# Factor Analysis for System Development to Encourage Customer Action

# 顧客行動を促進するシステム開発のための要素分析

March 2018

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# Chapter 1

# Introduction

## 1.1 Background and Objectives

In "Japan Revitalization Strategy 2016" [1], a recently published article by the Japanese government, the realization of the fourth industry revolution with IoT, big data, AI, and the robot is one of the primary strategies, which aims to create a total value of 30 trillion yen by 2020. It is vital to think of marketing in order to build this new industry. In addition, it is necessary to evolve marketing techniques themselves to correspond to these technologies and to create an effective marketing method.

In fact, the variety of data available for marketing is rapidly increasing according to the evolution of IoT, big data, ICT technology, and so on. As shown in Table 1.1, questionnaires, interviews and sales data were used conventionally. However, recently, various data such as point of sales (POS) data, social data, location data, image/sensor data and so on can be easily used and marketing methods corresponding to these data have been proposed.

For example, one method of analyzing POS data is Marketing Basket Analysis [2], which extracts purchasing rules of customers such as products often purchased together, which are useful for planning marketing strategies. With regards to the data of E-Commerce, personalized product recommendation is conducted [3]. Moreover, with the spread of social media, the enormous amount of data that customers produced can be used. Utilizing this social data, a method of analyzing product reviews is proposed [4] and promotion using social networking service (SNS) such as making fan pages on SNS [5] has been conducted. Within location data, there is research to grasp the movement trajectory of customers in the store [6], and to make it useful to improve the layout of stores and so on. There is also a example such as recommendation/navigation of peripheral information based on location information [7]. In image/sensor data, measuring the effectiveness of advertising by eye-tracking [8] has been proposed.

**Table 1.1. Changes in data related to purchasing behavior.**

| | Data | Utilization |
|---|---|---|
| Traditional | Questionnaire / interview / sales data | Customer satisfaction survey, sales forecast |
| New | POS data (including E-Commerce) | Marketing strategy planning using purchasing rules and the like, advertisement distribution based on web browsing history |
| | Social data (Text data) | Analysis of SNS (text analysis)<br>Promotion using SNS (used as communication tool) |
| | Location data | Improvement of store layout etc.<br>Recommendation/navigation of peripheral information |
| | Image/sensor data | Measuring the effectiveness of advertising |

In this way efforts are being made to try to utilize new data, but it is still under development. Therefore, creation of marketing methods corresponding to new data is one of the important issues in Japan with the aim of creating new industries by IoT, big data and so on.

Looking at the history of marketing, around 1900, it is said that marketing was born in the backdrop of mass production and mass consumption in the United States.

According to Philip Kotler, a famous professor of marketing, marketing history has changed from product-driven marketing (what Kotler named Marketing 1.0) and customer-centric marketing (Marketing 2.0) to human-centered marketing (Ultimately human-centric marketing Marketing 3.0 / 4.0) [9]. In Marketing 1.0, the purpose was to enhance the function of the product and to sell it to a mass market, in which communicating the characteristics of the product to consumers is emphasized. In Marketing 2.0, we also began to look at consumer satisfaction. For example, research on modeling customer satisfaction as a target variable became popular. In Marketing 3.0, it became a human-centered age (Ultimately human-centric marketing), an era of value co-creation and self-realization. It has become necessary to target not only individual consumers but also society as a whole and their inner−thinking processes. The Covariance Structure Analysis [10] and the Bus Model [11] can be useful marketing methods in modern times, but research that takes the internal human conditions into consideration is under development. Now, in a newly proposed Marketing 4.0, in addition to traditional marketing methods, the strategies of Marketing 3.0 are being further expanded in combination with new digital marketing techniques such as using social media. Although research analyzing the effectiveness of existing digital marketing has been widely conducted, the variety of proposed systems and services that create new value for the customer such as the Product Recommendation System [3] is limited. In other words, in order to create a new business, focusing on the internal aspects of individuals and exploring and developing new marketing methods is also an important issue.

Taking the above into account, it is necessary to create new marketing methods suitable for the emergence of new data, and changes in behavioral pattern and sense of values. Out of the ten marketing schools in the marketing field, the two mainstream schools are "marketing management school" and "consumer behavior school" [12]. The marketing management school deals with the activities of companies that generate the profit of goods and services. The consumer behavior school deals with human behavior in purchasing and consumption, and has a broad range of social sciences. The above-mentioned issues also fall within the purview of these two schools, especially the consumer behavior school.

Therefore, in this research, the objective is as follows.

- Based on "consumer behavior research" and "marketing management research," we create new marketing methods, focusing on customers' internal aspects by utilizing ICT technology.
- We also propose marketing methods that lead to new services, not just analysis tools.

## 1.2 Approach

In this research, we focus on motivation as an approach related to customers' internal aspects. In this section, we describe "Motivation" and "Persuasive Technology" as research related to motivation, and "Consumer Behavior" as research related to marketing. Finally, we explain our approach to research purpose.

### 1.2.1 Related Works 1: Motivation

Motivation is a series of actions that make a person initiate and act towards a certain goal [13]. A factor that is inside a person and causes his behavior is called "desire," and a factor inducing the behavior of a person from outside is called "incentive." Motivation is caused by both these factors [13]. The various theories about motivation have been proposed mainly in the field of psychology, and applied to education, work, and health fields.

A relatively recent theory is self-determining theory [14]. In this theory, it is said that human beings have three desires: "autonomy," "competence," and "relatedness." The desire of "autonomy" is considered to be particularly important. Although motivation is largely classified into two types: extrinsic and intrinsic [15], this theory asserts that motivation can be divided into more styles according to the degree of autonomy as shown in Figure 1.1.

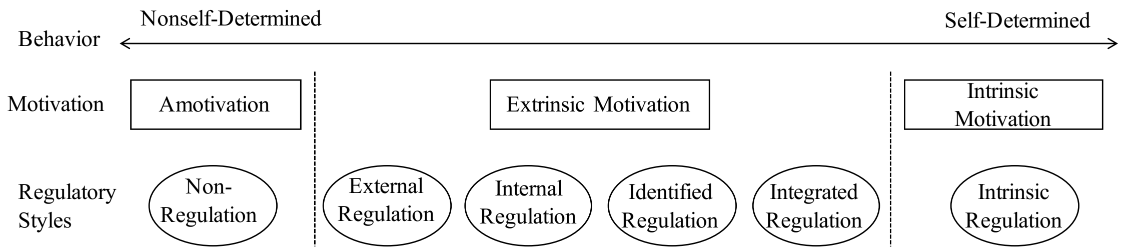


**Figure 1.1. Degree and motivation of self-determinism (autonomy) (referring to [14]).**

The features of each motivation style are as follows [14].

- Amotivation: a state of being without the intention of an action.
- Extrinsic Motivation: a state of being with a purpose or reward other than an action.
  - External Regulation: acting under external forces.
  - Internal Regulation: acting to avoid guilt and anxiety.
  - Identified Regulation: acting consciously, accepting the value of an action.
  - Integrated Regulation: acting in the state of being that the value of an action is fully integrated with one's other values.
- Intrinsic Motivation: a state of being that an action itself is a purpose.

Of these six phases, autonomous motivation consisting of identified, integrated, and intrinsic motivation is reported to be more effective in terms of performance, sustainability, and so on [14]. Therefore, we focus on autonomous motivation in this research and aim to offer motivation with a long-term effect. To achieve this goal, for example, we propose to strengthen the attractiveness of products and services themselves rather than temporary motivation using coupons.

### 1.2.2 Related Works 2: Persuasive Technology

Technology that is designed to change people's behavior is called Persuasive Technology [16] and its research is being applied to a wide range of areas from health to energy saving activities. For example, there are many applications in the health field particularly [17] including the development of health promotion applications for smartphones [18].

One of the theoretical behavioral models of Persuasive Technology is the Fogg Behavior Model [19] (Figure 1.2). This model asserts that for a behavior to occur, the person must have sufficient motivation, sufficient ability, and an effective trigger. In other words, (1) motivation and (2) ability are necessary when (3) a trigger is offered. Examples of motivation factors are pleasure, hope, and social acceptance. Examples of ability are time, cost, and a lack of physical burden.

In this research, we focus on “motivation” that is mainly related to customers’ internal aspects. Furthermore, we design the proposed methods and analyze the effective factors encouraging customer action based on the three elements of this model.

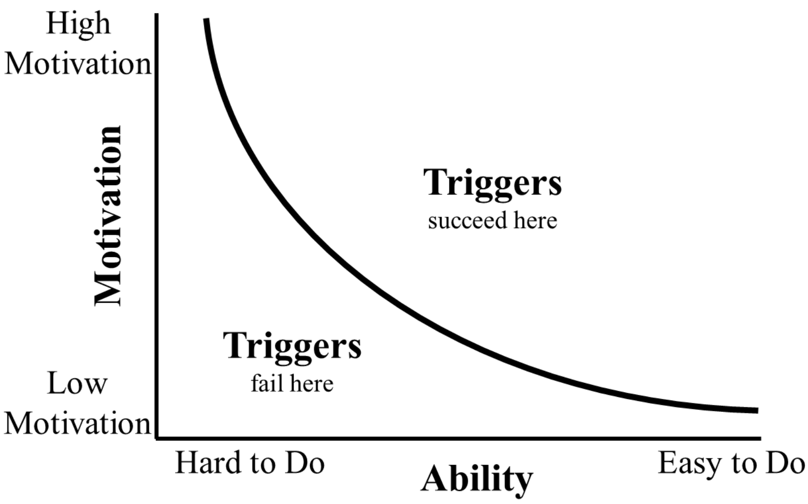


**Figure 1.2. Fogg behavior model (referring to[19]).**

### 1.2.3 Related Works 3: Consumer Behavior

The Consumer Behavior School deals with human behavior in purchasing and consumption, and has a broad range of social sciences [12]. A lot of models explaining the consumer decision process and purchase behavior have been proposed. A famous consumer decision process model is the EBM model [20] as shown in Figure 1.3. In this model, consumer behavior is roughly divided into information and decision process, and mutual relationship is explained.

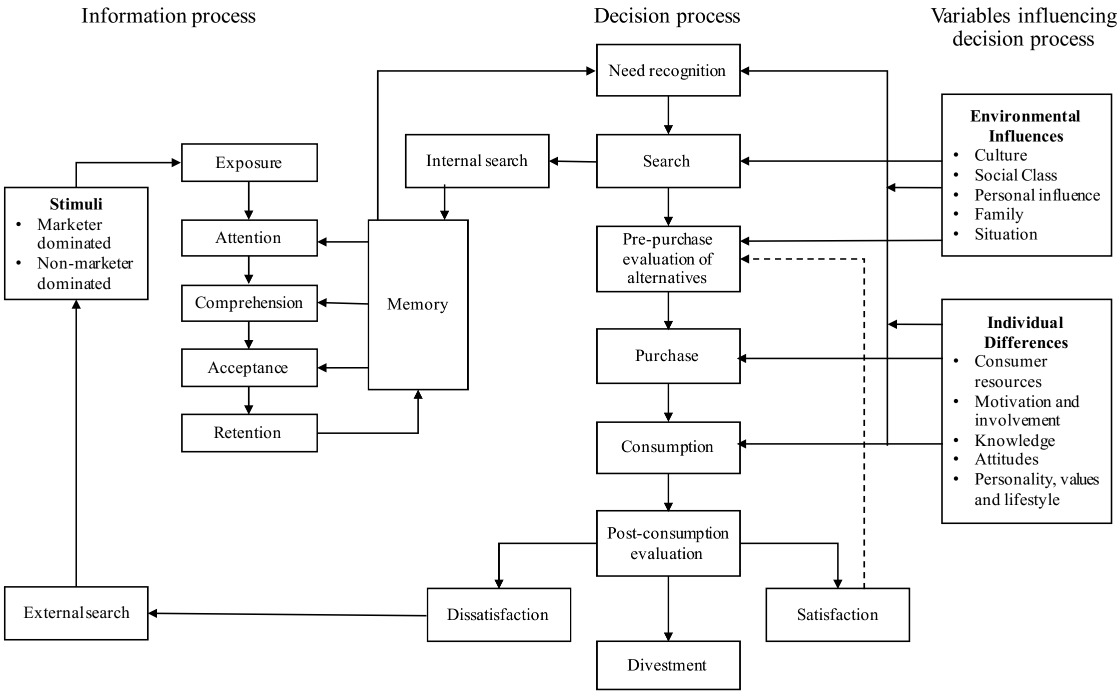


**Figure 1.3. EBM model – the Consumer Decision Process model (referring to [20]).**

This model is useful to understand the overview of consumer behavior. In this research, we explain the proposed methods along with the decision process so that we can grasp the relation with marketing measures.

## 1.2.4 Our Approach

In this research, as we mentioned in 1.2, we focus on "motivation" and propose three approaches:

(1) Show purposes of specific products/services to increase motivation (Analysis of large-scale text data).
(2) Analyze and strengthen marketing elements to encourage purchasing (Analysis of large-scale POS data).
(3) Incentivize purchasing through communication among customers (Proposal of communication tool).

Figure 1.4 summarizes the proposed methods of our research and related marketing methods according to the consumer decision process mentioned in 1.2.3. In the proposed methods, POS data and social data are utilized among the new data described in Table 1.1. The first and second methods are approaches that utilize useful information extracted from large-scale data. As the first approach, we propose a method for extracting the purpose for an action from social media and motivate customers by showing the purposes. This approach provides a solution to the question of what kind of information should be offered with specific products/services to increase motivation, and this is corresponding to conventional advertising. We explain the implementation of information provision services as an example. In the second approach, we focus on the environment beyond the products and address the question about the kind of environment that increases motivation. We propose a method to analyze marketing elements to encourage purchasing from POS data and create a marketing strategy. This is related to 4P (price, product, promotion, and place), STP (segmentation, targeting, and positioning), and brand theory. The third approach is an advanced method to focus not only on traditional customer/company relationships but also on mutual interaction between customers. It is a method to promote communication between customers by using social media as a tool rather than large-scale data and aims to increase customers' additional purchase or return visits. These proposed methods have novelty in data and methods compared to related marketing methods.

Based on the above approaches, we propose systems that lead to new services. Then, we analyze the effectiveness of motivation and effective factors.

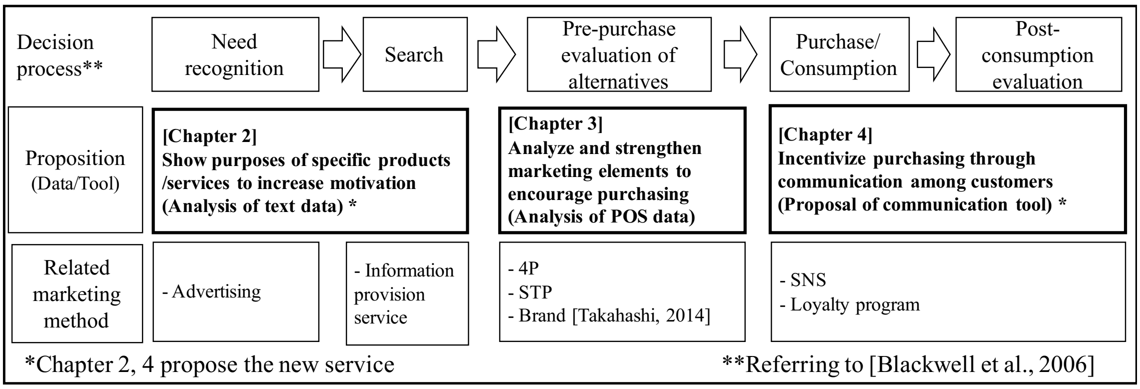


**Figure 1.4. Overview of proposed method.**

## 1.3 Organization of Dissertation

The contents of this thesis are shown in Figure 1.5. In Chapter 1, the background and purpose of the research are described. In Chapter 2, “Show purposes of specific products/services to increase motivation” system, we propose a method for extracting the purpose for an action from social media, and an information system that motivates users’ action by using the extracted purpose [21][22]. In Chapter 3, “Analyze and strengthen marketing elements to encourage purchasing” system, we propose a method to determine effective marketing elements from POS data to encourage purchasing behavior and lead to planning of further marketing strategy [23]. In Chapter 4, “Incentivize purchasing through communication among customers” system, we propose a self-marketing system in a restaurant [24]. Each chapter in Chapter 2–4 explains the details of the proposed system that lead to new services and reports the results of analyzing the effect on motivation and its effective factors. Finally, in Chapter 5, we show the conclusion and future prospects. The main target industry of the proposed systems is retail trade and services (eating and drinking places/amusement, hobbies, and entertainment services) with physical locations, and the combination of used systems is up to the user. The guidelines of the system usage are also described in Chapter 5.

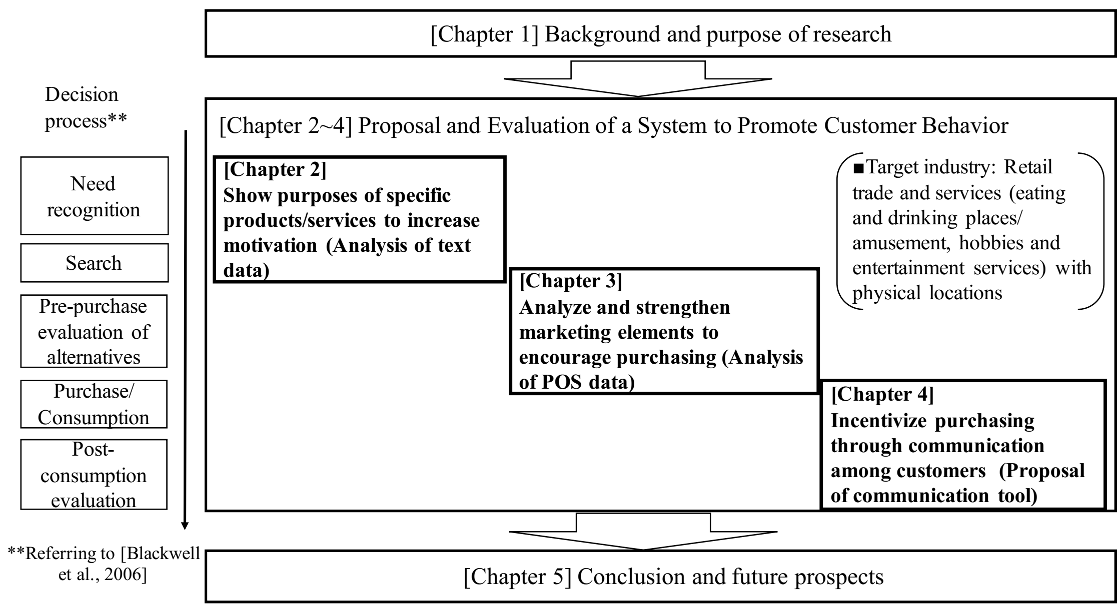


**Figure 1.5. Organization of dissertation.**

# Chapter 2

# Show purposes of specific products/services to increase motivation

## 2.1 Introduction

There are many web services from which we can obtain the required information to form an action plan. For example, before going out for lunch, we can use restaurant sites like “Yelp” [25], and when we want to travel we can use travel sites like “TripAdvisor” [26]. Moreover, location-based services like “Foursquare” [27] are increasing and we can get information related to many types of action near the current area or the target area at the same time.

One of the goals of these information provision services is to offer information suitable to the user and that encourages the user to perform a target action. In traditional services, categorizing facilities by area and offering precise information is thought to make it easier to initiate the action. Although these services suit users who have decided the target action (“I want to eat something” or “I want to go to museum” etc.), they are not suitable for users who have no particular action in mind (“I want to do something but I’m not sure what”).

We address this problem by using the Fogg behavior model [19] we mentioned in 1.2.2. This model asserts that for a behavior to occur, the person must have sufficient motivation, sufficient ability, and an effective trigger. In other words, (1) motivation and (2) ability are necessary when (3) a trigger is offered.

For example, when the target action of a web service is *walking*, users who want to do something refreshing (high motivation) are good candidates because *walking* will not be seen as a difficult task (high ability) (Figure 2.1). Conversely, lack of motivation or barriers to action are typical causes of action failure. Two key issues are (1) increasing motivation and (2) eliminating perceived barriers.

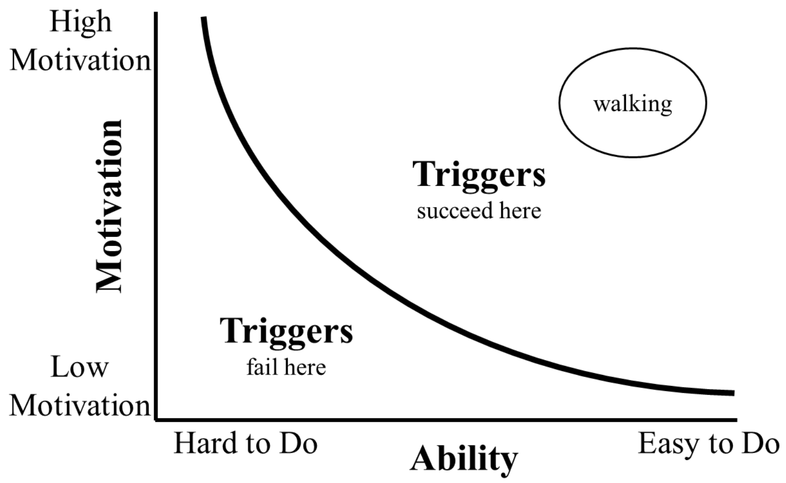


**Figure 2.1. Fogg behavior model (referring to [19]).**

Examples of perceived barriers to an action are time and cost, and it is difficult to lower these barriers quantitatively. However, a barrier might be over-rated, and information that helps the user rate the barrier correctly might lead to action initiation. The cost of gathering information is another barrier. “Yelp” offers information on facilities like distance and price that lowers the barrier to action initiation.

Current solutions to the other main issue, motivation, are limited. Examples of motivation factors are pleasure and hope. Coupons target economic motivation; they are seen as effective and used frequently. However, the application range of coupons is limited and a more comprehensive method is needed.

This research focuses on providing motivation through information to encourage action initiation. Motivation can be achieved by showing purpose-for-action (PfA hereafter) and triggering an information cascade [28] by showing others' experiences. PfA and experience information can be collected about the various actions possible and solve the motivation problem. For example, the user can be introduced to appropriate facilities and their PfA, which should encourage user action.

Information provision services come in various forms. However, here we assume a user-location-centered information service that has two steps as shown in Figure 2.2. A typical application image is shown in Figure 2.3. In the first step, the service displays near-by actions with PfAs and experience information aimed at increasing the user’s motivation. In the second step, it displays details of the selected action. The second step is the same as ordinary information services. The focus of this chapter is the first step, which is indicated by the frame in Figure 2.2, and the goal is to motivate people into demanding details of the target action of interest or actually performing the action. As an initial step in achieving this goal, this chapter collects PfAs.

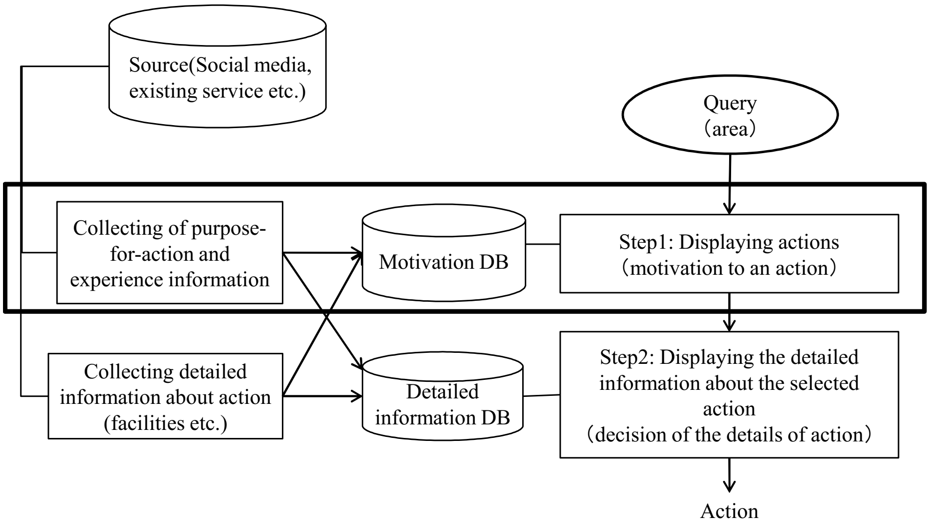


**Figure 2.2. Target area of this chapter.**

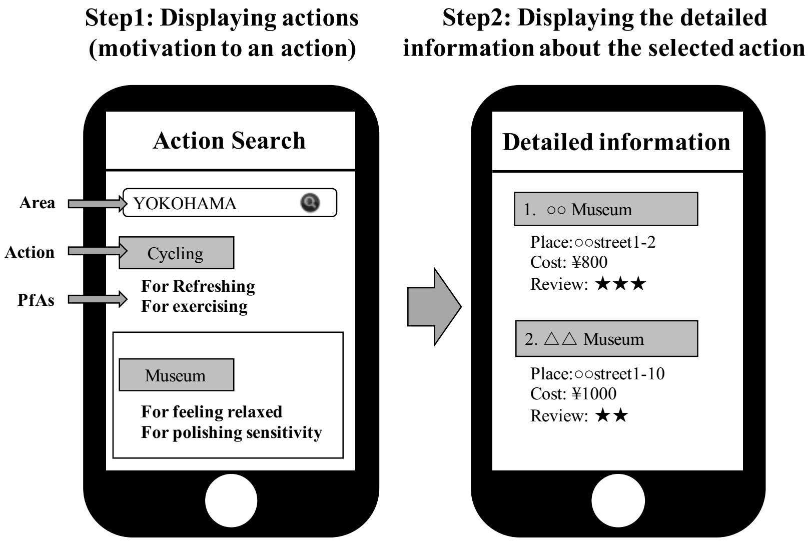


**Figure 2.3. Example of application image.**

We collect PfAs from experience information that contains a large variety of PfAs as shown in Figure 2.4. Social media texts are used as the source material as they contain descriptions of a wide variety of experiences and PfAs. We also conduct a user experiment and evaluate whether showing PfA yields effective motivation.

I went to travel in Hakone to refresh. I saw the autumn leaves and …

Action PfA

Experience information

**Figure 2.4. Extracting PfA from experience information.**

## 2.2 Related Works

### 2.2.1 PFA extraction method

Two approaches can be adopted to extract PfAs from texts.

(1) Identify keywords that directly express purpose, for example, words like "lose weight" are registered in a dictionary.
(2) Identify expressions that indicate purpose but do not use keywords, for example, sentences that contain expressions such as "in order to" are processed and the word/words associated with the expressions are used as PfA.

Approach (1) is effective when the purpose is expressed by keywords, even if the relation between purpose and action is not explicitly written. However, it requires building a dictionary. Approach (2) is far more flexible, but it requires that the relation between purpose and action be explicitly written.

Research based on approach (1) includes a study that extracts PfAs from travel blogs [29]. In this research, only travel actions are considered, so for our purpose the dictionary must be extended to extract PfAs related to many other kinds of actions. One study constructs a dictionary related to a large variety of actions by targeting long-term goals [30]. In this study, PfA topics are extracted by using LDA from twitter including "new year resolutions." While they extract purpose itself, we try to extract purpose-action pairs. Purpose-action pairing is related to the extraction of cause information.

The techniques of (2) are widely used to extract cause information from news articles [31][32][33] ; for example, it may be extracted by using statistical information and initial clue expressions [31]. All these studies assume that the source material consists of formal sentences like news articles. Moreover, they do not distinguish cause/reason and purpose. We target social media, which will certainly contain grammatical errors and inconsistent spelling, and we collect only purpose without cause/reason. Therefore, the extracted PfAs must be filtered.

We combine both approaches. First, we use approach (2) and extract PfAs by using clue expressions. Next, by using the dictionary approach (1), we aim to increase extraction cases.

In this chapter, we propose a method of extracting PfAs by approach (2), using clue expressions. Though machine learning appears to provide some benefit, we start with a rule-based method and leave machine learning for future work.

### 2.2.2 Support of action planning

There are a lot of web services from which we can acquire the information needed to form an action plan. For example, by using location-based services like "foursquare," we can get information about the current area. These services offer information on facilities like distance, which may lower the barrier to action initiation. Moreover, showing others' experiences can trigger information cascade and may also provide motivation.

However, PfAs are not explicitly written and the number of experiences is limited. Our method can strengthen the rise in motivation and encourage user action.

From another viewpoint, there are studies that aim to offer information suitable to users' preference and contexts. As examples of considering the users' preference, "Google" [34] uses search history and "Amazon" [3] similarly uses users' information and recommends contents and items. With regard to studies on context-aware recommendation, there are many studies considering time, companion etc. [35]. Though recommendations based on users' preference and contexts may be one form of motivation, it requires the users' information. In this chapter, we propose an information provision technology that assumes general situations, thus not requiring users' information or situation. Moreover, these techniques focus on selection of items and do not consider additional information such as PfAs. Combining these techniques and our method is future work.

## 2.3 Problem setting

This study extracts the PfAs of a specified action from texts containing grammar errors and inconsistent spelling and aims to improve the accuracy of extracting PfAs. Here, we define PfA as the action or statement the writer wants to achieve through action or the effect of an action that is clear to the reader (Figure 2.5). For example, if a sentence is "I ran to refresh", "refresh" is PfA because it is the goal of "run". If the sentence is "I ran and felt refreshed", "refreshed" is also PfA because "refreshed" clearly seems to be the

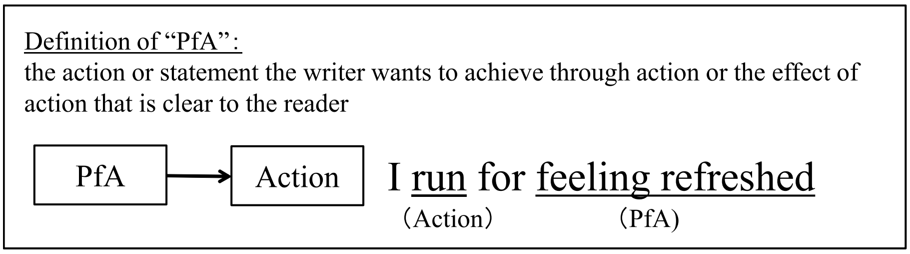


**Figure 2.5. Definition of PfA.**

result of “ran”. The target actions considered here are those associated with whether we act or not from the viewpoint of behavior selection support. As one of all possible action areas, this chapter focuses on leisure activity due to its sheer size (especially, activities outside the house). We define the words used in this chapter as follows.

**Definition 1: Clue expressions.**
Expressions necessary to understand the relation between purpose and action in a sentence. We call expressions connecting purpose and action such as “in order to” clue expressions and use them in extracting PfAs.

**Definition 2: PfA class**.
If several extracted PfAs have similar purposes, we bring them together to create a PfA class. For example, the given two sentences of “for health maintenance” and “for maintenance of health”, we group them together as “for health maintenance” class.

## 2.4 Preliminary analysis

In this section, we explain the dataset used and describe the results of an analysis of the clue expressions used in the selected dataset. We describe work done on a dataset in Japanese, but the analysis and method can be applied to other languages.

### 2.4.1 Dataset

The key requirement of the dataset is that it contains a large number of experiences and PfAs, both of which are described clearly. From the candidates of microblogs, Q&A sites, and blogs, we chose blogs because they have a large amount of information in one place. We are planning to enhance the dataset in the future.

### 2.4.2 Analysis of dataset (usage of clue expressions)

We confirm the clue expressions. Previous work, which extracts cause information, pointed out that the use of clue expressions changes with the dataset. Therefore, we calculated the accuracy rate of common clue expressions found in this dataset.

First, ten very common actions were chosen from leisure activities [36], and PfAs were manually extracted from 100 blogs per action. It is sometimes difficult to judge whether an expression is a PfA. Our criterion was that a PfA was present if the sentence appeared to be related to one of the 12 reasons used in an opinion poll [37]. For example, the sentence “I have grown in strength” is appears to be related to the reason of “for health and building up physical strength”, therefore it is judged as containing PfA. As a result, 430 PfAs were extracted.

Next, we extracted expressions connecting action and PfA as clue expressions. We targeted only the sentence in which action and PfA are shown in the same sentence. The results are shown in Table 2.1. There are two types of constructions.

(1) purpose, clue expression, action
(e.g. “*kenko no* (health) *tameni* (for) *hashiru* (run)”)
(2) action, clue expression, purpose
(e.g. “*hashi* (run) *tara* (and) *kibun tenkan dekita* (feel refreshed)”)

In addition, the clue expressions used as both types are categorized in type (3). Constructions (1) and (2) exhibited almost equal usage frequency. As the initial investigation, we consider only expressions of type (1) construction.

**Table 2.1. Clue expressions extracted from blogs.**

| | |
|---|---|
| (1)purpose ⇒ action | *wo kanete, tame, tameni, no tameni, wo motomete, to omoukara, to omotte, niha, nanode, takute, toiu kataniha, to omoi, to iukotoninari, karatte kotode, yoto, ga, wo, ni,*<br>These are the meaning of "for ", "due to", "in order to" etc. |
| (2)action ⇒ purpose | *ha xx no tame, ha xx ga mokuteki, tara, demo, ga, toki no, mo, te misemasu, kotode, shitari, dakedemo, mo, noga, kedo*<br>These are the meaning of "and ", "the purpose of xx is" etc. |
| (3) both | *de, kara, ha, node, shite, te, to, shi, no, kotode*<br>These are the meaning of "so" etc. |

**Table 2.2. Accuracy rate of clue expressions.**

| Clue expression | The number of examples | The number of correct examples | Accuracy rate |
|---|---|---|---|
| *wo kanete* | 2 | 2 | 1.00 |
| *tame* | 8 | 4 | 0.50 |
| ***tameni*** | **15** | **12** | **0.80** |
| *no tameni* | 9 | 7 | 0.78 |
| *wo motomete* | 1 | 1 | 1.00 |
| *to omotte* | 1 | 0 | 0.00 |
| ***niha*** | **69** | *2* | *0.03* |
| ***nanode*** | **24** | *1* | *0.04* |
| *takute* | 3 | 3 | 1.00 |
| *to omoi* | 1 | 1 | 1.00 |
| *yoto* | 2 | 2 | 1.00 |
| Total | 137 | 35 | 0.26 |

We further investigated construction (1). To raise the accuracy, we deleted clue expressions that consisted of a single character leaving us with 15 clue expressions. We extracted "clue expression + action" sentences and judged whether the words immediately before the clue expression described a PfA. We processed the roughly one million blogs entered on one day (February 1, 2013). From among the above-mentioned ten actions, we focused on five (travel, dining out, museum, amusement park, and cycling). Following the definition in 2.3, the sentence "*ame ga hutta tame saikuringu ha* *chushi* (cycling was canceled due to rain)" describes reason thus not a PfA. The result is shown in Table 2.2. Clue expressions that yielded zero examples are not listed in the table.

The two requirements for the clue expressions we want to find are that it is used in many sentences and its accuracy rate is high. From this viewpoint, "*niha* (for)" "*nanode* (for)" are used in many sentences, but their accuracy rate is low. "*tameni* (for)" has the second largest number of examples and its accuracy rate is high. From this analysis, we selected "*tameni* (for)" as the clue expression. It is considered that a sufficient number of cases can be extracted from the denominator in which PfA is explicitly described. If effective PfA for motivation cannot be extracted, we will consider other approaches.

## 2.5 PfA extraction method

In this section, we detail the automated PfA extraction method using clue expression "*tameni* (for)".

The proposed method is composed of two parts, extracting PfA and categorization. We explain each part.

### 2.5.1 Extracting PfA

We extract PfA by using the clue expression and modification structure. Extraction of PfA using modification structure is similar to the previous work [33], but in this chapter, we devised the number of bunsetu to automatically determine the target actions. It is also different from the previous work [33] in that the cause/reason and the other errors are excluded. Here, "bunsetu" is a basic block in Japanese. As shown in Figure 2.6, the PfA extraction method is composed of the following 4 steps.

**Step 1.** The sentences including clue expression and target action are extracted.

**Step 2.** The sentences are parsed by the Japanese dependency analyzer, JDEP [38].

**Step 3.** A bunsetu (we call this first bunsetu) modified by a clue expression is extracted and the nearest bunsetu modifying the first bunsetu is also extracted as the second bunsetu. We extract first and second bunsetu and judge whether the two bunsetu include a target action.

**Step 4.** If the answer of step 3 is *yes*, the first bunsetu that modifies the clue expression is extracted and the nearest bunsetu that modifies the first bunsetu is extracted as the second bunsetu. We extract the first and second bunsetu as PfA.

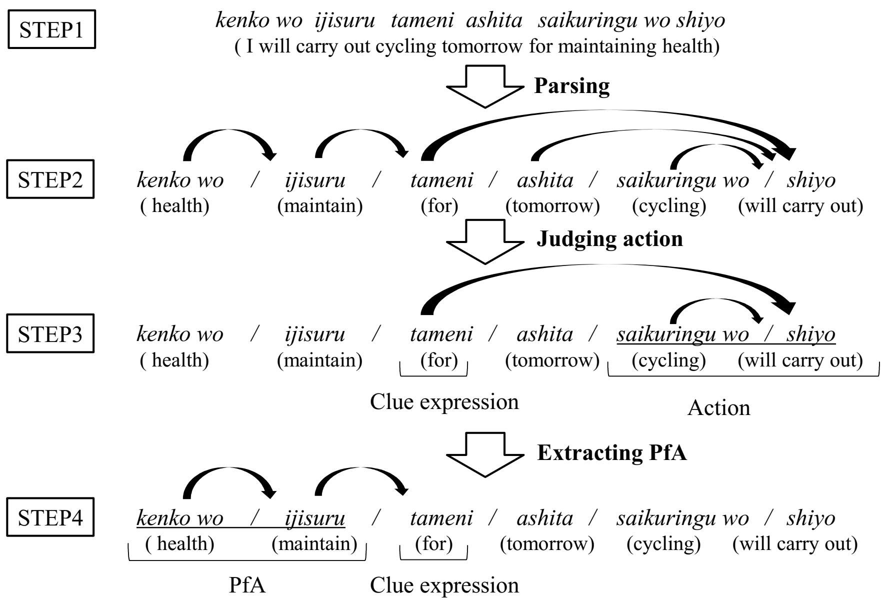


**Figure 2.6. PfA extraction using clue expression and modification structure.**

The number of bunsetu (two) was decided so as to extract the expression of "verb + object". As mentioned in section 2.5.2, the extracted PfA must be filtered. Section 2.5.2 introduces one filtering method. We examine the results and propose other rule-based methods in 2.6.1.

## 2.5.2 Categorization (improvement of precision)

We categorize PfAs and adopt the PfA classes with high frequency to reduce the noise in the extracted PfAs. This is because the probability that the same wrong PfA is extracted from sentences containing grammatical errors or broken expressions is considered to be low. The procedure of categorization is as follows:

**Step 1.** PfA is decomposed into morphemes, and nouns and verbs are extracted from the morphemes.

**Step 2.** The PfAs with same nouns and verbs are categorized into a PfA class.

**Step 3.** The class name is the PfA with the highest frequency or the PfA consisting of the largest number of characters.

**Step 4.** The PfA classes including more than two PfAs are adopted.

## 2.6 PfA extraction experiment

We conducted experiments to confirm the validity of the proposed method. We evaluate the proposed method by precision, recall and F-measure.

We used the roughly 20 million blogs entered over a one month period (February 2013) and used five actions as the query terms. The actions are travel, dining out, museum, amusement park, and cycling.

### 2.6.1 PfA extraction

We conducted an experiment to extract PfAs related to the five actions.

The proposed method extracts PfA by using "*tameni* (for)" and the modification structure of 2.5.1. The range of action search in step 3 is two bunsetu. In addition, we examined 3 other patterns, "one bunsetu", "three bunsetu" and "all bunsetu (after clue expression and till bunsetu modified by clue expression)".

As baselines, we used the following two methods.

BL1: the range of searching action is the bunsetu immediately after clue expression

BL2: the range of searching action is all bunsetu after clue expression

The range of PfA extraction is two bunsetu with the aim of extracting "verb+object" in both proposed methods and baselines.

The PfAs extracted by each method were manually judged as being correct or not and precision, recall and f-measure were calculated. When both action and PfA were correct, the PfA was judged as correct. Five actions (travel, dining out, museum, amusement park, and cycling) were judged to be correct when the queries were meant to extract information related to traveling, dining out, going to museum, going to amusement park, or cycling. For example, the sentence, "*kenko no tameni gaisyoku wo hikaeru* (refrain from dining out for health)" is judged as incorrect. PfA is judged as correct when the purpose is an action or statement that the writer wants to achieve or the effect of an action is something that the reader can readily understand.

Regarding the calculation of recall, BL2 is the softest judgment because the extent of action search is the largest. Therefore, the number of correct examples of BL2 was regarded as the denominator in calculating recall for all methods.

We show the results in Table 2.3, Table 2.4 and Table 2.5. As Table 2.5 shows, the proposed methods ("1 bunsetu" and "2 bunsetu") demonstrated higher precision than the baselines. As the result of BL1 shows, the PfAs are not always correct when the action query immediately follows the clue expression. The sentence "*konohi no tameni ryoko no toki ni omiyage wo kata* (I bought souvenir at the traveling for this day)" could be excluded by using this knowledge. "1 bunsetu" has the highest precision but F-measure is low. F-measure is the highest in "2 bunsetu." Therefore, we think that "2 bunsetu" is the best method.

**Table 2.3. Number of correct examples.**

| Action | BL1 | BL2 | 1 bunsetu | 2 bunsetu | 3 bunsetu | All bunsetu |
|---|---|---|---|---|---|---|
| Travel | 58 | 245 | 55 | 177 | 180 | 194 |
| Dining out | 18 | 31 | 19 | 27 | 28 | 29 |
| Museum | 9 | 44 | 6 | 29 | 31 | 35 |
| Amusement park | 8 | 15 | 3 | 11 | 12 | 15 |
| Cycling | 3 | 20 | 6 | 15 | 15 | 16 |
| Average | 96 | 355 | 89 | 259 | 266 | 289 |

**Table 2.4. Number of extracted examples.**

| Action | BL1 | BL2 | 1 bunsetu | 2 bunsetu | 3 bunsetu | All bunsetu |
|---|---|---|---|---|---|---|
| Travel | 108 | 700 | 81 | 298 | 322 | 421 |
| Dining out | 30 | 112 | 30 | 55 | 62 | 76 |
| Museum | 13 | 94 | 6 | 35 | 40 | 55 |
| Amusement park | 11 | 23 | 3 | 13 | 14 | 17 |
| Cycling | 3 | 30 | 8 | 18 | 18 | 20 |
| Average | 165 | 959 | 128 | 419 | 456 | 589 |

**Table 2.5. Extraction accuracy.**

| | Precision | Recall | F-measure |
|---|---|---|---|
| BL1 | 0.58 | 0.27 | 0.37 |
| BL2 | 0.37 | **1.00** | 0.54 |
| 1 bunsetu | **0.70** | 0.25 | 0.37 |
| 2 bunsetu | 0.62 | 0.73 | **0.67** |
| 3 bunsetu | 0.58 | 0.75 | 0.66 |
| All bunsetu | 0.49 | 0.81 | 0.61 |

In PfA extraction, the proposed method wrongly identified sentences as containing PfAs. We call this mistake False positive (FP). We analyzed FP and found the following causes.

(1) Problem of clue expression

・a cause expression is extracted (e.g. *ame no tameni* (due to rain))
・a fixed form expression is extracted (e.g. *nanno tamni* (for what purpose))

(2) Problem of action extraction

・the PfA of a negative action is extracted (e.g. refrain from dining out)
・extracted action is wrong (e.g. I apply for travel insurance)

(3) Problem of PfA extraction

・ PfA is incomplete (e.g. *miru tameni* (for seeing))

(4) Problem of action extraction / PfA extraction

・mistake in modification structure (e.g. cases in which actions are written in parallel)

(5) Problem of preprocessing

・spam

Then, as mentioned in 2.5.1, we applied a further method to remove these FP. Table 2.6 shows the result of this initial improvement policy. For example, to remove cause/reason errors, we conducted the following tense judgment and the paraphrase judgment because linguistic studies show that the verbs associated with cause/reason tend to be past tense and the cause/reason tends to be negative.

**Step 1 (tense judgment).** If the tense of PfA is past, it is removed as cause/reason.
**Step 2 (paraphrase judgment).** The clue expression of “*seide* (due to)”, which shows cause/reason, is connected to the PfA, then the number of examples of the sentence in the dataset is calculated. If the number of examples is higher than that of examples wherein connection is “*tameni* (for)”, the PfA is removed as cause/reason.

As a result, the number of mistakes is greatly decreased as shown in Table 2.7 and the precision increases to 78% from 62% and the F-measure increases to 70% from 67%.

**Table 2.6. Initial improvement policies.**

| Error factor | Rough improvement policy |
|---|---|
| Cause/reason | Tense judgment and the paraphrase judgment |
| Stable sentence | Stop word (“or what purpose”) |
| Negative action | Dictionary (the PfA of negative action are stored in a dictionary) |
| Wrong action | Connecting noun (remove the case that noun is immediately after query) |
| Parallel | Stop word (for xx and yy) |
| Incomplete PfA | The object before the PfA (remove the case that the word before PfA is object) |

**Table 2.7. Change in the number of errors (close test).**

| Error factor | The number of errors | The number of errors (after removal) |
|---|---|---|
| Cause/reason | 15 | **4** |
| Stable sentence | 3 | **0** |
| Negative action | 30 | **15** |
| Wrong action | 64 | **21** |
| Modification structure | 14 | **8** |
| Incomplete PfA | 23 | **12** |
| Spam | 11 | **2** |
| （Total） | 160 | **62** |

**Table 2.8. Removal of errors (open test).**

| | Precision | Recall | F-measure |
|---|---|---|---|
| BL2(before removal) | 0.31(189/611) | **1.00** | 0.47 |
| 2 bunsetu (before removal) | 0.57(166/289) | 0.88 | 0.69 |
| BL2(after removal) | 0.38(166/442) | 0.88 | 0.53 |
| 2 bunsetu (after removal) | **0.75(145/194)** | 0.77 | **0.76** |

Moreover, in order to ensure that the error elimination method does not depend on the data set and works effectively in general, we analyzed the method using another dataset. We used the blogs entered over one month (February 2014). For the purpose of extraction, the proposed methods, 2 bunsetu and BL2 were used. The reason for selecting BL2 is that the recall rate of BL2 was the highest, and the possibility that its F-measure exceeds the proposed method is thought to be high by using this error elimination method. Table 2.8 shows the result of each method. We confirmed the improvement of precision and F-measure by the error elimination method. We also confirmed the effectiveness of the proposed method in comparison with BL2.

The precision of the proposed method is close to 80% and the number of examples is large. This is thought to be sufficient for practical use. Moreover, by considering a way to judge target actions and length of purpose, further improvements can be expected.

### 2.6.2 Categorization (improvement of precision)

The proposed method can output FP as shown in 2.6.1. To remove these mistakes, we bring together similar PfAs. We categorized the results of Table 2.7 and created PfA classes; for these we calculated $P@Nc \geq 2$ (the average precision of the classes with more than two PfAs) using the correct/incorrect label used in 2.6.1. The result is shown in Table 2.9.

The number of cases of amusement park, cycling, dining out, and museum is small and it is difficult to evaluate the results. We intend to increase the data size and conduct new evaluations. As for travel, an improvement in precision was confirmed. Examples taken from the PfA classes include “food” “meeting people” “congratulation” and so on; many kinds of PfAs were extracted. However, compared with the results before categorization, the number of cases becomes extremely small. From these results, it can be said that it is better to use the result after error elimination as it is from the viewpoint of the F-measure. It can also be said that the categorization is useful in a case where high precision is desired and the number of cases is not important. Improvement of precision without dropping the number of cases is a future task.

**Table 2.9. Categorization.**

| Action | Precision(P) after error elimination | P@Nc≧2 |
|---|---|---|
| Travel | 0.80(154/193) | **0.94(15/16)** |
| Dining out | 0.62(23/37) | **1.00(2/2)** |
| Museum | 0.81(25/31) | **1.00(3/3)** |
| Amusement park | 0.82(9/11) | 0 |
| Cycling | 0.92(12/13) | 0 |

## 2.7 User evaluation experiment

We conducted a questionnaire survey to evaluate the effect of motivation by showing the extracted PfAs. We judged that the proposed method is effective if at least one PfA shows effectiveness in motivation. The method to select the effective PfA is a future task.

### 2.7.1 Experiment setup

Content of questions

Question 1.

We told the respondents to assume the situation in which an information search service (service in which some actions are recommended when a place is input) recommends an action ("How about running?" etc.). The respondent was asked to judge whether he or she would take the recommended action.

Question 2.

We told the respondents to assume the same situation but a PfA was shown together with the action ("How about running for health?" etc.). The respondent was asked if his/her motivation for doing the action was increased (five level scale was used) (Table 2.10).

If the person answered "yes" in question (1), we let him or her assume the situation where he or she didn't want to do the action and then showed them question (2). This is because our aim is to motivate people who don't want to do the "action" when the only action is displayed.

**Table 2.10. Examples of question 2.**

| Running | Motivated or not | | | | |
|---|---|---|---|---|---|
| ↓ PfA | Increase a lot | Increase | Unchanged | Decrease | Decrease a lot |
| Exercise | ☐ | ☐ | ☐ | ☐ | ☐ |
| Maintain health | ☐ | ☐ | ☐ | ☐ | ☐ |
| Lost in thought | ☐ | ☐ | ☐ | ☐ | ☐ |
| ⋯ | ☐ | ☐ | ☐ | ☐ | ☐ |

Actions and PfAs

We employed 11 actions (running, cycling, cinema, museum, dining out, karaoke, travel, amusement park, shopping, barbeque, esthetic) including the five actions used in 2.6. These actions were selected from five subcategories written in a white paper on leisure [36].

PfAs were extracted by the method of 6.1 from roughly 400 million blogs entered over a one-year period (from January 2013 to December 2013). After extraction, we manually categorized PfAs and created PfA classes to analyze the effectiveness of maximum possible PfAs. We used the affinity diagram technique to gradually raise the level of categorization [39]. Considering the burden of the respondents, the number of PfA classes was determined to be 50 at the maximum. We got about 18~50 (average 36) PfA classes for each action and used them in the questionnaire.

Respondents

400 people responded per action.

## 2.7.2 Results and discussion

The result of each action raised in Question 2 is shown in Table 2.11. In this table, the number of effective PfAs(x) that a respondent answered positively (increase a lot + increase) was divided into six categories, and the number of people belonging to each category is shown. The average number of people in x> 0 indicates that the respondent is motivated by one or more PfAs. This number was 342 (about 85% people). Consequently, we confirmed that showing PfAs extracted from the blogs can encourage people to perform the target actions.

The positive scores (increase a lot + increase) range from 7% to 75% for each PfA so clearly different PfAs have different levels of effectiveness. Examples of PfA scores about running are shown in Table 2.12. The highly scored PfAs were "health," "refreshing," "fun," and so on and these seem to be PfAs that are suitable for many people. In contrast, "preparing for a role" "writing blogs" are more user-specific PfAs and their average scores were low. From this result, we found that the effective PfAs are those that match the user's desire or situation. The number of effective PfAs are 13 on average and it accounts for 36% of the displayed PfAs. Therefore, even when the PfAs are filtered, the possibility that the system can show the effective PfAs is high. Identification of the most effective PfA in accordance with user's preference and situation is future work.

**Table 2.11. Evaluation of the effect of motivation.**

| Action | x=0 | 1<x<10 | 10≦x<20 | 20≦x<30 | 30≦x<40 | 40≦x |
|---|---|---|---|---|---|---|
| Running | 69 | 102 | 72 | 67 | 49 | 41 |
| Cycling | 76 | 130 | 157 | 37 | 0 | 0 |
| Cinema | 51 | 121 | 134 | 85 | 9 | 0 |
| Museum | 58 | 107 | 156 | 79 | 0 | 0 |
| Dining out | 47 | 133 | 131 | 65 | 24 | 0 |
| Karaoke | 61 | 132 | 89 | 64 | 28 | 26 |
| Travel | 32 | 73 | 92 | 81 | 72 | 50 |
| Amusement park | 50 | 188 | 162 | 0 | 0 | 0 |
| Shopping | 50 | 105 | 108 | 63 | 42 | 32 |
| Barbeque | 56 | 189 | 155 | 0 | 0 | 0 |
| Esthetic | 87 | 86 | 56 | 59 | 54 | 58 |
| Average | 59 | 123 | 119 | 55 | 25 | 19 |

**Table 2.12. Examples of PfA scores (Running).**

| Ranking | PfA | Motivated or not | | |
|---|---|---|---|---|
| | | Increase a lot + Increase | Unchangeable | Decrease a lot + Decrease |
| 1 | Health | 0.54 | 0.43 | 0.03 |
| 2 | Improvement in physical strength | 0.52 | 0.45 | 0.03 |
| 3 | Improvement in basal metabolism | 0.51 | 0.45 | 0.04 |
| 4 | Calorie consumption | 0.47 | 0.48 | 0.05 |
| 5 | Refreshing | 0.46 | 0.47 | 0.07 |
| .<br>.<br>. | | | | |
| 41 | Physical strength consumption | 0.22 | 0.60 | 0.18 |
| 42 | Killing time | 0.21 | 0.63 | 0.17 |
| 43 | Event (date, travel etc.) | 0.19 | 0.67 | 0.14 |
| 44 | Get away from loneliness | 0.16 | 0.68 | 0.17 |
| 45 | Preparing for a role | 0.12 | 0.71 | 0.17 |

## 2.8 Summary

In this chapter, we proposed a method for extracting purpose for motivation from social media texts and described how a service could use such a purpose with the aim of motivating people to perform a target action. We explained it by adopting information provision services as an example. We evaluated our method and confirmed its effectiveness in extracting purposes and raising motivation. We also found that the effective purposes are those that match the user's desire or situation.

In future, we will try to extract 5W1H (who, what, when, where, why, how) information from more experiences, and select purpose and action to suit the user's situation. As shown in Figure 2.2, detailed information about actions is also necessary along with motivation. We will collect information offered by existing services and establish an information navigation system that encourages people to perform a target action.

# Chapter 3

# Analyze and strengthen marketing elements to encourage purchasing

## 3.1 Introduction

With the evolution of information technology, the variety of marketing elements (values that customers get from a company) used by retail stores to retain customers is increasing. Examples of traditional marketing elements include offering customers high quality products and courteous service whereas online shopping, SNS, and check-in services are examples of new, recently developed marketing elements. Although these marketing elements represent effective ways to retain customers, they can be very costly. Therefore, stores have to choose their marketing elements carefully to follow a strategy. In this chapter, we aim to quantitatively identify effective marketing elements and improve return on investment (ROI).

In present research measuring the effects of marketing elements, there are many studies focusing on particular marketing elements such as advertising [40][41] or discounts [42]. However, few studies examine several marketing elements simultaneously. Research measuring various marketing elements includes a study that evaluates the effect of marketing elements using a questionnaire [10]; however, conducting questionnaires can be very costly. Therefore, we propose a simple method to evaluate the effect of marketing elements using obtained data instead of a questionnaire. In addition, as we mentioned in 1.1, there is a growing trend of using big data in business [43][44]. From this point of view, our proposal, which utilizes purchase data that can be acquired automatically, is useful.

In this chapter, we pose the following research questions.

**RQ1.** What types of marketing elements are there and how is the awareness of marketing elements devoted to customers calculated?

**RQ2.** How is the effectiveness of each marketing element with regard to customer purchase actions evaluated?

With regard to RQ1, we organize marketing elements based on previous research [10] , and propose a method to calculate the awareness of marketing elements devoted to each customer using purchase data. In relation to RQ2, we propose a method to analyze the effect of marketing elements on different groups of customers using covariance structure analysis. We also conduct experiments using the large-scale purchase data and determine whether our method is effective in evaluating marketing elements.

## 3.2 Related Works

### 3.2.1 Evaluating the effect of marketing elements

In the research measuring the effects of marketing elements, there are many studies focusing on advertising. For example, the relation between advertising and purchase intention is analyzed using difference-in-differences [40], and the effectiveness of paid search ads is analyzed through a large-scale field experiment at eBay [41]. In the research analyzing other marketing elements, the relationship between marketing effectiveness and discounts is investigated [42].

However, there is little research that analyzes various marketing elements simultaneously. Research measuring various marketing elements includes a study that investigates the relationship between retail brand equity and behavioral loyalty [10]. In this research, equity drivers are organized based on previous studies, and the relationship between retail brand equity and behavioral loyalty is investigated using a questionnaire.

### 3.2.2 Use of big data in business

As we mentioned in 1.1, beyond the evaluation of marketing elements, the use of big data by businesses has also been expanding. Web services and e-commerce businesses in particular are at the forefront of this trend [43]. For example, Google [34] uses the search histories of users and Amazon [3] uses information from similar users to recommend content and products [44]. In addition, the opinions of customers are extracted using text analysis of SNS [45]. Among the goals of these analyses are improving sales and customer satisfaction. In this chapter, we analyze the effectiveness of marketing elements with regard to sales.

## 3.3 Proposed Method

The proposed method is composed of two parts: calculating the awareness of marketing elements devoted to each customer (corresponding to RQ1) and evaluating the effectiveness of marketing elements (corresponding to RQ2). We first present the purchase data used in our methods in greater detail and then explain each of these two parts.

### 3.3.1 Purchase data

Because the purpose of this study is to analyze the effectiveness of various marketing elements, it is desirable to obtain data on various marketing elements, such as having a real store, having an online store, or offering a check-in service. Therefore, we use the purchase data provided by the Joint Association Study group of Management Science (JASMAC) in the 2014 data analysis competition. This includes a large amount of data, including POS data for real/online stores and check-in service history, among others. The data cover the period from May 2013 to July 2014 and represent about eight million customers. Details of the contents of the data are shown in Table 3.1.

**Table 3.1. Details of the contents of data.**

| Category | Content |
|---|---|
| Purchase history | POS data for real/online store |
| | Check-in service history |
| | SNS service history |
| Other | User information (sex, age) |
| | Store information |
| | Item information |

### 3.3.2 Calculating awareness of marketing elements devoted to each customer

We first organize marketing elements and explain how we calculate the awareness of marketing elements devoted to each customer related to RQ1.

Based on [10], we selected 7 marketing elements for which purchase data provides information, as shown in Table 3.2. The 7 marketing elements are product quality, product variety, atmosphere, location convenience (major city), cost performance, events, and loyalty program.

Because the location convenience of online stores and retail atmosphere of real stores are the same, we exclude location convenience (online store) from the estimated marketing elements. In addition, because the number of SNS users is small, we also exclude loyalty program (SNS).

We explain the way to calculate the awareness of each marketing element in the following subsubsections. Each marketing element is calculated per customer.

**Table 3.2. Organization of marketing elements.**

| Category | Sub category | Marketing elements | Target | Calculating method of awareness |
|---|---|---|---|---|
| Merchandising | Product | Product quality | ○ | Rate of expensive product purchases |
| | Assortment | Merchandise / Selection | ○ | Rate of long tail product purchases |
| Facilities for Store | Store Design | Atmosphere/Layout | ○ (real store) | Purchase rate at real stores |
| | Location | Convenience | △ (online store) | Purchase rate in an online store *excluded as this is the same as purchase rate at real stores |
| | | | ○ (major city store) | Purchase rate at stores in major cities |
| Service/ Support | Service | Store effort | × | |
| | | Effort to retain customers | × | |
| | Cost Performance | Value for money/Price | ○ | Discount product purchase rate |
| | Promotion | Event | ○ | Rate of purchases at events. |
| | | Coupon | × | |
| | | Loyalty Program | ○ (check-in) | The number of check-in service uses |
| Corporate | | Reputation | × | |
| | | Community | △ (SNS) | The number of SNS service uses *excluded as too few people use SNS |

#### 3.3.2.1 Product quality

Customers that get value from product quality buy the products even when they are expensive. Therefore, we calculate product quality by the rate of expensive product purchases per customer as in the following equation.

$$product\ quality = \frac{\textbf{number of expensive products purchased}}{\text{total number of products purchased}}$$

We define expensive products as those in the top 20 % when all products are listed by price, as shown in Figure 3.1.

#### 3.3.2.2 Product variety

Customers that value product variety should buy a variety of products, especially long-tail products. We therefore calculate this using the rate of long-tail product purchases per customer, as in the following equation.

$$product\ variety = \frac{\textbf{number of long} - \textbf{tail products purchased}}{\text{total number of products purchased}}$$

Figure 3.2 illustrates the definition of long-tail products, which are those in the bottom 20 % when products are arranged by the number of sales.

#### 3.3.2.3 Atmosphere

Customers that value retail store atmosphere should prefer real stores over the online shop. Therefore, atmosphere is calculated by the rate of purchases in real stores:

$$atmosphere = \frac{\textbf{number of purchases in real stores}}{\text{number of purchase in both the real and online stores}}$$

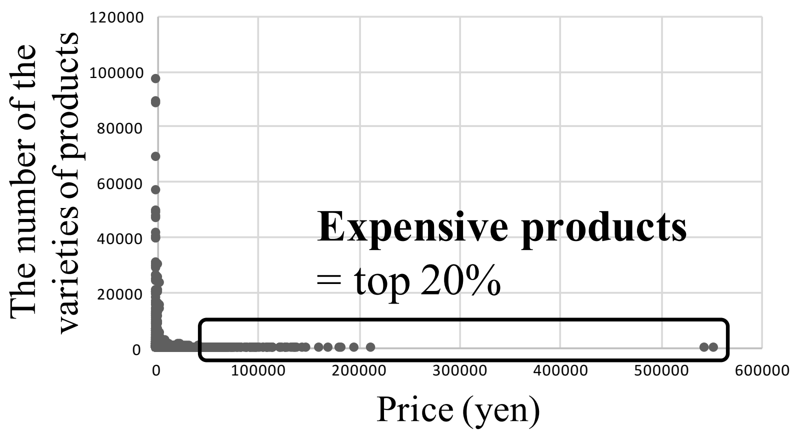


**Figure 3.1. Definition of expensive products.**

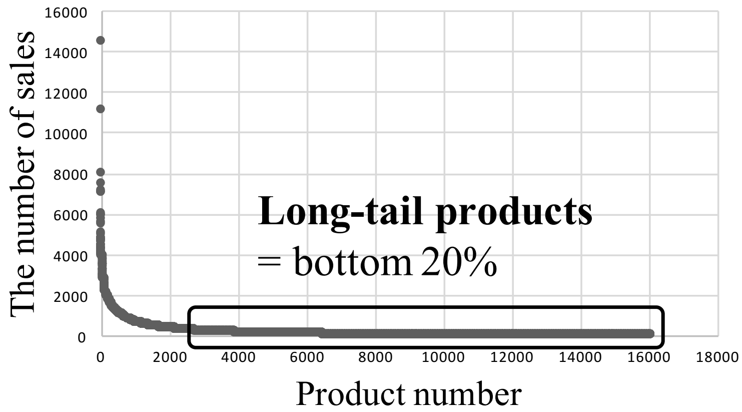


**Figure 3.2. Definition of long-tail products.**

**Table 3.3. Daily passengers arriving and departing in 2012 (referring to [46]).**

| Ranking | Station | Numbers of daily passengers |
|---|---|---|
| 1 | Shinjuku | 3,235,584 |
| 2 | Ikebukuro | 2,524,933 |
| 3 | Shibuya | 2,470,009 |
| 4 | Yokohama | 1,981,075 |
| 5 | Kita-senju | 1,190,222 |
| 6 | Umeda | 1,113,146 |
| 7 | Tokyo | 931,146 |
| 8 | Shinagawa | 901,705 |
| 9 | Takadanobaba | 878,723 |
| 10 | Shinbashi | 854,887 |
| 11 | Osaka | 827,228 |
| 12 | Akihaara | 699,087 |
| 13 | Omiya | 672,863 |
| 14 | Nanba | 577,001 |
| 15 | Kyoto | 566,595 |
| 16 | Ueno | 562,173 |
| 17 | Nishi-funabashi | 525,337 |
| 18 | Tennoji | 514,519 |
| 19 | Machida | 509,762 |

#### 3.3.2.4 Location convenience (major city)

We expect that customers that value convenient locations would buy products in stores located in major cities. Therefore, we calculate location convenience by the rate of purchases in stores located in major cities:

$$\mathit{Location}\text{ convenience } = \frac{\textbf{number of purchases at shops located in major cities}}{\text{number of purchases in both real and online stores}}$$

We define stores located in major cities as those located near large terminal stations. Table 3.3 shows the terminal rankings by number of daily passengers according to data published by the Ministry of Land, Infrastructure, Transport and Tourism of Japan in 2012 [46]. We selected the top 19 stations above 500 thousands people as major city locations, a total of 32 stores.

#### 3.3.2.5 Cost performance

Customers that value cost performance should purchase discounted products. Therefore, we calculate cost performance by the rate of discounted product purchases, as in the following equation.

$$\text{Cost performance} = \frac{\textbf{number of discount products purchased}}{\text{total number of products purchased}}$$

#### 3.3.2.6 Events

Customers that value events should buy products during an event period. Therefore, we calculate event using the rate of purchases during an event period:

$$\text{Event } = \frac{\textbf{number of purchases during an event period}}{\text{total number of purchases}}$$

#### 3.3.2.7 Loyalty program

Customers that value loyalty programs (in this case, a check-in service) should use the program frequently. We standardize the number of check-in service uses to adjust the scale to other marketing elements.

### 3.3.3 Evaluating the marketing elements' effectiveness

To address RQ2, we evaluate the effectiveness of each marketing element in terms of customer purchase actions.

As an analysis technique, we use covariance structure analysis to construct a flexible model. We define "behavioral loyalty" as the effect of each marketing element in terms of customer purchase actions and model illustrated in Figure 3.3, which draws on [10]. $x_1$ to $x_8$ are observed variables, and $f_1$ to $f_4$ are latent variables. This marketing elements model is the result after eliminating the subjective factors from [10] in order to analyze effectiveness with the use only of big data. In addition, we explore the hypotheses and analyze the effectiveness of each marketing element for different groups of customers, such as by age or sex, using covariance structure analysis.

**Hypothesis:** The awareness and effectiveness of the marketing elements employed differ according to variables such as age or sex.

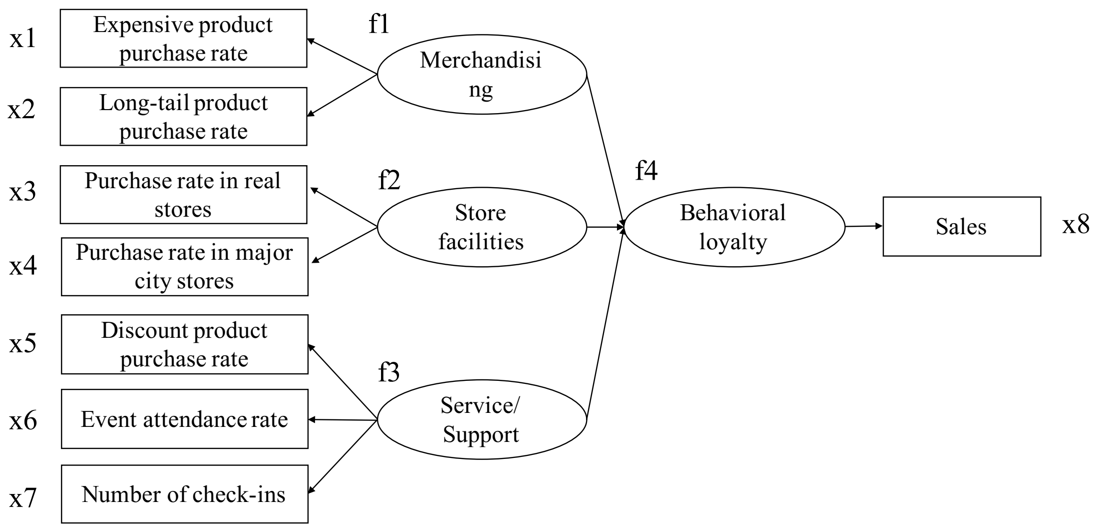


**Figure 3.3. Marketing elements model.**

## 3.4 Evaluation

Using the large-scale purchase data explained in 3.3.1, we evaluate the effectiveness of calculating the awareness of marketing elements and our marketing elements model.

### 3.4.1 Results of covariance structure analysis

We evaluated the proposed methods of 3.3.2 and 3.3.3 using a covariance structure analysis. We used the data for about 100 thousand customers randomly extracted from the purchase data in June 2013, as explained in 3.3.1.

We used the SEM function in the R [47] software package for the covariance structure analysis. In addition, we used four fit indexes, CFI (Comparative Fit Index), TLI (Tucker-

Levis Index), RMSEA (Root Mean Square Error of Approximation), and SRMR (Standardized Root Mean Square Residual). If each index satisfies the following conditions, the model is considered to be moderate.

CFI > 0.95
TLI = the closer 1, the better
RMSEA<0.05
SRMR= the closer 0, the better

Table 3.4 provides the results, and shows that each index satisfies the upper conditions, so we confirm that the calculation methods and marketing elements model for RQ1 are effective.

**Table 3.4. Fit indexes.**

| Fit index | Score |
|---|---|
| $\chi 2$ | 2646.574 |
| Degree of freedom | 15 |
| p-value | 0.000 |
| CFI | 0.981 |
| TLI | 0.964 |
| RMSEA | 0.042 |
| SRMR | 0.026 |

### 3.4.2 Tendencies for the awareness of marketing elements in each group

If the hypothesis in 3.3.3 is correct, then it is more effective to analyze the marketing elements for different groups. Therefore, we examined the tendencies for the marketing elements devoted to customers in each group.

We used the data of about 270 thousand customers randomly extracted from purchase data from June 2013, as explained in 3.3.1. We calculated the averages for each of the marketing elements for each sex and age group during a month, and report the results in Tables 3.5 and 3.6.

**Table 3.5. Awareness of marketing elements (males).**

| Age | 10s | 20s | 30s | 40s | 50s | 60s |
|---|---|---|---|---|---|---|
| Number of customers | 1060 | 9884 | 21099 | 12672 | 4170 | 1354 |
| Sales (purchase amounts) | 3529 | 5029 | 5287 | 5139 | 5010 | 5064 |
| x1: Expensive product purchase rate | 0.22 | 0.33 | 0.32 | 0.32 | 0.34 | 0.36 |
| x2: Long-tail product purchase rate | 0.24 | 0.24 | 0.25 | 0.26 | 0.29 | 0.30 |
| x3: Purchase rate in real stores (⇔online store) | 0.83 | 0.73 | 0.69 | 0.70 | 0.69 | 0.68 |
| x4: Purchase rate in major city stores | 0.13 | 0.15 | 0.11 | 0.10 | 0.09 | 0.09 |
| x5: Discount product purchase rate | 0.59 | 0.61 | 0.64 | 0.65 | 0.63 | 0.62 |
| x6: Event attendance rate | 0.51 | 0.52 | 0.55 | 0.56 | 0.54 | 0.54 |
| x7: Number of check-ins | 2.88 | 4.54 | 4.28 | 4.40 | 3.31 | 1.22 |

**Table 3.6. Awareness of marketing elements (females).**

| Age | 10s | 20s | 30s | 40s | 50s | 60s |
|---|---|---|---|---|---|---|
| Number of customers | 2823 | 27045 | 79882 | 46420 | 13891 | 4885 |
| Sales (purchase amounts) | 2920 | 4587 | 5193 | 5191 | 5265 | 4989 |
| x1: Expensive product purchase rate | 0.17 | 0.23 | 0.23 | 0.25 | 0.28 | 0.27 |
| x2: Long-tail product purchase rate | 0.20 | 0.19 | 0.19 | 0.20 | 0.21 | 0.22 |
| x3: Purchase rate in real stores (⇔online store) | 0.89 | 0.79 | 0.71 | 0.73 | 0.78 | 0.84 |
| x4: Purchase rate in major city stores | 0.13 | 0.13 | 0.08 | 0.07 | 0.08 | 0.08 |
| x5: Discount product purchase rate | 0.61 | 0.65 | 0.70 | 0.71 | 0.68 | 0.67 |
| x6: Event attendance rate | 0.53 | 0.56 | 0.62 | 0.62 | 0.59 | 0.58 |
| x7: Number of check-ins | 3.32 | 3.84 | 2.21 | 1.62 | 0.96 | 0.14 |

From Tables 3.5 and 3.6, we confirmed the following tendencies:

- The number of customers is large for men in their 30s and 40s, and for women in their 20s, 30s, 40, and 50s, though especially for women in their 30s and 40s.
- The purchase amounts are higher for men than for women.
- The rate of expensive product purchases is higher for men than for women.
- The rate of long-tail product purchases for men in their 40s and 50s is slightly higher than for other groups.
- Purchase rates at real shops for people in their teens and women in their 60s are higher than for other groups.

- Purchase rates in major city stores for those in their teens and 20s are higher than for other groups.
- Discount product purchase rates for women in their 30s, 40s, 50s, and 60s is higher than for other groups.
- Women in their 30s and 40s attend events at a higher rate than other groups.
- Men in their 20s, 30s, and 40s use check-in services at a higher rate than the other groups.

Because we confirmed that the awareness of marketing elements devoted to each customer differ according to age and sex, we consider the analysis for difference groups as an effective answer to RQ2. Therefore, we analyze the differences in the effectiveness of each marketing element for different customer groups using covariance structure analysis, as described in 3.4.3.

### 3.4.3 Results from the covariance structure analysis

Using the marketing elements model verified in 3.4.1, we evaluate the effectiveness of each marketing element for different customer groups.

We used the data from 1000 customers from each group randomly extracted from purchase data from June 2013, as explained in 3.3.1, for 12 groups ( [man, woman]×[10s, 20s, 30s, 40s, 50s, 60s ]).

We used the SEM function in the R software package for the covariance structure analysis as in 3.4.1, and four fit indexes, CFI, TLI, RMSEA, and SRMR to evaluate the fitness of our model. Moreover, we evaluated the marketing elements' effectiveness in behavioral loyalty using a path coefficient.

Tables 3.7 and 3.8 report the results. Though the RMSEA values for three groups (men in 20s, 30s, and 50s) are slightly above 0.05, the other scores satisfy the conditions of four fit indexes, confirming the validity of our model. Therefore, we further analyze the effectiveness of the marketing elements for each group.

**Table 3.7. Effectiveness of marketing elements (males).**

| Age | | 10s | 20s | 30s | 40s | 50s | 60s |
|---|---|---|---|---|---|---|---|
| Number of data | | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| Fit index | $\chi 2$ | 45.218 | 59.198 | 52.408 | 46.349 | 56.996 | 24.791 |
| | Degree of freedom | 15 | 15 | 15 | 15 | 15 | 15 |
| | p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.053 |
| | CFI | 0.983 | 0.967 | 0.965 | 0.969 | 0.956 | 0.994 |
| | TLI | 0.969 | 0.939 | 0.934 | 0.942 | 0.918 | 0.988 |
| | RMSEA | 0.045 | 0.054 | 0.050 | 0.046 | 0.053 | 0.026 |
| | SRMR | 0.037 | 0.033 | 0.038 | 0.033 | 0.039 | 0.024 |
| Path coefficient | f1 =˜ x1 (Expensive product) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | f1 =˜ x2 (Long-tail product) | 0.182 | 0.458 | 0.518 | 0.517 | 0.552 | 0.504 |
| | f2 =˜ x3 (Real store) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | f2 =˜ x4 (Major city store) | 0.079 | 0.304 | 0.213 | 0.189 | 0.210 | 0.021 |
| | f3 =˜ x5 (Discount) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | f3 =˜ x6 (Event) | 0.655 | 0.749 | 0.911 | 0.808 | 0.826 | 0.567 |
| | f3 =˜ x7 (Check-in) | -0.020 | 0.441 | 0.343 | 0.392 | 0.236 | 0.046 |
| | f4 =˜ x8 (Sales) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | f4 (behavioral loyalty) ~ f1 (Merchandising) | 0.466 | 0.766 | 0.852 | 0.970 | 0.716 | 0.494 |
| | f4 (behavioral loyalty) ~ f2 (Store facilities) | -0.036 | -0.068 | 0.038 | -0.032 | -0.118 | -0.004 |
| | f4 (behavioral loyalty) ~ f3 (Service/Support) | 0.036 | 0.964 | 1.049 | 1.114 | 1.034 | 0.007 |

**Table 3.8. Effectiveness of marketing elements (females).**

| Age | | 10s | 20s | 30s | 40s | 50s | 60s |
|---|---|---|---|---|---|---|---|
| Number of data | | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| Fit index | χ2 | 33.227 | 29.575 | 25.052 | 43.960 | 41.751 | 22.906 |
| | Degree of freedom | 15 | 15 | 15 | 15 | 15 | 15 |
| | p-value | 0.004 | 0.014 | 0.049 | 0.000 | 0.000 | 0.086 |
| | CFI | 0.989 | 0.988 | 0.991 | 0.971 | 0.976 | 0.995 |
| | TLI | 0.979 | 0.978 | 0.983 | 0.946 | 0.955 | 0.99 |
| | RMSEA | 0.035 | 0.031 | 0.026 | 0.044 | 0.042 | 0.023 |
| | SRMR | 0.032 | 0.023 | 0.026 | 0.030 | 0.029 | 0.029 |
| Path coefficient | f1 =~ x1 (Expensive product) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | f1 =~ x2 (Long-tail product) | 0.147 | 0.536 | 0.385 | 0.520 | 0.446 | 0.583 |
| | f2 =~ x3 (Real store) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | f2 =~ x4 (Major city store) | 0.005 | 0.177 | 0.140 | 0.185 | 0.061 | 0.015 |
| | f3 =~ x5 (Discount) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | f3 =~ x6 (Event) | 0.681 | 0.655 | 0.798 | 0.737 | 0.819 | 0.599 |
| | f3 =~ x7 (Check-in) | -0.002 | 0.438 | 0.311 | 0.330 | 0.202 | 0.020 |
| | f4 =~ x8 (Sales) | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | f4 (behavioral loyalty) ~ f1 (Merchandising) | 0.870 | 1.131 | 0.648 | 1.098 | 1.320 | 1.061 |
| | f4 (behavioral loyalty) ~ f2 (Store facilities) | 0.000 | 0.027 | -0.070 | 0.017 | 0.058 | 0.000 |
| | f4 (behavioral loyalty) ~ f3 (Service/Support) | 0.126 | 1.114 | 0.877 | 1.054 | 1.174 | 0.097 |

As an overall tendency, there was a large difference between the groups of teens and those in their 60s, and those in the 20s to 50s age groups. The influence of merchandising is high for the former, and the influence of merchandising and service support is high for the latter. Service support has a larger influence for groups of men in the 20s, 30s, 40s, and 50s age groups, and for women in their 30s.

We further analyzed the groups of customers in the 20s, 30s, 40s, and 50s age groups. For these groups, the influence of merchandising indicated by expensive product purchase rates is high, while the long-tail product purchase rate is half that. Moreover, the influences on service support are discounts, events, and check-ins, in that order.

From these analyses, discounts and events are good marketing elements for people in their 20s to late 50s, especially for men. Moreover, the influence of check-in services on service support for those in their 20s is higher than for the other age categories, so this marketing element is especially suited to young people.

Furthermore, comparing the results from the tendency analysis in 3.4.2, we propose the following marketing strategies for men in their 30s and 40s, and women in their 20s, 30s, 40s, and 50s, which have a very high number of customers.

- Because the use ratio is lower than for women while the effect of the marketing element is large, improving discounts and events for men can improve sales by advertising discounts and events targeting men in their 30s or 40s.
- Because the use ratio is lower than for men while the effect is large, the check-in services targeting women under 40 could increase sales by advertising the benefits of the check-in service.

## 3.5 Summary

In this chapter, we proposed a method for calculating the awareness of marketing elements devoted to each customer and analyzing the effectiveness of marketing elements on different customer groups using covariance structure analysis with the aim of utilizing purchase data and improving return on investment (ROI). We explained it by adopting retail industry as an example. We evaluated our method and confirmed its effectiveness in identifying effective marketing elements. Moreover, we proposed marketing strategies comparing the awareness of marketing elements devoted to each customer and the effectiveness of marketing elements for different customer groups.

We will evaluate our method using other data, such as for other seasons. Further, we will also propose other uses for the data.

# Chapter 4

# Incentivize purchasing through communication among customers

## 4.1 Introduction

Co-creation is a new marketing strategy gaining attention. Value co-creation is an activity in which consumers create value with the firm through direct and indirect collaborations across one or more stages of production and consumption [48].

As one form of co-creation, we focus on self-marketing services, which we define as the marketing activities performed by customers. These include product reviews, new product planning, or store remodeling as popular forms of co-creation. For example, self-production and self-service do not match a restaurant's atmosphere in some cases.

One goal of a restaurant's co-creation service involves encouraging interaction with customers and increasing the number of users, customer satisfaction, and return visits. Traditional services, such as the restaurant's page on a SNS are helpful in increasing customer satisfaction and return visits [49]; however, a limited number of people use these services.

We address this problem by using Fogg's behavioral model [19] we mentioned in 1.2.2. This model asserts that for a behavior to occur, a person must have sufficient motivation and ability, and an effective trigger. Conversely, a lack of motivation, barriers to action, and no trigger are typical causes of action failure. For a restaurant's page on an SNS, concern for privacy [50] might be a barrier to action for some people, and it is difficult to provide a trigger for those who have never used an SNS.

Our goal involves identifying a more comprehensive self-marketing approach. We achieve this by considering the disadvantages of traditional self-marketing services and creating a new self-marketing system that motivates customer actions, including the use of this system and return visits.

We conduct two experiments with 321 persons in total, and compare the traditional approach and our proposed system.

## 4.2 Related Works

### 4.2.1 Co-creation

Nearly all examples of a co-creation service belong to two types: self-production or self-service [51].

Self-production is the active engagement of consumers in the creation of end products [52]. Assembling furniture and a dinner kit are some examples [53]. Alternatively, self-service occurs when customers perform all aspects of a specific service encounter [54], such as in self-service restaurants and automated hotel checkout [55]. These co-creation services have a positive impact on customer's satisfaction [56][57]. However, self-production and self-service do not match the restaurant's atmosphere in some cases. Therefore, this study focuses on self-marketing services.

### 4.2.2 Self-marketing service

Restaurant pages on an SNS and word-of-mouth communication sites for restaurant search, such as Yelp, are examples of self-marketing services.

This type of social media is the most-used marketing element of restaurateurs [58]. It is not only an advertising and promotional tool but also an effective communication tool between customers and firms [59][60]. For example, a brand's fan pages on an SNS facilitate customer loyalty [61] and induce positive actions in customers, including an increase in number of visits and positive word-of-mouth [62].

However, social media can be disadvantageous. For example, some customers do not often use SNS owing to privacy concerns [50]. Therefore, this necessitates a more comprehensive method.

The use of paper-based questionnaires at restaurants is also an example of self-marketing service. Questionnaires help improve a firm's products and services; however, answering the questionnaire itself does not lead to customer satisfaction. A system is necessary to increase customer satisfaction, such as co-creation services and SNS.

## 4.3 Our approach

Our goal involves developing a self-marketing system that encourages interaction between customers and the store, and especially increases the motivation for return visits among those who do not often use SNS.

We achieve this goal by proposing a tablet-based communication system placed in a restaurant to compensate for the disadvantages of SNS, including privacy concerns and the lack of a trigger. This system, placed on a restaurant table, does not require users to create an account. By eliminating privacy concerns, we aim to change the customer's position from negative to positive, and encourage customer action, as Figure 4.1 demonstrates.

As noted in Figure 4.2, this system has three functions to enable interaction between customers and the store. These functions are detailed as follows:

**Function 1:** Customers can view the comments of other customers and click a "like" button.

**Function 2:** Customers can provide comments or requests for the store.

We prepare many categories to induce customer comments or requests. Customers can select the category and subcategory, and then comment about the category.

Our system flows as follows:

Select Category -> Select Subcategory -> Write Comment or Request

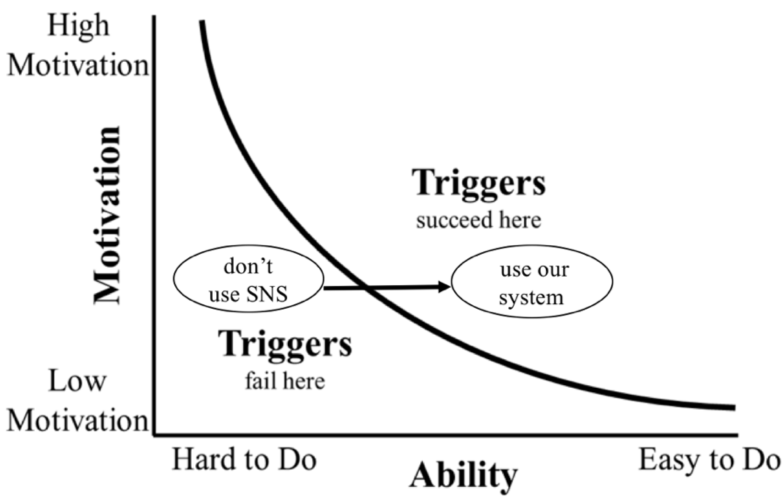


**Figure 4.1. Effect of our approach (referring to** [19]**).**

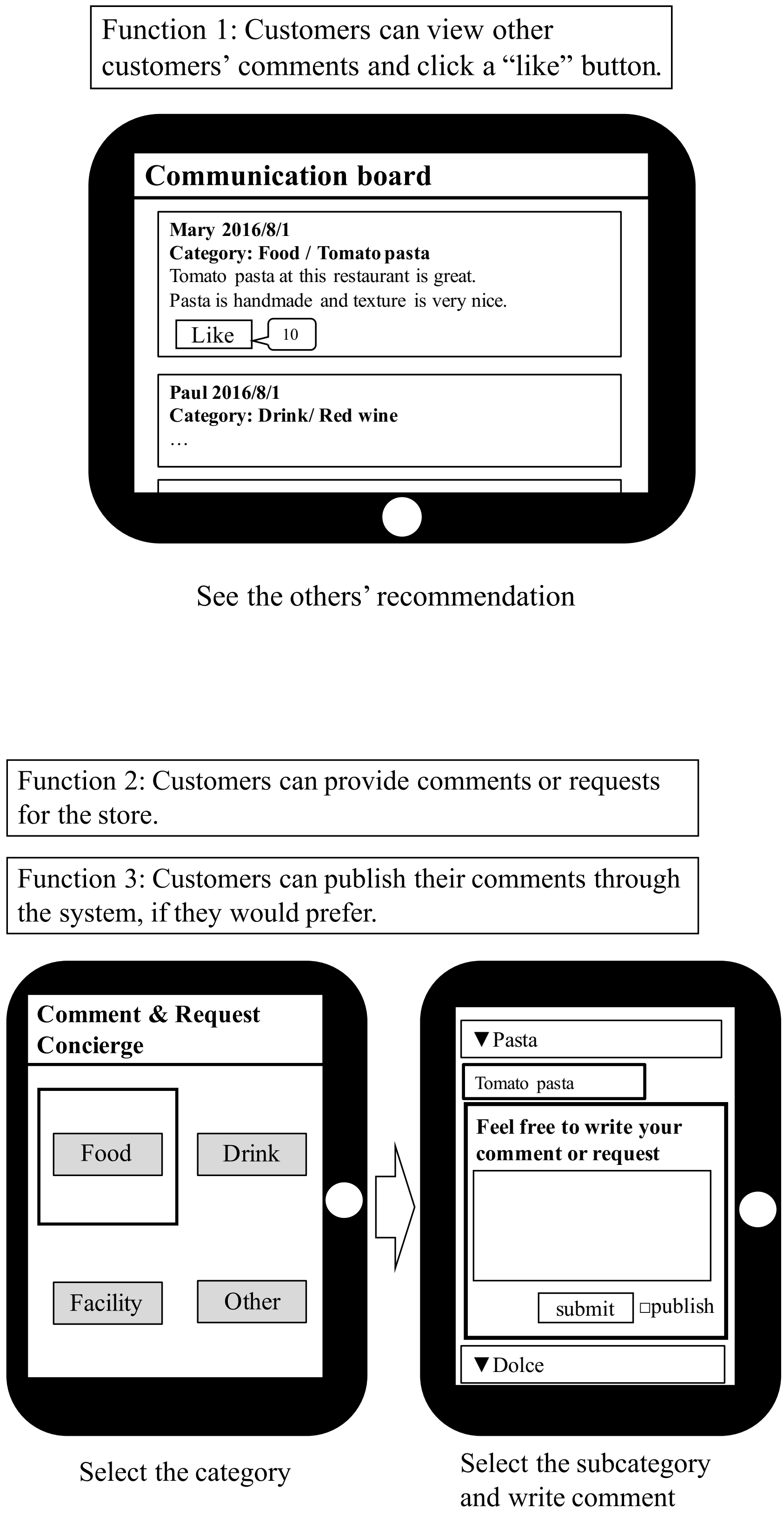


**Figure 4.2.** Outline of our system.

The categories and subcategories include:
- Category: Food, Drink, Facility, and Other
- Subcategory (Food/Drink): Food/drink menu items
- Subcategory (Facility): Atmosphere/layout, convenience
- Subcategory (Other): Service, this self-marketing system

**Function 3:** If they prefer, customers can publish their comments through this system.

These functions allow users to easily conduct self-marketing activity, and communicate with the store and other customers.

## 4.4 Experimental methodology

### 4.4.1 Research question

We analyze our system's effectiveness by posing the following research questions:

RQ1. Is this system effective for those who do not use SNS? Does this system eliminate the barrier to action (privacy concerns)?
RQ2. What factors increase customers' motivations?
RQ3. Is this system effective in increasing sales?

We conducted two experiments to answer these questions. The first experiment involves a hypothetical questionnaire, which targets a range of respondents. The second experiment is a field survey, in which we install our system at a restaurant and collect data from real situations. We analyze both data and confirm the three aforementioned research questions.

### 4.4.2 Data collection

1) Experiment 1: Hypothetical Questionnaire

We conducted an Internet-based questionnaire survey to collect data from a range of respondents.

a) Content of questions

The questionnaire has two parts.

The first asks about a customer's daily activities regarding social media. The details are noted in Table 4.1.

In the second part, we request the respondents to recall their last visit to a restaurant, and assume a situation in which our system is installed at the restaurant. The respondent is asked to judge whether he or she would use our system. The details are displayed in Table 4.2.

b) Respondents

A total of 300 people responded to our survey.

We created 12 groups based on sex and age ([men, women] × [10s, 20s, 30s, 40s, 50s, 60s]), and each group had the same number of respondents.

**Table 4.1.** Part 1 questions (Daily activities regarding social media).

| Category | Question |
|---|---|
| Personal attributes | Q1-1. Age (10s ~ 60s) |
| | Q1-2. Do you like new challenges?<br>(1: think so; 2: maybe think so; 3: maybe do not think so; 4: do not think so) |
| | Q1-3. Frequency of eating out<br>(1: more than twice a week; 2: two to four times a month; 3: less than once a month, 4: seldom perform this activity) |
| Social media activity | Q1-4. Frequency of posting activity on SNS<br>(4-point scale, which is same as Q1-2) |
| | [*For those who answered 3 or 4]<br>Reason for the above frequency<br>(1: time consumption; 2: privacy concerns, 3: no trigger/do not have an account; 4: other) |
| | Q1-5. Frequency of reading activity on SNS<br>(4-point scale, which is same as Q1-2) |
| | Q1-6. Do you refer to others' experience written on the Internet?<br>(4-point scale, which is same as Q1-2) |
| | Q1-7. Have you ever been concerned about the privacy of personal information on the Internet?<br>(4-point scale, which is same as Q1-2) |

**Table 4.2.** Part 2 questions (Hypothetical questions about the proposed system).

| Category | Question |
|---|---|
| Recall your last restaurant visit | Q2-1. Type of restaurant you visited |
| | Q2-2. How satisfied were you with the restaurant? (1: think so; 2: maybe think so; 3: maybe do not think so; 4: do not think so) |
| After showing the system's instruction images | |
| Hypothetical question<br><br>*4-point scale (1: think so; 2: maybe think so; 3: maybe do not think so; 4: do not think so) | Q2-3. Would you use this system? |
| | Q2-4. Would you use Function 1 (reading others' posts)? |
| | Q2-5. Would you use Function 2 (posting comments)? |
| | Q2-6. Would you use Function 3 (publish comments on the comment-sharing page)? |
| | Q2-7. Would you like to try the menus others have posted? |
| | Q2-8. Would you like to peruse other menus and post comments using this system? |

2) Experiment 2: Field Survey

We installed our system at a restaurant (Nepal cuisine restaurant) and conducted the field survey.

a) System

As we mentioned in the previous section, we developed a tablet-based communication system, which has three functions. This system is built by using PHP, MySQL and jQuery.

In function 2 (posting comments), customers can select the category and subcategory, then write a comment about the category. We also prepared some questions for this experiment to analyze this system.

Our system flows as follows:

Select Category (Food, Drink, Facility, and Other)

-> Select Subcategory (about 180 categories including all food/drink menu)

-> Write comment or Request (customers can publish their comments if they would prefer)

-> Answer Questions (we explain in the following subsection b)

We analyze the effective factors using question responses.

b) Content of questions

The questions are the almost the same as in experiment 1. In the system, the respondents are asked to judge from Q2-2 to Q2-8 in Table 4.2. At this time, it is not a hypothetical question but one in an actual situation. After a field survey, the respondents are also asked to answer Part 1 questions in Table 4.1.

c) Experiment period

21 people (9 men and 12 women in their 20s, 30s, 40s, 50s, 60s) participated in this field survey.

### 4.4.3 Data analysis

As we mentioned in the previous subsections, we conducted two experiments to answer the research questions. The first experiment targets a range of respondents but it is hypothetical question. The second experiment is a real situation but the number of respondents is limited. Therefore, we analyze both data in the same way, and compare the results. If the results are the same, the claim can be strengthened. If there is a difference, there can be a difference in experimental settings.

We confirm each research question as follows.

RQ 1: We categorize results by the frequency of SNS usage and compare motivation for system use.

RQ 2: Using logistic regression analysis [63], we analyze the factors leading to willingness to use the system. The following equation is used in the logistic regression analysis.

$$p = Pr\{Y = 1|X\} = \frac{1}{1 + exp[-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)]}$$

$p$ is the probability of $Y = 1$, which is a positive answer to the willingness of the system usage (Q2-6: Publishing comments / Q2-4: Reading comments). $\beta_0$ is constant, and $\beta_1$, $\beta_2$, $\beta_k$ are regression coefficients, and $x_1$, $x_2$, $x_k$ are explanatory variables, which is an answer to Q1-1 to Q1-7 in this study. The significance level in the statistical hypothesis test is 10%.

RQ 3: We evaluate the positive answer rate to sales related questions: Q2-7 and Q2-8. If those rates are high, we can confirm the effectiveness for increasing sales.

## 4.5 Results and discussion

### 4.5.1 Categorizing by SNS activity corresponding to RQ1

RQ1. Is this system effective for those who do not use SNS? Does this system eliminate the barrier to action (privacy concerns)?

We answer RQ1 by categorizing the users into three groups based on the answers regarding their social media activities.

Group 1 is composed of active SNS users who post and read comments on an SNS. Respondents, who answered “one” or “two” to the question on frequency of posting activity on an SNS, belong to this group.

Group 2 is composed of SNS users who do not post, but do read comments posted on an SNS. Respondents who do not belong to Group 1 and answered “one” or “two” to the question on the frequency of SNS reading activity belong to this group.

Group 3 is composed of respondents who do not use an SNS. Respondents who do not belong to either Group 1 or Group 2 belong to this group.

Table 4.3 indicates the categorization results. Based on this categorization, we summarized the results as shown in Table 4.4 and Table 4.5. This displays the rate of respondents who answered “one” or “two” (or answered positively) for each question. This also shows the result of multiple comparison between groups.

Moreover, we questioned respondents regarding the reasons for low posting activity on an SNS (Q1-4), as noted in Table 4.1. The following are the options for this question: 1. time consumption; 2. privacy concerns; 3. no trigger/do not have an account; and 4. other. We extracted respondents who answered option 2 and calculated the rate of positive answers to Q2-6. The results are presented in Table 4.6.

We analyze the results of RQ1. As noted by Q2-3 in Table 4.4 and Table 4.5, some respondents belonging to Group 3 (those who do not use SNS) demonstrated willingness to use our system, which is its primary advantage.

Additionally, we found that the barrier for publishing comments on a communication site, which were caused by privacy concerns, was lower than that on a conventional communication site, as Table 4.6 shows. It seems to be effective that this system does not require users to create an account, and the publication scope is limited to the visitors of the restaurant. This satisfies one of the main purposes of this system as intended.

**Table 4.3.** Number of respondents.

| | Group 1: Post on SNS | Group 2: Only read posts | Group 3: Do not use SNS |
|---|---|---|---|
| Experiment1: Hypothetical Questionnaire | 77 | 91 | 132 |
| Experiment2: Field Survey | 4 | 8 | 9 |

**Table 4.4.** Results of experiment 1 (Rate of positive answer).

| Variables | Rate of positive answer | | | Multiple comparison (p-value) | | |
|---|---|---|---|---|---|---|
| | Group 1 (77) | Group 2 (91) | Group 3 (132) | Group 1-2 | Group 1-3 | Group 2-3 |
| Q1-4. Frequency of posting activity on SNS | 1.00 | 0.00 | 0.00 | - | - | - |
| Q1-5. Frequency of reading activity on SNS | 0.99 | 1.00 | 0.00 | - | - | - |
| <u>Q2-3. Would you use this system?</u> | <u>0.66</u> | <u>0.43</u> | <u>0.20</u> | 1.39 e-02* | 7.03 e-12*** | 1.68 e-05*** |
| <u>Q2-4. Would you use Function 1 (reading others' posts)?</u> | <u>0.70</u> | <u>0.42</u> | <u>0.22</u> | 1.30 e-04*** | 9.12 e-13*** | 6.23 e-04*** |
| Q2-5. Would you use Function 2 (posting comments)? | 0.61 | 0.34 | 0.17 | 2.77 e-04*** | 4.92 e-13*** | 2.07 e-04*** |
| Q2-6. Would you use Function 3 (publish comments on the comment-sharing page)? | 0.43 | 0.26 | 0.10 | 7.62 e-03** | 9.34 e-08*** | 8.55 e-03** |
| <u>Q2-7. Would you like to try the menus others have posted?</u> | <u>0.74</u> | <u>0.49</u> | <u>0.30</u> | 1.16 e-03** | 9.99 e-12*** | 6.20 e-04*** |
| Q2-8. Would you like to peruse other menus and post comments using this system? | 0.69 | 0.33 | 0.18 | 4.77 e-06*** | 6.13 e-13*** | 1.19 e-02* |

*** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1

**Table 4.5.** Results of experiment 2 (Rate of positive answer).

| Variables | Rate of positive answer | | | Multiple comparison (p-value) | | |
|---|---|---|---|---|---|---|
| | Group 1 (4) | Group 2 (8) | Group 3 (9) | Group 1-2 | Group 1-2 | Group 1-2 |
| Q1-4. Frequency of posting activity on SNS | 1.00 | 0.00 | 0.00 | - | - | - |
| Q1-5. Frequency of reading activity on SNS | 1.00 | 1.00 | 0.00 | - | - | - |
| <u>Q2-3. Would you use this system?</u> | <u>1.00</u> | <u>0.63</u> | <u>0.89</u> | 0.871 | 1.000 | 0.939 |
| <u>Q2-4. Would you use Function 1 (reading others' posts)?</u> | <u>1.00</u> | <u>0.75</u> | <u>0.78</u> | 0.214 | 0.904 | 1.000 |
| Q2-5. Would you use Function 2 (posting comments)? | 1.00 | 0.50 | 0.67 | 0.118 | 0.385 | 1.000 |
| Q2-6. Would you use Function 3 (publish comments on the comment-sharing page)? | 1.00 | 0.38 | 0.44 | 0.312 | 0.532 | 1.000 |
| <u>Q2-7. Would you like to try the menus others have posted?</u> | <u>1.00</u> | <u>0.75</u> | <u>0.78</u> | 0.387 | 0.904 | 1.000 |
| Q2-8. Would you like to peruse other menus and post comments using this system? | 0.75 | 0.50 | 0.56 | 1.000 | 1.000 | 1.000 |

*** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1

**Table 4.6.** Results of people with privacy concerns (Rate of positive answer).

| Variables | Experiment 1 | | Experiment 2 | |
|---|---|---|---|---|
| | Group 2 (53) | Group 3 (35) | Group 2 (5) | Group 3 (4) |
| <u>Q2-6</u> Would you use Function 3 (publish comments)? | <u>0.28</u> | <u>0.11</u> | <u>0.40</u> | <u>0.50</u> |

## 4.5.2 Logistic regression analysis corresponding to RQ2

RQ2. What factors increase the motivation of customers?

Considering the system's function, as Q2-4 in Table 4.4 and Table 4.5 demonstrates, reading activity more easily encouraged customers' actions because the barriers to reading activity are lower than barriers to posting activity.

For finding factors related to user attributes, we conducted logistic regression analysis. Table 4.7 to Table 4.10 indicates the results. Variables with statistically significant differences are underlined. As experiment 2 had a small number of data and no significant difference was observed, those with a relatively high P value were underlined.

1) Results of agreement in both experiments

As Q1-3 shows, publishing function is effective for people with low frequency of eating out. Also, publishing and reading functions are effective for people who refer to others' experience written on the Internet as Q1-6 shows.

From these results, we found that people with low frequency of eating out tend to be easily interested in our system. Moreover, it turned out that people who refer to the Internet posts of others tend to feel the benefits of the system and are willing to use it. These factors are advantageous in creating a marketing strategy for utilizing our system. For example, strengthening the reading function can be effective to increase the user of our system.

2) Difference in both experiments

In Experiment 1, there was an effective trend for those who do not care about privacy as Q1-7 shows, but in experiment 2 at real stores, there was no such tendency. This result shows that the real system eliminates privacy concerns better than what users assume.

**Table 4.7.** Publishing activity of experiment 1 (Relationship between the probability of publishing activity and explanatory variables).

| Variables | Regression coefficient | Std. Error | Z value | P(>\|z\|) |
|---|---|---|---|---|
| *(Intercept)* | 1.144 | 0.643 | 1.778 | 0.075. |
| Q1-1: Age | 0.086 | 0.100 | 0.863 | 0.388 |
| Q1-2: Adventure | -0.373 | 0.238 | -1.568 | 0.117 |
| Q1-3: Eating-out | 0.379 | 0.176 | 2.150 | 0.032* |
| Q1-4: Posting | -0.198 | 0.166 | -1.188 | 0.235 |
| Q1-5: Reading | -0.071 | 0.164 | -0.433 | 0.665 |
| Q1-6: Others | -1.238 | 0.248 | -5.001 | 5.69E-07*** |
| Q1-7: Privacy | 0.486 | 0.210 | 2.312 | 0.021* |

*** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1

**Table 4.8.** Publishing activity of experiment 2 (Relationship between the probability of publishing activity and explanatory variables).

| Variables | Regression coefficient | Std. Error | Z value | P(>\|z\|) |
|---|---|---|---|---|
| *(Intercept)* | 240.335 | 66667.155 | 0.004 | 0.997 |
| Q1-1: Age | 0.440 | 1.012 | 0.435 | 0.664 |
| Q1-2: Adventure | -2.342 | 1.838 | -1.274 | 0.203 |
| Q1-3: Eating-out | 2.231 | 1.715 | 1.301 | 0.193 |
| Q1-4: Posting | -50.927 | 14345.622 | -0.004 | 0.997 |
| Q1-5: Reading | -0.130 | 1.431 | -0.091 | 0.928 |
| Q1-6: Others | -2.083 | 1.331 | -1.565 | 0.118 |
| Q1-7: Privacy | -32.828 | 9757.336 | -0.003 | 0.997 |

*** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1

**Table 4.9.** Reading activity of experiment 1 (Relationship between the probability of reading activity and explanatory variables).

| Variables | Regression coefficient | Std. Error | Z value | P(>\|z\|) |
|---|---|---|---|---|
| *(Intercept)* | 2.998 | 0.63777 | 4.700 | 2.60E-06*** |
| Q1-1: Age | 0.040 | 0.08387 | 0.476 | 0.634 |
| Q1-2: Adventure | -0.194 | 0.20065 | -0.965 | 0.334 |
| Q1-3: Eating-out | 0.070 | 0.15496 | 0.449 | 0.654 |
| Q1-4: Posting | -0.231 | 0.15169 | -1.522 | 0.128 |
| Q1-5: Reading | -0.066 | 0.1345 | -0.491 | 0.624 |
| Q1-6: Others | -1.101 | 0.19842 | -5.548 | 2.89E-08*** |
| Q1-7: Privacy | 0.217 | 0.16839 | 1.291 | 0.197 |

*** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1

**Table 4.10.** Reading activity of experiment 2 (Relationship between the probability of reading activity and explanatory variables).

| Variables | Regression coefficient t | Std. Error | Z value | P(>\|z\|) |
|---|---|---|---|---|
| *(Intercept)* | 4.948 | 5.686 | 0.870 | 0.384 |
| Q1-1: Age | -0.342 | 0.990 | -0.345 | 0.730 |
| Q1-2: Adventure | -0.340 | 1.691 | -0.201 | 0.841 |
| Q1-3: Eating-out | 1.147 | 1.851 | 0.620 | 0.536 |
| Q1-4: Posting | -0.299 | 1.372 | -0.218 | 0.827 |
| Q1-5: Reading | 0.628 | 1.386 | 0.453 | 0.650 |
| Q1-6: Others | -1.454 | 1.004 | -1.448 | 0.148 |
| Q1-7: Privacy | -0.153 | 1.446 | -0.106 | 0.916 |

*** < 0.001 < ** < 0.01 < * < 0.05 < . < 0.1

### 4.5.3 Analysis of sales related questions corresponding to RQ3

RQ3. Is this system effective in increasing sales?

The results related to increasing sales are shown in Table 4.11. Some respondents answered that they would like to try the menus posted by others. This will encourage additional orders or return visits and lead to increase in sales. The sales effect is also higher in experiment 2 at a real store; therefore, it can be more effective than web questionnaires.

In experiment 2 at a real store, the large varieties of posts were published in our system as Table 4.12 shows. These comments will be useful for other customers. Moreover, in marketing field, it is said that a company can be more competitive if it can connect with communities of customers for co-creation [9]. These comments are also useful for restaurants.

**Table 4.11.** Result of sales effect (Rate of positive answer).

| Variables | Experiment 1 (300) | Experiment 2 (21) |
|---|---|---|
| Q2-7. Would you like to try the menus posted by others? | 0.47 | 0.81 |
| Q2-8. Would you like to peruse other menus and post comments using this system? | 0.36 | 0.57 |

**Table 4.12.** Number of posts in field survey.

| Category | Number of selected subcategory | Number of posts | Number of published posts |
|---|---|---|---|
| Food | 14 | 19 | 16 |
| Drink | 3 | 3 | 2 |
| Facility | 2 | 5 | 5 |
| Other | 2 | 3 | 3 |
| (Total) | 21 | 30 | 26 |

## 4.6 Summary

In this chapter, we proposed a self-marketing system as a new co-creation service, in which customers can write comments or requests and which enables communication between a restaurant and its customers. We consider SNS and word-of-mouth sites as existing self-marketing services, although the users for these services are limited. Our study considered the conventional function of communication between customers and restaurants including the disadvantages of existing services (privacy concerns and no trigger). Our system, therefore, eliminates these privacy concerns. We demonstrated that the self-marketing system can eliminate privacy concerns and effectively encourage action from those who do not use an SNS (This is the answer to RQ1). This is one of the main contributions of this system because we can provide the advantage of communication service to a wider range of people.

Moreover, we analyzed the effective factors of our system. It was revealed that reading function encourages customers' actions more easily. We also found that people with low frequency of eating out, and people who refer to internet posts of others tend to feel the benefits of the system and are willing to use it (This is the answer to RQ2). These findings are helpful in creating a marketing strategy to utilize our system. For example, if the function of reading other's comments is strengthened, the users of our system will increase.

If a restaurant uses our system, it may increase customer satisfaction and return visits (This is the answer to RQ3). Moreover, the restaurant can obtain user feedback and suggestions. This information is also useful to restaurants to become more competitive. In future, we will attempt to develop a method to utilize this feedback.

Chapter 5

# Conclusion

In this paper, as a method to improve customer motivation, we proposed three approaches: (1) Show purposes of specific products/services to increase motivation (2) Analyze and strengthen marketing elements to encourage purchasing (3) Incentivize purchasing through communication among customers, and analyzed the effectiveness of motivation and its effective factors.

The first and second approaches are methods to extract useful information from large-scale data and utilize it. In the system corresponding to the first approach, many purposes for customers' actions not as yet emphasized by companies are extracted from social data and shown to customers. We explained it by adapting to information provision services. It is also the solution to the question of what kind of information should be offered with specific products/services to increase motivation, which corresponds to conventional advertising. As a result of the evaluation experiment, we confirmed that the proposed method can extract customers' purpose for action with real-world accuracy. In addition, we confirmed the effectiveness of the motivation by showing purposes and found that a purpose that corresponded to the desires or situation of the user was more effective.

In the system corresponding to the second approach, the effectiveness of the marketing elements, previously analyzed using questionnaires, is analyzed and strengthened from large-scale purchasing data. We explained it by adapting to retail industry as an example. We focused beyond the products themselves on factors like environment and addressed the question about the kind of environment that can increase motivation. This is related to 4P, STP, and brand theory. The evaluation experiment confirmed the validity of the proposed structural hypothesis model. We also confirmed that effective marketing elements change depending on gender and age, and it is possible to develop a marketing strategy based on customer awareness of the marketing elements and their effectiveness.

The self-marketing system for restaurants corresponding to the third approach is a communication system targeting customers who have not used SNS. It is an advanced method, focusing not only on traditional customer/company relationships but also on mutual interaction between customers. It is a technique to promote communication between customers by using social media as a tool rather than large-scale data and eliminating privacy concerns of customers. As a result of evaluation experiments, we confirmed that the proposed self-marketing system can effectively promote the use of the system to customers who are not using SNS. This may lead to an increase in customers' additional orders or return visits. We additionally found effective elements encouraging the use of the system. For example, those who refer to others' posts on the internet tend to feel the advantages of the system.

As described above, all of these methods confirmed that it is an effective approach to encourage customer action and promote sales as compared to conventional methods and services. In addition, as a result of analyzing behavior encouragement factors, we found that the purpose consistent with the situation and desire of the user is particularly effective for all approaches. Furthermore, the proposed method also leads to new services such as information provision services that find the purpose of an action and encourage customers to advance through the purchasing process, and self-marketing services that create communication between customers.

Here, we describe usage guidelines for the three proposed systems. As explained in Chapter 1, the main targeted industry of the system is retail trade and services (eating and drinking places/amusement, hobbies, and entertainment services) with physical locations. The main strengthening phase of decision process, required data for the system, and usage procedures are summarized in Figure 5.1. There are no restrictions on the combination of systems as candidates. The candidate systems need to be considered and selected according to the phases to be strengthened in the decision process. However, necessary data has to be prepared for each system. In system (1), text data containing experiences such as blogs, SNS etc. is required. In system (2), purchase related data such as POS data is required. After preparing the data, we use the proposed system according to each usage procedure. In system (1), it is necessary to select actions related to the target industry. As shown in Table 5.1, for example, in the case of retailing, "Shopping" is selected. Then, using the proposed target extraction method, the purpose of action is extracted and used for information providing service, advertisement etc. In system (2), it is necessary to select marketing elements suitable for the target industry. Table 5.2 summarizes the relationship between 4P commonly described across industries, and retail and service marketing mix [64]. A company can select the candidates of the marketing elements that the company wishes to use for effect analysis, referring to examples shown in Table 5.2. It is preferable to select maximum possible marketing elements so that comprehensive effect analysis can be performed. Next, with reference to the seven awareness calculation methods proposed in this research, the company can consider a method of calculating awareness of selected marketing elements. Subsequently, using the proposed method, the company can measure the awareness and effectiveness of each marketing element and develop a marketing strategy. In system (3), it is necessary to select the categories to be used in the communication tool according to the target shop. As shown in Table 5.3, for example, in the entertainment industry, it is possible to select “Service,” “Facility,” and “Others.” The company can develop an appropriate communication system and introduce it to stores. In all systems, it is also important for companies to consider not only the necessary data and the ability to execute procedures but also the return on investment. Such evaluation is a future task.

Finally, we explain the future prospects. As development of the proposed system on the basis of the results of factor analysis, expanding functions to encourage action and continuous use, and evaluation in real world are future tasks. Moreover, as summarized in Table 1.1, in addition to the type of data used in this research, location data, image/sensor data, etc. can be cited as data available for marketing. The amount of data is expected to increase more and more in future. Although various data analysis techniques have been proposed, but we think that there are still few cases of application in marketing. We will continue research on the methods and applications for marketing, focusing on human behavior.

■Target industry: Retail trade and services (eating and drinking places/amusement, hobbies and entertainment services) with physical locations

**(1) Show purposes of specific products/services to increase motivation**

■Strengthening phase of decision process: Need recognition

■Required data:
Text data of experiences, for example, blogs and SNS

■Procedure:
・Select actions related to target industries (see Table 5.1)
・Extract purpose for action and use it for information provision services, advertisements and so on

**(2) Analyze and strengthen marketing elements to encourage purchasing**

■Strengthening phase of decision process: Pre-purchase evaluation of alternatives

■Required data:
Purchase data such as POS data

■Procedure:
・ Select the marketing elements suitable for target industry (see Table 5.2)
・Consider methods to calculate awareness of selected marketing elements
· Measure awareness and effect of each marketing element and create marketing strategy

**(3) Incentivize purchasing through communication among customers**

■Strengthening phase of decision process: Post-consumption evaluation

■Required data:
None (Social data is generated from this proposed system)

■Procedure:
・Prepare categories suitable for target stores (see Table 5.3)
・Develop a communication system and install in stores

There are no restrictions on the combination of candidate systems.

**Figure 5.1.** System guidelines.

**Table 5.1. Target industries and examples of actions.**

| Industry | Example of action |
|---|---|
| Amusement, hobbies and entertainment services | Running, cinema, museum, amusement park etc. |
| Eating and drinking places | Eating out, restaurant etc. |
| Retail trade | Shopping etc. |

**Table 5.2. Marketing elements of retail and service industry with physical locations (referring to [64]).**

| 4P | Retail mix | Example of marketing elements | Service marketing mix (eating and drinking places/ amusement, hobbies and entertainment services) | Example of marketing elements |
|---|---|---|---|---|
| Product | Assortment | Quality level of assortment<br>Breadth and depth of assortment | Service product | Service concept<br>Quality of service |
| Place | Location | Ease of access<br>Car and bicycle parking space | Place (location, channel) | Ease of access<br>Places where many people gather |
| | Store design | Store layout<br>BGM | - | - |
| | - | - | Physical evidence | Building appearance / interior, staff clothing |
| Promotion | Promotion and additional services | Staff attitude towards customers<br>Advertising, delivery | Promotion | Advertising<br>SNS |
| | - | - | Personnel | Good communication with customers |
| | - | - | Service delivery process | Quality of service delivery<br>(duration etc.) |
| Price | Price | Display price<br>Discount | Price | Price per service |

**Table 5.3. Target industries and examples of categories.**

| Industry | Example of category |
|---|---|
| Amusement, hobbies and entertainment services | Service, Facility, Other |
| Eating and drinking places | Food, Drink, Facility, Other |
| Retail trade | Product, Facility, Other |

# Acknowledgement

I would like to express my deep gratitude to Professor Shuji Hashimoto of Waseda University who gave me kind and careful guidance in conducting this research. This was invaluable in my finding a better direction. He was also understanding of my situation of working at the same time as carrying out research activities while giving me warm encouragement. In writing this paper, I would like to greatly thank Professor Hideyuki Sawada, Professor Shigeo Morishima and Professor Reiko Hishiyama for their valuable advice. Thanks to advice from a wide range of perspectives, I was able to improve the completeness of this thesis.

The research assistant Dr. Miwa and other people of Hashimoto Laboratory gave me useful advice on seminars and so on, which was very helpful. To the secretary Ms. Mizumura, I thank you very much for your cooperation in the various procedures involved in academic conferences and doctor degree acquisition. My thanks to everyone.

In addition, I would like to extend my thanks to NTT Group members for understanding and encouraging my research activities.

Finally, I am sincerely thankful to my parents, brothers, and family who always watched over me warmly.

# References


[1] Cabinet Office, “Japan Revitalization Strategy,” 2016. [online]. Available: https://www.kantei.go.jp/jp/singi/keizaisaisei/pdf/zentaihombun_160602_en.pdf.

[2] R. C. Blattberg, B. D. Kim, and S. A. Neslin, “Market basket analysis,” *Database Marketing: Analyzing and Managing Customers*, pp. 339-351, 2008.

[3] Amazon. [Online]. Available: http://www.amazon.com/

[4] B. Liu, *Sentiment Analysis and Opinion Mining.* San Rafael, CA: Morgan & Claypool Publishers, 2012.

[5] L. D. Vries, S. Gensler, and P. S. H. Leeflang, “Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing,” *J. of Interactive Marketing*, vol. 26, no. 2, pp. 83-91, 2012.

[6] S. K. Hui, P. S. Fader, and E. T. Bradlow, “Research note-The traveling salesman goes shopping: The systematic deviations of grocery paths from TSP optimality,” *Marketing Science*, vol. 28, no. 3, pp. 566-572, 2009.

[7] X. Luo, M. Andrews, Z. Fang, and C. W. Phang, “Mobile targeting,” *Management Science*, vol. 60, no. 7, pp. 1738–1756, 2014.

[8] P. Chandon, J. W. Hutchinson, E. T. Bradlow, and S. H. Young, “Measuring the Value of Point-of-Purchase Marketing with Commercial Eye-Tracking Data,” *INSEAD Business School Research Paper*, 2006.

[9] P. Kotler, H. Kartajaya, and I. Setiawan, *Marketing 4.0: Moving from Traditional to Digital.* Hoboken, NJ: John Wiley & Sons, 2017.

[10] H. Takahashi, “Customer-based Retail Brand Equity: Prototype Model Based on Equity Driver and Components of Japanese Supermarkets,” *J. of the University of Marketing and Distribution Sciences: Distribution Sciences & Business Administration*, vol. 26, no. 2, pp. 75-95, 2014.

[11] F. M. Bass, “A New Product Growth for Model Consumer Durables,” *Management Science*, vol. 15, pp. 215-227, 1969.

[12] E. H. Shaw and D. G. B. Jones, “A History of Schools of Marketing Thought,” *Marketing Theory*, vol. 5, no. 3, pp. 239–281, 2005.

[13] T. Muto, T. Mori, Y. Endo, and K. Tamase, *Psychology: science of heart and mind*. Tokyo, Japan: Yuhikaku, 2004 (in Japanese).

[14] R.M. Ryan and E. L. Deci, "Intrinsic and extrinsic motivations: classic definitions and new directions," *Contemporary Educational Psychology*, vol. 25, no. 1, pp. 54-67, 2000.

[15] H. F. Harlow, "Learning motivated by a manipulation drive," *J. of Experimental Psychology*, pp. 228-234, 1950.

[16] B. J. Fogg, *Persuasive technology: using computers to change what we think and do*. Burlington, MA: Morgan Kaufmann, 2003.

[17] S. Chatterjee and A. Price, "Healthy Living with Persuasive Technologies: Framework, Issues, and Challenges," *J. of the American Medical Informatics Association,* vol. 16, pp. 171–178, 2009.

[18] D. Yoganathan and S. Kajanan, "Persuasive Technology for Smartphone Fitness," in *Proc. PACIS 2013*, pp. 1–11.

[19] B.J. Fogg, "A Behavior Model for Persuasive Design," in *Proc. 4th International Conference on Persuasive Technology*, Article No. 40, 2009.

[20] R. D. Blackwell, P.W. Miniard, and J. F. Engel, *Consumer behavior*, 10th ed. Boston, MA: Cengage Learning, 2006.

[21] N. Yokoyama, K. Funakoshi, H. Toda, and Y. Koike, "Extracting Purpose-for-Action to Enhance Local Information Service," *Information Processing Society of Japan Transactions on databases (TOD)*, vol. 8, no. 1, pp. 17–26, 2015 (in Japanese).

[22] N. Yokoyama, K. Funakoshi, H. Toda, and Y. Koike, "Motivation System using Purpose-for-Action," in *Proc. Database and Expert Systems Applications (DEXA)*, 2014, pp. 66-80.

[23] N. Yokoyama, S. Yokoyama, and S. Hashimoto, "Evaluating the effectiveness of marketing elements using purchase data," *J. of international business and economics(JIBE)*, vol. 15, no. 3, pp. 95-106, 2015.

[24] N. Yokoyama and S. Hashimoto, "Self-Marketing System for a Restaurant to Enhance Customer Action," in *Proc. International Conference on Information Society (i-Society)*, 2017, pp. 54-59.

[25] Yelp. [Online]. Available: http://www.yelp.com/

[26] TripAdvisor. [Online]. Available: http://www.tripadvisor.com/

[27] Foursquare. [Online]. Available: https://foursquare.com/

[28] S. Bikhchandani and D. Hirshleifer, "I. Welch: Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades," *J. of Economic Perspectives*, vol. 12, no. 3, pp. 151-170, 1998.

[29] H. Wakaki, M. Ariga, K. Nakata, H. Fujii, K. Sumita, and M. Suzuki, “Building a Database of Purpose for Action from Word-of-mouth on the Web,” in *Proc. Forum on Information Technology*, 2011, pp.15-22.

[30] D. Zhu, Y. Fukazawa, E. Karapetsas, and J. Ota, “Intuitive Topic Discovery by Incorporating Word-Pair’s Connection into LDA,” in *Proc. IEEE/WIC/AIM International Conferences on Web Intelligence and Intelligent Agent Technology*, 2012, pp. 303-310.

[31] H. Sakai and S. Masuyama, “Cause information extraction from financial articles concerning business performance,” *IEICE Trans. on Information and Systems*, vol. E91-D, no. 4, pp. 959-968, 2008.

[32] H. Sakaji, H. Sakai, and S. Masuyama, “Automatic extraction of basis expressions that indicate economic trends,” in *Proc. PAKDD,* 2008, pp. 977–984.

[33] T. Inui and M. Okumura, “Investigating the characteristics of causal relations in Japanese text,” in *Proc. Workshop on Frontiers in Corpus Annotation II: Pie in the Sky*, 2005, pp. 37-44.

[34] Google. [Online]. Available: https://www.google.co.jp/

[35] G. Adomavicius and A. Tuzhilin, “Context-aware recommender systems,” in *Recommender systems handbook*. New York: Springer, 2011, pp. 217-256.

[36] The Japan Productivity Center, “White Paper of Leisure,” 2013 (in Japanese).

[37] The Public Relations Department of the Cabinet Office, “The opinion poll about lifelong learning (July, 2012 investigation),” 2012 (in Japanese).

[38] K. Imamura, G. Kikui, and N. Yasuda, “Japanese dependency parsing using sequential labeling for semi-spoken language,” in *Proc. ACL*, 2007, pp. 225–228.

[39] J. Kawakita, *A Scientific Exploration of Intellect (“Chi” no Tankengaku)*. Tokyo, Japan: Kodansha, 1977 (in Japanese).

[40] A. Goldfarb and C. Tucker, “Online Display Advertising: Targeting and Obtrusiveness,” *Marketing Science*, vol. 30, no. 3, pp. 389-404, 2011.

[41] T. Blake, C. Nosko, and S. Tadelis, “Consumer Heterogeneity and Paid Search Effectiveness: A Large-Scale Field Experiment,” *Econometrica*, vol. 83, no. 1, pp. 155-174, 2015.

[42] M. Andrews, X. Luo, Z. Fang, and J. Aspara, “Cause Marketing Effectiveness and the Moderating Role of Price Discounts,” *J. of Marketing*, vol. 78, no. 6, pp. 120-142, 2014.

[43] H. Chen, R. Chiang, and V. Storey, “Business Intelligence and Analytics: From Big Data to Big Impact.” *MIS Quarterly*, vol. 36, no. 4, pp. 1165–88, 2012.

[44] D. Barton and D. Court, “Making Advanced Analytics Work for You,” *Harvard Business Review*, vol. 90, pp. 79–83, 2012.

[45] B. Pang and L. Lee, “Opinion Mining and Sentiment Analysis,” *Foundations and Trends in Information Retrieval*, vol. 2, no. 1-2, pp. 1-135, 2008.

[46] Ministry of Land, Infrastructure, Transport and Tourism (MLIT), "National Land Numerical Information, The Number of Station Passengers Getting on and off data," 2012. [online]. Available: http://nlftp.mlit.go.jp/ksj-e/gml/datalist/KsjTmplt-S12-v2_1.html.

[47] https://www.r-project.org/

[48] K. R. Ranjan and S. Read, “Value co-creation: Concept and measurement,” *J. of the Aca. of Marketing Sci.*, vol. 44, no. 3, pp. 290–315, 2016.

[49] L. D. Vries, S. Gensler, and P. S. Leeflang, “Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing,” *J. of Interactive Marketing*, vol. 26, no. 2, pp. 83–91, 2012.

[50] S. Vinerean, I. Cetina, L. Dumitrescu, and M. Tichindelean, “The effects of social media marketing on online consumer behavior,” *Intl. J. of Business and Management*, vol. 8, no. 14, pp. 66-79, 2013.

[51] T. Haumann, P. Güntürkün, L. M. Schon, and J. Wiesele, “Engaging customers in coproduction processes: How value-enhancing and intensity-reducing communication strategies mitigate the negative effects of coproduction intensity,” *J. of Marketing*, vol. 79, no. 6, pp. 17–33, 2015.

[52] S. S. Atakan, R. P. Bagozzi, and C. Yoon, “Consumer participation in the design and realization stages of production: How self-production shapes consumer evaluations and relationships to products,” *Intl. J. of Res. in Marketing*, vol. 31, no. 4, pp. 395–408, 2014.

[53] S. V. Troye and M. Supphellen, “Consumer Participation in Coproduction: “I Made It Myself” Effects on Consumers' Sensory Perceptions and Evaluations of Outcome and Input Product,” *J. of Marketing*, vol. 76, no. 2, pp. 33-46, 2012.

[54] M. L. Meuter and M. J. Bitner, “Self-Service Technologies: Extending Service Frameworks and Identifying Issues for Research,” in *Proc. AMA Winter Educators’ Conf.*, 1998, vol. 9, pp. 12–19.

[55] M. L. Meuter, A. Ostrom, R. Roundtree, and M. J. Bitner, “Self-Service Technologies: Understanding Customer Satisfaction with Technology-Based Service Encounters,” *J. of Marketing*, vol. 64, pp. 50–64, 2000.

[56] K. W. Chan, C. K. Yim, and S. S.K. Lam, “Is Customer Participation in Value Creation a Double-Edged Sword? Evidence from Professional Financial Services Across Cultures,” *J. of Marketing*, vol. 74, no. 3, pp. 48-64, 2010.

[57] K. Matzler, R. Faullant, B. Renzl, and V. Leiter, “The relationship between personality traits (extraversion and neuroticism), emotions and customer self-satisfaction,” *Innovative Marketing*, vol. 1, no. 2, pp. 32–39, 2005.

[58] eMarketer, “Social serves many purposes for restaurant industry marketers: One-on-one connections, brand affinity among key benefits,” 2013. [online]. Available: http://www.emarketer.com/Article/Social-Serves-Many-Purposes-Restaurant-Industry-Marketers/1010366.

[59] J. Kang, L. Tangb, and A. M. Fiorec, “Enhancing consumer-brand relationships on restaurant Facebook fan pages: Maximizing consumer benefits and increasing active participation,” *Intl. J. of Hospitality Mgmt.*, vol.36, pp.145–155, 2014.

[60] S. Kim, Y. Koh, J. Cha, and S. Lee, “Effects of social media on firm value for U.S. restaurant companies,” *Intl. J. of Hospitality Mgmt.*, vol. 49, pp. 40–46, 2015.

[61] R. Bagozzi and U. M. Dholakia, “Antecedents and Purchase Consequences of Customer Participation in Small Group Brand Communities,” *Intl. J. of Res. in Marketing*, vol. 23, no. 1, pp. 45-61, 2006.

[62] U. M. Dholakia and E. Durham, “One Café Chain’s Facebook Experiment,” *Harvard Business Review*, vol. 88, no. 3, p. 26, 2010.

[63] D. R. Cox, “The regression analysis of binary sequences,” *J. of the Royal Statistical Society*, vol. 20, no. 2, pp. 215–242, 1958.

[64] M. Ozaki, M. Nomoto, and H. Wakita, *Retailing/service industry marketing*. Tokyo, Japan: gogensya, 2015 (in Japanese).

# List of Publications

## [Papers of Journals]


I. Noriko Yokoyama, Shin-ichiro Yokoyama, and Shuji Hashimoto, "Evaluating the effectiveness of marketing elements using purchase data", Journal of international business and economics(JIBE), vol. 15, no. 3, pp. 95-106, 2015.

II. 横山法子, 船越要, 戸田浩之, 小池義昌, "地域情報提供サービスのための行動目的抽出", 情報処理学会論文誌 データベース(TOD), vol. 8, no. 1, pp. 17–26, 2015.


## [Papers of International Conferences]


I. Noriko Yokoyama, and Shuji Hashimoto, "Self-Marketing System for a Restaurant to Enhance Customer Action", International Conference on Information Society (i-Society 2017), pp. 54-59, 2017.

II. Noriko Yokoyama, Kaname Funakoshi, Hiroyuki Toda, and Yoshimasa Koike, "Motivation System using Purpose-for-Action", Database and Expert Systems Applications (DEXA 2014), pp. 66-80, 2014.

III. Noriko Yokoyama, Tomoyuki Yamaguchi, and Shuji Hashimoto, "Care Giving System Based on Consciousness Recognition", Human Interface and the Management of Information, vol. 6771, pp. 659-668, 2011.

[Oral Presentations]

I. 横山法子, 船越要, 戸田浩之, 鷲崎誠司, “webからの行動目的ネットワークの構築”, 電子情報通信学会技術研究報告 AI, vol. 113, no. 332, pp. 95-100, 2013.

II. 横山法子, 船越要, 佐藤隆, 鷲崎誠司, “オントロジーを用いた行動目的の抽出に関する検討”, FIT2013（第12回情報科学技術フォーラム）講演論文集, vol. 12, no. 2, pp. 283-284, 2013.

III. 横山法子, 山口友之, 橋本周司, “意識状態の推定に基づく能動的な学習支援システムの開発”, 情報処理学会第74回全国大会講演論文集, no. 4, pp. 181-182, 2012.

IV. 横山法子, 山口友之, 橋本周司, “人間の動作認識による能動的な人間支援システムの開発”, 情報処理学会創立50周年記念（第72回）全国大会講演論文集, no. 4, pp. 173-174, 2010.

# List of Awards

Ⅰ. 【FIT Young Researcher Award】
横山法子, 船越要, 佐藤隆, 鷲崎誠司, “オントロジーを用いた行動目的の抽出に関する検討”, FIT2013（第 12 回情報科学技術フォーラム）講演論文集, vol.12, no. 2, pp. 283-284, 2013.