reuse rate 1 as well as the DoU extension ratio were found to have a very significant impact on GHG emissions. When the criteria for classification into a behavioral group were used as being in the top 10% or bottom 10% in terms of both TMR and GHG emissions, the impact of each parameter was generally the average of its respective impacts on the two indicators.

Measures to increase the amount of recycling are shown to have a strong impact on TMR. This is because the study assumes that the recycling process can recover precious metals that have very high TMR coefficients with high yields. The large impact of the collection rate on TMR can be attributed to Japan's SHAR law, under which a very high percentage of the discharged products that are collected flow into the recycling process. This means that an increase in the collection rate directly translates into an increase in the amount of recycled materials.

In terms of GHG emissions, reuse rate 1 was shown to have an especially large impact as it eliminates GHG emissions associated with the manufacturing process, the biggest contributor to GHG emissions in the product life cycle. Since GHG emissions from the manufacturing process account for a particularly large share of GHG emissions associated with smartphones, the impact of reuse rate 1 is relatively large. The fact that the DoU

TABLE 1 Kolmogorov–Smirnov (KS) test statistics.

	Digital cameras						Smartphones					
	Top 10%			Bottom 10%			Top 10%			Bottom 10%		
	TMR	GHG	Both	TMR	GHG	Both	TMR	GHG	Both	TMR	GHG	Both
Reuse rate 1	0.28	0.46	0.40	0.37	0.43	0.39	0.19	0.54	0.46	0.29	0.52	0.40
Reuse rate 2	0.13	0.17	0.17	0.04	0.09	0.07	0.05	0.20	0.19	0.03	0.20	0.11
Remanufacturing rate	0.05	0.22	0.15	0.03	0.09	0.04	0.07	0.08	0.10	0.05	0.05	0.05
Recycling rate 1	0.21	0.08	0.16	0.11	0.05	0.07	0.34	0.04	0.27	0.12	0.03	0.07
Recycling rate 2	0.28	0.13	0.25	0.49	0.21	0.33	0.38	0.06	0.35	0.57	0.06	0.29
Rental rate	0.04	0.16	0.10	0.10	0.27	0.11	0.11	0.06	0.05	0.16	0.04	0.10
DoU extension ratio	0.15	0.20	0.21	0.17	0.23	0.18	0.21	0.50	0.45	0.26	0.62	0.43
Collection rate	0.57	0.37	0.50	0.52	0.37	0.43	0.52	0.12	0.42	0.44	0.13	0.28
DoU ratio of reused products	0.21	0.28	0.30	0.13	0.21	0.16	0.07	0.19	0.19	0.08	0.17	0.13
Rental period	0.03	0.10	0.08	0.02	0.29	0.17	0.02	0.05	0.07	0.02	0.04	0.02
Usage frequency ratio of rental products	0.03	0.04	0.05	0.04	0.09	0.07	0.05	0.04	0.06	0.03	0.06	0.03
Strategy implementation period	0.10	0.11	0.12	0.04	0.03	0.03	0.11	0.14	0.21	0.05	0.03	0.03

Note: The colors in the table darken as the test statistic values increase (red: top 10% criterion; green: bottom 10% criterion).
Abbreviations: GHG, greenhouse gas; TMR, total material requirement; DoU, duration of use.

extension ratio had a significant impact on GHG emissions only for smartphones can be attributed to the projected shift in product demand. This is discussed in Section 4.

4 | DISCUSSION

Based on the results of our RSA, we next consider measures to change the key parameters. Collection rate, reuse rate 1, and the DoU extension ratio were identified as those whose impact is common to both products when the criteria for classification into a behavioral group were used as being in the top 10% or bottom 10% in terms of both TMR and GHG emissions (see Table 1). Therefore, as a common characteristic of both products, it was confirmed that these three parameters had a major impact on both evaluation indicators regardless of the binary criteria employed. With regard to the collection rate, continued efforts to increase the amount of discharged products collected under the SHAR system seem clearly in order. Of course, the importance of increasing the collection rate has long been recognized, and various efforts in this regard are already underway. However, the results of this case study are significant in that they demonstrate through a quantitative evaluation of multiple indicators the importance of the small home appliance collection rate. Regarding reuse rate 1, one possible policy implication would involve subsidizing an expansion of the reuse market through the Internet's used goods distribution market and used goods stores. In addition to such subsidies, removing or reducing barriers to increasing consumer demand for used products and expanding businesses that enable various types of distribution will be essential. A variety of methods should be considered for extending product DoUs, such as supporting the development of technology for designing products with longer service life and increasing efforts to promote maintenance and repair. In addition, measures to reduce discharges due to relative obsolescence, where no product failure has occurred but use has been discontinued, should be pursued. Such measures would include educating consumers to be more aware of the need to reduce their resource consumption. Passive factors may also contribute to this effort; for example, a slowdown in the technological innovation of products could significantly reduce early replacement demand. To identify the causes in more detail and link them to specific measures, it will be important to conduct detailed analyses of consumer behavior, including product replacement, to lengthen DoU.

In terms of the differences between products, the contribution of the DoU extension ratio to the results is generally stronger for smartphones than for digital cameras. For products for which demand is growing, strategies that reduce both future emissions and future shipments are effective as the impact of future stock flows on the cumulative value of the evaluation indicator is significant. Therefore, for products for which demand is expected to grow, it will be necessary to focus on measures to extend service life, including long-life design.

The above findings are largely independent of the purpose of introducing CE strategies. To identify findings that should be considered according to the purpose of introducing CE strategies, we would need to consider variables whose influence tends to be affected by the setting of the binary criterion. Parameters that exhibit large values when the binary criterion is in the top 10% but relatively small values when the binary criterion is

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in the top 90% include recycling rate 1 for TMR (both products) and remanufacturing rate for GHG (digital cameras). To achieve the best results, it would seem that an important priority should be to increase recycling rate 1, which serves as the last resort under the SHAR system to circulate or process. On the other hand, considering the case where the criterion is set as the top 90%, the relative impact would be considered smaller due to the greater contribution of other parameters that have more room for improvement. Remanufacturing rate is relatively large when the criterion is set as the top 10% for digital camera GHG emissions, which are characterized by higher discharges than shipment during the simulation period since remanufacturing rate works to reduce the environmental impacts of manufacturing by utilizing the discharged product. However, for digital cameras, the risk of a rebound effect due to rentals is large, and their influence is relatively lower when the top 90% is used as the criterion. Strategy implementation period had a larger impact when the top 10% is set as the criterion for both products and evaluation indicators; however, even in this case, the values are smaller than the parameters listed above. Although these parameters have a degree of influence on the best results, overall, it can be said that the emphasis should be on setting appropriate goals and proceeding steadily rather than on the speed at which the strategy is carried out. In other words, it is important to focus on parameters for which there is significant room for improvement and to improve those elements over time.

Parameters with large values when the criterion is in the top 90% but relatively small values when the criterion is in the top 10% include recycling rate 2, which is common to all but smartphone GHG emissions, and rental rate and rental period, which are limited to digital camera GHG emissions. It can be said that these parameters are particularly important when considering only whether they lead to undesirable results. Recycling rate 2 is a means of circulation outside the scope of the SHAR Law system. It plays the role of diverting flows that have been omitted from collection under the SHAR system to circulation use. As such, it can be viewed as a safety net in that it provides a means for avoiding the worst-case outcome. From a policy perspective, it is an element that should be considered for further improvement in risk management. As for rental rate and rental period, our results show that, for digital cameras, the GHG emissions rebound effect of rentals is significant. This may be attributed to the relatively small environmental impact of digital cameras during product manufacturing. It should be recognized that for such products, promoting rentals is likely to increase the risk of a rebound.

Such analysis according to the purpose of implementing CE strategies is difficult to achieve with other methods of global sensitivity analysis. Figures S7 to S10 show the results of analyzing the influence of each parameter using Sobol's method, a typical method of variance-based global sensitivity analysis. This result is generally consistent with the RSA results shown in Table 1, which indicate that collection rate and reuse rate 1 generally have a significant impact, but for smartphone GHG emissions, the DoU extension ratio instead of the collection rate. However, recycling rate 1 for TMR, for example, did not show significant influence, and we were unable to find what we discussed in this section about the importance of recycling rate 1 to obtain good results for TMR (both products). On the other hand, Sobol's method suggests the presence of a particularly large interaction involving the collection rate, which is a reasonable result given the nature of this model (Figure 3), where various parameters are applied to the flow into the SHAR route, which is determined by the collection rate. RSA is unable to explicitly account for the presence of such interactions, which is an advantage of Sobol's method.

Finally, we tested whether the use of a uniform distribution would make any difference in the main findings discussed in this section. The results of the test confirmed the reliability of our methodology (see Figure S11 to S14 of Supporting Information S1).

5 | LIMITATIONS

This study is not without limitations. Notably, the simulations do not incorporate factors such as economic developments and consumer decision-making. Furthermore, it is necessary to consider barriers to the introduction of CE strategies separately.

It is expected that new information will be introduced via the variable distributions used in the Monte Carlo simulations to make the simulations more realistic. Whenever significant new information regarding technological developments and changes in consumer behavior is available, it will need to be incorporated into the analysis by updating the variable distributions and rerunning the simulations.

6 | CONCLUSION

This study shows the applicability of RSA to the dynamic MFA model and establishes its usefulness in analyzing the benefits of pursuing multiple CE strategies—something that has not been quantitatively evaluated in prior studies. Specifically, two evaluation indicators, TMR, which focuses on the amount of natural resource input by the social economy, and GHG emissions, which serves as a representative indicator of climate change, were analyzed in detail for the two products under study. Through our analysis, we provided insights applicable to all cases, as well as insights to be considered individually in light of introducing particular CE strategies, that is, seeking ambitious environmental impact reduction or avoiding a catastrophic environmental impact. The application of RSA makes it possible to discuss in quantitative terms product and circulation targets that should be aimed for in the future.

The featured case study showed that the parameters collection rate, reuse rate 1, and DoU extension ratio played a particularly important role in the comprehensive improvement of the evaluation indicators. When the top 10% criterion was used, strategy implementation period also showed a degree of influence; however, its influence was inferior to that of the aforementioned three parameters. On the other hand, when the top 90% criterion was used, recycling rate 2 was identified as important in most cases. Furthermore, it was found that the magnitude of the risk of a GHG emissions rebound effect due to rental varies depending on the product characteristics and that the degree of influence of the DoU extension ratio on the evaluation indicators differs.

These findings suggest that, in implementing CE strategies, it is important to stimulate the flow of end-of-life products into collection channels specifically intended for reuse and recycling and to encourage consumers to use products over a longer period by adopting approaches such as improving consumer awareness of the need to reduce resource consumption. It was also suggested that, for ambitious reductions in environmental impacts, the achievement of appropriate targets should be given priority over the speed at which a strategy is implemented, and that in order to avoid catastrophic environmental impacts, the first step should be to ensure higher recycling rates using well-developed collection routes.

As the study shows, RSA makes it possible to examine in depth the impact of each operational variable on the resource cycle. This is a major step forward from simply forecasting future cycles with the dynamic MFA model, which has been widely done in the increasingly important field of industrial ecology. In this context, and to provide useful and practical insights in this growing field, a method capable of considering uncertainty and producing insights into a variety of factors and indicators is essential. This study has shown that RSA can be a useful tool to meet such needs.

Left to future work is the development of evaluation indicators that can be used to assess the efforts of individual companies to realize CE. Indicators such as those used in this study should be developed from the perspective of how much impact a company's efforts will have on society as a whole and serve as an important element in societal efforts to increase company-led initiatives aimed at realizing CE. To this end, it is essential to effectively model CE strategies and organize related data. We believe that our study provides a useful roadmap.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the supporting information of this article.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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