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Data-driven simulation method for strategic decision-making in circular economy business design

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ABSTRACT: The circular economy (CE) seeks to replace traditional linear models by focusing on resource reuse and circulation. However, developing effective CE business strategies is difficult due to complex user behaviors and product flows. Existing scenario analysis tools often rely on survey-based conjoint methods, raising concerns about discrepancies with real purchasing patterns. This study introduces a data-driven simulation approach that employs a consumer preference model and product circulation processes based on actual operational data. Applied to a second-hand PC rental business, our method more accurately reproduces market behavior and reveals that targeting certain customer segments can enhance profitability and resource utilization. These findings underscore the approach's value as a practical tool for pre-evaluating strategies in CE businesses.

KEYWORDS: circular economy, simulation, service design

1. Introduction

In recent years, there has been growing attention to the circular economy (CE), which emphasizes resource reuse and circulation, as an alternative to the traditional linear economy driven by mass production, consumption, and disposal. This economic system aims to circulate products and components while maintaining their high value (Bocken et al., 2014). In particular, CE business models such as reuse and sharing focus on product use rather than ownership, thereby enabling companies to provide value that balances both economic and environmental considerations (Tukker, 2004).

Nonetheless, designing and operating such CE businesses remains fraught with challenges. Effective decision-making in product supply requires methodologies that accurately capture customer demand and systematically enhance supply efficiency (Bressanelli et al., 2024). In CE businesses, it is particularly important to consider diverse customer needs, as differences in usage frequency and duration directly affect maintenance, collection, and procurement. In addition, product and component conditions shift dynamically in response to various factors—including usage patterns, maintenance and repair history, and potential failure risks—yet no established method exists to fully model these changes, posing a major obstacle to corporate decision-making (Linder and Williander, 2017; Stahel, 2016).

While conjoint analysis based on consumer surveys is widely used to study demand in terms of user preferences and usage periods (Koide et al., 2023), it remains unclear whether this approach, which models consumer decisions for hypothetical services, accurately reflects preferences in real-world consumption (Allenby et al., 2019). To capture actual consumption behavior, a quantitative, data-driven approach is indispensable.

This study proposes a simulation method to achieve both economic and environmental objectives in CE businesses. By employing a data-driven simulation to precisely reconstruct product supply processes and customer demand, we quantitatively evaluate both economic and environmental performance under various design variables related to product supply. In this paper, we treat the proportion of user preference segments as the primary design variable, comparing multiple scenarios with different proportions to measure their impact on product dynamics. Previous research suggests that using actual market data rather than conjoint analysis more faithfully reflects real consumer behavior and thus improves the realism of demand estimation (Allenby et al., 2019). Furthermore, leveraging actual data to reproduce product circulation in simulations has been shown to contribute to operational efficiency (Charnley et al., 2019). Such an approach makes it possible to formulate product supply strategies that were previously difficult to realize (Eggert et al., 2014; Kumar et al., 2018). In this paper, we apply our method to the used PC rental business and evaluate its validity and practicality as a decision-support tool.

2. Literature review: CE business simulation

Simulation methods play a central role in product management and in the design and operation of business models as tools for analyzing complex and dynamic models like those in CE businesses (Bal & Badurdeen, 2022; Roci and Rashid, 2023). Enhancing the accuracy of market demand reproduction in such CE business simulations requires a precise understanding of consumer preferences, which can significantly impact the growth of CE businesses (Johnson & Plepys, 2021; Koide et al., 2023).
Existing research often models consumer behavior through agent-based (AB) approaches (Bal & Badurdeen, 2022; Roci and Rashid, 2023) or system dynamics (SD) (Franco, 2019), employing estimated values from prior studies (Johnson & Plepys, 2021; Franco, 2019) and actual market data (Bal & Badurdeen, 2022; Franco, 2019; Roci and Rashid, 2023) as data sources. However, such macro-level data alone cannot adequately capture consumer heterogeneity. Choice-Based Conjoint (CBC), which is recognized for its effectiveness in capturing individual-level variability (Koide et al., 2023), is thus widely adopted in demand analysis for CE businesses (Fuchs & Hovemann, 2022; Koide et al., 2023; Lieder et al., 2017). In CBC, multiple options are presented to respondents in a survey, and the choice they prefer the most is used to estimate their preferences.
Nevertheless, several issues have been pointed out regarding such survey methods (Allenby et al., 2019):

- **Discrepancy from real-world behavior**: The method relies on hypothetical purchasing scenarios, which may deviate from actual consumer behavior.
- **Limited data availability**: Data collected through surveys may be insufficient in quantity.
- **Non-representative sampling**: Survey sampling is often convenience-based, meaning the sample may not adequately represent the entire target market.
- **Complex choice design requirements**: Accurate demand estimation requires careful design of choice combinations.

Addressing these challenges will not only enhance the precision of demand analyses in CE businesses but also serve as an important step toward realizing a more sustainable society.

3. Data-driven simulation method for CE business design

This study proposes a data-driven simulation method designed for use during the growth stage of CE businesses, leveraging past operational data. We employ the procedure outlined by Davis et al. (2007). Building on the research questions and theoretical framework described in the preceding section, our simulation integrates both Discrete Event (DE) and Agent-Based (AB) approaches (Lieder et al., 2017). An AB approach is adopted to model the heterogeneity inherent in products and users, as well as their interactions (Macal and North 2010). Meanwhile, product circulation processes are represented using a DE model, a method widely applied in supply chain simulations (Oliveira et al., 2016) to replicate product inventory and maintenance/repair queuing systems (Fleisch & Tellkamp, 2005; Lieder et al., 2017).

3.1. Modeling user preferences

This method employs structural estimation to derive a user decision-making model from real operational data and replicates that model within an agent-based simulation. Structural estimation, an empirical approach that integrates real-world data with economic theory to identify the components of consumer preferences, not only enables modeling of actual decision-making behaviors but also excels at counterfactual reasoning. As a result, it offers a highly versatile framework for simulation applications (Berry, 1994; Berry et al., 1995).
We employ a static discrete choice model to analyze user decision-making. A static discrete choice model examines situations where an economic agent selects one option from a finite set of alternatives,

assuming that all choices are independent. This assumption defines user decisions within a static and straightforward framework that excludes consideration of their past choices or the decisions of others. In rental and sharing services, past decisions are considered to have limited effects on present or future decisions, and strategic interactions with others are also minimal. Thus, adopting a static discrete choice model is reasonable. This model simplifies the analysis of user preferences, enabling more efficient evaluation. The utility function U_{ij} for user i selecting product j is defined as follows:

$$U_{ij} = \sum_{k \in K} \beta_k x_{kj} + \epsilon, \tag{1}$$

where K represents the set of product attributes, such as screen size, specifications, and transaction price for used PCs in this study. β denotes the regression coefficients corresponding to attribute k, x is the value of attribute k for product j, and ε represents the error term, which captures individual differences in user decision-making and is assumed to follow a Type I extreme value distribution.

To analyze the user decision-making model in detail, we combine the Conditional Logit Model with Latent Class Analysis (LCA). The Conditional Logit Model assumes that users are exposed to different contexts (choices), allowing for the analysis of decisions influenced by varying alternatives. LCA, on the other hand, estimates partial utilities based on users' choice behaviors and segments users according to the similarity of these utilities. This method classifies users based on latent preferences, enabling a more detailed analysis of user diversity (Boxall & Adamowicz, 2002). The probability P_{ij} of user i selecting product j is expressed as follows:

$$P_{ij} = \sum_{s} \pi_{is} \frac{\exp(\sum_{k \in K} \beta_{ks} x_{kj})}{\sum_{l \in C_i} \exp(\sum_{k \in K} \beta_{ks} x_{kl})}, \tag{2}$$

where π_{is} is the probability that user i belongs to segment s, and C_i is the set of products presented to user i.

By combining Conditional Logit Model and LCA, this approach accurately captures the diversity of user choice behaviors, enabling a more sophisticated analysis of decision-making processes in circular economy contexts.

3.2. Product circulation

Products offered through rental and sharing services are employed by a diverse range of users, undergoing multiple processes such as transportation, maintenance, repair, and disposal. This supply chain is modeled using a discrete event approach and is divided into four sections: the procurement phase, maintenance and repair phase, transportation phase, and usage phase.

The process begins with demand generation, driven by user interactions over time. This demand triggers the need for procurement, transitioning into the procurement phase.

During the procurement phase, products are sourced in accordance with demand and the business model. Various decisions are involved, such as the types of products to acquire, whether to purchase new or used products, the quantity to procure, and the purchase price. Once procurement is completed, the products are matched to users and proceed through the transportation phase to the usage phase.

In the usage phase, products are utilized based on the number of units contracted by users and the duration of the contract. After usage, the products return through the transportation phase to the maintenance and repair phase.

In the maintenance and repair phase, the returned products are first inspected for malfunctions. Since the failure rate increases with extended usage, the failure rate is derived using a Weibull distribution. The Weibull distribution is widely employed in reliability engineering and lifetime data analysis as it effectively models product failure times. Specifically, the Weibull distribution is characterized by two parameters: the shape parameter (shape factor) and the scale parameter (scale factor), which flexibly express the time dependence of the failure rate. Generally, the survival rate $S(t)$ and failure rate $F(t)$ at time t are expressed as follows using the scale parameter η and shape parameter m:

$$S(t) = \exp\left[-\left(\frac{t}{\eta}\right)^m\right] \tag{3}$$

$$F(t) = 1 - S(t) \tag{4}$$

If no failure is detected, the product enters the maintenance queue, undergoes the maintenance process, and is subsequently returned to inventory. Conversely, if a failure is identified, the product's remaining useful life is assessed to determine whether it should be repaired or discarded. Products requiring repairs are placed in the repair queue, undergo the repair process, and are then returned to inventory.
Time requirements are established for both maintenance and repair processes, specifying the number of days required. Additionally, operational constraints, such as the maximum number of units that can be processed per day in each phase, are defined to ensure efficient workflow management.

3.3. User-product matching

This simulator replicates the transaction process as a matching mechanism between participating users and the available product inventory. Users conduct transactions on a first-come, first-served basis and express their preferences based on a decision-making model. Products are allocated to each user according to these preferences and the current state of the inventory. Similarly, in real-world rental and sharing businesses, inventory status is updated in real-time, and the products contracted vary depending on the prevailing inventory conditions.
User selection and product procurement associated with the matching process can differ significantly depending on the characteristics of the service provided. To accommodate this variability, the simulator is designed to be flexibly adaptable to different business models. This design enables the creation of a versatile simulation framework applicable to a wide range of business models, facilitating scenario comparisons for corporate strategy development.

4. Application

4.1. Case description and methodology

To validate the utility of the simulator in corporate strategy formulation, this study applied it to a PC rental business and conducted scenario comparisons. This business primarily sources second-hand PCs and provides short-term rental services to meet diverse needs, such as training sessions and events. By allowing users to rent PCs only for the required duration, the business achieves efficient resource circulation. In implementing this case study, transactional data, inventory data, failure data, and procurement data were incorporated into the simulator, and the actual business processes were meticulously replicated based on these inputs and supplementary interviews.
Additionally, scenarios with varying compositions of user segments were constructed and analyzed to evaluate their impacts. The objective of this analysis was to quantitatively pre-assess how different user segment compositions influence revenue and product utilization rates, providing actionable insights into customer marketing strategies. Specifically, the findings aim to inform which segments should be prioritized as target customers to optimize business performance.

4.2. Estimation of user preference parameters

This study estimates user preference parameters using transactional and inventory data obtained from an actual business. A total of 23,812 transactions, containing all the necessary information for the estimation, were utilized for the analysis. The variables used in the estimation include:

- **Screen Size**: A categorical variable representing the screen size of the product involved in the transaction (13.3 inch, 14 inch, 15.6 inch).
- **Specification**: A continuous variable indicating the generational gap from the most recent product generation at the time of the transaction.
- **Transaction Price**: A continuous variable representing the price offered during the transaction.
- **Lending and Return Dates**: Date information related to the lending and return of the products.

Among these variables, screen size, specification, and transaction price were used as explanatory variables for estimating user preference parameters. Meanwhile, lending and return dates were recorded to track transaction timing but were not included in the estimation model itself.
The analysis dataset includes products selected by users ($y = 1$) and the unchosen alternatives presented at the time of the transaction ($y = 0$). When generating the choice set, factors such as discounts based on contract duration and relative specifications at the time of the transaction were considered. The observed value y_{ij} is an indicator function, defined as $y_{ij} = 1$ if user i selected product j, and $y_{ij} = 0$ otherwise. The

preference parameters were estimated using Maximum Likelihood Estimation (MLE), maximizing the following likelihood function $L_p(\boldsymbol{\beta})$:

$$L_p(\beta) = \prod_{i \in N} \prod_{j \in C_i} P_{ij}^{y_{ij}} \tag{5}$$

where N represents the users included in the transaction data, and C_i is the set of choices available to user i. This latent class analysis was conducted using the flexmix package in the statistical analysis software R (Grün & Leisch, 2008). The number of segments was varied from 1 to 3, and model fit was evaluated using log-likelihood, AIC, and BIC criteria (Table 1). Based on the fit evaluation, the number of segments was set to 3, and the parameter estimates obtained from this segmentation were applied in the simulation (Table 2).

Table 1. Model fit evaluation

Number of Segments	1	2	3
Log-Likelihood	-45975	-44414	-44404
AIC	91959	88845	88835
BIC	92000	88939	88981

Table 2. Estimated parameter values

Coefficient	Segment A	Segment B	Segment C
Price	1.59 e-4	-3.57 e-2	1.08 e-3
Number of Generational Decline	0.196	91.9	0.444
13.3 inch	0	0	0
14 inch	-2.54	-275	3.28
15.6 inch	3.58	-461	6.12
Composition Ratio	**0.49**	**0.23**	**0.28**

4.3. Setting for product circulation

4.3.1. Demand and supply generator

Users are generated at intervals of one day, with the number of users generated each day determined based on the average monthly user counts derived from actual transaction data, accounting for seasonal fluctuations such as peak demand periods. Additionally, the segment composition ratios are adjusted monthly to reflect observed variations (Figure 1).

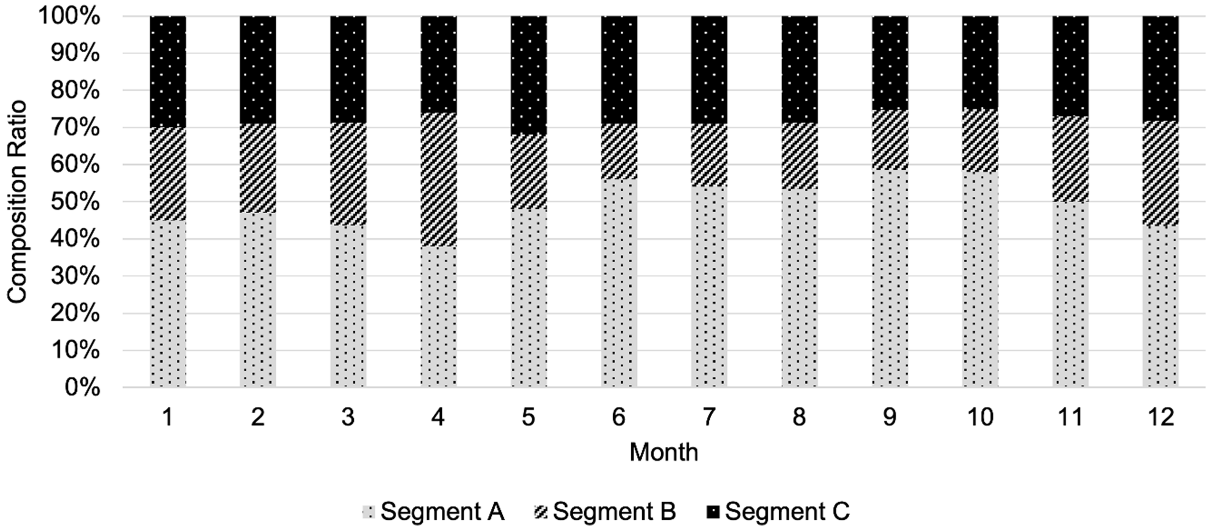

Figure 1. Monthly segment composition ratios

For each segment s, the user's duration of use D_s and the number of units used Q_s are defined. The duration of use D_s is probabilistically sampled based on the mode m and its frequency distribution $P(D_s = m)$ obtained from empirical data. On the other hand, the number of units used Q_s is assumed to follow a Poisson distribution, with its mean λ_s derived from actual data. Specifically, the number of units is generated as $Q_s \sim Poisson(\lambda_s)$.

Procurement is modeled in accordance with the business model of the targeted operation. For unmatched users or when existing inventory is insufficient, the most preferred product for those users is procured additionally and offered. The procurement price incorporates actual pricing data, adjusted for the number of days elapsed since the product's sales date. In this simulation, product procurement is strictly based on user preferences, ensuring alignment with the business context under study.

4.3.2. Settings related to failures

Based on interviews with the relevant business operators, the product lifespan is assumed to be 10 years. In the decision-making process for repairing or discarding defective products, repairs are conducted if the product's remaining lifespan exceeds two years.

The failure rate was calculated by estimating the parameters of a Weibull distribution using actual transaction and failure data, and deriving the failure rate based on the estimated values. The failure data included records where failures ($z = 1$) were confirmed either during the rental period or upon return (N=1120), while transaction data identified cases where no failures occurred during the rental period ($z = 0$, N=98761). Using these data, the conditional survival function $S_c(t)$ and the conditional failure rate $F_c(t)$ at observation times $t > t_s$, where t_s represents the rental start time, are defined as follows:

$$S_c(t|t > t_s) = \frac{S(t)}{S(t_s)} \tag{6}$$

$$F_c(t|t > t_s) = 1 - S_c(t|t > t_s) \tag{7}$$

The observed value Z_i is an indicator function denoting whether the product rented to user i failed ($z_i = 1$) or not ($z_i = 0$). The parameters are estimated by maximizing the following likelihood function $L_f(\eta, m)$ using Maximum Likelihood Estimation (MLE):

$$L_f(\eta, m) = \prod_{i \in N} [z_i F_c(t_i) + (1 - z_i) S_c(t_i)] \tag{8}$$

where t_i is the observation time for events related to user i. The estimation results yielded a scale parameter η of 6,700 and a shape parameter m of 2.89.

4.3.3. Settings related to maintenance and repair

Based on interviews with the relevant business operators, the number of days required for each process is set at one day for both maintenance and repairs. Additionally, the maximum daily processing capacity is set at 250 units for maintenance and 25 units for repairs.

4.4. Setting for user-product matching

The matching process between users and products is conducted based on the business processes of the targeted operation, following the flow illustrated in Figure 2. First, the participating users for the day and the available inventory are prepared, and the matching is performed on a first-come, first-served basis. During the matching process, the products with a positive utility for the user are sequentially evaluated in order of preference. If a preferred product is available in inventory, it is assigned to the user. If a user is dissatisfied with the offered products and does not select any, the matching process terminates at that point, resulting in an unsuccessful match. For users for whom matching is unsuccessful, the most preferred product is procured additionally and offered.

4.5. Scenario setting

Scenarios with varying user segment composition ratios were created to quantitatively evaluate their impacts on revenue and product utilization rates. These scenarios were developed through workshops with the business operators to derive insights that contribute to the marketing strategy of the targeted operation.

Table 3 outlines the scenarios considered in this study. Scenario 1 serves as the baseline scenario, adopting the segment composition ratios derived from empirical data presented in Table 2. In contrast,

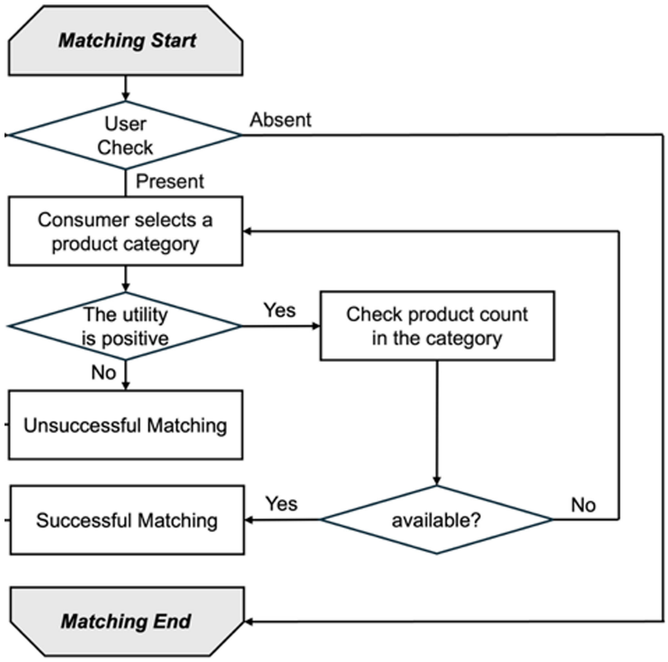

Figure 2. Matching algorithm for users and products

Table 3. Segment composition ratios in each scenario

Scenario Number	Segment A	Segment B	Segment C	Note
1	0.49	0.23	0.28	Default scenario for baseline.
2	0.82	0.08	0.10	High composition ratio of Segment A.
3	0.26	0.60	0.14	High composition ratio of Segment B.
4	0.23	0.11	0.66	High composition ratio of Segment C.

Scenarios 2 through 4 represent hypothetical cases where the composition ratios of Segments A, B, and C are increased, respectively. These scenarios were designed to compare the impacts of prioritizing specific user segments.

5. Results of the application of the simulation model

In this study, the reproducibility of the simulation was validated by comparing its results with empirical data from 2021 to 2023. The simulation was conducted over a three-year period, focusing on data from the final year. Figure 3 compares the daily revenue data from the empirical records and the simulation results. All values were scaled using the daily average revenue from the 2021–2023 period as the baseline, dividing all data points by this baseline value.
As a measure of comparison, the Mean Absolute Error (MAE) was calculated, yielding an MAE of 0.6726. This indicates that the simulation successfully captures overall trends and general patterns in demand to a certain extent. Furthermore, the fact that the order of revenue magnitudes matches between the simulation and actual data demonstrates that procurement and supply were appropriately aligned with the generated demand.

6. Results of comparative analysis of scenarios

A comparative analysis was conducted based on the scenarios outlined in Table 3. The simulation covered a three-year period, with the analysis focusing on data from the final year. Figure 4 illustrates the variations in average revenue and average utilization rates across the scenarios. Average revenue was scaled by using the daily average revenue from Scenario 1 as the baseline, with all values normalized to this reference point.

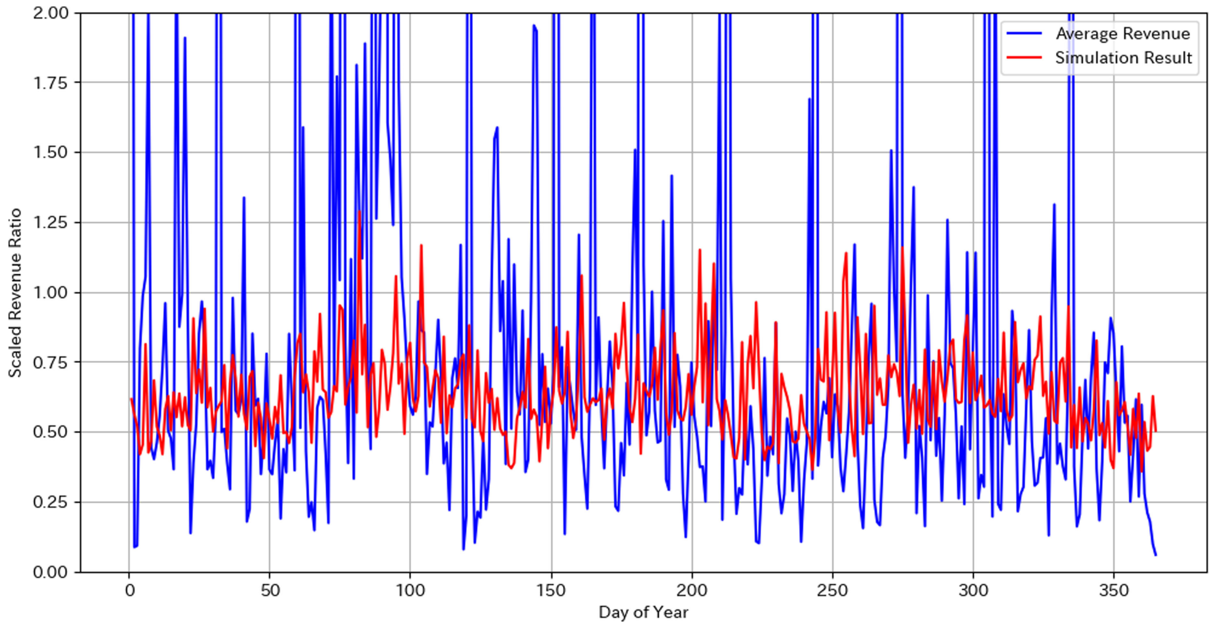

Figure 3. Comparison of sales results (line graph)

The comparison revealed that Scenario 2 exhibited the highest revenue. This result is attributed to Segment A's preference for relatively higher-specification products compared to other segments. Conversely, Scenario 3 demonstrated the highest utilization rate, which is likely due to the concentrated preferences within the segment that result in successful matching only for a specific product category. In Scenario 4, both revenue and utilization rates exceeded those of Scenario 1, which represents the current situation. This outcome is explained by Segment C's positive utility across a wide range of product categories, facilitating a higher likelihood of successful matching.

In the short term, focusing sales efforts on Segment A, which generates the highest revenue, appears to be a rational strategy. However, from a long-term perspective that considers resource circulation, concentrating on Segment C, which has the potential to enhance both revenue and utilization rates, emerges as an economically and environmentally optimal approach. Furthermore, the findings suggest that adopting a marketing strategy that balances efforts between Segment C and Segment A may yield even better results, offering a comprehensive strategy for sustainable business growth.

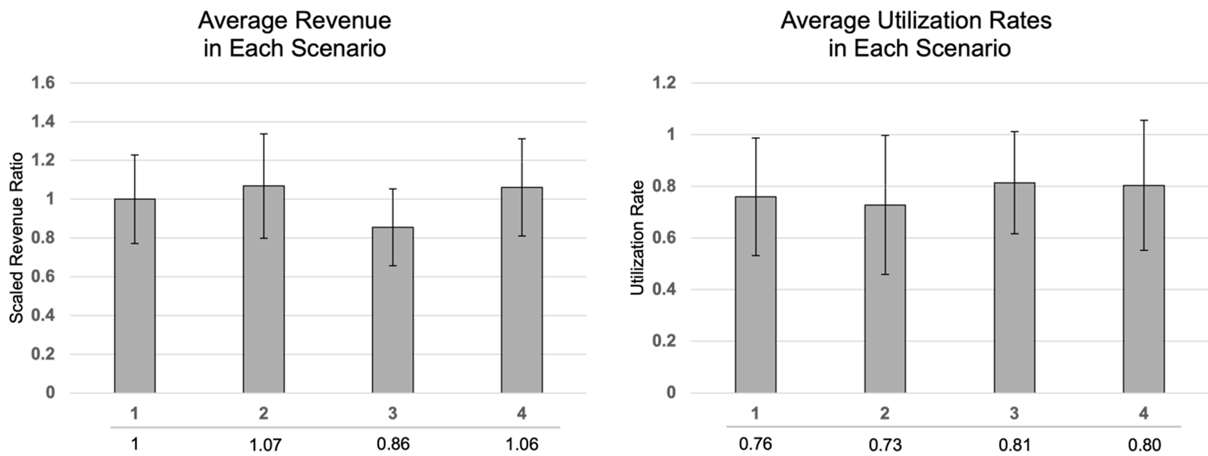

Figure 4. Comparison of average revenue and utilization rate

7. Discussion and conclusion

By leveraging real data, this simulator meticulously reproduces user preference models, product circulation processes, and the matching of users and products in a manner closely aligned with real-world business settings. A case study on a PC rental business was conducted to validate the plausibility of the simulation results and to compare different scenarios. Consequently, the simulator successfully replicated the target business, and by varying user segment compositions across multiple scenarios, it was demonstrated that the simulator can offer valuable preliminary evaluations for customer marketing, thereby supporting corporate decision-making.

Although existing studies have proposed tools for systematically quantifying, exploring, and optimizing various business scenarios, what distinguishes this research is its detailed modeling of user decision-making. In conventional data-driven product-circulation simulations, data used to model customer demand typically originates from macro-level sources such as market data, making it difficult to capture consumer heterogeneity. By contrast, this study leverages operational data that can identify individual consumers in detail, thereby accurately modeling heterogeneous factors such as utility functions by segment, seasonality, and variations in contract volume and duration. This extension proves particularly beneficial for formulating customer marketing strategies that had previously been difficult to evaluate. Thus, the simulation model proposed in this study serves not merely as a service-design support tool but also demonstrates practical and academic significance as a method for supporting a wide range of strategic corporate decisions. On the other hand, because it presupposes the availability of operational data, it may not be suitable for companies lacking sufficient data immediately after transitioning to a CE model. Additionally, the exclusion of maintenance and repair costs highlights an area for further improvement.

Looking ahead, changes in consumer-segment composition can influence not only the number of years since the product's manufacturing but also its associated maintenance and repair costs. We intend to extend our model to accommodate such factors. Moreover, skewing the customer base through certain marketing strategies may accelerate the wear and tear of specific products, potentially escalating environmental impact via rebound effects. These effects are well-documented in the context of CE businesses, underscoring the need for more precise methods of environmental impact assessment. The utilization rate employed here for environmental evaluation is insufficient to capture these effects comprehensively. Introducing life-cycle assessment techniques capable of deriving a more accurate measure of environmental impact will help better account for the environmental consequences of consumer heterogeneity. Such advancements in simulation will contribute to the development of sustainable corporate strategies that effectively balance environmental and economic considerations.

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