Chapter 20
Exploring Information Processing Behaviors of Consumers in the Middle of Their *Kaiyu* with Smartphone

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Abstract At a year-end sale held in the Tenmonkan district, the city center commercial district of Kagoshima City, Japan, we carried out a social experiment that attempted to measure the effect of information provision on visitors by using a smartphone application developed by FQBIC that was able to simultaneously record users' positions and their interactions with information contents provided by the town such as flyers and the like. This study, as a first step, analyzes the logs obtained through this social experiment, which record the interactions between visitors and information provided by the town, and investigates what kinds of information contents and forms would most effectively induce visitors' *Kaiyu* within the city center district.

The Sections 1–3 of this chapter are based on the paper, Mamoru Imanishi, Kosuke Yamashiro, Masakuni Iwami, Saburo Saito [1], "Measurement and Analysis of Effects of Providing Information to Visitors during a year-end sale at a city center commercial district," *Papers of The 30th Annual Meeting of The Japan Association for Real Estate Sciences*, pp. 65–70, 2014, in Japanese, which is revised for this chapter. The Sections 4 and 5 of this chapter are based on the paper, Kosuke Yamashiro, Mamoru Imanishi, Masakuni Iwami, Saburo Saito [10], "What kind of information provision most effectively induces *Kaiyu*? A social experiment using smartphones during a year-end sale," the paper presented at the 52nd Annual Meeting of Japan Section of Regional Science Association International (JSRSAI), 2015, which is revised for this chapter.

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1 Purpose of This Study

In recent years, when using the GPS functionalities and accelerometers mounted on smartphones, obtaining "big data" has become much easier than before. Thus, also in the field of urban planning, it has begun to be gaining the attention on how to make use of big data (Cf. [2]). However, by and large, the attention has remained chiefly at the level of replacing conventional "hard" facility planning with planning related to information technologies that are likely to be implemented by ICT, such as traffic information and digital signage. The attention has rarely been talked in connection with the goal of urban development and the scientific evaluation of urban development policies.

On the other hand, the argument that big data should be connected with clarifying the goal of urban development and increasing the value of the town and should be used as a tool for the scientific evaluation of urban development policies has been highlighted by Saito [3–6]. In particular, it should be noticed that Saito has been paying much attention to the great possibility of big data generated from individual consumer's real-time micro-decision-making including interactions with information.

While this study stands on the same viewpoint as Saito's, in order to realize his perspective in a more concrete setting, we have decided to employ the following method. Taking up an actual city center commercial district at a regional core city as an experiment field, we have established there the temporal information environment equipped with a system that can generate a big data which can record the real-time micro-behavior history data of consumers who visited there concerning what kinds of interactions and what kinds of decisions they have made with the provided information, and then we analyze the particulars of the big data so obtained.

More specifically, we focused on *Tenmonkan*, which is the name of the city center commercial district at Kagoshima City,[1] Japan, and developed a smartphone application in conjunction with the year-end sale at Tenmonkan. By measuring the location of smartphones inside and outside of shops as well as providing flyer information for the year-end sale through the app, interactions between visiting consumers and provided information were prompted. With these devices, we established an integrated location/content information platform to enable one to store the logged records of consumers' transactions with provided information as big data.

[1]Kagoshima City is located at the southern part of Kyushu island, Japan, whose population is 599,814 (2015 census). Kagoshima City is a capital city of Kagoshima Prefecture and serves as a core city in this region. The 1.5% Kagoshima metropolitan area has 1,087,447 population (2010 census).

Furthermore, we recruited general participants among the shoppers visiting at the year-end sale who agreed to use the app on this platform in order to carry out the social experiment for collecting log data.

Until now, under the traditional information technology environment, it has been extremely difficult to measure and verify what kind of information provision has caused consumers to change their behaviors and how it has induced their *Kaiyu*.

The aim of this study is to take a major step toward overcoming this situation by making use of new information technologies.

Speaking further, our ultimate goal is to revitalize the town with stimulating visiting consumers' *Kaiyu* by providing them with real-time on-site information to support their on-site decision-makings. Toward that goal, we build an information platform that can scientifically verify the most effective ways of providing what information to which consumers for what purpose, and from there we intend to construct a model to explain the interactions between consumers and information provided using big data obtained there.

Here, as a first step toward this aim, the purpose of our study is set to carrying out a fundamental analysis of the information provision effect, which is related to the question as to what kind of information provision has what sort of effects on what type of visitors, based on data obtained from the social experiment of information provision through our smartphone app conducted in conjunction with the end-of-year sale of the Tenmonkan at Kagoshima City.

2 Overview of the Social Experiment

2.1 Outline of the Social Experiment

This study takes the Tenmonkan district, the city center commercial district of Kagoshima City, as the subject area for our social experiment. We obtained the cooperation of the local TMO (Town Management Organization), whose name is "We Love Tenmonkan Council." In conjunction with the year-end sale of Tenmonkan, our social experiment of information provision had been carried out for 3 days from Friday, December 13 to Sunday, December 15, 2013. The experiment utilized location information technologies such as GPS, the QZSS[2] (Quasi-Zenith Satellite System), and the IMES (Indoor MEssaging System). This social experiment was a part of our research supported by the competitive research fund from the Ministry of Internal Affairs and Communications (MIC) under the program, Strategic Information and Communications R&D Promotion Program (SCOPE). Our research title is "A development study on the system for measuring tourist movements around wide area using auto-GPS and IMES, and for an effective information provision to trigger *Kaiyu*."

[2]GNSS (global navigation satellite system) developed and operated by Japanese Government

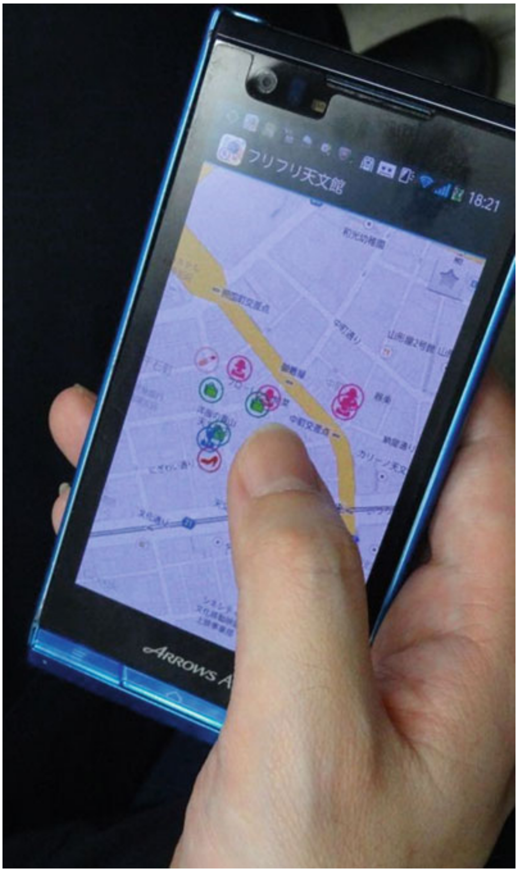

Fig. 20.1 Smartphone app screen

In the social experiment, we used a smartphone app we developed and named "*Furifuri* Tenmonkan" (Fig. 20.1), through which the sale information was randomly presented to the experiment participants, and investigated the information provision effects on the participants.

IMES[3] (Indoor MEssaging System)

IMES transmitters using IMES technology were installed in 67 individual shops in the Tenmonkan district, which allows location measurements to be taken seamlessly both inside and outside buildings. Until now, there were some cases in which

[3]Indoor location positioning system developed by JAXA (Japan Aerospace Exploration Agency). IMES installs an indoor GPS transmitter (module) using the same radio format as the GPS satellite and transmits "position information" of the transmitter instead of time information from the transmitter.

Fig. 20.2 Locations of IMES installed (Cf. [7])

multiple IMES transmitters had been installed within the same commercial facility, but this study represents the first attempt to install IMES on a community-wide scale (Fig. 20.2). Because positioning by conventional GPS can sometimes result in errors of up to 50 m, and smartphones are unable to perform GPS positioning inside buildings, we cannot easily check for visits to shops from the GPS position log. However, here by installing IMES in shops, we have had the benefit of obtaining a reliable history of shop visits, even to adjacent shops.

Participants in the Social Experiment

On the day of the social experiment, we set up a reception desk for the experiment on Tenmonkan-*Hondori* Street and asked visitors with android-based mobile phones to volunteer to participate in the social experiment. At the same time as participants were asked to install the social experiment app from the Google Play Services, we also provided them with the loan of IMES receivers. Afterward, as the participants loaded the app, we asked them to shop around the Tenmonkan district, and when they returned back to the reception point, we asked them to answer a post-questionnaire survey when they were returning the IMES receivers.

A total of 87 participants took part in our social experiment (the number of who responded to the post-questionnaire survey). In order to encourage participation in the social experiment, participants were provided with three raffle tickets for free. At the year-end sale, shoppers were given one raffle ticket for each of their 5000 yen

(50 dollars) purchases. While a sample size of 87 may seem small in relation to usual questionnaire surveys, when we include the various log data records – including search results, page browses, and favorites – as well as the interview post-questionnaire survey data collected by researchers for later verification, it can be said that the resulting data was quite rich. In fact, it contains 50,000 records.

Smartphone App

For this study, we developed a smartphone app that conducted simultaneous positioning using GPS, IMES, and Wi-Fi technology and provided information to users according to their location. The app, after obtaining participants' consent, transmitted the acquired position information to our database server at regular intervals (of 10 s) along with participants' anonymized and encrypted identification numbers and the date and time of acquisition.

On the other hand, when the participants shook their smartphones, they would be presented on the map with ten icons corresponding to randomly selected shops within a 100 m radius of their current location. This setting was set for this social experiment and can be changed.

The information provided was about 145 shops participating in the year-end sale whose discount information was listed on their application form for the year-end sale. Of these, we chose 54 shops which were also featured in a color flyer, and in order to verify this visual effect, the information of each of these 54 shops we trimmed from the color flyer was added to each shop information as a banner in the app.

The shops were divided into nine categories, including men's fashion, ladies' fashion, bags, jewelry, beauty, shoes, health, and others. The nine shop categories have different icons in the app, and each shop is displayed in the app by the icon corresponding to the category each shop belongs to.

Because there was a flood of information about restaurants and bars in a variety of different media formats, these shops were excluded from the scope of the experiment. As a result, we have eight shop categories.

2.2 *Data Obtained by the Social Experiment*

From our social experiment, we have obtained the following log data:

1. Participants' shop-around log (every 10 s)
2. Information search and display log (where did consumers search for information?)
3. Details and history of information search and display (which shops were displayed?); shake
4. Information browsing history (as to which shops did consumers view information?); tap

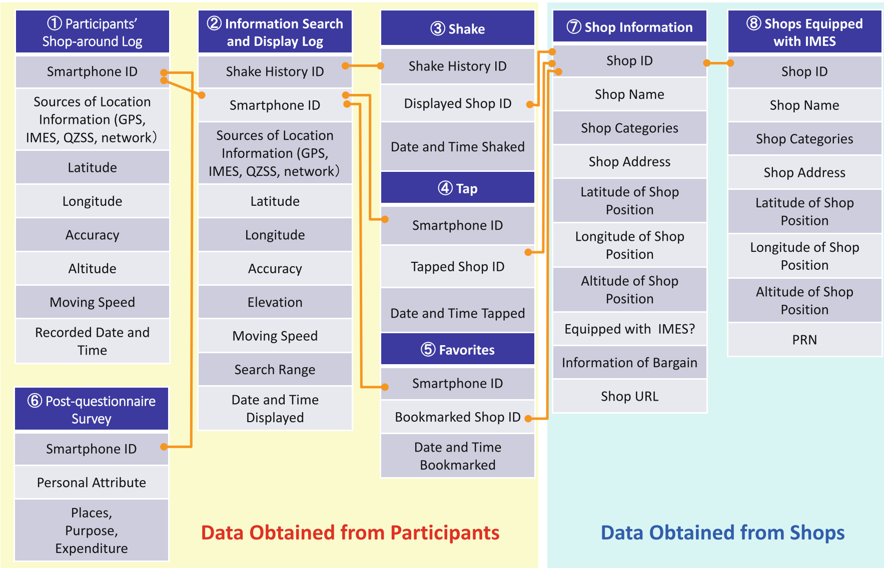

Fig. 20.3 Interrelationship among various log history data

5. Favorites (whether consumers saved a location in their favorites)
6. Post-questionnaire survey (interview survey)
7. Shop information
8. Shops equipped with IMES
9. User list

The above log data are interrelated with each other. A somewhat complicated interrelationship among these log data is displayed in Fig. 20.3. Key items that make these log data to be interrelated with each other are time, smartphone ID, and location (latitude, longitude, and altitude).

The behavioral and information transaction history of each consumer who visited and has interacted with information in the city center retail environment is recorded in movement, search, and display log data. By integrating these three logs, we can recover the history of information transactions with the retail environment for each consumer. In other words, we are able to know how consumers are transacting with the information provided by the retail environment, while they are moving around the city center.

Figure 20.4 displays the instance of history of one sample recovered by integrating above log data. From this figure, we see where the sample searched or wanted information by shaking and where the sample displayed or requested the detail information about shops by tapping icons.

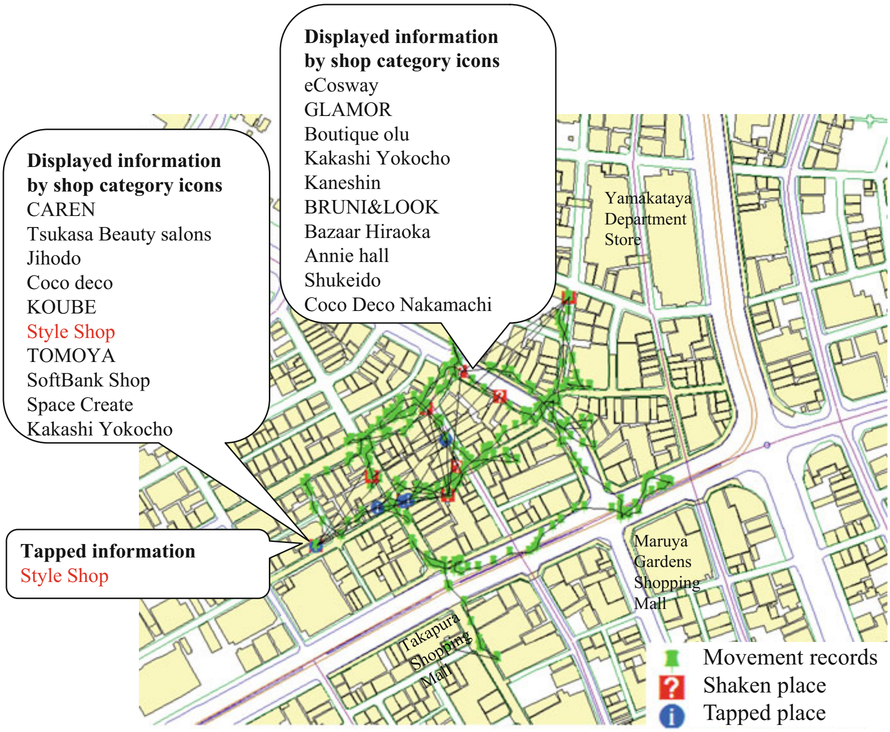

Fig. 20.4 History of information transactions by one sample (Cf. [7])

2.3 How to Measure Consumer Information Processing Behaviors?

In this section, for ease of understanding, we summarize the scheme of how we conceptualize the information processing behaviors of consumers which can be measured by our smartphone app, while consumers are using the app. Keywords are "shake" and "tap."

The scheme is succinctly depicted in Fig. 20.5. In our smartphone app, users shake their smartphones to request the app to provide the information of retail environment near them on the screen of their smartphones. Thus, the "shake' by consumers can be regarded as their "search for information" behavior in their information processing behaviors.

Under the setting in this social experiment, the result of "shake" is the randomly selected ten shops near the present location of the smartphone holder. The ten selected shops are displayed on the map at those locations with icons corresponding to the categories those shops belong to.

On the other hand, as for the "tap" in our app, users tap some icon displayed in their smartphone to request the app to show the detailed information about the shop

Fig. 20.5 Shake and tap for searching and focusing and the forms of information contents

of the tapped icon. Thus, the "tap" by consumers can be thought of as their "focus on the detail information" behavior in their information processing behaviors.

3 Analysis of Shake, Tap, and *Kaiyu* Visualization

3.1 Kaiyu *Visualization*

Figure 20.6 displays the log of spatial movements by shop-around behaviors of all participants within the Tenmonkan district. From the visualization in the figure, we see that their shop-around movements are centralized among major shopping streets and a department store such as between *Tenmonkan-Hondori* Street, *Haikara-Dori* Street, the *Senichi* Arcade, and *Yamakataya* department store.

Most previous studies traditionally have remained at the level of visualizing consumers' spatial movements recorded as location log by utilizing GIS and tried to apprehend consumers' shop-around behaviors according to this kind of visualization [8, 9]. However, visualization is just describing the results of consumers' decision to shop-around so that it does not explain why consumers decided to do such shop-around behaviors.

In order to carry out the urban development based on the scientific evidences using big data, it becomes important to analyze micro-behavioral data of individual consumers.

For this reason, the smartphone app we developed this time was designed to become a system that makes it possible to statistically verify what kind of information provision causes what kinds of changes to the shop-around behaviors of the app's users.

More specifically speaking, as shown in Fig. 20.3 about the interrelationship among logs, our app is designed to be a system that allows the statistical analysis of

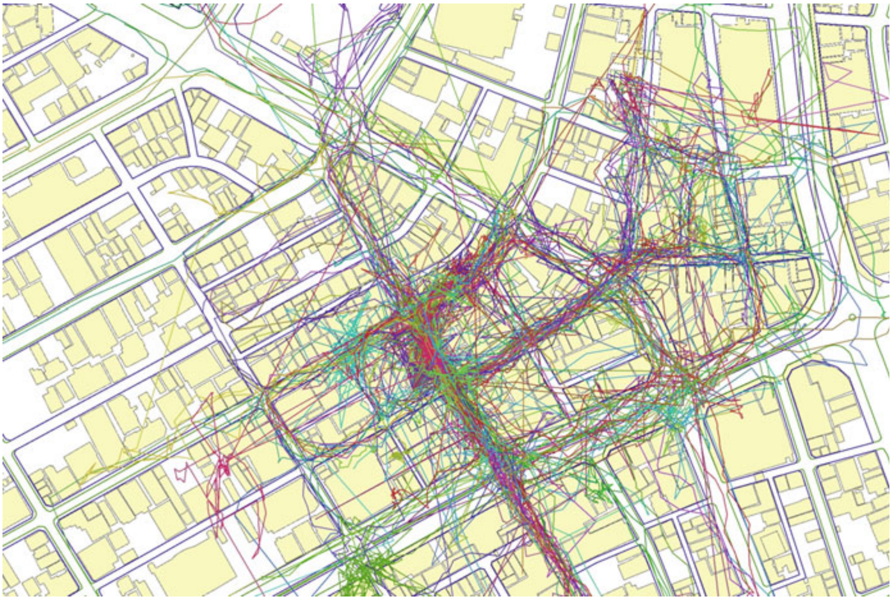

Fig. 20.6 Behavior log of all participants within Tenmonkan district (Cf. [7])

Table 20.1 Average number of information searches by shakes

N	Mean	Std	Median	Mode	Max
91	18.13	29.982	9	7	243

why the selected result was chosen by users from among the presented alternatives by recording alternatives presented as a log in addition to the selected result.

Hence, it is necessary to focus not only on visualization, but also on the analysis of micro-behaviors of individual consumers. Therefore, in this study, we went beyond visualization to carry out the analysis of individual consumers' behaviors.

3.2 Feature of Shake for Searching

Table 20.1 shows how much information the participants retrieved by shaking their smartphones. Users did so 18 times on average. While the sample size of 91 was larger than the 87 participants in our social experiment, this is due to the presence of users who activated the app without enrolling in the social experiment. Although they did not take part in the post-questionnaire survey, they are included in the analysis since their log data is usable.

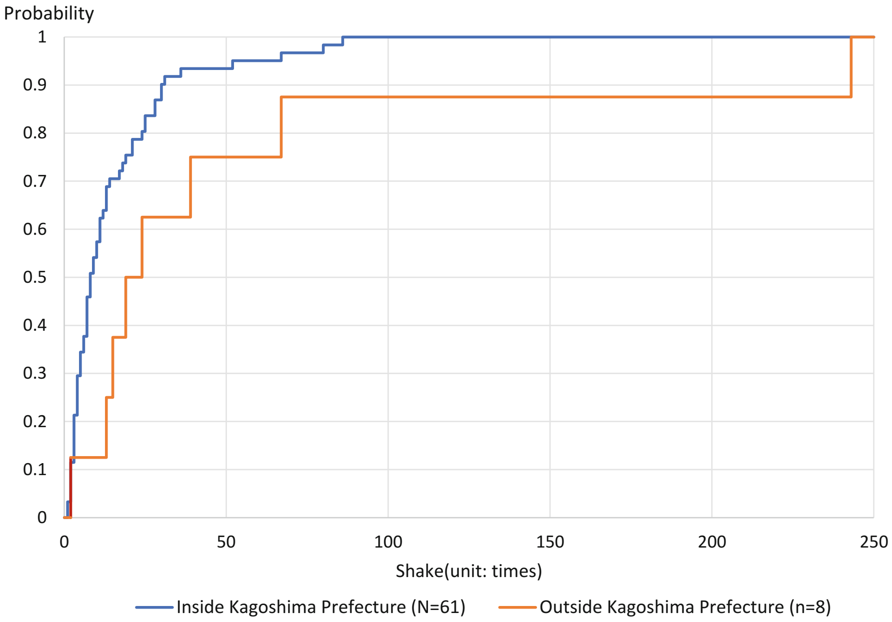

Fig. 20.7 Numbers of information searches by residence

In addition, from Fig. 20.7, although the sample size is small, we obtained a result which shows that participants from outside of the prefecture searched for information more often than did prefectural residents.

On the other hand, it is informative to see where participants shake more often. Figure 20.8 displays where participants shook their smartphones for searching for information.

3.3 *Feature of Tap for Focusing on the Detail Information*

Figure 20.9 illustrates the stacked bar chart showing the numbers of times icons were displayed and tapped with the number of shops registered in database belonging to each shop category. All of these numbers are expressed as percentages to the total numbers given in the lower part of the figure. The top bar in the stacked bars for each shop category expresses the percentage of the number of shops registered in database belonging to that category, the middle bar the number of times the icon of that shop category is displayed for the icons of the randomly selected shops by the app, and the bottom bar the number of times the icon of that shop category is tapped.

Since our app for this time randomly chooses shops and displays them on the map of the smartphone, the percentages of shop categories for displayed shops should be

Fig. 20.8 Locations of shakes for searching (Cf. [7])

proportional to those registered in database. From the figure, we see this simple fact in the top and middle bars in the stacked bar chart.

Interesting is that the numbers of taps, while tapping is user's decision, are also proportional to those displayed by the app.

Table 20.2 displays the average number users tapped icons to view detail shop information. They tapped icons for browsing detail shop information for about seven shops on average. From Fig. 20.10, it may be seen that when we look at area of residence, visitors from outside of Kagoshima Prefecture tended to browse detail shop information more frequently.

3.4 Feature of Visit

Table 20.3 displays how often users visited a shop directly after browsing detail shop information on the app. Since IMES was installed in the interior of shops, and the system's radio waves do not reach outside the shops, as for the shops where IMES was installed, users can reliably be adjudged to have visited these shops when IMES location logs at these shops have been detected. As for shops that were not installed with IMES, these were determined from GPS logs. While the analysis of shop visits based on GPS logs has become a study in its own right, here, if users remained within 50 m of the central point of the shop for a 1-min period, it was simply judged

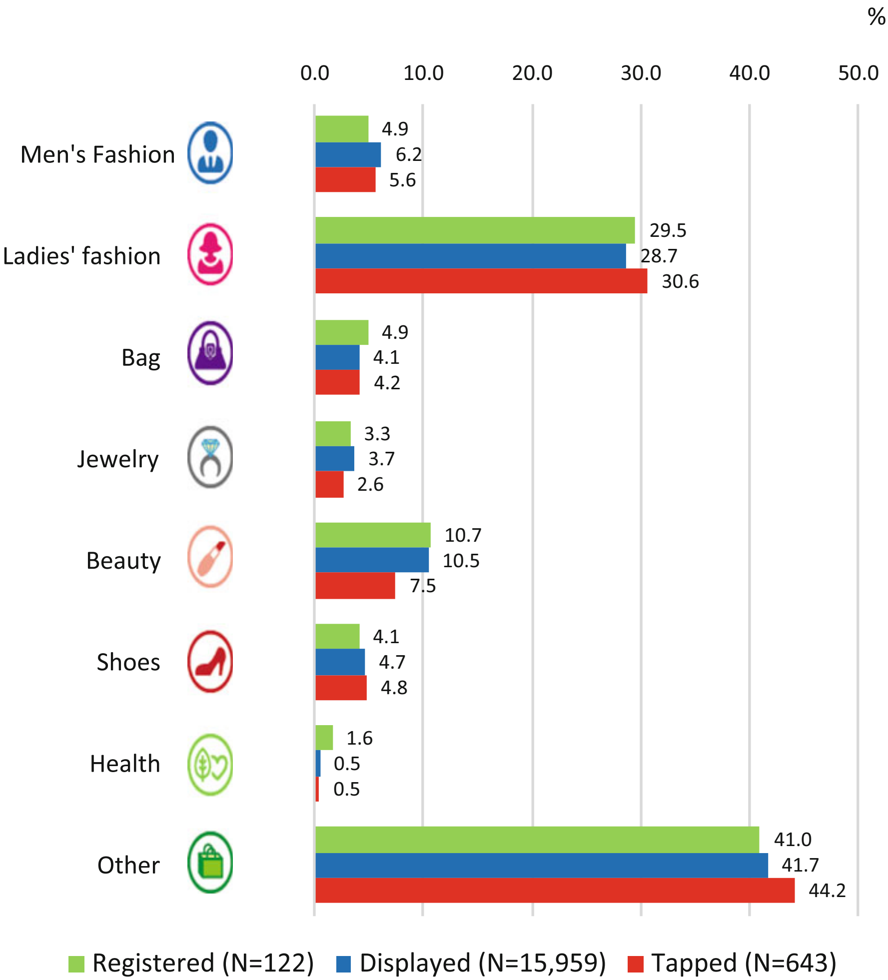

Fig. 20.9 Percentages of shop categories displayed, tapped, and registered in database

Table 20.2 Average number of taps for detail shop information

N	Mean	Std	Median	Mode	Max
91	7.14	10.853	3	1	73

that they had visited the shop in question. Thirty-two people actually visited two shops on average.

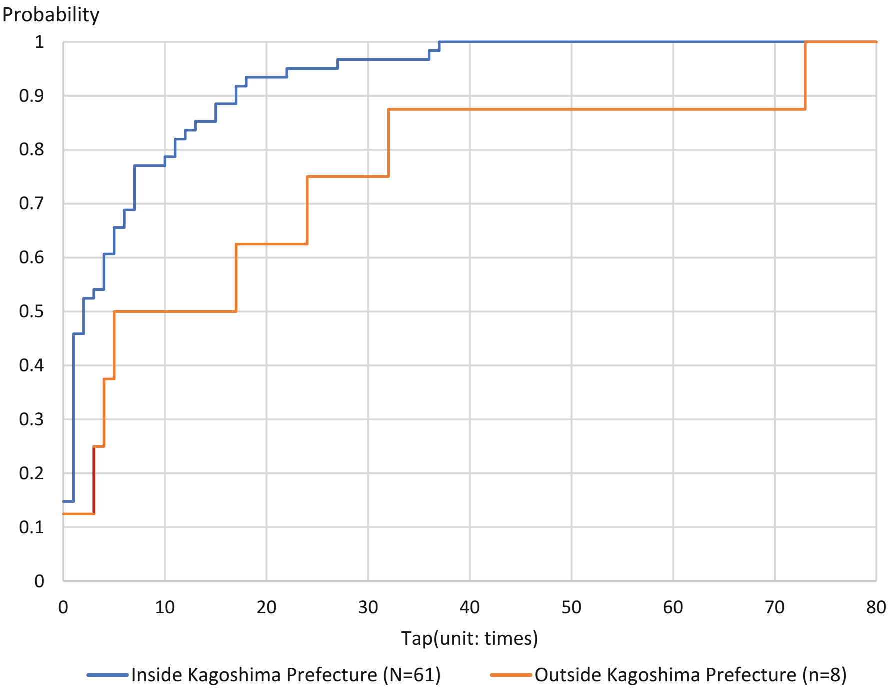

Fig. 20.10 Numbers of taps for detail shop information by residence

Table 20.3 Users actually visited the tapped shop?

N	Mean	Max	Min
32	2.25	15	0

Table 20.4 Percentage of the number of taps to that of shakes

N	Mean	Std	Median	Mode	Max
91	0.43	0.350	0.33	1.00	1.00

Table 20.5 Percentage of the number of taps to that of icons displayed by shakes

N	Mean	Std	Median	Mode	Max
91	0.057	0.07662	0.033	0.00	0.167

3.5 *Feature of Transition Rates*

Table 20.4 shows the percentage of how many times icons were tapped to the number of "shakes" for searches. The percentage of the number of taps to that of shakes was 43%.

Table 20.5 shows the percentage of the number of taps to the total number of icons displayed. In this social experiment, when the smartphone is shaken once, ten icons corresponding to the randomly selected shops come up by the app. Thus, the total number of displayed icons is about ten times as large as that of shakes. From the table, we see that the percentage was 5.7%, which is larger than 4.3%, tenth of the percentage in the previous Table 20.4.

This is because while one tap corresponds to one icon, users are possible to tap more than once by returning to the original shake result screen, or partly because when the size of the candidate shops from which the ten shops are randomly selected is less than 10, the number of icons to come up becomes smaller than 10.

4 What Kind of Information Provision Stimulates Tap by Consumers

4.1 A Logit Model to Investigate What Information Factors Affect "Tap" by Consumers

We are concerned with how to stimulate *Kaiyu* by information provision. For that purpose, we must explore the most effective way to provide information to induce consumers' *Kaiyu* behaviors. In this study, we divided consumers' information processing behaviors into three phases, shake, tap, and visit. In this framework, raising the transition rate becomes the key. In short, how to raise the transition rate from displaying to tapping and from tapping to visiting becomes the key point.

In this section, we investigate what kind of shop information is likely to be tapped by using a logit model.

What sorts of shop information should best be provided to consumers? As one hypothesis, it may conceivably be necessary for consumers to be provided with information about shops as near at hand as possible. Alternatively, it might be necessary for them to be provided with information about shops in their walking direction. So it might not be needed to provide them with shop information existing in the opposite direction to their walking direction.

Hence, in order to examine this question, we estimated the parameters relating to distance and direction using a logit model. We also add the explanatory dummy variables corresponding to the nine shop categories.

The choice probability for consumer i to tap icon m out of n displayed icons is expressed as the following logit model:

$$p_m^i = \frac{\exp\left(V_m^i\right)}{\sum_{j=1}^{n} \exp\left(V_j^i\right)}, \ m = 1, \ldots, n \tag{20.1}$$

where V_m^i represents the deterministic utility obtained by consumer i by tapping icon m.

In addition, this deterministic utility, as a linear function relating to direction dir, distance des from the current location to the shop, and dummy variables for nine shop categories, is expressed as follows:

$$V_m^i = \alpha \mathrm{des}_m^i + \beta \mathrm{dir}_m^i + \sum_{k=1}^{8} \gamma_k \delta \mathrm{cat}_{\mathrm{mk}} \tag{20.2}$$

Here, $\mathrm{des}_m^i, \mathrm{dir}_m^i$ represents the distance and direction from the location where consumer i shakes the smartphone to the shop represented by icon m.

For direction, we took inner product of the directional vector $\overrightarrow{\mathrm{AB}}$ from a consumer's past position at coordinates A to the current position at coordinates B and the directional vector $\overrightarrow{\mathrm{BC}}$ from the consumer's current position at coordinates B to the coordinates C of the icon that was displayed.

Dummy variables $\delta \mathrm{cat}_{\mathrm{mk}}$ corresponding to the nine shop categories are defined as $\delta \mathrm{cat}_{\mathrm{mk}} = 1$ if the icon m belongs to shop category k, 0 otherwise.

Parameters α, β, γ_k, $k = 1, \ldots, 8$ are estimated by the maximum likelihood estimation method.

4.2 *Estimated Results*

Table 20.6 shows the estimated results of the parameters. From the table, we see that the distance to the destination and the direction to the icon strongly affect the tapping icon behaviors.[4]

These findings accord to our hypothesis. The two facts that the more the shops are closer, the more frequently those icons are tapped and that the shops existing in the same direction as the walking direction are more frequently tapped are simple but they are a starting point to explore further.

5 What Kind of Information Provision Most Effectively Induces *Kaiyu*?

5.1 *Visit Ratios of Tapped Shops*

In this section, we will perform the analysis of what kind of information provision about the shop effectively induces the visit to that shop.

[4]Three shop categories, beauty, health, and others, had not been tapped so that their dummy variables are deleted from the explanatory variables.

Table 20.6 Estimated results of parameters

Variable	Parameter estimate	SD	t value	$Pr > \lvert t \rvert$
Distance	−10.5684	0.404	−26.16	<0.0001
Direction	0.3678	0.089	4.15	<0.0001
Men's fashion	−0.5028	0.094	−5.38	<0.0001
Ladies' fashion	0.0345	0.045	0.77	0.4419
Bag	0.2593	0.090	2.88	0.004
Jewelry	−0.1659	0.098	−1.7	0.0889
Shoes	−0.1714	0.091	−1.88	0.0605
Loglikelihood with all parameters set to zeros		$L(0)$	−7069	
Loglikelihood with estimated values of parameters		$L(\widehat{\beta})$	−6674	
−2 × Likelihood ratio		$\rho = -2\left[L(0) - L(\widehat{\beta})\right]$	788.92	
McFadden's R-square		$\rho^2 = 1 - L(\widehat{\beta})/L(0)$	0.0558	
Adjusted R-square		$\overline{\rho}^2 = 1 - \left(L(\widehat{\beta}) - K\right)/L(0)$	0.0543	

$n = 3070$

From the analysis of users' tapping and visiting behaviors, we found that as a whole, among the 643 views about shops displayed with tapping by users, the number of shops users actually visited was 100 shops. The average percentage of transition from tapping to visiting was 15.6%.

In order to investigate more details about the transition, we analyzed the transition rate from tapping to visiting for each individual shop as the analysis of visit ratios for individual shops. The obtained results of visit ratios by shops are ordered from the highest in the decreasing order. Table 20.7 shows these results. The table shows only the shops which indicate their visit ratios are equal to or larger than 20%.

From the figure, we see that the highest visit ratio was 87.5% and a wide variation of visit ratios exists among shops.

5.2 How the Forms of Information Contents Affect Shop Visits?

Furthermore, we investigate whether or not the forms of information contents provided for the shop affect the visit ratio to that shop.

The forms of shop information contents we consider were depicted in the rightmost column of Fig. 20.5. They are banners, headlines, explanatory notes, and supplements.

Table 20.7 Visit ratios by shops with the numbers of taps and visits

ShopID	Shop Name	Category	Number of Taps	Number of Visited	Visit ratio
29	Baggage Higuchi	Bags	8	7	87.5%
32	coco deco	Ladies' fashon	8	6	75.0%
6	Daruma-ya Cosmetic Store	Beauty	8	5	62.5%
143	216 Junction STORE	Others	14	8	57.1%
130	Thank You Mart	Others	7	4	57.1%
94	Megane no Yonezawa (Tenmonkan)	Others	6	3	50.0%
135	Iki-ya	Others	4	2	50.0%
7	Futam-iya	Others	2	1	50.0%
59	BRUNI&LOOK	Ladies' fashon	2	1	50.0%
55	Minoru-en Green Tea Shop	Others	10	4	40.0%
96	Boushi-ya Hat Shop	Others	5	2	40.0%
116	chandelie	Ladies' fashon	6	2	33.3%
105	Futon no Kondo	Others	3	1	33.3%
108	Shobi-do Shoe Store	Shoes	3	1	33.3%
120	Paris Miki Glasses Store (Tenmonkan)	Others	13	4	30.8%
118	SWALLOW	Mens' fashon	7	2	28.6%
128	R's Stage	Ladies' fashon	18	5	27.8%
3	Jiho-do Clock Store	Jewelry	8	2	25.0%
113	Edo-ya (Shoe Store)	Shoes	8	2	25.0%
138	TOMOYA	Ladies' fashon	8	2	25.0%
9	Petit Bero	Ladies' fashon	4	1	25.0%
98	Megane Super (Naya Dori)	Others	4	1	25.0%
30	Daicyu	Others	13	3	23.1%
56	Makino	Others	13	3	23.1%
142	REGISTA Armadio	Mens' fashon	9	2	22.2%
58	Meishi-do	Others	10	2	20.0%
72	Day Light	Ladies' fashon	5	1	20.0%
123	Boutique Ol	Ladies' fashon	5	1	20.0%
129	KOUBE	Others	5	1	20.0%

With or Without Banners and Visit Ratios

Table 20.8 shows that while for the shops without banners in their displayed information, the average of visit ratios to these shops is 8.6%, those shops with banners attain the average of visit ratio to their shops, 20.2%.

With or Without Headlines and Visit Ratios

Similarly, Table 20.9 gives the result of the case for with or without headlines. In this case the shops with headlines lowered their average visit ratio. This result might be contrary to the intuition. One possible reason for this result may be that the place where headlines are written is located above banners so that headlines had not so much appeal. At any rate, further investigations are needed.

With or Without Explanatory Notes and Visit Ratios

Table 20.10 shows the case for with or without explanatory notes. The shops with explanatory notes increased their average visit ratios. The average of visit ratio for the shops with explanatory notes is 14.5% in contrast to 9.0% for that without explanatory notes.

Table 20.8 With or without banners and visit ratios

Group	N	Mean	Std	Min	Max
With banners	28	0.202	0.3136	0	1
Without banners	117	0.086	0.1743	0	1

t(143) = −2.65, $p < 0.01$

Table 20.9 With or without headlines and visit ratios

Group	N	Mean	Std	Min	Max
With headlines	74	0.091	0.1879	0	1
Without headlines	71	0.126	0.2349	0	1

t(143) = 0.99, $p < 0.05$

Table 20.10 With or without explanatory notes and visit ratios

Group	N	Mean	Std	Min	Max
With explanatory notes	48	0.145	0.2574	0	1
Without explanatory notes	97	0.090	0.1845	0	1

t(143) = −1.49, $p < 0.05$

Table 20.11 With or without supplements and visit ratios

Group	N	Mean	Std	Min	Max
With supplements	46	0.151	0.2612	0	1
Without supplements	99	0.088	0.1831	0	1

t(143) = −1.69, $p < 0.1$

With or Without Supplements and Visit Ratios

In the same way, Table 20.11 gives the case for with or without supplements. Similar to the case of the explanatory notes, the shops with supplements indicate the higher average of visit ratio, 15.1% than the average of visit ratio for those without supplements, 8.8%.

6 Conclusion and Future Challenges

The most significant contribution of this study, we believe, is that though temporal, we developed an integrated location/content information platform that enables one to obtain a big data concerning consumers' real-time micro-behavioral choice history data of how they have interacted with on-site information provided by retail environment in a way that allows statistical analyses of these consumers' choices. Moreover, we have also demonstrated that by leveraging our original smartphone app, the interactions between consumers and information actually can be analyzed and the micro data such as obtained here has a great possibility to advance our understanding consumers' interactions with information.

In this study, as a first step, we found a simple fact that consumers are more likely to tap the information provision about shops existing closer to their present location and in the same direction as their walking direction.

As for our future challenges, since a big data such as obtained here is a rich data related to consumers' decision at the deep micro level concerning choice of information provided, shop information, and possibly purchase, the deep analysis of this kind of big data is indispensable for the development of effective information provision technologies to induce *Kaiyu*. Thus, one of our future works is to continue to carry out the detailed analyses of interactions between consumers and information while establishing a methodology to consistently analyze a rather complicated micro data obtained here.

Another future challenge is that we transform above various analyses into a toolkit to develop a cloud computing service that provides the consumers who visit the city center with real-time on-site decision-making support services to enhance the value of the city center.

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