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RESEARCH ARTICLE

Prospective life cycle and circularity assessment of circular business models using an empirically grounded agent-based model

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Abstract

Despite the need for methodologies that support early-phase decision-making in the transition to a circular economy, current sustainability assessments often lack a prospective method that dynamically accounts for consumer decision-making based on empirical evidence. This study addresses this need by evaluating the circularity and environmental impacts of circular business models over a 30-year period, using an empirically grounded agent-based model coupled with life cycle assessment and material flow analysis. We developed a methodology to parameterize agents' decision-making using data from demographically representative surveys and to prospectively assess the sustainability impacts of circular strategies. The case study examines the reuse, refurbishment, and subscription models of refrigerators and laptops in Japan. Results from Morris Elementary effects method and scenario analyses revealed that manufacturer-led refurbishment could reduce emissions of the whole society by 10%–12% and extend product lifetimes by 30%–33%. In contrast, the subscription model shows minimal benefits, with improvements of only 0%–3%, primarily due to consumer preferences for new products. Our consequential approach extends beyond technical strategies to evaluate the effectiveness of strategies targeting consumer behavior, including pricing, advertisements, and improvements in repair and collection services. The findings highlight the need for combining synergistic circular and diffusion strategies and suggest the need for a reorientation of policy efforts from end-of-life material recovery to refurbishment, reuse, and repair, supported by intensive campaigns and substantial price reductions in circular offerings. The methodology presented here facilitates prospective, dynamic, and consequential assessments of circular economy strategies to enhance consumer acceptance and ensure sustainability gains.

KEYWORDS
agent-based modeling, circular business model, consequential life cycle assessment, consumer survey, industrial ecology, product-service system

1 | INTRODUCTION

Transitioning to a circular economy is inherently complex, as it involves a diverse array of stakeholders adopting different practices at various temporal levels, leading to emergent macro-level behaviors (Bicket, 2020). This complexity presents the dual challenges of overcoming limited consumer acceptance, interest, and awareness (Camacho-Otero et al., 2018; Kirchherr et al., 2018) while ensuring sustainability gains and addressing concerns associated with rebound effects (Harris et al., 2021; Koide et al., 2022). Given these challenges, agent-based modeling (ABM) has emerged as a promising approach for modeling the circular economy, and its application in this field is steadily increasing (Rizzati & Landoni, 2024; Walzberg et al., 2023). ABM is a computational simulation technique that models dynamic processes resulting from interventions through a set of interacting agents, each following micro-level behavioral rules within macro-level constraints (Bianchi & Squazzoni, 2015). Due to its ability to simulate the decisions and interactions of various actors, as well as capture emergent system behaviors, ABM can address the limitations inherent in conventional assessment methods, such as material flow analysis (MFA), life cycle assessment (LCA), and discrete event simulation (DES) (Davis et al., 2009; Kraines & Wallace, 2008; Walzberg, Lonca et al., 2021). Early-phase assessments of the combination of diverse policy instruments are also crucial for making informed decisions (Bicket, 2020; Kravchenko et al., 2019). ABM has been proposed as a tool for the consequential LCA of policies across various domains (Palazzo et al., 2020), including mobility transition (Florent & Enrico, 2015), emission trading systems (Bing et al., 2010), market behaviors (Xu et al., 2009), and circular business models (CBMs) (Koide et al., 2023b).

A significant challenge in applying ABM in the circular economy lies in its empirical basis, particularly for consumer decision-making. Empirical ABM has become mainstream in a variety of areas, including energy, agriculture, consumer goods, and information technology, where real-world business practices are widely implemented and empirical data are relatively more accessible (Laatabi et al., 2018; Zhang & Vorobeychik, 2019). In contrast, within the context of the circular economy, consumer behaviors and decision-making are typically not observable, and numerous circular strategies have yet to be fully implemented in practice. Given these constraints on data availability, surveys are a useful approach for sourcing data for empirical agent-based simulations (Smajgl & Barreteau, 2017; Smajgl et al., 2011). A recent systematic literature review revealed that, among several ABM applications of CBMs to consumer durables, the utilization of primary data such as surveys and company-specific data is extremely limited (Assefa et al., 2025). Although there are some examples of utilizing survey or census data (Lieder et al., 2017a; Raihanian Mashhadi et al., 2019; Roci & Rashid, 2023), a robust methodology for mapping survey data to agents' decision-making rules within ABM frameworks and the circular economy has not yet been established.

This study applied an ABM to CBMs using the original model and numerical examples previously published by some of the authors (Koide et al., 2023b). Empirical data were used to extend this model to case studies examining the environmental impacts associated with consumer durables. Specifically, the analysis focused on three types of circular strategies: reuse, refurbishment, and subscription services. Using original survey data derived from users of refrigerators (Koide et al., 2023a) and laptops (Koide et al., 2025), we developed a method to parameterize the behavioral rules of agents for effective simulation of CBMs. These two products were selected due to their distinct characteristics and environmental impact profiles; for laptops, functional and aesthetic characteristics are prioritized, and most environmental impacts occur during the production phase, whereas for refrigerators, the opposite is true (Glöser-Chahoud et al., 2021). In this study, CBM refers to a model with a combination of circular strategies with product life cycles to create value toward the circular economy (Lüdeke-Freund et al., 2019; Salvador et al., 2021). Among the strategies considered, refurbishment involves a more comprehensive inspection and overhaul of damaged products, while reuse involves no significant changes to products (Lüdeke-Freund et al., 2019). This study focused on refurbishment conducted by an original equipment manufacturer, which was found to attract higher consumer acceptance than refurbishment by a third party (Koide et al., 2023a; Xu et al., 2017). In contrast to ownership-based models, subscription represents a type of product-service system that provides access to a product through regular payments (Jonker et al., 2022; Tukker, 2004). Through a series of simulation experiments, we aimed to address the following research question: *Which CBMs, that is, reuse, refurbishment, or subscription service, are most effective for improving circularity and reducing greenhouse gas (GHG) emissions in the coming 30 years?* We employed the Morris elementary effects method to identify critical parameters within the model and conducted simulation experiments across six scenarios to investigate the effectiveness of each CBM.

2 | METHODS

2.1 | Agent-based model

This study adopted an ABM of consumer-oriented CBMs and simulated examples of which have been published previously by some of the authors, although the model has not yet been applied to real case studies using empirical data (Koide et al., 2023b). We modified the model to reflect the case products and incorporate the survey data obtained in this study. The model is designed to clarify the impacts of various policy scenarios that combine both circular and diffusion strategies (Figure 1a). Specifically, the model simulates bottom-up behaviors and interactions among three types of agents (i.e., consumers, products, and supply chains) throughout the life cycle of consumer durables (Figure 1b). The model was implemented in NetLogo 6.1.1 (Wilensky, 1999) with a temporal resolution of 1 month, and simulations were run for periods spanning several decades. An overview

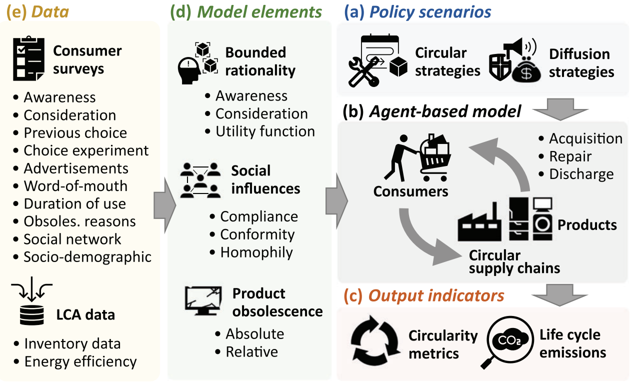

FIGURE 1 Conceptual framework of the study. (a) Policy scenarios; (b) agent-based model; (c) output indicators; (d) model elements; (e) data. LCA, life cycle assessment. Obsoles, Obsolescence.

of the model is provided below; full details, including process scheduling, initialization, input data, and sub-models, are described in Supporting Information S1 in accordance with the Overview, Design concepts, and Details (ODD) protocol, a widely used standard for describing agent-based models (Grimm et al., 2020).

In the model, three consumer decision-making processes within the circular economy are considered: (i) choosing among circular business models when *acquiring* products, (ii) deciding to *repair* broken products, and (iii) *discharging* end-of-use products (Figure 1b and Sections 1.3.5–1.3.9 of Supporting Information S1). Here, consumer decision-making is assumed to be boundedly rational, that is, not fully rational, primarily due to limited cognitive capacity. This bounded rationality is operationalized as a three-stage decision-making process: formulating *awareness* sets, developing *consideration* sets (Roberts & Lattin, 1991), and selecting a final alternative based on the utilities derived from product-service attributes (Manski, 1977) (Figure 1d and Sections 3.3.2–3.3.5 of Supporting Information S1). Another key component of the model is social influence (Cialdini & Goldstein, 2004), which is considered in three ways. The first is *compliance*, expressed as direct responses to communication through word-of-mouth via social networks, which is also influenced by exposure to advertisements. The second is *conformity*, which reflects responses to the observed behaviors of others and is facilitated by learning from peers within social networks (Figure 1d and Section 3.3.6 of Supporting Information S1). The third is *homophily*, where similar households are more likely to form connections in social networks (McPherson et al., 2001), which is considered through the use of a degree-calibrated network generation method (Boguñá et al., 2004; Talaga & Nowak, 2020) (Section 3.1.1 of Supporting Information S1).

In modeling product circulation, two forms of product obsolescence are considered (Yamamoto & Murakami, 2021). The first is *absolute obsolescence*, where products fail due to malfunction, which is modeled using a two-phase partitioned survival model (Woods et al., 2013) that accounts for occasional malfunctions progressing to complete failure. The second is *relative obsolescence*, which arises due to socioeconomic factors other than malfunction and is modeled using proportional hazard models (George et al., 2014) that consider the heterogeneity of household characteristics (Figure 1d and Section 3.3.1 of Supporting Information S1). The model can simulate consequential changes in consumer decision-making and product circulation by introducing two categories of strategies (Figure 1a). First, circular strategies are implemented by supply chain agents, including manufacturers, service providers, and reuse shops. These strategies include *repair* of broken products, *refurbishing* collected products by a manufacturer, preparation for *reuse* by a third-party reseller, preparation of products for *subscription* services, and *recycling* of end-of-life products (Sections 1.3.12–1.3.16 of Supporting Information S1). Second, diffusion strategies, such as pricing adjustments, advertisements, and service improvements, such as free repair warranty and scratch removal, can be introduced to influence consumer decision-making (Sections 3.3.1–3.3.7 in Supporting Information S1).

As outputs of the model (Figure 1c), life cycle GHG emissions are quantified based on the inventories collected from various technical processes (e.g., production of components, preparation for reuse), employing a soft coupling between the ABM and LCA (Micolier et al., 2019; Section 3.3.8 of Supporting Information S1). In addition, the circulation of products within the ABM provides the data for the dynamic MFA at the product level, which permits quantification of circularity metrics, such as product lifetime and reuse rate. Energy efficiency was considered during the product use phase, as well as variations in the emission intensity of grid electricity (Section 3.3.7 of Supporting Information S1). For more details, please refer to the updated version of the ODD protocol in Supporting Information S1 and the original model publication (Koide et al., 2023b).

2.2 | Data to agent mapping

In this study, data-to-agent mapping directly maps survey respondents to household agents in the ABM (Figure 1d,e and Section 3.2.3 of Supporting Information S1). This approach was selected to preserve the heterogeneous characteristics of survey responses (e.g., estimated utility functions of each household), rather than approximating these through assumed distributions (e.g., means and standard deviations derived from survey data). Two online cross-sectional surveys were conducted: one from June 22 to July 31, 2022, focusing on refrigerators ($N = 911$) (Koide et al., 2023a), and the other from October 11 to November 8, 2023, covering laptops ($N = 1{,}023$) (Koide et al., 2025). Both surveys sampled demographically representative Japanese households that use the target products for private purposes, recruited through major online survey panel companies (Figure 1e and Sections 3.2.1 and 3.2.2 of Supporting Information S1). Due to the presence of missing data, multiple imputations were used, generating 20 imputed datasets for each product type (Section 3.2.4(1) of Supporting Information S1). The initial status of household and product agents was set based on survey data (Sections 3.1.1 and 3.1.2 of Supporting Information S1). The summary statistics of the surveys, which were used as input data for agent initialization (e.g., initial status of years since manufacture) and decision-making parameters (e.g., price sensitivity, preference for reused products) are included in Tables 1–4 of Supporting Information S2.

Utility functions are estimated based on choice experiments that evaluate preferences among various circular offers (e.g., reuse, refurbish, and subscription), decisions to repair malfunctioning products, and options for disposing end-of-use products via different routes (e.g., recycling or selling to reuse shops; Figure 1d,e and Section 3.2.4(2) of Supporting Information S1). Hierarchical Bayes conjoint analysis was employed to estimate individual utility weights for CBMs, following a methodology developed by some of the authors (Koide et al., 2023a). In addition, the threshold for consideration by each household in phases of product acquisition, repair, and disposal was estimated using methods adapted from marketing sciences (Roberts & Lattin, 1991; Section 3.2.4(3) of Supporting Information S1).

To assess the impact of social influences, the status of receiving word-of-mouth, exposure to advertisements, and other consumer behaviors in social networks were surveyed (Figure 1d,e). The effects of these social influences on the utility functions and awareness of different CBMs were estimated using a causal inference approach using inverse probability weighting (Pishgar et al., 2021; Section 3.2.4(4) of Supporting Information S1). In addition, the degree of social network connectivity was calibrated using the number of acquaintances with whom respondents regularly discuss consumer products, based on the social distance attachment model (Boguñá et al., 2004; Talaga & Nowak, 2020; Section 3.1.1 of Supporting Information S1).

To estimate the probability of product obsolescence, data were collected on the duration of product use, reasons for obsolescence, and the timing and causes of malfunctions (Figure 1d,e). For absolute obsolescence, scale and shape parameters for two-phase partitioned survival models (Woods et al., 2013) were estimated for each major component (Section 3.2.4(9) of Supporting Information S1). For relative obsolescence, the shape parameters and weights of household characteristics for the parametric proportional hazard model (George et al., 2014) were estimated, capturing the heterogeneity of consumers (Section 3.2.4(8) of Supporting Information S1).

In addition to survey data, we used company data, findings from a previous LCA study (André et al., 2019), a life cycle inventory database (National Institute of Advanced Industrial Science & Technology, 2021), and energy efficiency studies (The IEA Technology Collaboration Programme on Energy Efficient End-Use Equipment, 2016; Urban et al., 2021) to set parameters for calculating the environmental impacts (Figure 1e). Detailed descriptions of the data structure, transformation, and mapping are described in Supporting Information S1, which follows the ODD + Decision + Data (ODD+2D) protocol (Laatabi et al., 2018).

As a result of these data transformations, the input data for the ABM were prepared as agent-level individual variables (a total of 65 parameters across 911–1023 agents, resulting in approximately 60,000 or more data points) and global parameters (totaling 95 parameters for each product case). A summary of the input data is included in Tables 1–6 of Supporting Information S2.

2.3 | Morris elementary effects method

To evaluate various configurations of the CBMs, including combinations of circular strategies (e.g., availability of reuse, repair, and subscription services) and diffusion strategies (e.g., pricing, advertising, and service levels), our ABM incorporates a number of policy, uncertainty, and contextual parameters. The Morris elementary effects method (Campolongo et al., 2007; Morris, 1991), a well-established one-factor-at-a-time approach that assesses global sensitivity through multiple-start perturbation, was employed to identify the most important parameters specific to the target products. The Morris method has frequently been used in ABM studies to comprehensively understand parameter impacts (Pianosi et al., 2016; Thiele et al., 2014).

In this study, two output indicators were considered: total life cycle GHG emissions ($kgCO_2e$) and product lifetimes (years). As a first step, all policy and uncertainty parameters, including the availability of various circular strategies, were analyzed. As described in Section 3, this initial phase highlighted the critical importance of circular strategies. Consequently, as a second step, a detailed analysis using the Morris method was repeated specifically for each CBM (i.e., selling reused products, offering refurbished products, and subscription services), with these circular strategies held constant. Following recommendations in the literature (Herman et al., 2013), each parameter was evaluated using 20 samples. Different random seeds were then assigned to 20 imputation sets, which resulted in up to 52,000 simulation runs for each product case. The ranges of policy and uncertainty parameters (e.g., price range of reused products, frequency of advertisements, and energy efficiency improvement rate) were set based on existing business practices, theoretical possibilities, and the expert knowledge of the authors (Table 7 of Supporting Information S2).

TABLE 1 Comparison of different circular business models (CBMs) across moderate (Mod.) and ambitious (Amb.) scenarios.

	Reuse (Mod.)	Reuse (Amb.)	Refurbish (Mod.)	Refurbish (Amb.)	Subscription (Mod.)	Subscription (Amb.)
Availability of circular strategies						
Reuse for selling	✓	✓	✓	✓	✓	✓
Refurbish for selling	–	–	✓	✓	–	–
Brand-new/reuse for subscription	–	–	–	–	✓	✓
Refurbish for subscription	–	–	–	–	–	✓
Functional upgrading[1]	–	–	–	✓	–	✓
Price and promotion						
Price of CBM[2]	−50%	−**70%**	−30%	−**70%**	−50%	−**60%–80%**
Advertisement frequency[3]		50%	30%	**70%**	30%	**70%**
Product and service						
Warranty period for CBM[4]	–	**3 years**	**3 years**	**4–8 years**	**Cont.**	**Cont.**
Scratch removal for CBM	–	–	–	✓	–	✓
Longer after service[5]	–	✓	–	✓	–	✓
Repair service improvement[6]	–	✓	–	✓	–	–
Collection service improvement[7]	–	✓	–	✓	–	–

[1]Refurbished products with functional upgrades for either selling or subscription.
[2]Relative price of the corresponding CBM (reused, refurbished, or leased products) compared to brand-new purchase prices. For the subscription (ambitious) scenario, the price range shows the price of reused and refurbished products for subscription.
[3]Probability that a household will receive an advertisement for the corresponding CBM per year.
[4]Free repair warranty applied to the corresponding CBM. For refurbishment, the range indicates coverage durations for laptops (4 years) and refrigerators (8 years). "Cont." refers to continuous warranty applied throughout the subscription contract.
[5]Increasing the maximum years for component stock availability and the possible years since manufacturing for refurbishment eligibility.
[6]Combined strategy involving reducing repair fees and advertising repair services.
[7]Combination of reducing collection fees, transparency of collection services, and advertisement of collection services (refurbish ambitious scenario) or increasing profit for resale and advertisement for resale service (reuse ambitious scenario).

2.4 | Scenario analysis

Simulation experiments using an ABM with six scenarios were conducted to evaluate the contributions of CBMs toward enhancing circularity and reducing GHG emissions over the next 30 years. The development of these scenarios was informed by the preceding analysis using the Morris method, which identified the most influential policy parameters. The focus of this study was to compare different configurations of CBMs that can be shaped by the decisions of policymakers and business managers engaged in the circular economy. Accordingly, grid electricity and energy efficiency were excluded from the main scenarios and considered only in the sensitivity analyses. As detailed in Section 3, the types of circular offers were found to be critical, while the second priority parameters involved a wide range of CBM configurations. In this study, we employed a three-by-two design consisting of three CBMs (selling *reused* products, selling *refurbished* products, or offering *subscription* services) and two levels of ambition (*moderate* or *ambitious*), resulting in six scenarios (Table 1). Here, the level of ambition refers to the extent of improvement in products and services to enhance customer appeal. Compared to the "*moderate*" scenario, the "*ambitious*" scenario assumes substantially lower prices, more frequent advertisements, extended free repair warranties, and increased promotion of repair and collection services. In addition, the subscription services in the "*ambitious*" scenario may include a range of product conditions, including brand-new, reused, and/or refurbished products (including functionally upgraded products). As reuse already exists in the current market, reuse is retained under all scenarios, and a "moderate" reuse scenario is considered the *business-as-usual (BaU)* scenario.

Simulation experiments were conducted with 10 random seeds × 20 imputation sets, which gave 200 simulation runs per scenario. The simulations were executed over a period of 30 years (360 time steps) to cover several typical product lifetimes and to capture the long-term effects of policy parameters on the diffusion of CBMs. A functional unit for quantifying the life cycle of GHG emissions was defined as access to a product for one household for one year (in kgCO_2e/household/year). Such a functional unit based on per user per period has been used in LCA studies on product service systems (Kjaer et al., 2017) and adopted in the present study as we focus on consumer behaviors and business models instead of technology improvements of products. The number of replication runs considering uncertainty in random seeds and imputation sets (200 runs per scenario) was validated based on the convergence of the standard error of the mean with additional simulation runs (Figures 1 and 2 of Supporting Information S3). As part of the sensitivity analyses, the annual rates of improvement in product energy efficiency and grid electricity emission intensity were varied within each scenario. Following the method developed for the original model (Koide et al., 2023b), a burn-in period of 120 time steps was employed prior to the simulation period to stabilize the initial status of product circulation and stocks. Further details regarding the setting of policy parameters and data sources are shown in Tables 8 and 9 of Supporting Information S2.

2.5 | Validation and verification

The model and simulation results were verified and validated following the procedures recommended in previous studies (van Dam et al., 2013). We conducted a series of multi-agent tests with extreme parameters and sanity checks to ensure the correct implementation of the model code and its expected functionality. The model successfully met all verification criteria, as described in Section 5 of Supporting Information S3. Given that the scenario analyses in this study involve emerging CBMs that are not yet fully implemented in society, quantitative validation was only conducted for *BaU* scenarios. It was confirmed that the simulated product lifetimes, recycling rates, reuse rates, and repair rates fit reasonably well with publicly available statistics, as shown in Table 1 and 2 of Supporting Information S3. For scenarios other than *BaU*, validation was conducted using expert input and literature comparison, including interviews with marketing and technical experts from a manufacturer and comparison of the simulated results with stylized facts reported in the literature, as summarized in Section 4 of Supporting Information S3.

3 | RESULTS

3.1 | Key parameters identified by Morris elementary effects method

Analysis using the Morris method revealed the critical roles of circular strategies and other configurations of CBMs. Figure 2 shows the overall ranking of parameters based on their elementary effects, μ^*, on GHG emissions. In addition to energy efficiency and grid electricity intensity, the availability of circular strategies was found to be a major determinant of total GHG emissions. This includes the availability of refurbishment ($\mu^* = 240$–460; with the range indicating the results for two products), reuse ($\mu^* = 220$), repair ($\mu^* = 140$–180), and subscription services ($\mu^* = 70$–200) (red bars in Figure 2).

In addition to circular strategies, price and advertising efforts were identified as critical parameters. For example, the impact of advertising for reuse showed a μ^* range of 40–150, shown as green bars, and the price on reuse had a μ^* range of 40–150, shown as yellow bars in Figure 2. The relevance of these two parameters was observed not only for product offers, but also for collection (e.g., $\mu^* = 60$–130 for collection fees) and repair services (e.g., $\mu^* = 40$–120 for advertising repair). In addition, several service-related factors, such as free repair warranties ($\mu^* = 50$–80 for reuse), availability of repair parts ($\mu^* = 40$–190), and the transparency and convenience of collection services ($\mu^* = 50$–110, shown as purple bars), as well as several product offerings, such as scratch removal (e.g., $\mu^* = 30$–80 for refurbishment) and maximum years of refurbishment ($\mu^* = 30$–150, shown as blue bars), also markedly influenced GHG emissions (Figure 2).

The sign of elementary effects, μ, confirmed that the impacts of the parameters are as expected, that is, lower prices or more frequent advertisements of CBMs correspond to reduced emissions (values in square brackets in Figure 2). Furthermore, the extent of interaction effects, σ, is substantial for many parameters, including price and advertisement (values in parentheses in Figure 2). These findings imply that the effects of CBM configurations are largely dependent on each other, and thus, a mixed policy approach is advisable rather than implementing strategies in isolation.

Additional results of analysis using the Morris method, in which the availability of reuse, refurbishing, and subscription services was held constant, are shown in Figures 3 and 4 of Supporting Information S3. The results of product lifetimes showed similar trends in the identification of influential parameters (Figures 5–7 in Supporting Information S3). These results informed the structuring of the subsequent scenario analyses in this study, which primarily focused on the comparison of CBM offers with two levels of ambition.

3.2 | Scenario analysis of different CBM configurations

3.2.1 | Diffusion of CBMs

The scenario analyses demonstrated a high diffusion potential for selling refurbished products and offering subscription services under "*ambitious*" scenarios. Figure 3 shows the proportion of decision-making households that opted for CBMs (excluding brand-new products for ownership) by the end of the 30-year simulation period. The CBMs achieving the highest market share were "*refurbishing (ambitious)*," with a mean market share of 28% and 38% for refrigerators and laptops, respectively, and "*subscription (ambitious)*" scenarios, with 28% and 32%, respectively. In contrast, traditional reuse scenarios "*reuse (ambitious)*" recorded relatively modest market shares that were comparable to those of "*subscription (moderate)*"

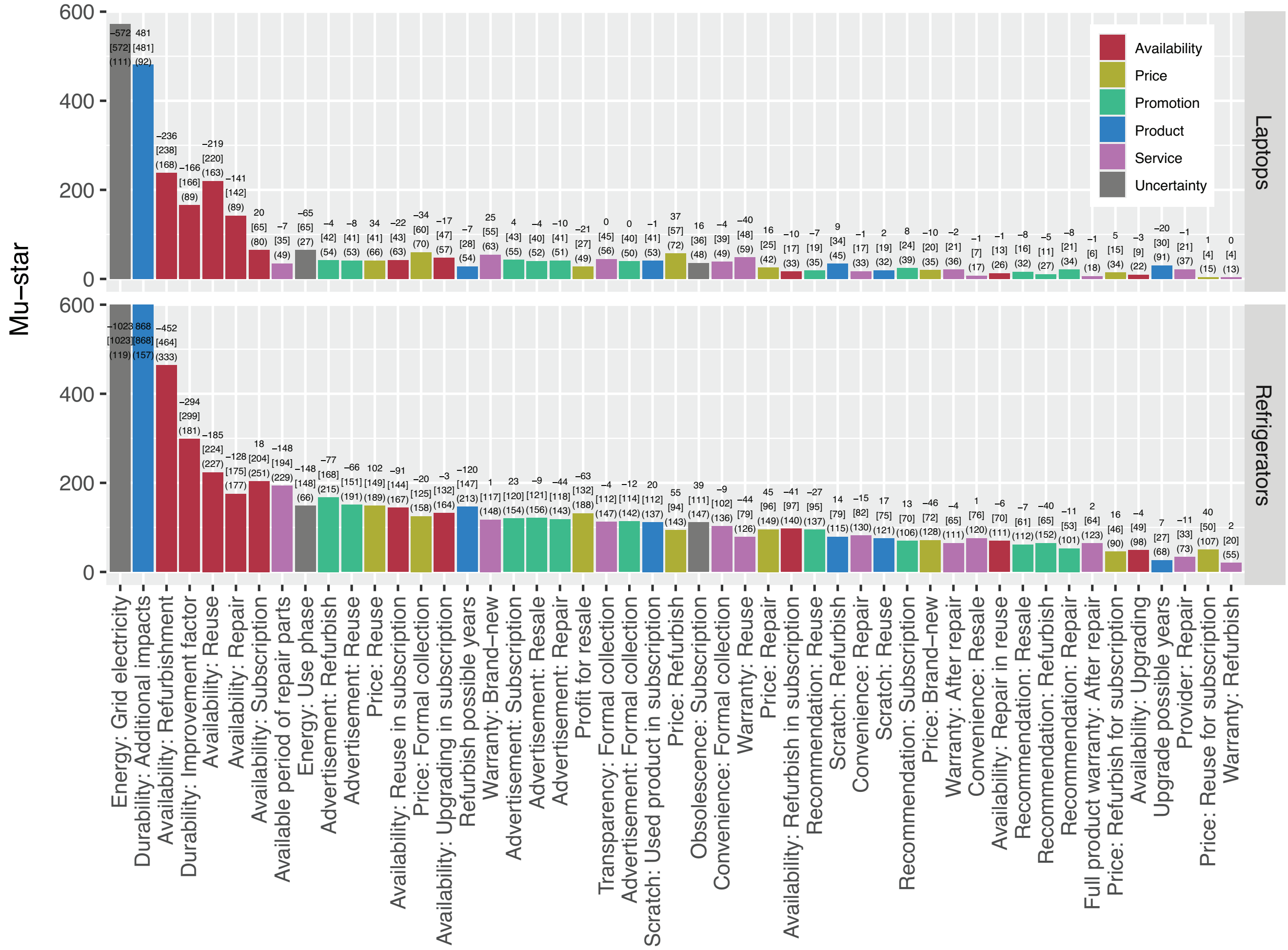

FIGURE 2 Ranking of parameter elementary effects on greenhouse gas emissions based on the Morris method (all circular business models). The color of each bar indicates the type of parameter. The height of the bars and the values in square brackets at the top of each bar represent the overall influence, μ^*, which indicates the absolute size of effects regardless of direction. The primary value above each bar represents the mean elementary effects, μ, reflecting both the direction and magnitude of the effects. Values in parentheses denote the standard deviations of elementary effects, σ, representing the extent of the interaction effects. Underlying data for this figure are available in Table 1 of Supporting Information S4.

and "*refurbishing (moderate)*," which ranged from 16% to 19% for refrigerators and 27% to 30% for laptops. Compared to refrigerators, laptops generally exhibited a higher uptake of CBMs under both the *BaU* and all alternative scenarios, although the relative rankings of expected market shares for CBMs were similar for the two products.

The dynamic diffusion process of CBMs exhibited signs of saturation over time. The trend in household stock of in-use products over the 30-year-period is shown in Figure 4. Ownership models, such as refurbished and reused products, diffused relatively quickly, nearly stabilizing in market share by the end of the simulation period. In contrast, the shift from ownership to the subscription model was characterized by a longer diffusion time. The simulation results also showed that different CBMs compete with each other. The market share for traditional reuse under the "*refurbish (ambitious)*" and "*subscription (ambitious)*" scenarios was notably smaller at 2% and 8%–15% for refrigerators and laptops, respectively, compared to the "*reuse (ambitious)*" scenario (16% and 30%, respectively). These findings indicate that the market segments receptive to CBMs are limited and tend to overlap. The simulation also showed that, even under the "*ambitious*" scenarios, the majority of in-use products in households remained brand-new, exceeding 70% for refrigerators and 60% for laptops.

3.2.2 | Extension of product lifetime and status of product circulation

The simulation results showed the contributions of CBMs to improving circularity over a 30-year simulation period. The "*refurbishing (ambitious)*" scenario substantially extended product lifetimes by 33% (from 13 to 17 years) for refrigerators and by 30% (from 7.7 to 10 years) for laptops

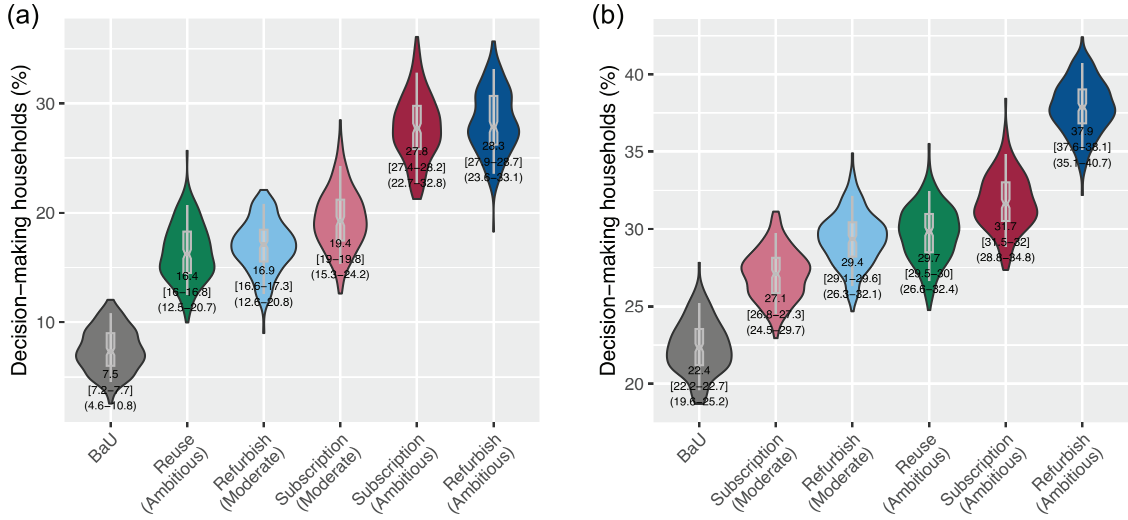

FIGURE 3 Decision-making share of circular business models (CBMs) (mean of the final 3 years of the simulation period). (a) Refrigerators. (b) Laptops. Share of decision-making households that opted for CBMs other than brand-new purchases, expressed as a percentage. Values without brackets and boxes represent the mean and inter-quartile ranges. Notches on the boxes and the ranges in square brackets correspond to the 95% confidence interval about the mean. Whiskers and ranges in parentheses represent the 5–95th percentiles, based on 200 simulation runs. Colors indicate different CBMs (green: reuse, blue: refurbishment, red: subscription), and the intensity of the color indicates the ambition level (light: moderate, dark: ambitious). Underlying data for this figure are available in Table 2 of Supporting Information S4. BAU, business-as-usual.

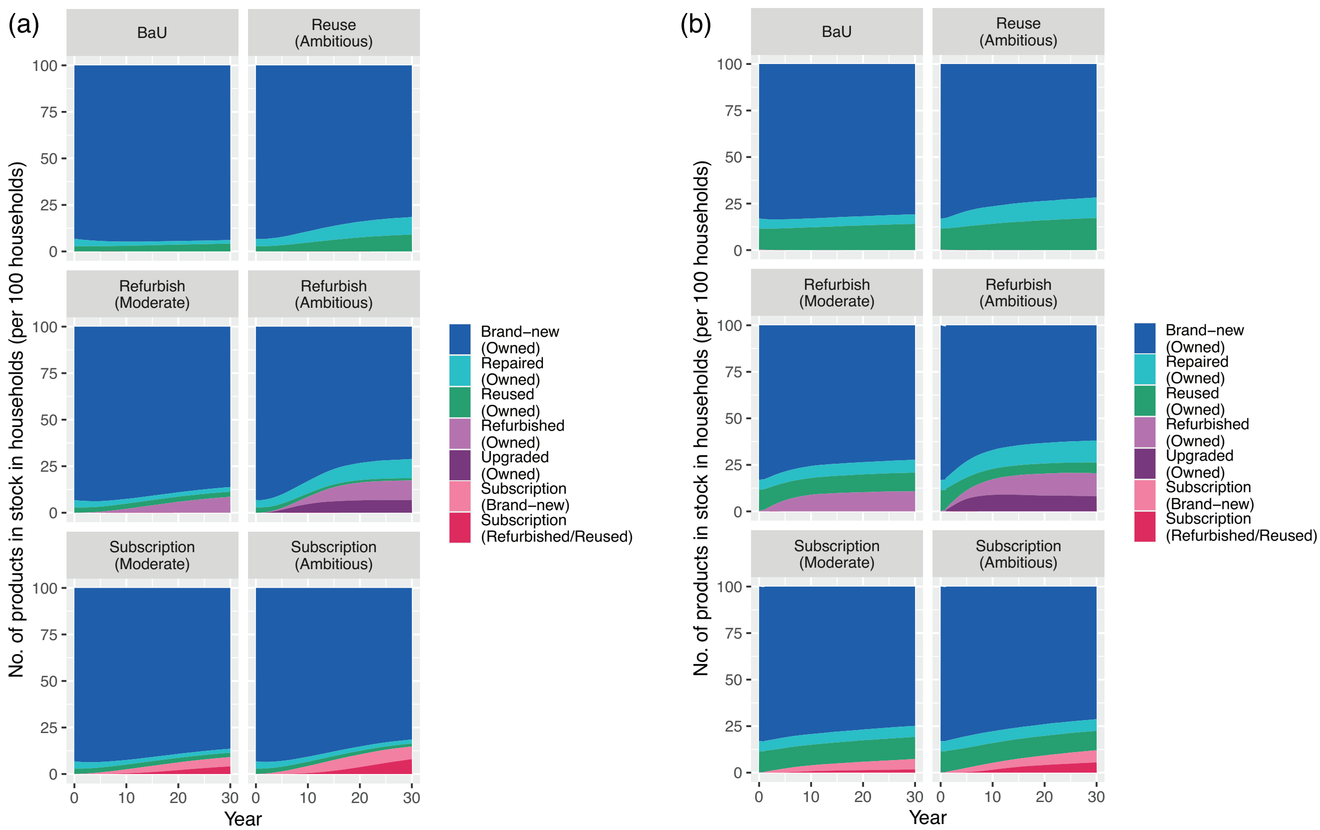

FIGURE 4 In-use product stocks in households by different circular business models over a 30-year simulation period (mean of 200 simulation runs). (a) Refrigerators. (b) Laptops. Underlying data for this figure are available in Tables 3 and 4 of Supporting Information S4. BAU, business-as-usual.

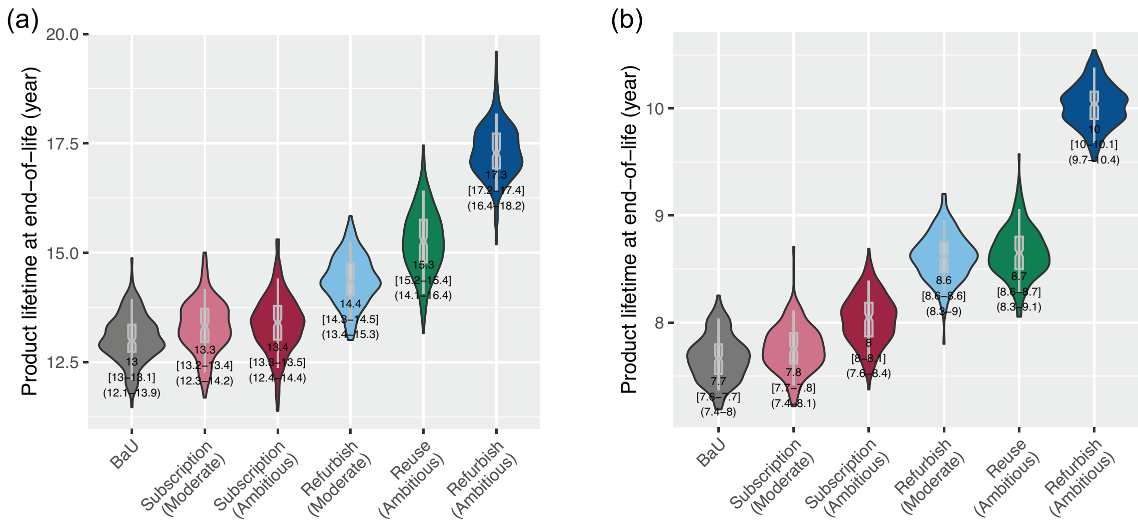

FIGURE 5 Product lifetime by circular business models (CBMs) (mean of the final 3 years of the simulation period). (a) Refrigerators. (b) Laptops. The average lifetime of products disposed (recycled) each year is shown for different CBMs over the final three years of the simulation. Values without brackets and boxes represent the mean and inter-quartile ranges. Notches on the boxes and the ranges in square brackets correspond to the 95% confidence interval about the mean. Whiskers and ranges in parentheses represent the 5–95th percentiles based on 200 simulation runs. Colors indicate different CBMs (green: reuse, blue: refurbishment, red: subscription), and the intensity of the color indicates the ambition level (light: moderate, dark: ambitious). Underlying data for this figure are available in Table 5 of Supporting Information S4. BAU, business-as-usual.

(Figure 5). Furthermore, the "*reuse (ambitious)*" scenario also extended product lifetimes by 13%–18% (range shows results for both products). Despite the high market share achieved by the subscription service, it resulted in only a modest improvement in product lifetime, with increases of 3.1%–3.9% in the "*subscription (ambitious)*" scenario. This limited impact may be due to consumer preferences for renting brand-new products and the reduced market share of traditional reuse, primarily due to competition with subscription services.

A closer investigation of product stock and flow revealed additional aspects of circularity. Under the "*refurbished (ambitious)*" scenario, end-of-use product circulation rates increased from 22% to 37% (5.9 out of 15.9 units) for laptops and from 7.3% to 28% (2.2 out of 8.0 units) for refrigerators, compared to the *BaU* scenario (Figures 8a and 9a of Supporting Information S3). This enhancement in product circulation contributed to a reduction in the amount of end-of-life treatment by 23%–24% (13 to 10 units for laptops and 7.6 to 5.8 units for refrigerators). Conversely, the "*subscription (ambitious)*" scenario did not achieve a comparable level of higher product circulation or extended use periods. Under this scenario, only 62%–78% of products (1.6 out of 2.6 units for laptops and 1.8 out of 2.3 units for refrigerators) were offered as reused or refurbished products in new subscription contracts (Figures 8b and 9b of Supporting Information S3).

3.2.3 | Reduction in life cycle GHG emissions

The results from the life cycle GHG emissions analysis revealed varying impacts between the refurbish and subscription models. Selling refurbished products reduced overall life cycle emissions by 5%–12% for refrigerators and 5%–10% for laptops, with these ranges representing "*moderate*" and "*ambitious*" scenarios (Figure 6). Conversely, reductions attributed to subscription services were modest, at only 2%–3% for refrigerators and 0–1% for laptops. Interestingly, a slight backfire effect was observed in the laptop "*moderate*" scenario, although the differences were not statistically significant. These limited or potentially adverse impacts could be attributed to consumer preferences for brand-new products under subscription models and the cannibalization of other CBMs, such as traditional reuse. Conversely, more aggressive diffusion of traditional reuse appeared to be moderately effective, resulting in emission reductions of 7% for refrigerators and 5% for laptops.

The most significant driver of emissions reductions was the decreased need for manufacturing new products (Figure 7). These reductions were primarily due to increased product circulation (from refurbished and reused items) and extended product use. Despite a minor increase in use-phase emissions due to the lower efficiency of older products and emissions induced by transport for refurbishment and preparation for reuse, these factors did not negate the substantial savings achieved in manufacturing emissions. Furthermore, the negligible emission reductions observed under the "*subscription (moderate)*" scenario can be attributed to unrealized savings from manufacturing, as consumers opting for subscription services continued to prefer new products, thereby shortening the duration of product use.

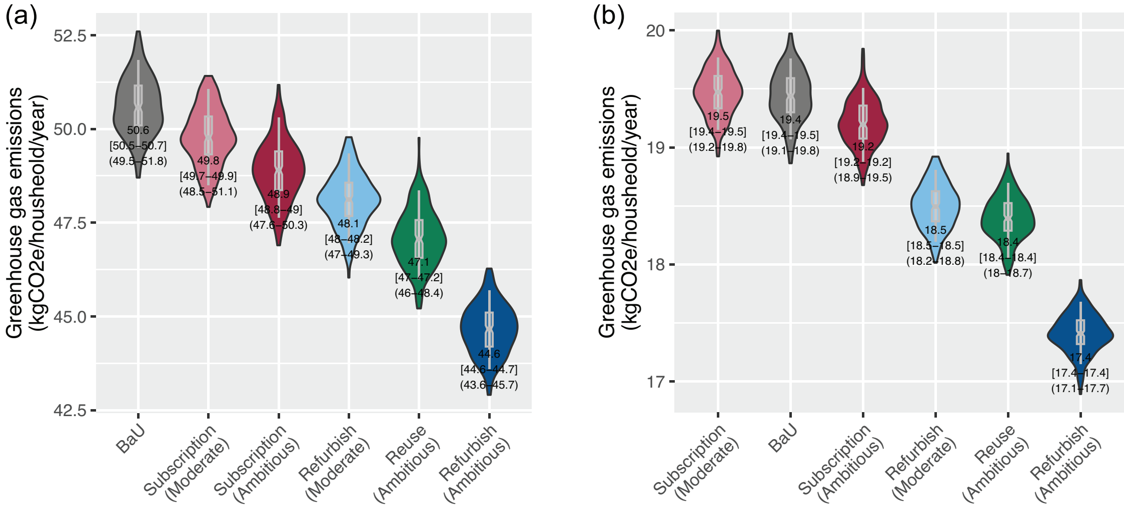

FIGURE 6 Total life cycle GHG emissions by circular business models (mean of final 10 years of the simulation period). (a) Refrigerators. (b) Laptops. Values without brackets and boxes represent the mean and inter-quartile ranges. Notches on the boxes and the ranges in square brackets correspond to the 95% confidence interval about the mean. Whiskers and ranges in parentheses represent the 5–95th percentiles based on 200 simulation runs. Colors indicate different circular business models (CBMs, green: reuse, blue: refurbishment, red: subscription), and the intensity of the color indicates the ambition level (light: moderate, dark: ambitious). This indicator was calculated as the mean of the final 10 years of the simulation period, as it is cumulative and reflects the entire life cycle of the products, which typically spans several years to a decade. Underlying data for this figure are available in Table 6 of Supporting Information S4. BAU, business-as-usual.

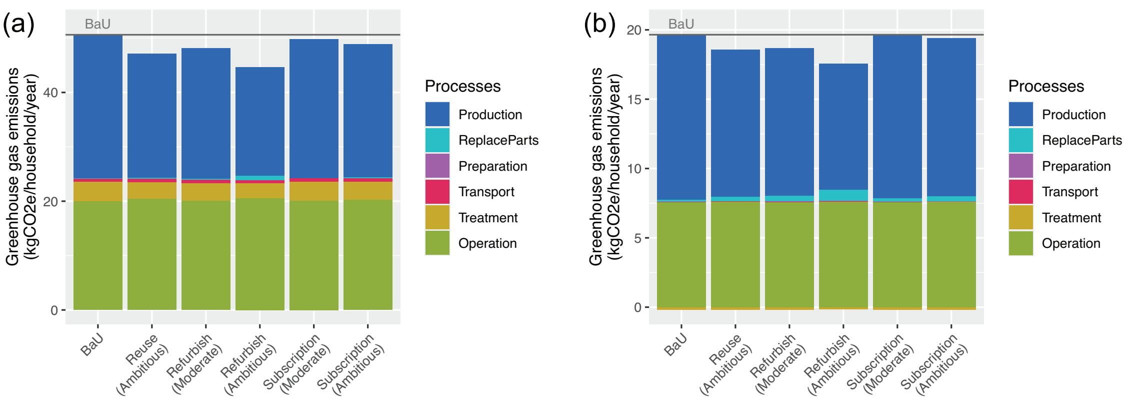

FIGURE 7 Breakdown of life cycle GHG emissions by circular business model (mean of final 10 years of the simulation period). (a) Refrigerators. (b) Laptops. Emissions are grouped into six components: production, replacement parts, preparation, transport, treatment, and operation. Each bar represents one scenario: business-as-usual (BaU), and moderate and ambitious versions of reuse, refurbished, and subscription models. Blue indicates emissions from production, light blue from replacement parts, purple from preparation, red from transport, and light green from operation. Underlying data for this figure are available in Table 7 of Supporting Information S4.

Given the critical role of energy efficiency on overall GHG emissions (see Figure 2 for Morris elementary effects method), we conducted a sensitivity analysis to evaluate the impact of varying levels of annual improvements in product energy efficiency (ranging from 1% to 5%) and grid electricity emission intensity (ranging from 4% to 8%). The results of this analysis confirmed that the overall conclusions remained consistent despite variations in these key parameters (Figures 10 and 11 of Supporting Information S3).

4 | DISCUSSION

This study prospectively assessed life cycle GHG emissions and circularity of CBMs using simulation experiments with an ABM coupled with LCA and MFA. Compared to conventional LCA, MFA, and DES studies, our model offers the following three key contributions. First, the scale of analysis differs. Conventional LCA studies typically focus on the life cycle of a single product, while existing DES studies, which simulate the circulation of product entities handled by stylized consumers represented as a process, concentrate on customers of a specific circular business (Kumazawa & Kobayashi, 2006; Umeda et al., 2000). In contrast, our study addressed the national scale by representing the entire market of a country. Second, the scope of our system analysis is broader; our method explicitly modeled the decision-making processes of multiple stakeholders within a socio-technical system, including complex consumer behavior. This approach enabled the evaluation of "what-if" scenarios involving diffusion strategies as explicit policy parameters, such as price adjustments and advertising campaigns, which have not been considered in previous MFA and DES studies (Glöser-Chahoud et al., 2021; Kumazawa & Kobayashi, 2006; Lieder et al., 2017b). Third, unlike previous LCA studies that assume a fixed product lifetime or address variability only through sensitivity analyses (Baxter, 2019; Boldoczki et al., 2020; Hischier & Böni, 2021; Iraldo et al., 2017), our study incorporated dynamic and heterogeneous assessments of product lifetime and circularity.

Our findings on the positive contribution of product lifetime to GHG emission reductions corroborate existing dynamic MFA studies, which concluded that the optimal product lifetimes of refrigerators and laptops have tended to increase over previous decades (Bakker et al., 2014; Glöser-Chahoud et al., 2021). However, the results obtained from previous LCA studies have been somewhat mixed. These studies concluded that GHG emission reductions are highly dependent on several factors, including the timing of replacement choices, energy efficiency, and electricity mix, with estimated impacts ranging from a 60% reduction to a 57% increase in emissions (Baxter, 2019; Boldoczki et al., 2020; Hischier & Böni, 2021; Iraldo et al., 2017). Unlike these LCA studies, which focus on typical individual products, our study considers a mix of dynamically circulated products within society, leading to an estimated 10%–12% emission reduction under the "*refurbish (ambitious)*" scenario.

In terms of product-service systems, previous DES studies demonstrated that shifting to rental or leasing services for laptops or washing machines can reduce CO_2 emissions by 15%–46% (Kumazawa & Kobayashi, 2006; Lieder et al., 2017b). However, these studies typically focus on customers of a specific business and assume full market diffusion of the new CBM. In contrast, our ABM covers entire market segments with more realistic future scenarios, resulting in limited emission reductions of 0–3% under the "*subscription (ambitious)*" scenario. In addition, our findings on key diffusion strategies corroborate those of previous ABM studies on the circular economy across different product categories. These studies concluded that price, advertising, consumer attitudes, and social networks are major drivers of CBM diffusion and higher levels of circularity (Lieder et al., 2017a; Raihanian Mashhadi et al., 2019; Walzberg, Carpenter et al., 2021).

Compared to previous studies on the application of ABMs to the circular economy, the present study makes the following contributions. First, our approach enables a broader comparison and combination of multiple CBMs, including reuse, refurbishment, and subscription services, in contrast to most existing ABM studies, which focus on a single or a limited number of circular strategies. According to a recent systematic review, such an extensive comparative approach is largely absent from the current literature (Assefa et al., 2025), despite the common integration of multiple circular strategies in practice. Second, our ABM integrates boundedly rational and socially influenced consumer decision-making, rather than assuming perfect rationality. We employed a three-phase screening process for circular alternatives, incorporating awareness and consideration sets (Roberts & Lattin, 1991), as well as social influences grounded in compliance and conformity (Cialdini & Goldstein, 2004), across all phases of the product life cycle, that is, discharge, repair, and acquisition. This approach contrasts with previous studies that either lack clearly defined theoretical foundations of consumer decision-making, as identified in a recent systematic literature review (Assefa et al., 2025), or assume utility-maximizing behavior based on perfect rationality (Lieder et al., 2017a; Raihanian Mashhadi et al., 2019). Although one existing study incorporates a more nuanced consumer decision-making framework grounded in psychological theory, specifically the theory of planned behavior (TPB) (Walzberg, Carpenter et al., 2021), a detailed comparison between TPB and our approach lies beyond the scope of this study. Third, to the best of the authors' knowledge, this study is the first to conduct and apply a large-scale, demographically representative survey on consumer preferences and behavioral patterns to parameterize an ABM in the context of the circular economy. In contrast, previous ABM studies have often relied on existing statistics, census, and company data (Lieder et al., 2017a; Roci et al., 2022), or data from the existing literature (Walzberg, Carpenter et al., 2021), with few exceptions involving surveys of narrow demographic groups such as students (Raihanian Mashhadi et al., 2019).

Our findings have the following implications for policymakers and businesses. Our analyses showed that introducing manufacturer-led refurbishment, while maintaining consumer ownership, is potentially the most effective strategy in the next 30 years in Japan. Conversely, the adoption of subscription models should be approached with caution from a sustainability perspective. While subscription-based services may come to occupy a greater market share, their contribution to sustainability may be limited, even when offering refurbished and reused products as options. Our scenario analysis also suggests that an approach based on ambitious diffusion of reuse, particularly in combination with enhanced repair services, has the potential to substantially increase circularity and reduce emissions. However, such shifts and the promotion of CBMs cannot rely solely on private sector efforts; however, they can be supported through a range of public policies, including regulatory coherence, targeted support for research and development, strengthened extended producer responsibility, and the realignment of fiscal incentives (OECD, 2019).

Another important implication for policymakers arising from our findings is the need to set CBM pricing substantially lower than that of brand-new products, complemented by intensive promotional campaigns. For example, the "*ambitious*" scenario in our study assumes that circular products are priced 70% lower than brand-new products. This significant price difference suggests the need to reconsider the profit models of manufacturers and retailers, either by raising the prices of brand-new offers and/or lowering the prices of circular offers. It may also necessitate policies that increase price differences in favor of circular rather than linear product offerings that promote cultural shifts towards strong sustainable consumption (Lorek & Fuchs, 2013; O'Rourke & Lollo, 2015). Furthermore, our findings underscore the importance of ensuring that CBMs are both known to and considered by consumers in their purchasing decisions. The "*ambitious*" scenario in our simulation assumed that advertising for refurbishments, reuse, repair, and collection should reach 50%–70% of the population annually. Achieving this level of awareness will likely require the collaboration among retailers, manufacturers, and policymakers. Moreover, the findings of the Morris method highlight the interplay among different diffusion strategies, indicating the effectiveness of integrating pricing strategies with extensive campaigning rather than relying on one approach in isolation.

The third policy implication is to ensure that sustainability gains from CBMs extend beyond consumers' choices at the point of product acquisition to include aspects of repair and collection. Under the "*ambitious*" scenario, our model assumes that free repair warranties are provided for 3–10 years, depending on the type of products, and repair fees are proposed to be reduced to a third of their BaU rates. Such policy and business initiatives aimed at promoting repair and collection services would ensure the availability of products for circulation and extend product lifetimes. Policymakers may need to shift the focus of current legal frameworks, which focus predominantly on the recovery of materials, to prioritize product circulation through manufacturer-led refurbishment.

5 | CONCLUSION

This study prospectively assessed life cycle environmental impacts and circularity of CBMs using simulation experiments based on an ABM coupled with LCA and MFA. We developed a methodology that employs an empirically grounded ABM, parameterized using decision-making data from demographically representative surveys, to enable prospective assessment of the sustainability impacts of CBMs. This study addressed the following research question: "*Which CBMs, that is, reuse, refurbishment, and subscription services, are most effective for improving circularity and reducing GHG emissions in the coming 30 years?*" Our conclusion is that manufacturer-led refurbishment, while maintaining consumer ownership, is likely the most effective strategy over the next 30 years in Japan. In contrast, the sustainability contributions of subscription models are limited. The empirically grounded ABM developed in this study offers a new approach for the prospective, dynamic, and consequential assessment of CBMs, enabling analysis that addresses the dual challenges of consumer acceptance and the realization of sustainability gains during the circular transition.

The limitations of this study are primarily associated with the data and the modeling approach. First, the surveys were cross-sectional, conducted in specific years, and focused on the Japanese market, which is shaped by a distinct local context. Although our methodological approach, including the representation of consumer behavior, simulation model, and data-to-agent mapping procedures, is transferable to other contexts, applying it to other countries or timeframes would require the collection of context-specific data. Although utility weights were derived from choice experiments and causal inference methods were employed to assess the impact of social influences, not all parameters were identified within a causal framework, due to the constraints of the cross-sectional data. In the model, although utility functions, obsolescence functions, household composition, and social network topology were represented as heterogeneous, they were assumed to remain constant for the duration of the simulation period. In addition, the model assumed that each household only used one product and did not account for informal treatment, export of used products, or product hibernation. GHG emission intensities were uniformly applied to all products produced within the same timestep, except where changes in use-phase energy efficiency and adjustments in the grid electricity mix were explicitly modeled.

Future studies could extend the application of this ABM approach to a broader range of products, such as clothing and mobility equipment, and markets outside Japan. Also, the data-to-agent mapping method employed in this study could be improved by incorporating alternative techniques, such as the use of synthetic populations, longitudinal surveys, or real-world data derived from pilot projects. Refinement of the behavioral models to account for long-term changes in consumer values and psychological attitudes also represents a promising direction for research. Further, a more comprehensive coupling of ABM with a prospective LCA framework (Sacchi et al., 2022) would allow for a more comprehensive analysis that extends beyond grid electricity and energy efficiency improvements. In addition, participatory social simulation could be adopted in future studies to facilitate greater stakeholder involvement and to help ensure that policy and management implications are translated into practice (Ramanath & Gilbert, 2004). Finally, further exploration of the robustness of strategies under a deep uncertainty framework (Kwakkel & Pruyt, 2013), with a focus on ambitious circularity targets and the conditions required to achieve them, should be considered in future work.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data are available on request, due to privacy/ethical restrictions.

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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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