Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Changes in the use of mobile devices during the crisis: Immediate response to the COVID-19 pandemic

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ABSTRACT

We analyze the smartphone usage behavior of individuals against the background of the spread of the corona-virus disease (COVID-19) to classify usage behaviors and examine the factors that lead to change. Specifically, we examine the differences in smartphone usage between the first wave and the second wave of the epidemic in Japan. On average, the frequency of use increased, especially during the first wave of the epidemic. Next, we classify the changes in usage behavior and examine the differences between individuals whose smartphone usage time increased and those whose usage time decreased. Our analysis using personal characteristics as explanatory variables suggests that demographic variables may explain behavioral changes. We were able to classify the factors into three categories: positive factors that promote an increase in usage time, negative factors that promote a decrease, and variation factors that promote fluctuations.

1. Introduction

The novel coronavirus infection (COVID-19), which spread in Asia from the beginning of 2020 and then worldwide, has had an unprecedentedly large impact on the world's economy and society and is changing the social lives of consumers (e.g., World Health Organization, 2021; Maria et al. 2020). The impact on corporate activities and consumer behaviors is significant, and analysis from various angles is being attempted in the field of business research (e.g., Donthu & Gustafsson, 2020). Especially for consumer behavior, some theoretical perspectives for analyzing dynamic behavior change are presented (e.g., Kirk & Rifkin, 2020; Sheth, 2020). For companies to continue their business in the new normal environment, it is necessary to utilize these theories and empirically examine how the psychology and behavior of consumers have changed during the COVID-19 pandemic.

During the period of the spread of COVID-19, urban lockdowns were enforced in many regions of the world, and people were forced to stay home and restrict their activities. In addition, various schools were closed. While the impact on consumers has advanced from behavioral and psychological perspective (e.g., Grashuis, Skevas, & Segovia, 2020), the major change is the trend of digital media usage. For example, Sheth (2020) analyzed the immediate behavioral change of consumers and the persistence of the changed behavior and examined how the new lifestyle affects consumers, and also mentioned proficiency in information technology. In addition, Verma and Gustafsson (2020) bibliometrically examined the research trends of COVID-19 with particular attention to research in the business field and found clusters of research with "information technology" as the keyword. Similarly, in Carracedo, Puertas, and Marti (2021), Cheng, Cao, and Liao (2020), and Kirk and Rifkin (2020), information technology is considered an important factor in examining consumer transformation in the era of COVID-19. In addition, online learning and mobile learning have been introduced, and various results have been reported for educational effectiveness (Naciri et al., 2020; Kondylakis et al., 2020; Saikat, Dhillon, Wan Ahmad, & Jamaluddin, 2021; García-Peñalv, 2021) .

With the increasing popularity of smartphones, the use of their apps has also become more common among consumers. However, in fields such as management information studies, although research has been

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conducted from the perspective of how information technology is introduced, the impact of specific events on the increase or decrease in the use of information technology has not been sufficiently examined. The purpose of this study is to examine how consumers' smartphone usage behavior changed when the major shock of the COVID-19 pandemic occurred and what demographic variables (Elena-Bucea, 2020) influenced this change.

The structure of this study is as follows. First, Section 2 provides an overview of previous studies and proposes three research questions (RQ1 to 3). Then, Section 3 outlines the regions analyzed and the data to be used. Sections 4 to 6 present and discuss the results of the analysis corresponding to three RQs, respectively. Finally, Section 7 presents future work and conclusions.

2. Theoretical background

2.1. Increase in mobile app usage during disasters

Compared to desktop computers, mobile devices have the great advantage of being able to access the Internet from anywhere (Figge, 2004). Therefore, mobile apps have become a powerful service delivery channel for companies to provide consumers with a variety of products and services on the go. In particular, the impact of COVID-19 has been analyzed using mobile device usage behavior and geolocation data (Dey, Al-Karaghouli, & Muhammad, 2020; Grantz et al., 2020; Peixoto, Marcondes, Peixoto, & Oliva, 2020).

According to statistics by Statcounter (2021), global mobile traffic surpassed desktop PC traffic in 2016, and mobile traffic continued to increase after 2016. The growth of mobile services is linked to the adoption rate of smartphones, but most studies on mobile app adoption have been done earlier, starting roughly in 2012 (Gera, Chadha, & Ahuja, 2020). For example, various adoption models, such as TRA (Theory reasoned action), TAM (Technology acceptance model), TPB (Theory of planning behavior), UTAUT (The unified theory of acceptance and use of technology), and DoI (Diffusion of innovation), have been used to study under what circumstances mobile apps are used (Malik, Suresh, & Sharma, 2017). Extensions to these models have been examined, focusing on variables such as perceived usefulness and perceived ease of use (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). Using these models, the adoption behavior of mobile apps is examined with the constructs of perceived usefulness and perceived ease of use, which are core components of the adoption model. These adoption models have been used in a number of empirical studies, such as a study that used TAM to analyze the usage behavior of car navigation applications (Yang, Bian, Zhao, Liu, & Yao, 2021) and a study that used an extended model of UTAUT to analyze the adoption behavior of mobile payment services (Oliveira, Thomas, Baptista, & Campos, 2016). A number of studies have also used these adoption models to analyze the state of adoption of mobile learning, which has received a lot of attention due to the COVID-19 pandemic (Huang et al., 2020; Sánchez-Prieto, Hernández-García, García-Peñalvo, Chaparro-Peláez, & Olmos-Miguéláñez, 2019a; Sánchez-Prieto, Huang, Olmos-Miguelánez, García-Peñalvo, & Teo, 2019b). In a recent study, UTAUT has also been used in a study that empirically examined the outcomes of mobile learning under COVID-19 outbreak (Sitar-Tăut, 2021).

The antecedents of mobile app usage are largely considered to be factors belonging to the categories associated with individual characteristics, the app and particular devices, and society or environments. Factors associated with individual characteristics are those that rely on personal attributes that are separate from the app itself, such as personal values (Picot-Coupey, Krey, Huré, & Ackermann, 2021) and the purpose of app use (Malik et al.,2017), and include demographic factors (Elena-Bucea, Cruz-Jesus, Oliveira, & Coelho, 2020). Factors associated with the app and devices are evaluations of the app, such as ease of use, enjoyment (Tojib & Tsarenko, 2012), perception of time spent (McLean, Al-Nabhani, & Wilson, 2018), trialability, complexity (Mehra, Paul, &

Kaurav, 2020), functional or emotional value (Zolkepli, Mukhiar, & Tan, 2020), and screen size (McLean et al., 2018), as well as attributes related to the particular device on which it is used. Factors associated with society are attributes related to the environment in which the user is situated, such as critical mass (Yen, Lin, Wang, Shih, & Cheng, 2019), cultural influences (Chopdar, Korfiatis, Sivakumar, & Lytras, 2018), and the influence of the other people around the consumer (Veríssimo, 2018).

Studies focusing on technology acceptance have examined the antecedents of app use in stable situations. On the other hand, it has not been examined in situations where the usage of apps would decrease. When a disaster such as the COVID-19 pandemic occurs that has a significant impact on society, consumers are expected to behave differently than usual. How will consumers' mobile app usage behavior change in the event of such a disaster? Although few studies have focused on mobile applications, there have been studies on the use of information communication technologies (ICTs). The use of ICTs in disasters has been studied from two major perspectives, especially in terms of the purpose of use. One is information gathering. In the event of a disaster, information sources such as the internet and short messages will contribute more to the sufficiency of information (Sommerfeldt, 2015; Lai & Tang, 2018). Another is information sharing. Information sharing tools such as social media (Freeman et al., 2019) and communication apps (Jia, Jia, Hsee, & Shiv, 2017) are used more frequently during disasters. In Melumud and Kirmani (2020), smartphone use was shown to provide consumers with psychological security, which is also discussed in Campbell, Inman, Kirmani, and Price (2020) as a mechanism to explain the increased use of digital devices during disasters.

It is clear from the above that the use of mobile applications is expected to increase in times of disaster. This trend is unlikely to change under the influence of the COVID-19 pandemic (Beaunoyer, Dupéré, & Guitton, 2020; Ågerfalk, Conboy, & Myers, 2020). Empirical studies have also shown that the perception of a personal threat from COVID-19 is positively related to the demand for location and tracking apps (Wnuk, Oleksy, & Maison, 2020).

2.2. Decline in mobile app usage during disasters

Many previous studies have shown that the use of mobile apps increases during disasters. However, is a disaster merely a trigger for increased mobile app usage? Previous studies have also pointed out the possibility that mobile app usage may decline.

First, several studies have been conducted in terms of why consumers top using products. One of them is the brand switching. Consumer behavior studies show that consumers' turning points in life affect brand switching (Andreasen, 1984; Hopkins, Roster, & Wood, 2006; Lee, Moschis, & Mathur, 2001; Mathur, Moschis, & Lee, 2008). One of the turning points are changes in life status, such as marriage and having children (Wikes, 1995), retirement (Hopkins et al., 2006), graduation and employment (Andreasen, 1984), all of which are triggers. Another is the impact of life events. The impact of success or stress caused by events is a subject of some consideration, and variables such as overseas travel, new hobbies, weight gain or loss (Lee et al., 2001), long vacations, and increased debt (Mathur et al., 2008) are discussed.

Another perspective is in the research about ICTs and human behavior. Research on social media has been conducted from the perspective of why users stop using it (Lee, Son, & Kim, 2016; Luqman, Cao, Ali, Masood, & Yu, 2017; Cao & Sun, 2018). Factors such as the three dimensions of overload information overload, communication overload, and system functioning overload, (Lee et al., 2016), excessive social, hedonic, and cognitive use (Luqman et al., 2017), invasion of privacy and invasion of life (Xiao & Mou, 2019), coping strategies for stress (Chen, Tran, & Nguyen, 2019), and the relationship between SNS (Social Networking Services) type and information overload (Matthes, Karsay, Schmuck, & Stevic, 2020) have been examined.

These studies show that the use of products and services declines

during phases of stress. However, these studies do not sufficiently consider the impact of macroscopic events, such as events in an individual's life or dependence on product usage. Studies suggesting the impact of major disasters such as the COVID-19 pandemic have also been conducted in several research areas.

How people react to fear-provoking events such as major disasters has been examined in the field of psychology (Gray, 1987; Bracha, 2004; Schauer & Elbert, 2015). When exposed to tension, people's behavior is either flight or fight. In other words, one can either try to escape the threat or fight against it. Furthermore, behavioral changes in disasters such as earthquakes have been examined in two areas: consumer behavior and health risk reduction behavior. For health risk reduction behavior, the RANAS (the risks, atitudes, norms, abilities and self-regulation) model (Mosler, 2012) and protection motivation theory (PMT) Timpka et al. (2014) have been used to examine what attributes influence evacuation behavior (Laato, Islam, Farooq, & Dhir, 2020). Constructs such as perceived severity (Rubin, Amlôt, Page, & Wessely, 2009) and health knowledge (Gamma et al., 2017) were addressed in terms of validity. In the field of consumer behavior, it is known that pressure and stress can lead to unusual behaviors such as impulsive purchasing (Baumeister, 2002). One illustration of this is that during the COVID-19 disaster, consumers who were exposed to excessive information showed unusual purchase intentions (Laato et al., 2020). This has led to information overload and information insecurity due to social media contact, leading to avoidance of information gathering (Soroya, Farooq, Mahmood, Isoaho, & Zara, 2021).

2.3. Research questions of mobile app usage changes due to the same stimuli

Previous studies have examined personal attributes to mobile app use and the impact of stressful events. However, these studies only examine the choice between two options: increasing or not/decreasing the use of mobile apps. Therefore, the relationship between "increasing," "decreasing," and "no change" in the use of mobile apps by reflecting external shocks is not sufficiently clear. Therefore, this study examines the following three research questions (RQ1 to 3).

RQ1. *What changes in aggregate mobile usage behavior will occur during a disaster?*

RQ2. *Given the overall trend in mobile app usage, are there subgroups that show different usage trends than the overall trend?*

RQ3. *Given the groups showing an increase or decrease in mobile app usage, what individual characteristics influence group affiliation?*

3. Data

3.1. The COVID-19 pandemic in Japan

This study provides an overview of the changes in consumer behavior related to various policy decisions made due to the spread of COVID-19 based on individuals' smartphone usage histories in Japan. In particular, we focus on the behavioral changes associated with the declaration of a state of emergency in all prefectures in Japan from April 7 to 16 and on the behavior of consumers who participated long-term in a consumer monitoring program.

To briefly summarize the history of COVID-19 in Japan, according to NHK (2021), the first case of infection in Japan was confirmed on January 16, 2020, in a Chinese person traveling from Wuhan. This was followed by the death of a woman in her 80s living in Kanagawa Prefecture on February 13, which was the first confirmed death in Japan. A major change occurred on Friday, February 27, when the government requested all elementary, middle, and high schools in the country to close temporarily. As a result, many elementary and secondary schools in the country were closed beginning on Monday, March 2. This was in

line with global trends at the time (Maria et al., 2020). Furthermore, on April 7, a state of emergency was declared for seven prefectures. The declaration was extended to the entire country on April 16, and this led to the introduction of remote work (telecommuting) in many companies as well as in other countries (e.g., Venkatesh, 2020; Neeley, 2020). The declaration of a state of emergency was lifted in 39 prefectures on May 14 as the number of newly confirmed cases decreased but continued in eight prefectures. On May 25, the state of emergency was lifted in these eight prefectures, and the "new normal" lifestyle began in June.

Fig. 1 shows (a) the number of new cases, (b) the number of deaths, (c) the volume of searches for the keywords "coronavirus," "school closure," and "remote work" obtained from Google Trends, (d) the period during which the state of emergency was declared, and (e) the value of credit card sales compared to that of the previous year, divided into 16 periods (roughly every two weeks) from January 1 to August 31, 2020. Regarding the sales data, the macro sales data include total credit card usage in Japan nationwide and in the Kanto region, as published by JCB Consumption Now (2020). However, to estimate the changes described below, January 1 to February 1 is counted as one period that consists of four weeks.

3.2. Smartphone usage data

The smartphone usage log data from the *i-SSP (INTAGE single source panel)* were collected by *INTAGE Inc.,* which automatically records the history of application usage on an individual's smartphone and records the user who launched the application, the application used (application ID), the date and time of launch, and the usage time (duration). Since the usage time for all apps has been recorded, it is possible to calculate the time spent operating the smartphone by summing all the data. The total number of users was 818, and the log data points analyzed in this study were 56,106,597, covering 16 months.

The analysis focuses on the period from January to August 2020, before and after the spread of the disease and the declaration of a state of emergency. In addition, the data from January to August 2019 are used for the analysis to compare usage behavior, giving a total of 16 months of data. From this dataset, we focus on 658 respondents who used their smartphone more than 1 h a day on average from January to August 2019. Since our research questions examine changes in behavior, we need to focus on frequent users before the epidemic. A total of 658 consumers who participated in the panel during all 16 months were included in the analysis. For the consumer profile, we use the information available as of April 2020. In terms of gender, 349 (53.0%) consumers were female, and 309 (47.0%) were male. The average age is 45.9. Of the 658 respondents, 522 (79.3%) were employed, including students, and 136 were homemakers or unemployed/other (20.7%). Observations of children and the elderly are missing, but the observations cover the working age group (15–65 years old), so there are no problems with using the sample to examine trends among the employed. Regarding place of residence, all respondents resided in Tokyo or in one of six prefectures in the Kanto region. Of these, 551 (83.7%) lived in Tokyo, Kanagawa, Saitama, and Chiba, where a state of emergency was declared on April 7, and 107 (16.3%) lived in Ibaraki, Gunma, and Tochigi, where a state of emergency was declared on April 13.

4. Estimation of the usage change

4.1. Changes by time and day

Before discussing research questions, we analyzed some basic behavioral changes. In the aggregated data, a day is divided into 144 time bands of 10 min each, and the differences in each time band are examined. Let u_{ti}^z denote the app-usage behavior of user i in time band z of day t. u_{ti}^z is the share of app-usage time in the time band. The value is 1 if the user has been running an application during the entire time band,
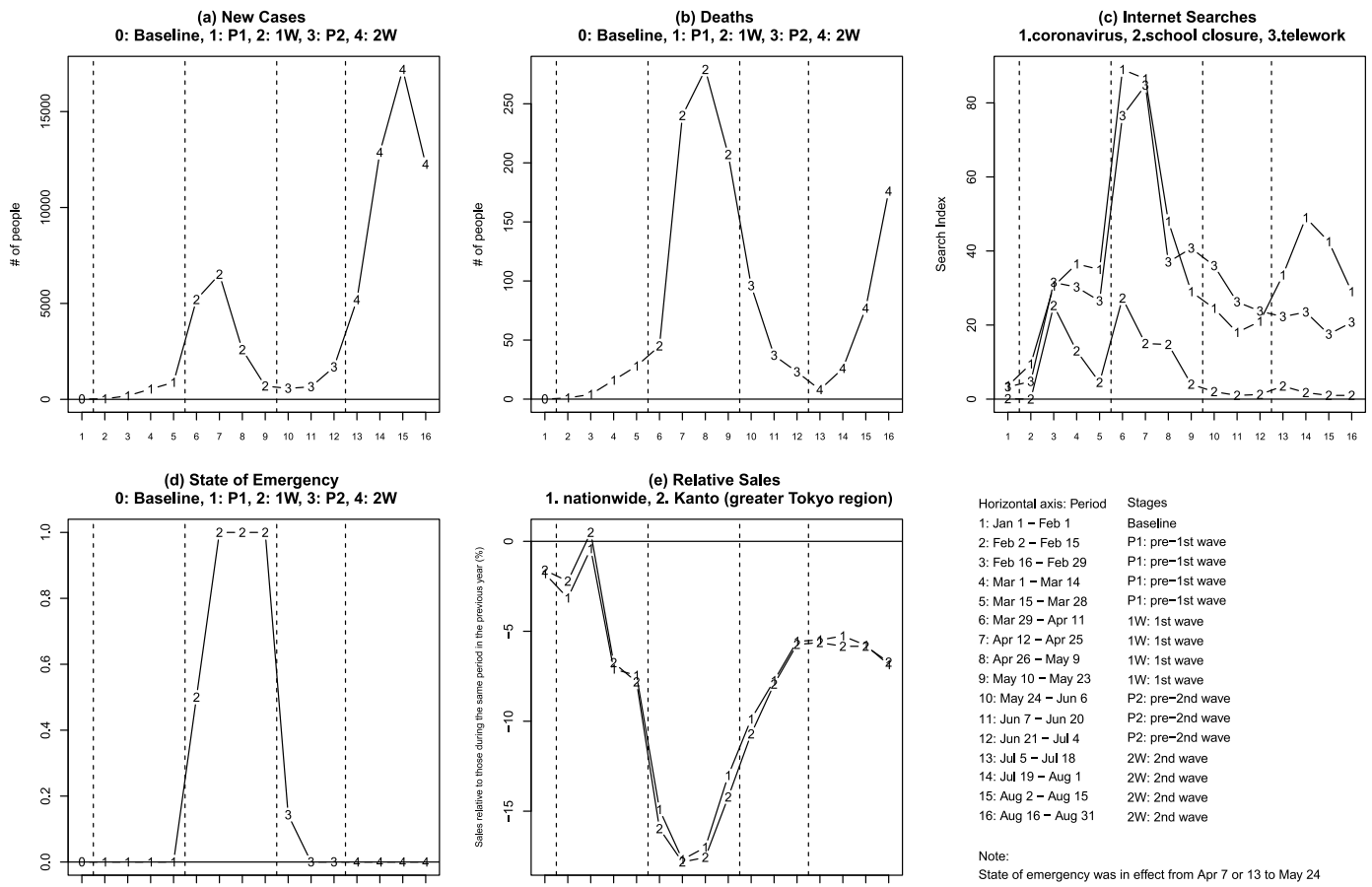
Fig. 1. Number of new cases and related indicators in Japan (January–August 2020).

0 if the user has not run an application during the time band, and 0.5 if the user has run an application for 5 min out of the 10 min in the time band.

First, in this section, we statistically examine behavioral changes using the following regression model by time band to examine the overall trends. For the following equation, m is a two-week period (Sunday to the following Saturday), and the model divides January to August into 16 periods. However, since January 4 was the first Sunday in 2020, $m = 1$ and $m = 16$ include some extra days (see Table 1), so technically, we have used some intervals that are longer than two weeks.

The exact dates of each period are given in Table 1.

The model examines variation based on the first period of January 2020 before the spread of COVID-19 ($m = 1$) compared to the same period in 2019.

$$u_{ti}^z = \beta_{i0}^z + \beta_{i1}^z Y_t + \beta_{i2}^z H_t + \beta_{i12}^z Y_t H_t$$
$$+ \sum_{m=2}^{M} \beta_{i3m}^z W_t + \beta_{i13m}^z Y_t W_{mt} + \beta_{i23m}^z H_t W_{mt} + \beta_{i123m}^z Y_t H_t W_{mt} + \varepsilon_{ti}^z \quad (1)$$

In the model, Y_t is a year indicator variable that takes a value of 0 for 2019 and 1 for 2020. Additionally, H_t is a variable that takes a value of 1

Table 1
Periods and days.

Period	2019			2020		
	Start date	End date	# of days	Start date	End date	# of days
1	2019–01–01	2019–02–02	33	2020–01–01	2020–02–01	32
2	2019–02–03	2019–02–16	14	2020–02–02	2020–02–15	14
3	2019–02–17	2019–03–02	14	2020–02–16	2020–02–29	14
4	2019–03–03	2019–03–16	14	2020–03–01	2020–03–14	14
5	2019–03–17	2019–03–30	14	2020–03–15	2020–03–28	14
6	2019–03–31	2019–04–13	14	2020–03–29	2020–04–11	14
7	2019–04–14	2019–04–27	14	2020–04–12	2020–04–25	14
8	2019–04–28	2019–05–11	14	2020–04–26	2020–05–09	14
9	2019–05–12	2019–05–25	14	2020–05–10	2020–05–23	14
10	2019–05–26	2019–06–08	14	2020–05–24	2020–06–06	14
11	2019–06–09	2019–06–22	14	2020–06–07	2020–06–20	14
12	2019–06–23	2019–07–06	14	2020–06–21	2020–07–04	14
13	2019–07–07	2019–07–20	14	2020–07–05	2020–07–18	14
14	2019–07–21	2019–08–03	14	2020–07–19	2020–08–01	14
15	2019–08–04	2019–08–17	14	2020–08–02	2020–08–15	14
16	2019–08–18	2020–08–31	14	2020–08–16	2020–08–31	16

if the day is a holiday (weekend day and national holiday) and 0 if it is a weekday; W_{mt} is a variable that takes a value of 1 if the t-th day is included in period m and 0 otherwise. Here, if the coefficient β^z_{i13m} is significant, then consumer i's usage behavior on weekdays during time band z in 2020 can be considered to have changed relative to that consumer's usage behavior in the case in which there was no COVID-19 pandemic. In addition, if the coefficients $\beta^z_{i13m} + \beta^z_{i123m}$ are significant, then the behavior of consumer i on a holiday during the time band z in 2020 is different relative to that consumer's usage in the case in which there was no COVID-19 outbreak. Fig. 2 illustrates the relationship between the parameters in the model and the behavioral changes in 2020 compared to 2019. This model is analogous to a difference-in-differences (DID) design (e.g., Wang, Lau, & Xie, 2021).

4.2. Estimation results for usage change by time band

Fig. 3a and b shows the average estimated usage time for each individual in each period for weekdays and holidays based on the estimation results by time band. The bold lines are the estimation results including the interaction terms β^z_{i13m} and β^z_{i123m} with COVID-19 as a factor, and the thin lines are the estimation results assuming no effect from COVID-19. First, the shape of the estimation results without a COVID-19 effect (thin line) is almost consistent with that of the results of a survey conducted by the Ministry of Internal Affairs and Communications (2020) for both weekdays and holidays and is considered to be a reasonable estimation result. Based on this, when the impact of COVID-19 is examined, almost no impact of COVID-19 can be seen in the second period, but the fluctuations became larger after March, and usage behavior changed significantly from April to June. In particular, the increase in usage time during daytime hours is notable. We can see that usage behavior had returned to a state closer to normal by the end of August but was still not completely back to normal.

4.3. Definition of usage change

Fig. 3a and b suggest that usage change is heterogeneous between weekdays and holidays and may also be different between daytime and nighttime hours. Therefore, from the obtained parameters, we redefine the degree of behavioral change for {daytime, nighttime} and {weekday, holiday}.

To examine the variation in this change in usage behavior, the vector d_{im} is defined as follows: element d_{im1} is consumer i's behavior change on a weekday during the daytime in the m-th period, d_{im2} is the change on a weekday during the nighttime, d_{im3} is the change on a holiday during the daytime, and d_{im4} is the change on a holiday during the nighttime.

$$
\begin{aligned}
d_{im} &= \qquad (d_{im1}, d_{im2}, d_{im3}, d_{im4})' \\
&= \left(\sum_{z \in Z_D} \beta^z_{i13m}, \sum_{z \in Z_N} \beta^z_{i13m} + \beta^z_{i123m}, \sum_{z \in Z_N} \beta^z_{i13m}, \sum_{z \in Z_N} \beta^z_{i13m} + \beta^z_{i123m} \right)'
\end{aligned} \quad (2)
$$

Although behavioral change d_{im} can be obtained for each consumer, Fig. 4 shows the average of the values for all consumers $\bar{d}_m = \text{mean}(d_{im})$ as a macrolevel behavior.

From Fig. 4, we see that the sum of all trends exhibits a large increase during the first wave and then a gradual return to normal. Regarding behavior during the daytime, usage time increased significantly from March to May and then gradually decreased, but usage time was still longer than normal at the end of August. On the other hand, for holidays, usage time was slightly lower than normal until March, longer than normal until May, then declined and remained lower than normal until the end of August. The data on credit card spending published by JCB Consumption Now (2020) in Fig. 2 (e) are very similar to the data on changes in daytime behavior. The correlation between the change in consumption in the Kanto region where the sample resides and weekday daytime usage (W) is -0.790, weekday nighttime usage (w) is -0.597, holiday daytime usage (H) is -0.897, and holiday nighttime usage (h) is -0.793, indicating a strong relationship.

4.4. Discussion on overall usage change

RQ1 asks what changes in aggregate mobile usage behavior will occur during a disaster. In particular, there is a large increase during the daytime hours on weekdays. For this period of time, there is a tendency for an increase before and after the first declaration of a state of emergency, followed by a gradual decrease. The volume of simple information and communication traffic has been increasing with the spread of the coronavirus both in Japan and worldwide, as shown by the Japan Ministry of Internal Affairs and Communications (2021) in Japan. This trend is also observed in this study.

The trends may be affected by the increased use of mobile apps for information gathering (Sommerfeldt, 2015; Lai & Tang, 2018) and sharing (Freeman et al., 2019; Jia et al., 2017). In particular, the large increase in March–April 2020, when the COVID-19 threat was not yet fully understood, suggests that information was actively collected and shared to gather unknown information. It is also possible that there were consumers who used smartphones to gain psychological stability, as discussed by Melumud and Kirimani (2020), due to perceived threats.

5. Classification by usage change

5.1. Classification of behavioral changes

Since the average behavioral change (Fig. 4) is the trend within the entire group of consumers under analysis, more specific trends may differ. Therefore, we use the k-means method to classify consumers into clusters and examine the characteristics of each cluster. To determine the number of clusters, we checked the intra-cluster SSE (sum of squared errors) while increasing the number of clusters one by one and finally chose K = 5, the number of clusters for which the improvement in SSE
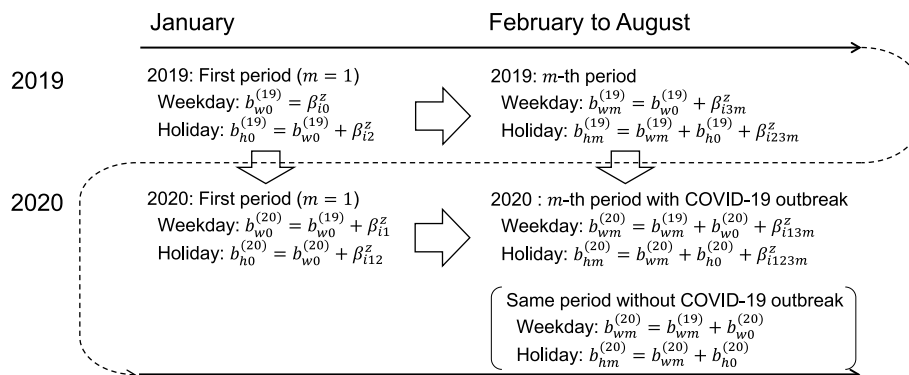
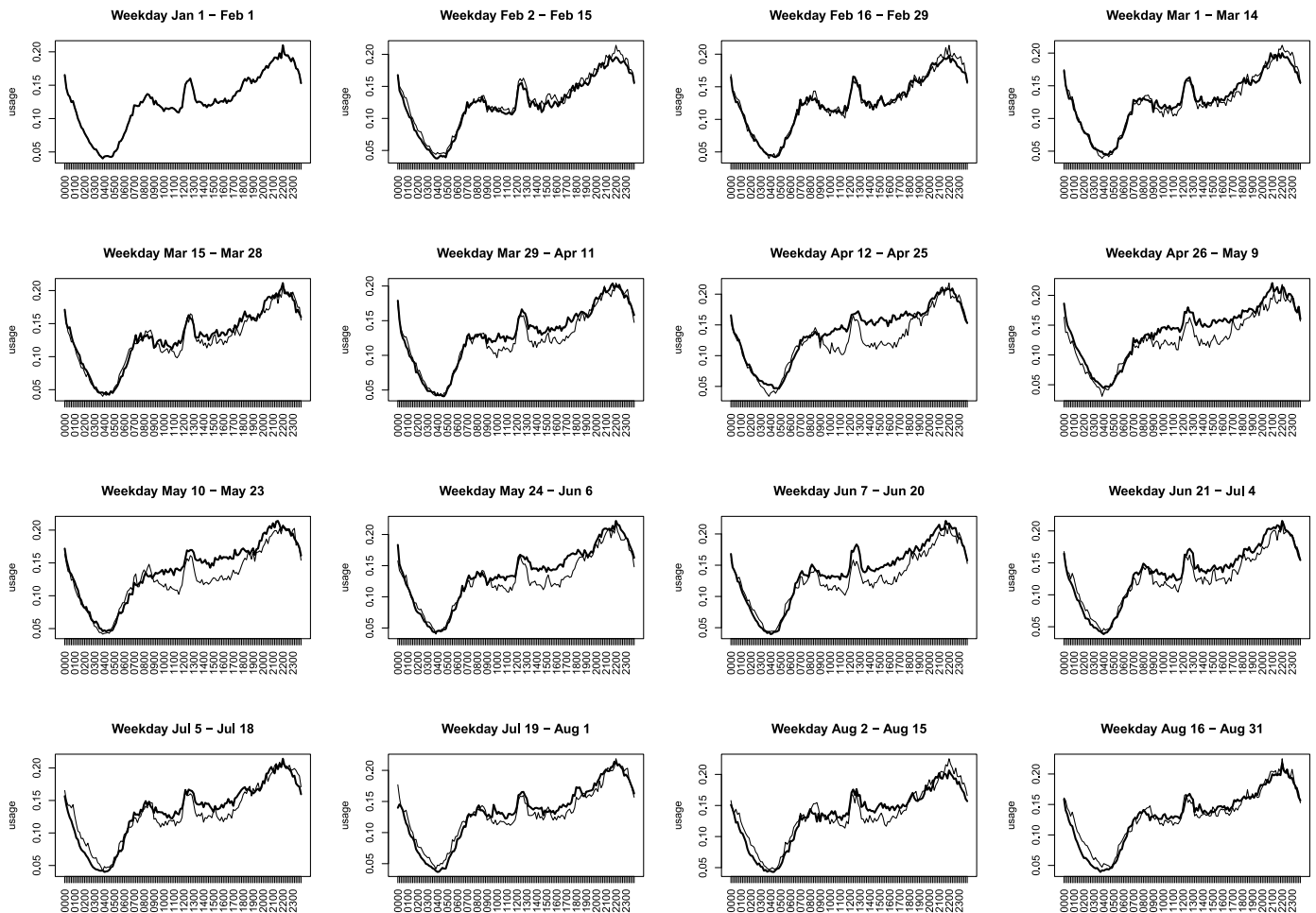**Fig. 2.** Interpretation of parameters of usage.

Fig. 3a. Results by time band (weekdays).

slowed down. The impact of COVID-19 must be examined in an exploratory manner. Carracedo et al. (2020) also applied clustering to find topics of research papers related to COVID-19.

Fig. 5 shows the cluster means for Cluster 1 to Cluster 5. As in Fig. 4, W is for weekdays, H is for holidays, upper case is for daytime, and lower case is for nighttime. The clusters have both increasing and decreasing trends, which is different from the overall trend. In addition, in the aggregate, the trends for daytime (W, H) and nighttime (w, h) were roughly the same, but when divided, many clusters showed different trends. Usage in Clusters 3 and 4 increased, that in Clusters 1 and 5 decreased, and that in Cluster 2 remained unchanged, so we have given each cluster a related name. Cluster 2 (Moderate_Increasing) and Cluster 4 (Steep_Increasing) show an increase over the analysis period, with the increase in usage time overlapping the first wave (1 W) and the second wave (2 W). This may be a behavior change in response to the threat of an increase in the number of infected people (Campbell et al. 2020) and may include both utilitarian usage increases, such as information gathering (Sommerfeldt, 2015; Lai & Tang, 2018), and hedonistic usage increases (e.g., Melumad & Pham, 2020). Both Cluster 1 (moderate decreasing) and Cluster 5 (steep decreasing) exhibit decreasing usage, but usage in Cluster 1 seems to have decreased during the first wave and remained low in the second wave, suggesting that the behavioral changes caused by the first wave continued during the second wave. Usage in Cluster 5 shows a monotonic decrease without much relation to the wave of the epidemic, suggesting that members of this cluster had moved away from smart devices, possibly due to cyberchondria, as described in Laato et al. (2020).

5.2. Discussion on usage change of subgroups

This section examines the issue from the perspective of whether there are subgroups that show different usage trends from the overall trend of mobile app usage, which was posed as RQ2. By categorizing consumers through cluster analysis, we were able to capture the diversity of consumers. First, it was shown in the previous section that mobile app usage behavior is on the rise. In addition, the results showed that there were five clusters and that there was no simple change in behavior.

First, the cluster with the highest composition was the cluster with no change (Stable, Cluster 2), with 45% of all consumers. Therefore, 55% of the total number of consumers changed their usage. This validation shows that COVID-19 was an event that affected 55% of consumers. In the current situation where mobile apps are not sufficiently widespread to reach the elderly, it is believed that the impact was quite significant.

Next, there are two clusters where the use of mobile apps increases, with 7% of consumers showing a large increase (Steep Increasing, Cluster 4) and 23% showing a slight increase (Moderate Increasing, Cluster 3), for a total of approximately 30%. However, there are two clusters where the use of mobile apps declines, with 5% of consumers experiencing a significant decline (Steep Decreasing, Cluster 5) and 20% experiencing a slight decline (Moderate Increasing, Cluster 1), for a total of 25%. Since there are more people in the increase cluster than in the decrease cluster, the results of the previous section that overall usage was increasing. We also found that there were three groups of people who maintained, increased, or decreased their usage in response to external shocks.

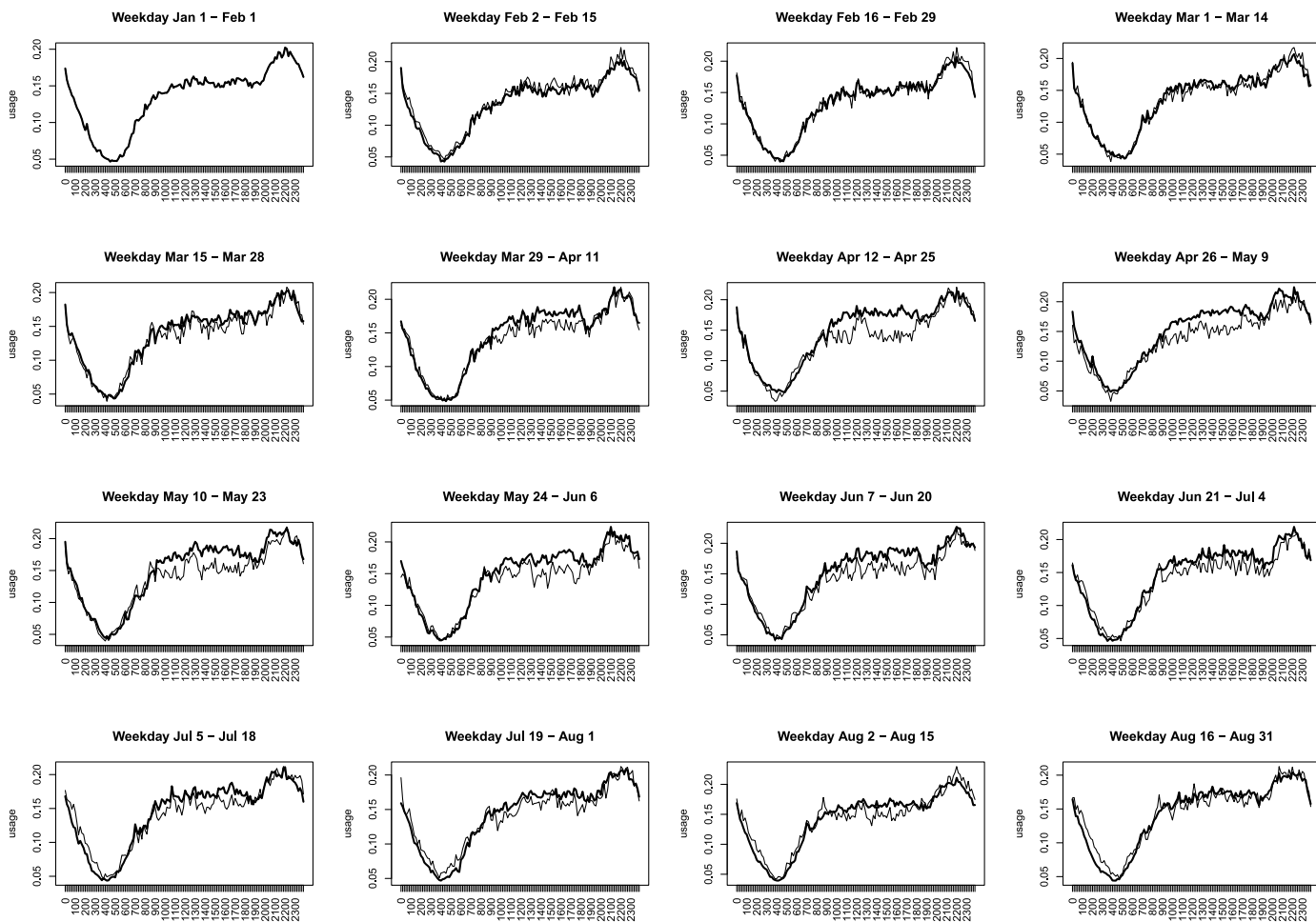Furthermore, it was found that there was asymmetry in the behavior

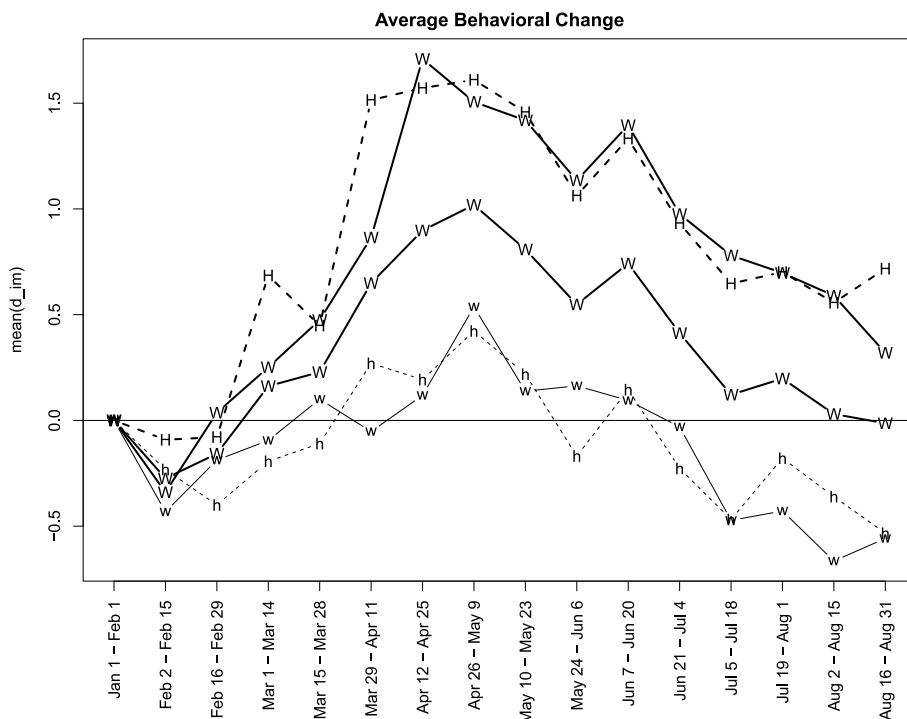**Fig. 3b.** Results by time band (holidays).

Fig. 4. Average behavioral change.

of the increasing and decreasing clusters. There is complex behavior in the increasing and decreasing trends. Both of the increasing clusters (Clusters 1 and 5) increased from P1 to W1 and then stabilized or slightly decreased in P2 and W2 with the increase in W1. In other words, the increase in mobile app usage obtained through stimulation by COVID-19 settles down. As consumers accumulate knowledge on their own, the need to collect and share information is reduced, suggesting that they may be limiting mobile app usage behavior in their everyday lives. In contrast, the decreasing clusters (Clusters 3 and 4) show a monotonous decreasing trend from P1 to W1, which continues until P2 and W2. This result suggests that consumers who experience information use anxiety (Soroya et al., 2021) as a result of an external shock will establish a different usage style for mobile apps than they did before the shock. It is possible that they return to traditional information gathering behavior, relying on traditional sources of information such as television and word of mouth (Sommerfeldt, 2015), or a shift away from information gathering that does not gather unnecessary information as a lifestyle behavior.

Thus, by conducting cluster analysis, this study finds two new contributions to the behavioral changes related to the use of mobile apps in response to external shocks. One is that the aggregate is composed of three groups: unchanged use, increase, and decrease, rather than two: maintenance of use and increase. The other is that the increase/decrease in use is not simple linear and not symmetrical.

6. Relationship between behavioral change and individual characteristics

6.1. Model and variables

Based on the results of the cluster analysis in the previous section, we examine the relationship between consumers' demographic variables and the patterns in their behavioral changes. We calculate the distance between the degree of behavioral change for individual i and the cluster mean for cluster k and let v_{ik} be the inverse of that distance; we obtain $v_i = (v_{i1}, \cdots, v_{iK})'$, $v_{ik} > 0, \forall k$. Each consumer is assigned to the largest element. In addition, since $v_{ik} > 0, \forall k$, the membership probability can be obtained from $p_{ik} = v_{ik} / \sum_{l=1}^{K} v_{il}$. This is the objective variable. However, the objective variable is the membership probability, where $p_{ik} \in (0,1)$, $\sum_{k=1}^{K} p_{ik} = 1$, and it is necessary to introduce constraints for estimation. Although several methods have been proposed for introducing constraints, such as the market share model of Berry (1994) or that of Cooper and Nakanishi (1989), in this study, we use Berry's (1994) method of introducing base categories, taking logarithms, and estimating the relative parameters. The base cluster is assumed to be Cluster 2 (Stable), which has almost no variation, as shown in Fig. 5. Let $k^* = 2$, and the model for estimating cluster affiliation can be defined as follows:

$$\log p_{ik} - \log p_{ik^*} = x_i \delta_k + \eta_{ik} \tag{3}$$

where x_i is an individual characteristics vector, δ_k is the effect of the individual characteristics on affiliation cluster k, and η_{ik} is an error term. For the personal characteristics vector, demographic variables, eco-
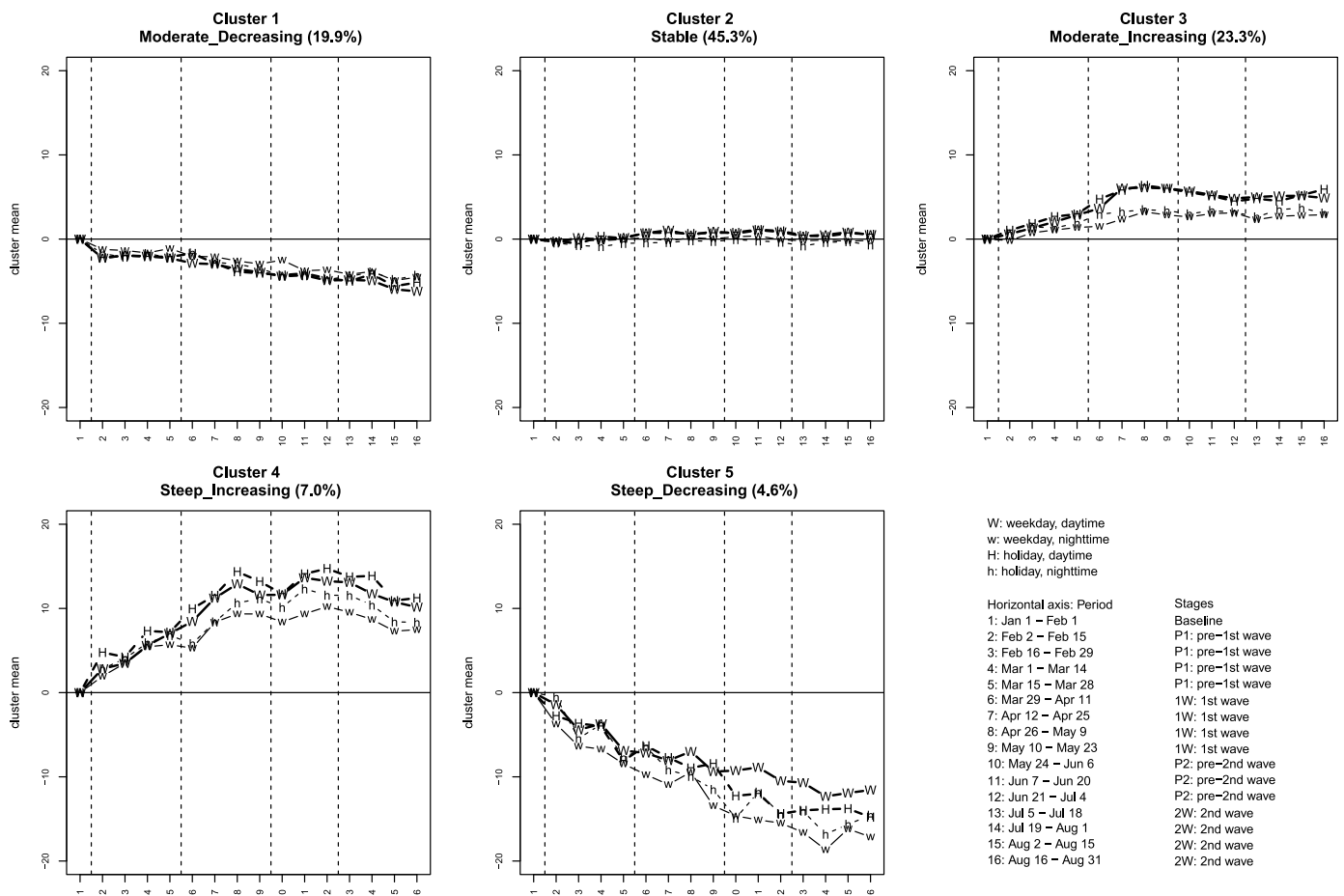

Fig. 5. Behavioral change by period for each cluster.

nomic variables such as income, and sociodemographic variables such as family size were used. The candidate explanatory variables are shown in Table 2.

The correlation coefficients between these candidate variables are not high, but instead of estimating parameters incorporating all the variables, we explore the best model that incorporates the appropriate variables by examining indicators for model fit. There are 14 candidate explanatory variables, and for each of the explanatory variables, there are two choices: to include the variable or not to include the variable in the model, so that $2^{14} = 16384$ models are available for comparison. In this study, we estimate all the models and select the model with the highest adjusted R-squared (the best model).

6.2. Results of the estimation of cluster affiliation

Table 3 shows the results of the parameter estimation of the best model: 11 out of 14 variables were incorporated; *Area*, *Edu* (education), and *FamSize* (family size) were omitted from the final model. Additionally, for each of the results, it is important to note that the parameters are relative impacts with the probability of belonging to Cluster 2 (Stable) as the baseline.

First, the bottom line, *Use19* (average usage time in the previous year), is positive and significant for Clusters 3, 4, and 5. This suggests that there are consumers who are classified as Cluster 2 (Stable) due to their low frequency of use. *Area* of residence had no effect on the basic demographic variables, but there was a significant effect for *age* and *gender*. *Age* had a negative impact on Clusters 3, 4, and 5. Regarding *gender*, positive and significant results were obtained for the probability of belonging to all clusters, indicating that females were more likely to change their behavior. Next, regarding personal income (*Income*) and household income (*FamIncome*), higher personal income is associated with a higher likelihood of belonging to Cluster 4. In addition, the presence of a child (*Child*) and the age of the youngest child (*YngChild*) are also significantly related to the probability of belonging to Clusters 4 and 5. The probability of belonging to Cluster 5 increases for families with children, while the probability of belonging to Clusters 4 and 5 decreases among those with younger children. The results for house and car ownership (*House*, *Car*) are also significant, and the probability of belonging to Cluster 5 decreases for house owners, while the probability of belonging to Clusters 3 and 4 increases for car owners.

6.3. Discussion on the relationship between individual characteristics and cluster affiliation

This section discusses the relationship between individual characteristics and cluster affiliation (RQ3) based on the results of the regression analysis using the market share model. We can classify the individual characteristic factors that affect the clusters associated with the three categories. The first is a "variation factor" that improves both the probability of belonging to clusters that increase usage time and the probability of belonging to clusters that decrease it. The second is a "positive factor" that improves the probability of belonging to a cluster that increases the relative time of use, and the third is a "negative factor" that improves the probability of belonging to a cluster that decreases the time of use. Table 4 summarizes which factors correspond to the explanatory variables from the results obtained. Especially for the variation factor, it is not a clear influence on the direction that has been examined in previous studies, such as the negative factor and positive factor (e.g., Beaunoyer et al., 2020; Elena-Bucea et al., 2020), but rather external shocks that affect the variability of usage time itself.

The variation factors include younger age (Age), lower household income (FamInc), longer time spent in the previous year (Use19), and older age of children (YngChild). These variables have led to an increase in the probability of belonging to both Cluster 4, where usage behavior increases significantly, and Cluster 5, where it decreases. The variation factor is thought to indicate the sensitivity to a stimulus. In this case, it is

Table 2
Candidate explanatory variables.

Label	Definition	Related studies
Area	1: Prefectures where the state of emergency was declared on April 7 0: Prefectures where the state of emergency was declared on April 13	The environmental conditions may be different between areas 1 and 0.
Age	Age (log)	The possibility of a digital divide due to age has been discussed by Ramsetty and Adams (2020), and age has also been identified by Elena-Bucea et al. (2020) as one of the main factors in information technology adoption.
Gender	1: Female 0: Male	Elena-Bucea et al. (2020) also identified gender as a factor in information technology adoption. Leung, Sharma, Adithipyangkul, and Hosie (2020) examined the macrolevel relationship between gender gap and COVID-19 infections.
Job	1: employed 0: homemaker	Workers may have changed their information technology usage behavior due to remote work (Venkatesh, 2020; Neely 2020).
FamIncome *DispIncome* *PerIncome*	Family (household) income Individual disposable income Personal income	Individual income and economic status can influence behavior related to usage of digital devices (Beaunoyer et al. 2020; Elena-Bucea et al., 2020).
Edu	Number of years of education (9: junior high school, 12: high school, 16: university (college), 18: graduate school)	Kim et al. (2020) examined the relationship between social class and the impact of COVID-19. In addition, Elena-Bucea et al. (2020) found that education is one of the factors that affects the adoption of information technology.
FamSize	Number of family members	In Campbell (2020), cases of domestic violence under the influence of COVID-19 were examined, and whether a person lives with a family or alone, and the number of family members, is thought to affect behavioral change.
Child	0: no children 1: with child(ren)	Consumer behavior is altered when children's schools are closed (Maria et al., 2020). The presence or absence of children and the age of the children are also thought to affect behavioral changes based on studies that considered the effects of COVID-19 on children (Van Lancker & Parolin, 2020).
YngChild	Age of the youngest child (if there are no children or the child is over 20 years old, the value is 20)	
House	0: Rental house 1: Own house	Home ownership is one indicator of economic status and can also be interpreted as a factor explaining residential location.
Car	0: Do not own cars 1: Car owner	Consumers who own their own cars are assumed to have a lower risk of infection from using public transportation (e.g., Hu et al. 2020), and their behavior is also expected to change.
Use19	Average usage time for all time bands on weekdays during 2019 ($T^{-1}\sum_{z \in 1}^{T} \beta_{i0}^{z}$).	Frequent users and infrequent users have different knowledge levels and attitudes toward mobile devices. This difference may also be related to differences in behavior change (e.g., Beaunoyer et al. 2020)

Table 3
Results of the best model.

	Cluster 1	Cluster 3	Cluster 4	Cluster 5
	Mod_Dec	Mod_Inc	Steep_Inc	Steep_Dec
Intercept	0.221	0.079	0.257	0.087
	(0.349)	(0.494)	(0.494)	(0.494)
Age	−0.027	**−0.155 ***	**−0.331 *** **	**−0.195 ***
	(0.067)	**(0.067)**	**(0.067)**	**(0.067)**
Gen	0.002	**0.072 †**	**0.106 ***	0.023
	(0.042)	**(0.042)**	**(0.042)**	(0.042)
Job	−0.036	−0.027	−0.068	−0.073
	(0.050)	(0.050)	(0.050)	(0.050)
Income	−0.001	0.013	**0.022 ***	0.011
	(0.010)	(0.010)	**(0.010)**	(0.010)
DispInc	0.642	−0.004	0.200	**0.928 †**
	(0.479)	(0.479)	(0.479)	**(0.479)**
FamInc	**−0.080 †**	−0.028	**−0.089 †**	**−0.148 ***
	(0.045)	(0.045)	**(0.045)**	**(0.045)**
Child	0.076	0.008	0.093	**0.177 ***
	(0.074)	(0.074)	(0.074)	**(0.074)**
YngChild	0.009	0.003	**0.012 ***	**0.019 *** **
	(0.006)	(0.006)	**(0.006)**	**(0.006)**
House	−0.146	0.031	−0.094	**−0.202 ***
	(0.092)	(0.092)	(0.092)	**(0.092)**
Car	−0.007	**0.065 †**	**0.087 ***	0.033
	(0.037)	**(0.037)**	**(0.037)**	(0.037)
Use19	0.075	**1.139 *** **	**2.272 *** **	**0.970 *** **
	(0.180)	**(0.180)**	**(0.180)**	**(0.180)**
R2/Adj. R2	0.392	0.381		
F-value	35.44 ***			
N	2632			

Note: Results are impacts relative to Cluster 2 (Stable). †: 10%, *: 5%, **: 1%, ***: 0.1%.

Table 4
Typology of factors.

Typology	Description	Variables
Negative factor	Improve the probability of belonging to clusters with decrease usage time.	●Higher disposal Income ●Not a house owner ●Larger number of children
Positive factor	Improve the probability of belonging to clusters with increasing usage time.	●Female ●Higher income ●Car owner
Variation factor	Improve the probability of belonging to both clusters with increasing and decreasing usage time.	●Younger in age ●Lower family income ●No children or older children ●Longer usage times in 2019

necessary to consider both the increasing and decreasing use of mobile apps as new behaviors. For example, compared to the elderly, young people are more sensitive to information and more likely to engage in new behaviors. At the same time, it is also easy for young people to stop using mobile apps and live an analog life, even if it is somewhat new for them, while it is difficult for the elderly to change their behavior immediately. Second, low household income consumers are vulnerable to external shocks. This indicates that they are forced to take new actions. Some may need to start new jobs due to the instability of their own income, while others may need to limit their activities as much as possible to reduce their living expenses. In addition, longer usage time in the previous year is an observed variable for familiarity with the use of mobile apps. In other words, it is a factor that is useful for seeking new usage styles such as further increases or decreases in usage when stimulated. The results of this study show that consumers with longer usage times may have even longer or shorter usage times. Finally, the existence

of older age child should be considered the background of the child's life. The parents' needs to support children's new behaviors will increase the use of mobile apps, while the need to keep children as close to parents as possible will decrease the amount of time spent on smartphones.

The positive factors that lead to an increase in the use of mobile apps are being female (Gen), having a high income (Income), and owning a car (Car). The negative factors that lead to a decrease in the use of mobile apps are high disposable income (DispInc), moving into rentals (House), and having many children (Child). However, it should be considered that these variables do not have an impact on the opposite direction. For example, female consumers increase the probability of belonging to Clusters 3 and 4, where usage behavior increases, but do not significantly decrease the probability of belonging to Clusters 1 and 5, where usage behavior decreases.

7. Future issues and conclusions

In this study, we analyzed in detail the impact of the spread of COVID-19 on consumers' smartphone usage behavior and the factors behind these behavioral changes. In particular, we focused on the first half of 2020 to analyze the changes relative to the same period in 2019. The contributions of this research are as follows. First, we quantitatively identified changes in smartphone usage behavior from 2019 to 2020 using smartphone usage log data obtained from a long-term consumer survey. In addition, changes in daily smartphone usage behavior over 10-min increments were estimated, and detailed changes were tracked and discussed. From the results, we found that usage behavior changed significantly beginning in March and returned somewhat closer to normal by August, but still had not completely returned to the normal state of affairs seen in 2019. Second, individual parameters were obtained from the usage logs, and the patterns of behavior were classified into 7 clusters. From this, it became clear that there were large differences in individual behavioral changes. There was a mixture of consumers with an upward trend and those with a downward trend, with 30% of all consumers having an upward trend and 25% having a downward trend. We were able to quantify the heterogeneity in individuals' responses to the COVID-19 threat. Third, we estimated the tendency to belong to each of the five clusters of behavioral change using individual characteristics as explanatory variables. As a result, we found certain relationships between consumer characteristics and the tendency to belong to different clusters. In addition, as a contribution of our study, we found three factors affecting the usage change: the positive factor that increases the time of use, the negative factor that decreases the time of use, and the variation factor that affects the variation of the time of use.

We mention three issues for future research. The first is the need for continuous observation. In this paper, we analyzed the period up to August 2020, but it is necessary to continuously observe changes after that. The second point is the need to focus not only on smartphone use but also on individual behaviors such as purchasing behavior and trends in the use of specific applications. In this paper, we first summarized and examined smartphone usage behavior as an overall trend, but in the future, we will need to focus on individual-specific problems for further analysis. For example, examining the impact of increased frequency of use on consumer psychology and social interaction, issues such as fake news need to be considered (e.g., Apuke & Omar, 2021). The third issue is the general interpretation of the COVID-19 threat; it is necessary to examine this event with reference to past threats, as in Sakurai and Chughtai (2020) and Eggers (2020), and to conduct a theoretical comparative analysis.

Declaration of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

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