Service Ecosystem Design Using Social Modeling to Incorporate Customers' Behavioral Logic

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Abstract. The Customer dysfunctional behaviors affect service providers' workloads. However, few studies on service ecosystem design have investigated how to prevent these behaviors. This study thus proposes a service ecosystem design tool that can analyze how dysfunctional behaviors affect other actors in the service ecosystem. To this end, customers' behavioral logic is incorporated into social modeling to analyze their dysfunctional behaviors. This study also uses goal-oriented requirement language as design and analysis tools. Then, structural equation modeling is used to analyze the effects of behavioral logics. A case study of a home delivery service demonstrates the applicability of this methodology to analyze the effects of customer behavioral logics on service ecosystem actors.

Keywords: Service design · Service ecosystem · Behavioral logic · Customer dysfunctional behavior

1 Introduction

Service value is co-created by service providers and customers [1], where customer dysfunctional behaviors affect the workload of service providers. However, service design has focused mainly on developing customers' cooperative behavior by shaping their service experience without sufficient consideration being given to customer dysfunctional behaviors [2]. Moreover, service value is not co-created in the interactions between employees and customers, but in those among various actors [1]. Teixeira asserted that the modeling methods of goal-oriented requirement engineering (GORE) are useful for designing a service ecosystem [3]. These methods can describe the dependent relationship between actors and non-functional requirements, which can be used to evaluate customer satisfaction. However, service design methods in GORE have not been developed to predict customer dysfunctional behavior.

According to Ullman, as design proceeds and knowledge about the design problem increases, it is more difficult to change the system and solve the problem [4]. Therefore, it is more effective to prevent customer dysfunctional behaviors in the service design phase than in the service provision one. For this reason, it is necessary that service

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design takes into account the characteristics of customers who exhibit dysfunctional behavior. Understanding behavioral logic is thus the fundamental solution to prevent customer dysfunctional behaviors.

However, there are few studies that examine how to prevent these behaviors. Our study fills this gap by focusing on customer behavioral logic and including it in service design. The purpose of this study is to propose a service design tool that incorporates customer behavioral logic. This study contributes to the service ecosystem literature by developing a design method that can predict customer dysfunctional behaviors in the service design phase by incorporating behavioral logic into the GORE methods.

The rest of this paper is structured as follows. Section 2 reviews previous studies on service ecosystems, service design, and system modeling. Section 3 describes the service design method of this study. Section 4 presents a case study of a home delivery service. Section 5 discusses the contributions of the study.

2 Literature Review

2.1 Service Ecosystem

For decades, goods-dominant (G-D) logic was widely accepted in both practitioners and researchers. It regards physical goods as the main value for customers, and service as an added value. Recently, however, there has been a shift to service-dominant (S-D) logic, which considers service the main value for customers because products have become more commodified [1, 5]. It is important to view the market as value co-creation and to design service with an understanding of the service ecosystem.

The service ecosystem is defined as a "relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange" [1]. Based on S-D logic, customers and service providers contribute equally to service success. If customers behave inappropriately, other actors in the service ecosystem will be negatively affected. However, previous studies on the service ecosystem do not sufficiently explain how to decrease customer dysfunctional behaviors.

2.2 Service Design

Service design methods are roughly divided into process design methods and system design methods. Represented by service blueprinting [6], process design methods establish each actor's tasks by focusing on service processes and product flows [7]. System design methods, represented by i* [8], create the service concept by considering the interactions among actors and focusing on actors' goal achievement levels and the dependent relationship among actors [8].

Service design has traditionally emphasized customer experience [3]. There are many process design methods, in which customer psychology is described as a journey map [9]. In each service process, services are designed based on customer psychology. However, since service providers' tasks are determined by customer needs and behaviors, it is difficult to use process design methods to design service ecosystems that can treat customers and service providers equally. To overcome this limitation, this study incorporates behavioral logic into the system design methods.

2.3 System Modeling

In business design, the system modeling method of social modeling is commonly used. Since social modeling focuses on interactions among actors, it can be adapted for use in a service ecosystem design. Intentional strategic actor relationship modeling (i*: “i-star”) is one of the social modeling methods that can be adapted for service ecosystem design. i* can clarify system requirements in business design and service design [8]. It can also be used to analyze how the change in an element value affects other actors. In i*, actors are described as circles. Actor rationales are described inside of these circles using notation links, including elements such as goals, tasks, and resources. Dependency relationships among actors are described outside of the actors’ circles. Goals are classified as hard or soft goals based on their nature. Hard goals are the objectives of actors and evaluated as achieved/not achieved. Soft goals reflect the nature or quality of goal achievement but is usually difficult to judge as achieved/not achieved.

i* can quantitatively evaluate the effects of the introduction of a new system on each actor’s goals and soft-goal achievement levels. To analyze the social effects on actors, each actor’s task achievement levels are intentionally determined by analysts. Each actor’s task achievement levels propagate each element by following the calculation rule defined in i*, and each actor’s goal achievement levels are evaluated. Since the elements described in i* are limited to four elements (i.e., goals, soft goals, tasks, and resources), task achievement levels are intentionally determined.

In this study, customer characteristics were incorporated into the social modeling method of i* to predict customer dysfunctional behavior in the design phase. This study focuses on behavioral logics as customer characteristics. Traditional social modeling methods first determine task achievement levels and then analyze propagated goal achievement levels. By contrast, this method first determines the value of behavioral logics, which propagate task achievement levels, and then analyzes the propagated goal achievement levels. This method can help predict not only intentional dysfunctional behaviors but also non-intentional dysfunctional behaviors.

3 Methodology

3.1 Overview of Methodology

This study achieves its objective in three steps. Figure 1 shows this approach.

(1) Model a service ecosystem by interviewing service providers and reviewing the relevant literature.
(2) Use a questionnaire to quantitatively analyze the effects of behavioral logics on customer behaviors in each customer segment.
(3) Reflect the calculated results on the service ecosystem model and quantitatively analyze the effects of behavioral logics on the goals of each actor in each customer segment.

i* can design a service ecosystem and roughly determine how the introduction of a new system affects each actor's goals and soft goals. The authors developed i*. Furthermore, quantitative analysis based on the customer rationales obtained by the questionnaires was used in combination with i* to analyze the effects of behavioral logics on other actors' goals and soft goals.

To analyze the effects of customer dysfunctional behavior, including non-intentional dysfunctional behavior, on other actors, this study focuses on customers' behavioral logic that determine customer behaviors. The variables of behavioral logics change for each customer segment. Goal achievement levels were calculated for each behavioral logic value in each customer segment. Finally, how the goal achievement levels change with behavioral logic was evaluated. This study defined behavioral logic as factors or concepts that affect behavior.

To quantitatively analyze the effects of behavioral logics on behaviors, structural equation modeling (SEM) was used. SEM quantitatively analyzes the effects of unmeasurable variables that cannot be analyzed by other methods, such as text mining, by using questionnaire data.

To quantitatively analyze the effects of behavioral logics on other actors, goal-oriented requirement language (GRL) was used. GRL is one of the i* framework methods and has the same notation as i*. Whereas i* can only qualitatively analyze 10 ranges, GRL can quantitatively analyze in a range of [−100, 100]. To compare the effects on each customer segment in detail, this study used GRL for system analysis.

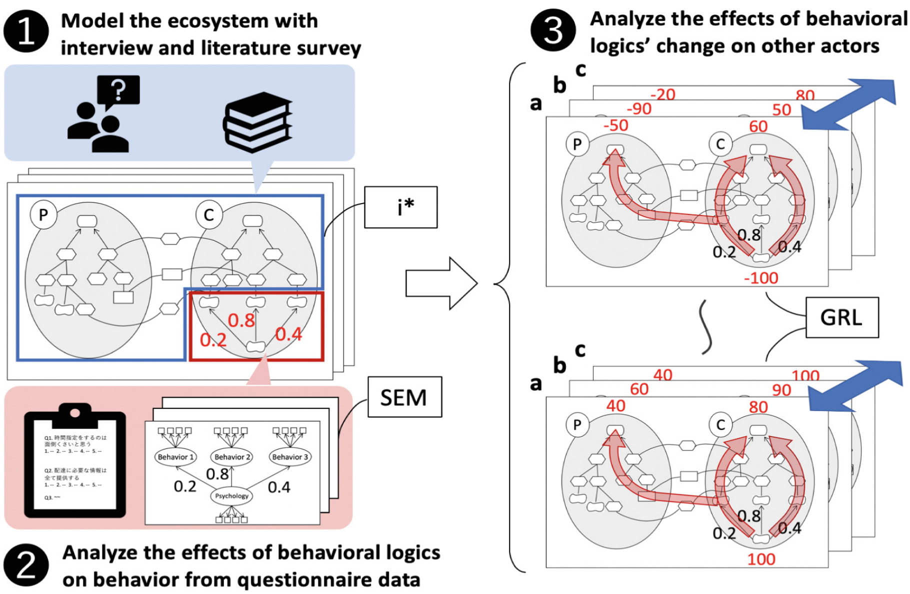

Fig. 1. Three-step approach of the proposed method

3.2 Service Ecosystem Modeling

This study followed the standard i* modeling, which is generally based on interviews with employees and literature reviews. The i* modeling procedure was as follows:

(1) Describe the actors. Actors in a service ecosystem are represented as gray-colored circles.
(2) Describe the actor goals in the actor circles. The objectives of each actor are represented as goals in the circles.
(3) Decompose goals into sub-goals and tasks, which are the processes followed to achieve actors' goals. Relationships among these elements are described as *Means-Ends* and *Decomposition-Links*.
(4) Describe the dependency relationship among actors. Other actors' activities, necessary for executing tasks or achieving goals, are described as *Dependency-Links* with tasks or resources.
(5) Describe criteria as soft goals. While goals are judged as achieved/not achieved, achievement quality and criteria were described as soft goals.
(6) Describe the effects of behavioral logic on behaviors. These effects are described as *Contribution-Links.* The procedure for this advanced notation is explained in the next paragraph.

The traditional i* does not have any notations to describe behavioral logic (e.g., psychology and knowledge) or the effects of behavioral logic on behaviors. The elements described in i* are limited to *goals,* which are objectives to be achieved by actors; *soft goals,* which are criteria to judge goal achievement quality; and *tasks* and *resources,* which are necessary for achieving goals and soft goals. This study advances the i* notation in two ways. First, behavioral logic is described as soft goals, that is, criteria for describing customers' natures. Second, the effects of behavioral logic on behaviors are described as *Contribution-Links* between soft goals that are behavioral logics and soft goals that are task achievement criteria decomposed from each task. The *Contribution-Links* notation in the traditional i* is limited to describing to what extent tasks affect soft goals or to what extent soft goals affect other soft goals. In other words, there are no notations to describe the effects of behavioral logic on behaviors. We decomposed task achievement criteria from each task and then applied *Contribution-Links* to describe to what extent behavioral logics affected behaviors. Figure 2 shows the notations for describing the effects of behavioral logic on behaviors in the studied home delivery service. In this figure, the left-hand side shows the traditional i* notation and the right-hand side shows the advanced i* notation. A circle in each side represents the customer as an actor. Inside the actor circle, a goal—*specify the delivery time*—is described. Two tasks—*specify the delivery time with a fee* and *follow the default specified delivery time*—are decomposed from the goal with *Means-Ends*. On the right-hand side, a behavioral logic—*psychological ownership*—was described as a soft goal at the bottom. Two task achievement criteria—*degree of specifying the delivery time with fee* and *degree of following default settings*—are decomposed from each task. The effects of psychological ownership on each behavior were described as *Contribution-Links*.

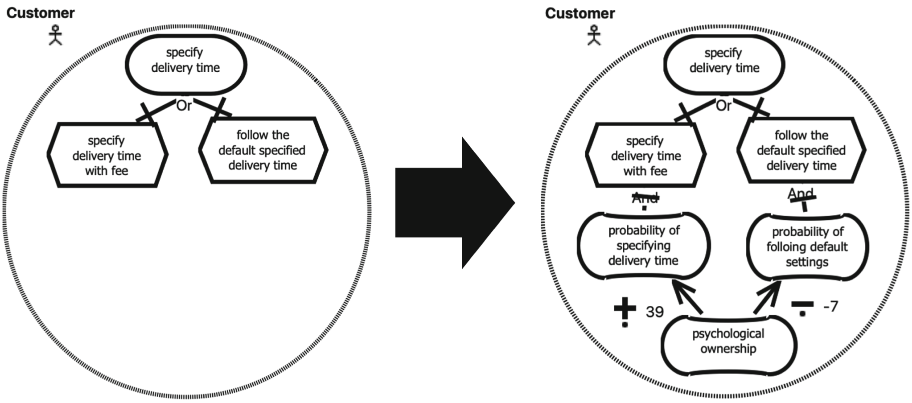

Fig. 2. Advanced i* notation for describing the effects of behavioral logics toward behaviors.

3.3 Quantitative Analysis in Customer's Rationale

SEM was used to quantitatively analyze the effects of behavioral logic on actors' behaviors. SEM is a statistical method used to identify causal relationships between latent, unmeasurable variables. It uses multiple regression and positive factor analyses.

This study describes behavioral logic and behaviors as latent variables and calculates the variables of the effects of behavioral logics on behaviors, setting observation variables for each latent value. A questionnaire survey was conducted to collect data for these observation variables.

3.4 Ecosystem Analysis with Behavioral Logics Change

SEM was used to calculate the variables reflected in the i* model. However, i* cannot be applied to quantitative analysis. Therefore, GRL [11], which can analyze both quantitatively and qualitatively, was used for quantitative analysis.

To analyze how the change in customer behavioral logics affected other actors, SEM was used to calculate variables that reflected *Contribution-Links* between behavioral logic and behaviors in GRL. The variables calculated by SEM were in the range of [−1, 1]; those calculated in GRL were in the range of [−100, 100]. The SEM variables were multiplied by 100 to substitute them for *Contribution-Links* in GRL. In GRL, each actor's goal achievements were quantitatively analyzed by changing the value of customer behavioral logics to the range of [−100, 100].

4 Case Study: Home Delivery Service

4.1 Subject: Home Delivery Service

We used a case study to verify the utilization of the proposed design method. A home delivery service—in particular, receiving goods bought via e-commerce through a home delivery service—was chosen as the subject of this case study. That is because the home delivery service ecosystem consists of many actors including customers, e-commerce providers, and delivery service providers (i.e., headquarters, branch offices, drivers, pickup persons, and delivery persons). If customers exhibit dysfunctional behavior, other actors will be affected by it. For example, recently, home delivery service providers in Japan have experienced heavy workloads caused by the increasing number of re-deliveries, which is caused by customer' absence during delivery time [12]. This study focused on *psychological ownership* and *visibility* as parts of the behavioral logic that affects customer behaviors.

The ministry of Land, Infrastructure, Transport and Tourism issued a questionnaire to customers about their home delivery service usage in 2015. More than 42% of subjects chose "*I forget I had ordered the delivery service*" as a reason for failing to receive their parcels on time [12]. This result can be explained by the fact that excessive demands from customers—specifically, their lack of psychological ownership towards receiving parcels—increased service providers' workload based on Japan's *Omotenashi* culture. Psychological ownership is defined as "the state in which individuals feel an object or a piece of one object as 'theirs'" [13]. In the context of a home delivery service, psychological ownership was defined as the state in which people felt that the collaborative behavior of receiving parcels was their duty. People who have psychological ownership are likely to engage with organizational employees [13]. Promoting psychological ownership is therefore necessary to decrease service providers' workload, as it encourages customers to exhibit the collaborative behaviors essential for service success.

Additionally, customers who have experience sending parcels exhibit behaviors essential for service success [14]. Their experiences meant that they were familiar with the roles and processes of service providers. Shostack defined the level of customer awareness as the *line of visibility* [6]. Accordingly, this study proposed and verified the hypothesis that the more *visibility* customers receive, the more collaborative behaviors they exhibit, which helps decrease service providers' workload. The case study followed the process below:

(1) The home delivery service ecosystem was modeled by i* using interviews and literature reviews.
(2) Customers were administered a questionnaire on *visibility* and *psychological ownership*.
(3) Based on responses to the questionnaire, customers were divided into four groups by their level of *visibility*.
(4) In each customer group, the effect of behavioral logic (*psychological ownership* and *visibility*) on behaviors was calculated using SEM.
(5) Variables of the effects of behavioral logic were substituted for *Contribution-Links* in the i* model.
(6) The value (−100, −50, 0, 50, 100) of *psychological ownership* was substituted in each customer group and each actor's goal achievement level in each group was calculated.

4.2 System Modeling in Home Delivery Service by I*

To model the home delivery service ecosystem using i*, interviews were conducted with employees in the headquarters of a home delivery service company on October 29, 2018 and employees in a branch office of the company on November 20, 2018. These interviews collected information about the service process, each actor's tasks, and the dependency relationship among actors.

Based on the interviews, i* was used to model the rationales of the actors in the home delivery service ecosystem and the dependency relationships among them, following the modeling rules in Sect. 3. Figure 3(a) shows the modeling result of the home delivery service ecosystem. The modeling process in this case study is as follows:

(1) Actors in the service ecosystem are shown as gray-colored circles in Fig. 3(a). Each circle indicates the boundary of each actor. The upper-left circle is the e-commerce provider; the lower-left is the head office; the lower-middle is the branch office; and the upper-middle is the customer. Additionally, pickup persons, drivers, and delivery persons were respectively described as employee roles for home delivery in the lower-right, middle-right, and upper-right.
(2) Each actor's goal (customers: *get the item*; e-commerce provider: *run the e-commerce website*; head office: *run delivery service*; branch office: *run branch office*; pickup persons: *sort parcels*; drivers: *deliver parcels by a car*; delivery persons: *deliver parcels*) was described as a hard goal.
(3) Each goal was divided into sub-elements such as sub-goals and tasks with *Decomposition-links* and *Means-Ends*. For example, customers' main goal (*get the item*) was divided into two sub-goals (*buy the item* and *receive the item*) with *Decomposition-links*. One of the sub-goals (*buy the item*) was decomposed into one task (*buy the item on the e-commerce website*) with *Means-Ends*. This task was divided into three subtasks (*select the item*, *enter the name and the address*, and *pay for the item*) with *Decomposition-links*.
(4) The dependency relationships between actor circles were described. For example, the *e-commerce provider* in the upper-left depends on the resource (*payment*) provided by customers to execute the task (*sell the item*). To produce the resource (*payment*), customers execute the task (*pay for the item*).
(5) The criteria of each actor were described as soft goals. In the case of customers, *low effort* was described as a soft goal.
(6) Customer behavioral logic and their effects on behaviors were described following the advanced i* notation. Behavioral logic (*psychological ownership* and *visibility*) was described in the bottom of the customer circle and was connected to each behavior with *Contribution-Links*. At this point, the strength of the *Contribution-Links* was set to *Some+* , because each link's strength would be substituted with the value calculated by SEM.

4.3 Quantitative Analysis in Customer Rationale by SEM

The effects of customers' behavioral logic on behaviors were quantitatively analyzed by SEM. Four kinds of customer behaviors—customer participation behavior, customer citizenship behavior, dysfunctional behavior, and optional behavior—were analyzed. Customer participation behavior is customer behavior that is necessary for the success of services, for example, *specify the delivery time* [15]. Customer citizenship behavior is customer behavior that is not necessary for service success, but helpful for service providers to deliver services smoothly, for example, *be kind regarding the delivery persons' minor mistakes* [15]. Dysfunctional behavior is customer behavior that disturbs service delivery, such as *pretend to be outside during the delivery time*. Optional behavior, which is located between customer participation behavior and customer citizenship behavior, is customer behavior that is not necessary, but helpful for customers to receive services correctly, for example, *receive notifications about the delivery*.

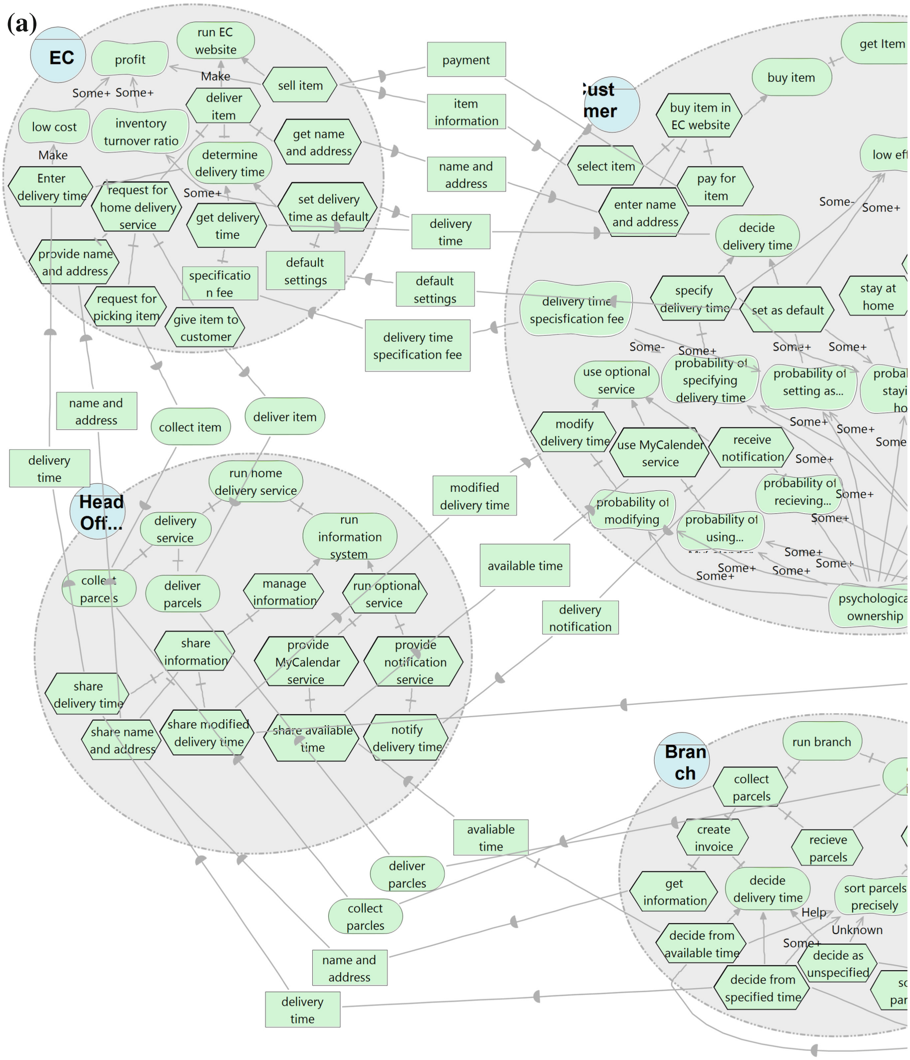

Fig. 3. Home delivery service ecosystem model by i*

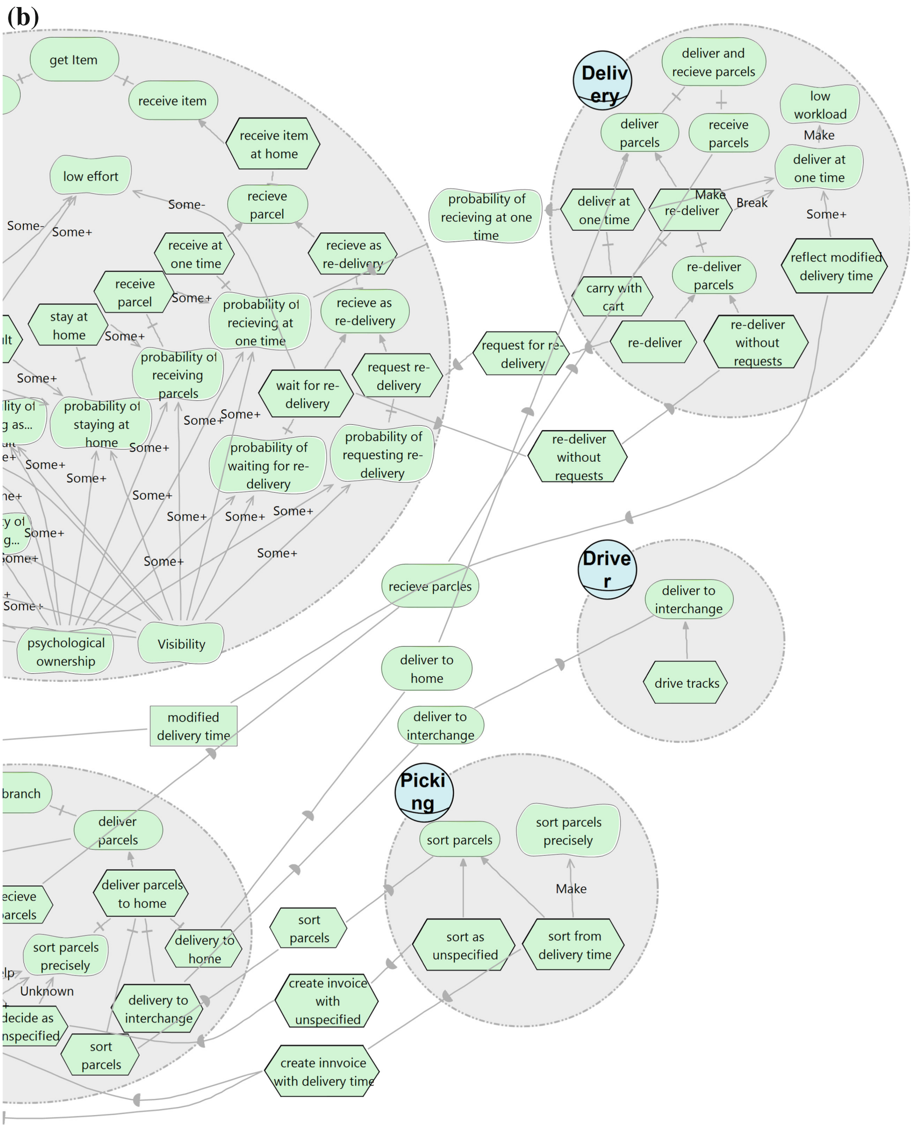

Fig. 3. (*continued*)

To analyze the effects of behavioral logics on these four behaviors, a hypothetical model was developed. In this model, each behavioral logic was connected to each behavior. To collect the observation variables that determined the latent variables (customer behaviors), a questionnaire survey was conducted in February 2019. The subjects were customers who were more than 15 years old and who used the home delivery service more than once a month. There was a total of 10,000 valid subjects. Their average age was 55.12 years; 52.2% were male and 47.8% were female. A total of 3,947 customers (39.5%) made "almost no" requests for re-delivery in the past year, 4,040 customers (40.4%) requested it for "about 20–30%" of deliveries, 1,301 (13.0%) customers requested it for "above 50%" of deliveries, 488 (4.9%) for "almost 70–80%" of deliveries, and 224 (2.2%) for "almost all" deliveries. In the aforementioned survey conducted by the government [16], 46.5% of customers made "almost no" requests for re-delivery in the past year ("I have not requested re-delivery" or "I haven't used the delivery service"), 27.5% requested it for "about 30%" of deliveries, 16.1% requested it for "over half" of deliveries; and 9.4% for "almost all" deliveries.

The results of the present survey were similar to those of the government survey. Therefore, the questionnaire data obtained in this study are highly generalizable.

Before analyzing the data using SEM, customers were divided into four groups based on the value of *visibility*. Observation variables of the latent variable (*visibility*) consisted of six questions. Customers were equally divided into four groups based on the average value of the six variables in the questions. Group (1) consisted of 1,960 respondents, group (2) of 2,062 respondents, group (3) of 3,323 respondents, and group (4) of 2,655 respondents. The boundary variables of the groups were 2.0, 2.83, and 3.3. After the hypothetical model in each group was analyzed, the variables (25, 50, 75, 100) were substituted for the value of *visibility* in GRL. Groups (1), (2), (3), and (4) were respectively called Visibility 25, 50, 75, and 100, respectively, referring to the *visibility* variables used in the GRL analysis.

SEM was used to analyze the variables of the effects of each behavioral logic on each behavior and the fitness value of the model in each customer group. AMOS graphics of IBM SPSS Statics 25 was used for the analysis. The questions used for the SEM analysis are listed in the appendix.

Tables 1 and 2 show the results of the effects of customer *psychological ownership* and *visibility* on each customer's behavior, respectively. The variables in each table show the strength of the effects of *psychological ownership* and *visibility* on each behavior. These variables were calculated in the range of [−1, 1] [10]. The fitness value of the hypothetical model was (goodness of fit index (GFI) = 0.907, adjusted goodness of fit index (AGFI) = 0.889, comparative fit index (CFI) = 0.840, and root mean square error of approximation (RMSEA) = 0.031).

Table 1. Effects of customer psychological ownership on customer behaviors.

	PO → CPB	PO → CCB	PO → OB	PO → MB
Visibility 25	0.53***	0.11***	0.15***	−0.24***
Visibility 50	0.63***	−0.07	0.19***	−0.62***
Visibility 75	0.51***	0.12***	0.19***	−0.48***
Visibility 100	0.42***	0.11***	0.15***	−0.33***

Table 2. Effects of customer visibility effects on customer behaviors.

	PO → CPB	PO → CCB	PO → OB	PO → MB
Visibility 25	0.53***	0.11***	0.15***	−0.24***
Visibility 50	0.63***	−0.07	0.19***	−0.62***
Visibility 75	0.51***	0.12***	0.19***	−0.48***
Visibility 100	0.42***	0.11***	0.15***	−0.33***

(PO: psychological ownership, VI: visibility, CPB: customer participation behavior, CCB: customer citizenship behavior, OB: optional behavior, MB: dysfunctional behavior)

4.4 Ecosystem Analysis in Service Ecosystem by GRL

The i* model was copied into GRL and the results from the SEM analysis were substituted for *Contribution-Links* between customer behavioral logics and behaviors in each customer group. Figure 3(b) shows the results of the analysis. In the case of the initial values of behavioral logic as follows: *psychological ownership* = 50 and *visibility* = 25 in group (1). The achievement level of each element was in the range of [−100, 100] with five colors (red, orange, yellow, yellow green, and green).

To evaluate each actor's goal achievement level, bar graphs were plotted. Figure 4 shows each actor's goal achievement for each *psychological ownership* value with four customer groups. From these graphs, differences in each actor's goal achievement levels can be seen. Even though customers' *psychological ownership* variables changed linearly, customers' goals (*get the item*) changed to a U-shaped curve. The branch office's goal (*sort parcels precisely*) changed in a mirrored L-shaped curve, and other actors' goals changed linearly. These different results were caused by different manners of propagation.

These results show the actual effects of customer behavior on actors' goal achievement levels. In the case of customers' goals (*get the item*), when their *visibility* increased, the goal achievement level increased in all *psychological ownership* variables. These results suggest that customers who are knowledgeable about service processes are more likely to receive service properly and customers who have high *psychological ownership* exhibit collaborative behaviors so that they can receive services properly. However, customers who have low *psychological ownership* can receive service as well as those who have high *psychological ownership*, because service providers compensate for customers' mistakes. In the case of the branch office and pickup persons, the results are mirrored L shapes. This means that, even though customers' *psychological ownership* was low, the branch office and pickup persons were not influenced by it. In the case of the head office and delivery persons, the results were linear. This means that customers' *psychological ownership* value equally affected their goal, so that when customers had low *psychological ownership*, they were negatively influenced by it. These two results explained the fact that customers who had low p*sychological ownership* exhibit dysfunctional behavior, which negatively influences the head office and delivery persons, but not the branch office or pickup persons. This is because customers have closer relationships with the head office (via using service options) and delivery persons (via receiving parcels) than with the branch office and pickup persons.

(a)

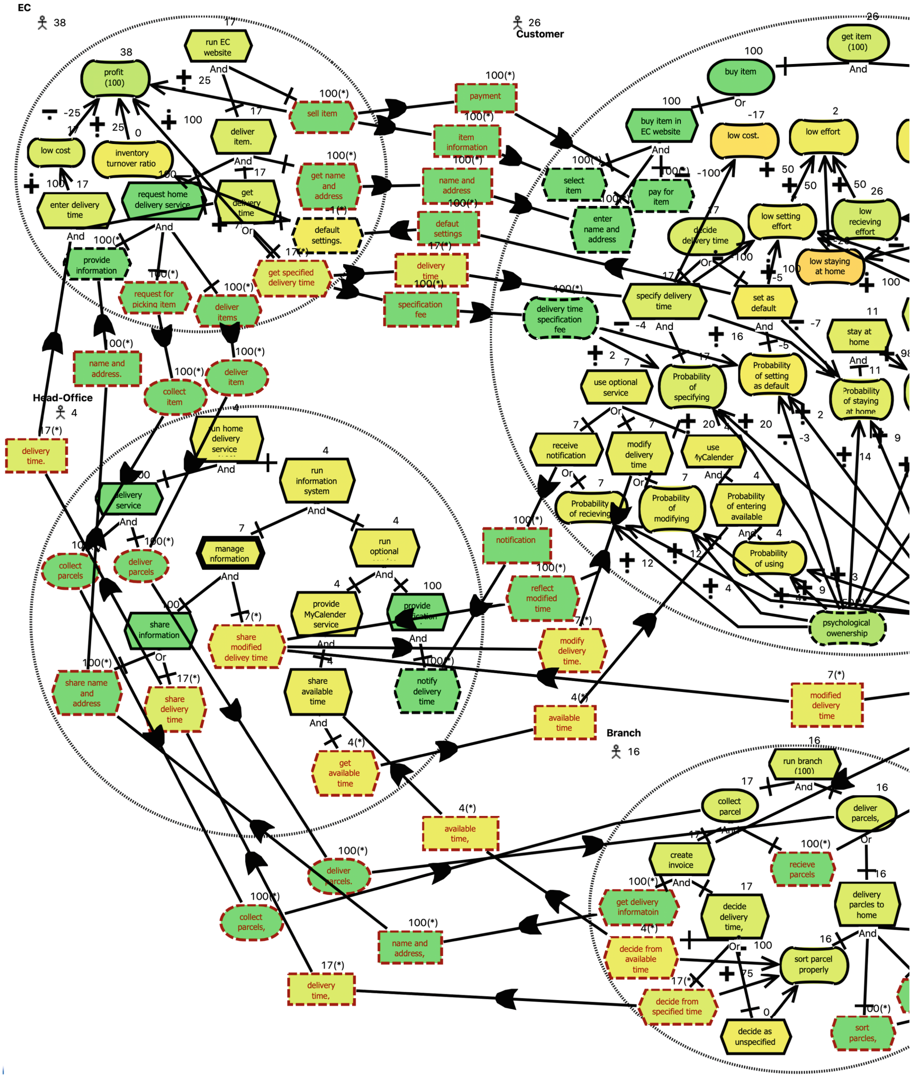

Fig. 4. Analysis results about the effects of behavioral logics on each actor's goal by GRL (in the case of psychological ownership: 50, visibility: 25) (Color figure online)

(b)

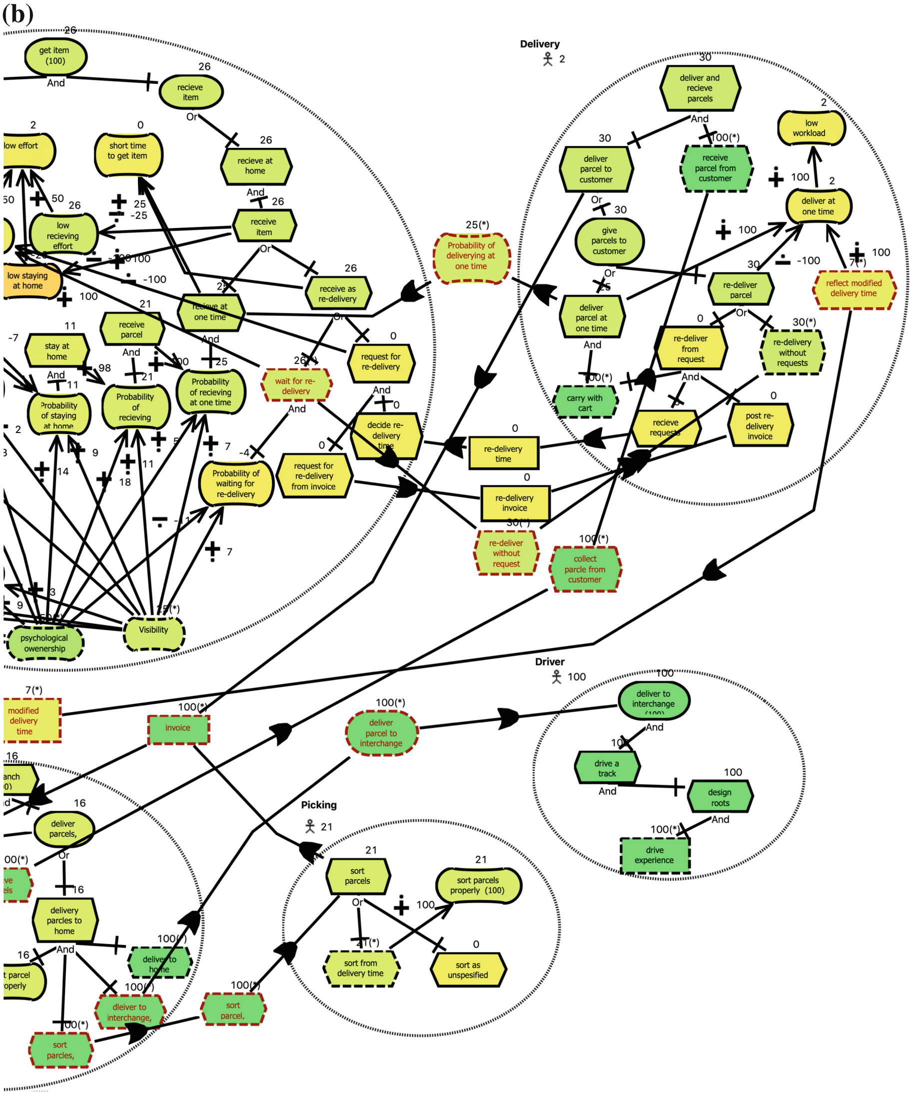

Fig. 4. (*continued*)

The results of this case study clarified that this methodology can analyze the effects of behavioral logics on actors' goal achievement in such detail that this methodology can reflect realistic customer behaviors in impact analysis (Fig. 5).

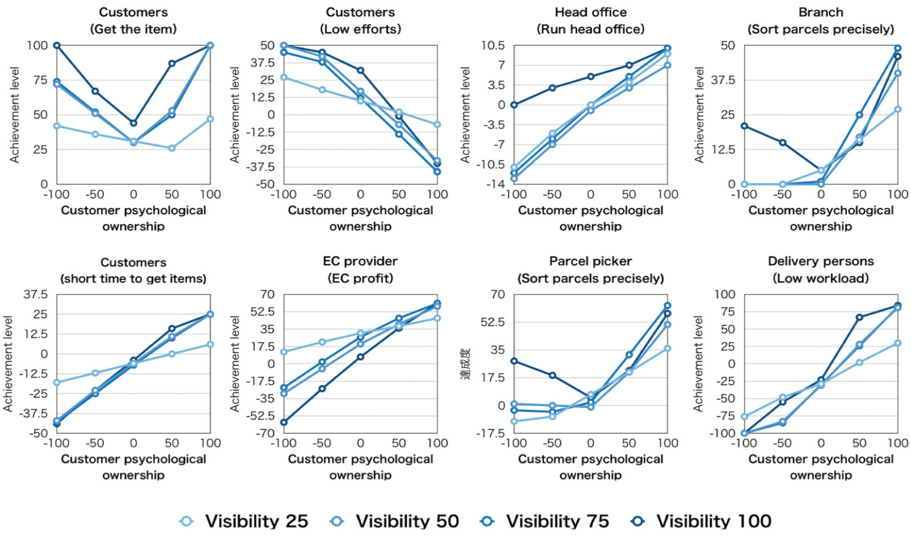

Fig. 5. Each actor's goal achievement level in different psychological ownership value with 4 different visibility groups.

5 Conclusions

5.1 Theoretical Contributions

This study proposed a service ecosystem design method to predict and evaluate how customer dysfunctional behavior affects other actors by incorporating behavioral logic in social modeling. Previous social modeling methods supported impact analysis. However, impact analysis has a limitation in analyzing the impact of customer dysfunctional behavior because the elements described in the methods were limited in goals, soft goals, tasks, and resources, impact analysis basically began from intentionally determining task achievement levels.

Customer dysfunctional behaviors are sometimes unpredictable, and thus, these behaviors cannot be described and analyzed using prior methods. Behavioral logic and its effects on behaviors were described and used for impact analysis. By incorporating behavioral logic into a social modeling method (i*), realistic customer behaviors were reflected in the impact analysis.

5.2 Managerial Implications

As the methodology of this study can predict customer dysfunctional behaviors and analyze their impact on other actors, it can be used for service design. Previous service design methods only focused on collaborative customer behavior. However, workers still needed to deal with customer dysfunctional behaviors. The service design method developed in this study contributes by decreasing the probability of customer dysfunctional behavior, which can also reduce service providers' workload.

This study, however, has a limitation in predicting dysfunctional behavior. Task achievement levels were analyzed by incorporating behavioral logic into i*. However, the advanced i* notation in this methodology still depends on describing tasks. Therefore, tasks which were not described in the i* model were not analyzed. Customer dysfunctional behaviors that were outliers cannot be analyzed. Therefore, further research is necessary to address this problem.

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Appendix

Table 3. Questions used for SEM analysis (questions were answered on a five-point Likert scale, ranging from 1 (totally disagree) to 5 (totally agree))

Visibility	• I have heard of the job role of delivery persons • I have heard of the job role of head office • I have heard of the job role of pickup persons • I understand the job role of EC provider • I understand the job role of delivery persons • I understand the job role of pickup persons
Psychological ownership	• It is important for me to confirm the current status of the parcel • If I meet delivery persons with cheerful personality, I feel happy • To reduce the number of re-deliveries, I need to cooperate • If consumers including me cooperate, working environment of delivery persons will improve • I can decrease the number of re-deliveries if I do my best • The reason for increasing number of re-deliveries is that consumers are not paying attention to their deliveries
Customer participation behavior	• I do not exhibit unnecessary behaviors which may cause problems with delivery persons • I am polite to delivery persons • I am kind to delivery persons • If wrong parcels are delivered, I immediately contact the service provider
Customer citizenship behavior	• If I come up with ideas for new, convenient services, I will tell them to the service provider • If I receive good service, I will spread it by word of mouth • If I receive good service, I will recommend this service to others

(*continued*)

Table 3. (*continued*)

Customer optional behavior	• I have used optional service in which we can change delivery time and delivery spot before the delivery time • I have used optional service which sends notification of delivery completion • I have used optional service which sends notification of shipment of parcels • I have used optional service in which we register the affordable time and parcels are delivered in registered time
Customer dysfunctional behavior	• Forgetting I had specified the delivery time, I have gone out and failed to receive parcels • I have pretended to be outside during the delivery time to escape meeting delivery persons • Even though I had known I could not have stayed at home during the delivery time, I have not changed the delivery time • Without requesting re-delivery, I have waited for delivery persons re-delivering

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