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Title

Relationship between Internet use and out-of-home activities during the first wave of the COVID-19 outbreak in Japan

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Highlights

Substitution relationship between Internet use and out-of-home activities was revealed by data collected from a web-based questionnaire survey during the first wave of the COVID-19 outbreak.

Internet use for socializing, exercise and leisure/entertainment had strong substitution relationship compared to online shopping.

The decline in outings during the survey period may first be attributed to the substitution of outings to restaurants and shopping malls with Internet use for leisure/entertainment purposes.

Abstract

Following the first wave of the COVID-19 outbreak, the Japanese government announced the declaration of a state of emergency in April 2020, which aimed to decrease contact between people and requested that residents refrain from outings. Even in the absence of penalties, outings decreased under the declaration. We are interested in how outings declined and studied the substitution relationship between Internet use and outings. A web-based survey was conducted to collect data on Internet use and outings in a retrospective manner. The period covered by our data is from mid-February to mid-May 2020. Multilevel analysis and binomial logistic regression analysis were performed to examine the relationship between Internet use and outings. The results clearly show that Internet use replaced outings. In particular, Internet use for socializing, exercise, and leisure/entertainment had a strong substitution relationship with outings. Internet use for socializing and leisure/entertainment was also associated with refraining from visiting restaurants. In contrast, there was a weak substitution relationship between Internet use for daily shopping and outings. Although telework tends to be an accepted focus of Internet use under the COVID-19 outbreak, it should not be overlooked that other uses of the Internet, such as for leisure/entertainment, also supported the decline in outings.

Keywords

COVID-19, Internet, substitution, out-of-home activities, travel behavior, Japan

1. Introduction

In Japan, the number of confirmed COVID-19 cases has been clearly increasing since late February 2020, and the peak of the first wave occurred around mid-April (Fig. 1). To prevent the spread of COVID-19, the Japanese government and local governments started to ask people to work remotely and refrain from holding large events in February. On February 27, the Japanese government also requested that elementary, junior-high, and high schools all over Japan close from March 2 until spring break. Finally, a declaration of a state of emergency for the metropolitan areas was announced by the Japanese government on April 7. The declaration was extended to all of Japan on April 16. It was lifted on May 14 for the nonmetropolitan areas and on

May 25 for the remaining metropolitan areas.

The aim of the declaration was to limit the spread of infection in order to reduce the burden on medical facilities. To this end, people were asked to refrain from leaving their homes, with the aim of reducing contact between people by 80%. To achieve with this aim, the following were requested in the declaration: people should work at home, except for those with jobs necessary to maintain the functioning of society; when people have to go out for necessities, the three Cs ("closed spaces with poor ventilation", "crowded places with many people", and "close contact with other people") should be avoided, and all must wear a mask. In addition, the declaration gave prefectural governors legal grounds to request the closure of facilities that host many people and shortened hours of operation for restaurant. In fact, most of the prefectures made these requests.

It is believed that reducing outings is effective in preventing the spread of infection by reducing contact between people, and some countries imposed severe restrictions on outings, including penalties (Alfano and Ercolano, 2020; Hale et al., 2020; Islam et al., 2020; Koh et al., 2020). The declaration of a state of emergency in Japan was similar to other countries' policies in that it aimed to reduce contact between people. However, the declaration was formulated as a request, not a mandate. Despite this, outings in Japan decreased (Arimura et al., 2020; Google, 2020; Yabe et al., 2020).

How was this reduction in outings achieved under a request-based policy with no penalties? Although there have been studies on the impact of lockdown policies on COVID-19 cases or epidemiological dynamics (Alfano and Ercolano, 2020; Dehning et al., 2020; Gatto et al., 2020; Islam et al., 2020; Koh et al., 2020), it is not clear how the reduction in outings was achieved in countries with relatively modest restrictions on outings. More precisely, it is self-evident that there has been a decrease in outings in countries with severe restrictions, but it is not clear what supports this decrease in outings in countries, such as Japan, with a request-based policy. However, few studies have tackled this problem, though one study on the association between risk perception and outings in Japan has been published (Parady et al., 2020). That study showed that fear for COVID-19 was associated with decrease in outings during the first wave of the COVID-19 outbreak. However, risk perception is unlikely to be the only factor that reduces outings. Understanding the factors associated with the reduction in outings will help us to plan measures that do not involve severe restrictions for subsequent waves of the disease.

In this study, we focus on Internet use as a factor related to the decrease in outings. Internet use as a substitute for outings has received much attention, and it has been reported that Internet use has actually increased in various ways, including because of telework and online shopping (Abigail Adams-Prassl, 2020; Beck and Hensher, 2020; Dannenberg et al., 2020; Li et al., 2020). However, there is little empirical evidence of the relationship between Internet use and outings under the COVID-19 outbreak, what kind of Internet use especially replaces going out, and to what extent.

Various studies had already been conducted on the relationship between Internet use and out-of-home activities before the COVID-19 outbreak (de Graaff and Rietveld, 2007; Farag et al., 2007; Julsrud et al., 2012; Shi et al., 2019). Existing research suggests that there are two main relationships between Internet use and outings: substitution and complementary (Metin and Kitamura, 2003). The substitution relationship is one in which outings decrease as Internet use increases. The complementary relationship is one in which outings increase as Internet use increases.

Among the purposes of Internet use, telework and online shopping have received much attention, and other purposes, such as online gaming or accessing online movies, have not been studied as much. Based on existing research, telework is clearly related to reduced outings, whereas online shopping is more complementary than substitutional (Andreev et al., 2010). For Internet use other than telework and online shopping, the relationship with outings is not clear. It is also not known which purpose of Internet use reduces outings to a greater degree. Each purpose of Internet use was examined independently in previous studies. Under the COVID-19 outbreak, people use the Internet for various purposes. Thus, it is important to examine the relationship between Internet use and outings while considering multiple purposes of Internet use.

The present study, therefore, aims to clarify the relationship between Internet use and outings while taking into account various purposes of Internet use at the same time. The period of investigation is from mid-February to mid-May 2020, which covers the duration of the declaration of a state of emergency. We expect a substitution relationship between Internet use and outings for that period. In the following, data are collected through a web-based survey and analyzed to determine the relationship between Internet use and outings.

2. Methods

2. 1. Questionnaire survey

A web-based questionnaire survey was conducted to collect data about Internet use and outings. The study participants were recruited from among the registrants of the survey company Cross Marketing Inc., which can access approximately 4.65 million registered monitors residing in Japan. In the recruitment process for this study, the quotas were defined according to the observed distributions in the Japanese population by age group (20s, 30s, 40s, 50s and 60s), gender (male and female) and place of residence (metropolitan and nonmetropolitan areas). The quotas were calculated based on the 2015 Japanese population census. This quota sampling of registered monitors is not a probability sampling of the target population. However, we adopted an online survey because it is an excellent method for rapid and non-face-to-face data collection in the midst of the COVID-19 outbreak. The web survey started on May 19 and ended on May 23, 2020. The target number of total participants was 1,200, and participants were accepted until that number was reached.

Unfortunately, the quota for participants in their 60s living in nonmetropolitan areas was not reached. Considering coverage error, the 60s age group in the sample were excluded from the following analyses. This is because the registration rate for monitors in their 60s is quite low compared to those in their 50s or less, so the Internet usage of respondents in their 60s is very unlikely to be similar to that of other age groups, as well as the general population in their 60s. Thus, the total sample size used in the following analyses is 928.

This questionnaire survey was approved by the Research Ethics Committee of the graduate school of engineering, Tohoku University (20A-3). Informed consent was obtained from all the respondents.

2. 2. Measuring Internet use and outings

This section describes how Internet use and outings were measured in the questionnaire survey. In the survey, we asked the following question about Internet use: "For what purposes has your use of the Internet increased after the COVID-19 outbreak?" The answers to that question can be selected from the following options: daily shopping, non-daily shopping, mail/messages, socializing (for example, online drinking parties), exercise, leisure/entertainment, and work/study. In addition, the following question was also asked about Internet access: “When you use the Internet at home, do any of the following apply to you?” The answers to that question can be selected from the following options: don’t have a broadband connection, traffic volume is limited, don’t know how to shop online, workplace doesn’t support telework, and don’t have a personal computer.

Two questions were asked about outings. In the first question, we asked for the time spent outside from mid-February to mid-May with a time interval of 10 days. That is, respondents reported their time spent outside from mid-February, late February, early March, and so on. Time spent outside was reported in integers relative to 10, which reflects the usual time spent outside before the COVID-19 outbreak. That is, if a respondent thinks that the time he or she spent outside during a certain period was half that spent outside before the outbreak, the respondent assigns a value of 5 to that time period. This value of time spent outside is subjective, but characteristic events in each time period were described in the survey to reduce recall bias. Parady et al. (2020) use the number of trips as the measure of outings, but it is possible to shorten the time spent outside without changing the number of trips. Taking these points into consideration, we decided that it would be preferable to ask the respondents directly about their time spent outside. The second question about outings was "Where do you refrain from going to?" The answers to that question can be selected from the following options: supermarket, convenience store, park, shopping mall, restaurant, and workplace/school.

2. 3. Multilevel analysis

The relationship between Internet use and outings was analyzed from two perspectives. The first explore what kind of Internet use especially replaces going out, and to what extent. The second explores for which destinations outings have decreased with increased use of the Internet. A multilevel linear regression model for longitudinal data (Singer and Willett, 2003) was applied to analyze the relationship between Internet use and time spent outside. That is, it addresses the first perspective described above.

The multilevel linear regression model is divided into level 1 and level 2. Level 1 describes the variation in time spent outside within an individual. The equation for level 1 is as follows:

$$Y_{ij} = \beta_{0j} + \beta_{1j} Time_{ij} + \beta_2 x_{1ij} + \beta_3 x_{2ij} + \beta_4 x_{3ij} + r_{ij} \qquad (1)$$

where Y_{ij} is respondent j's time spent outside in time period i, and i takes a value from 1 to 10 (from mid-February to mid-May). For example, time period i = 1 (mid-February) covers February 11 to 20, time period i = 2 (late February) covers February 21 to the end of February, and time period i = 3 (early March) covers March 1 to 10. β_{0j} is the intercept for respondent j, β_{1j} is the slope for respondent j, $Time_{ij}$ takes the value of i. For example, $Time_{1j}$ takes a value of 1 and $Time_{2j}$ takes a value of 2. r_{ij} is respondent j's variance in time period i assuming a normal distribution independent of each time period with a mean of 0. x_{1ij} and x_{2ij} are variables that control the effect of school closure and the declaration of a state of emergency, respectively. The variable x_{1ij} is a dummy variable that indicates the impact of the request for school closure nationwide that was implemented from March 2, and that takes a value of 0 until at the end of February (from i = 1 to 2) and 1 thereafter (from i = 3 to 10). The x_{2ij} variable is a dummy variable that indicates the impact of the declaration of a state of emergency on April 7 and 16. It takes a value of 0 until late March (from i =1 to 5) and 1 thereafter for seven prefectures that are largely metropolitan areas, including Tokyo. For the other 40 prefectures, it takes 0 until early April (from i =1 to 6) and 1 thereafter. Regarding this x_{2ij} variable, the declaration of a state of emergency was lifted for 39 prefectures that are largely nonmetropolitan areas on May 14. Thus, x_{2ij} takes 0 in mid-May (i = 10) for the 39 prefectures. The variable x_{3ij} takes the sum of the number of confirmed COVID-19 cases in time period i, and in a prefecture where respondent j lives. This variable controls the risk of infection as an objective measure. The data of confirmed COVID-19 cases by prefecture were obtained from J. A. G. JAPAN Corp. β_2, β_3 and β_4 are parameters for each variable.

Level 2 describes variations in intercept and slope from level 1 between individuals:

$$\beta_{0j} = \gamma_{00} + u_{0j} \qquad (2)$$

$$\beta_{1j} = \gamma_{10} + \sum_{n=1}^{k} \gamma_{1n} z_{nj} + u_{1j} \qquad (3)$$

where γ_{00} and γ_{10} are intercepts that capture the average of the sample, and u_{0j} and u_{1j} are between-respondent variance assuming a normal distribution with a mean of 0. Since the present study is interested in the slope from level 1, which represents the changes in outings over time well, explanatory variables z_{nj} are inserted only into the equation for β_{1j}. k is the number of explanatory variables.

The explanatory variables z_{nj} can be divided into four categories: 1) the purposes of Internet use that increased after the COVID-19 outbreak, 2) Internet access, 3) personal attributes (age and gender), and 4) commercial district.

The details of the variables are as follows. The purposes of Internet use consist of seven variables: daily shopping, non-daily shopping, mail/messages, socializing, exercising, leisure/entertainment, and work/study. Each variable takes 1 if the purpose of Internet use increased after the outbreak, and 0 otherwise. If we find a negative coefficient for γ_{1n} for an Internet use variable, we assume that there is a substitution relationship.

Internet access consists of five variables: don't have a broadband connection, traffic volume limits, don't know how to shop online, workplace doesn't support telework, and don't have a personal computer. Those variables take 1 if the Internet access option applies and 0 otherwise.

For personal attributes, respondents are divided into age groups (20s, 30s, 40s and 50s); there are three dummy variables, and the 20s age group is the referent. Gender is also a dummy variable that takes 1 for male and 0 otherwise. Commercial district is a variable that takes 1 if the respondent's residence is within a commercial district (Akiyama et al., 2013) and 0 otherwise.

Of the 928 samples, 906 were included in this multilevel analysis. The responses with a maximum time spent outside larger than 20 (7 respondents) were excluded as outliers; 15 respondents whose zip codes did not match their actual addresses were also excluded. The lmerTest package (Kuznetsova et al., 2017) in the R version 3.6.1 environment was used for the multilevel analysis.

2. 4. Binomial logistic regression analysis

A binomial logistic regression analysis was employed to address the second perspective above that explores for which destinations outings have decreased with increased use of the Internet. The multilevel analysis reveals which kind of Internet use especially substitutes for time spent outside. Based on the multilevel analysis, however, we do not know which destinations have seen decreased visits or which types of Internet use are associated with this decline. Therefore, the binomial logistic regression analysis is appropriate for further investigation of the relationship between Internet use and outings.

As the dependent variable in the binomial logistic regression, we used the destination respondents visited less, derived from the survey question “Where do you refrain from going to?”. Binomial logistic regression was performed for each of the six less visited destinations as the dependent variable. The six destinations are supermarket, convenience store, park, shopping mall, restaurant, and workplace/school. The dependent variable takes 1 if a respondent refrain from visiting a destination, and 0 otherwise. As in the multilevel analysis, the following were used as explanatory variables: 1) the purposes of Internet use that increased after the COVID-19 outbreak, 2) Internet access, 3) personal attributes (age and gender), and 4) commercial district and the number of confirmed COVID-19 cases by prefecture. In contrast to the multilevel analysis, this analysis targeted cross-sectional data, so the number of confirmed COVID-19 cases was the sum of the study period. The same 906 samples as in the multilevel analysis were also used in the binomial logistic regression analysis. The margins package in the R version 3.6.1 environment was used to calculate the average marginal effects of the latter analysis.

3. Results

3. 1. Descriptive statistics

The descriptive statistics of the survey sample are summarized in Table 1. On the right side of the table presents the results for all 928 samples collected in the survey. On the left side of the table, the statistics for the 906 samples used for the multilevel and the binomial logistic regression analyses are shown. Regarding the distribution by age, gender and place of residence, there seems to be little difference between this sample and all 928 samples on the right side of the table.

Notably, Internet use for leisure/entertainment purposes increased the most. Shopping malls and restaurants are the destinations that the most respondents refrained from visiting, at over 70% of respondents. Time spent outside decreased almost linearly from mid-February to early May; the increase in mid-May might be due to the lifting of the declaration of a state of emergency in 40 prefectures.

3. 2. Results of multilevel analysis

We first present the results for Model 1 (Table 2). Model 1 is the so-called unconditional means model that includes only the level 2 intercept γ_{00}. The purpose of Model 1 is to compare the magnitude of the within-individual and between-individuals variance. The within-individual variance is 6.871, the between-individuals variance is 4.012, and the between-individuals variance accounts for 37% of the total variance. This indicates that there are good reasons to fit the multilevel model to the data.

Next, all explanatory variables were inputted and analyzed. The results of the analysis are shown in Model 2. For all Internet use, negative coefficients are estimated, indicating that time spent outside decreases as the use of the Internet increases. The coefficient for a specific purpose of Internet use in the model is the estimate of the rate of decrease in time spent outside per time interval in this point unit. For example, the coefficient for socializing is -0.112, indicating a decrease of 0.112 points per time interval. In particular, the relation is strong for the socializing, exercise, and leisure/entertainment purposes. The coefficient for the use of the Internet for daily shopping is not as large. A positive coefficient is estimated for the variable representing the workplace not supporting telework. Thus, if a workplace does not support telework, the decline in the time spent outside is slower over time.

Regarding the other variables, positive coefficients are estimated for male and for living in a commercial district, both of which have a moderate relation with the decrease in time spent outside. Negative coefficients are estimated for school closure and the declaration of a state of emergency, indicating that these measures had the effect of reducing the time spent outside by approximately one point. Negative coefficients are also estimated for the number of confirmed COVID-19 cases, suggesting that an increase in cases is associated with a decrease in the time spent outside.

To better understand the results of the multilevel analysis, a graph that shows the estimated changes in time spent outside based on Model 2 is provided (Fig. 2). The number on the y-axis is the estimated time spent outside, and 10 points refers to the usual time spent outside before the outbreak. A decrease of 1 point means that the time spent outside decreased by 10% compared to that before the outbreak.

The baseline (dashed line) shows estimates calculated using only the slope γ_{00} and intercept γ_{10} of Model 2, without the explanatory variables. In this case, the time spent outside decreased to 5.1 points in mid-May. This means a 49% reduction in the time usually spent outside. The thin line shows estimates calculated by adding the coefficient of Internet use for leisure/entertainment to the baseline. This coefficient is chosen because most of the respondents used the Internet for leisure/entertainment according to Table 1. The slope of the thin line is steeper than that of the dashed line because the effects of Internet use for leisure/entertainment are included. The thin line reached 4.4 points in mid-May. The difference between the dashed line and the thin line is 0.7 points in mid-May. Therefore, Internet use for leisure/entertainment over the study period substituted 7% of the usual time spent outside. To elaborate, this 0.7 points (7%) decrease can be calculated from the coefficient of Internet use for leisure/entertainment -0.079. It is noted that the study period consists of 9 intervals. Thus, the use of the Internet for leisure/entertainment led to a decrease in the time spent outside of $-0.079 \times 9 = -0.711$ (7%) at the end of the study period. Finally, the bold line adds the effects of school closure (early March) and the declaration of a state of emergency (early April). For the bold line, the time spent outside reached 2.5 points in mid-May. Therefore, the usual time spent outside has been reduced by 75%. This bold line reflects the situation in metropolitan areas, where the declaration of a state of emergency was not lifted until May 25.

3. 3. Results of binomial logistic regression analysis

For the results of the binomial logistic regression, the average marginal effects of each variable are reported in Table 3. We examine which types of Internet use are related to the destinations that respondents refrain from visiting. When we focus on those with low p-values, Internet use for daily shopping is related to refraining from visiting supermarkets, convenience stores, and parks. In particular, the average marginal effects for supermarkets and parks were approximately 0.1. In other words, Internet use for daily shopping increases the probability of refraining from visiting supermarkets and parks by approximately 10 percentage points.

When we focus on those with low p-values, Internet use for mail/messages is related to refraining from visiting parks, shopping malls, and restaurants. In particular, the average marginal effects for shopping malls and restaurants were high, at approximately 0.1. Increasing Internet use for socializing is associated with refraining from visiting restaurants and workplaces/schools. These average marginal effects are characterized by a high value of approximately 0.15. Internet use for leisure/entertainment is associated with refraining from visiting shopping malls and restaurants. The average marginal effect for restaurants was high at 0.13. Internet use for work/study is associated with refraining from visiting workplaces/schools. With an average marginal effect of 0.228, we can say that the relationship is quite strong.

Regarding the variables of Internet access, the variable of "don't have a broadband connection" has a relationship with refraining from visiting restaurants. Since the average marginal effect of the variable is negative, the lack of broadband connection is associated with not refraining from visiting restaurants. The average marginal effect is -0.198 and it can be said that this variable also has a strong relationship with visiting restaurants.

4. Discussion and conclusion

The multilevel analysis revealed substitutive relations: the use of the Internet for purposes such as socializing, exercise, and leisure/entertainment substituted for time spent outside, which was not known in previous studies. A total of 10% of the usual time spent outside is substituted by Internet use for socializing. In addition, Internet use for exercise and leisure/entertainment each substituted 7% of the usual time spent outside. All of these Internet use purposes share a feature in common: they are time consuming. Socializing, such as joining an online drinking party, usually takes several hours, and a movie, an example of leisure/entertainment, takes approximately two hours. Online games also take a long time. In addition, some people are likely to spend more time exercising when viewing online videos, such as yoga and gymnastics videos, in their homes. Therefore, the relation between such Internet use and time spent outside may become stronger than online shopping.

The results of the multilevel analysis show that Internet use for daily shopping has a weaker substitution relationship with outings than other types of Internet use. A total of 3% of the usual time spent outside was substituted by Internet use for daily shopping. Research from Germany reported that the surge in demand for online shopping has not been satisfied due to supply shortages (Dannenberg et al., 2020). Even if the demand is met by online shopping, the relationship is likely to be weak in terms of substituting for time spent outside because the time spent shopping at nearby grocery stores is short.

Previous studies in the period before the COVID-19 outbreak have been clear about the substitution relationship between telework and going out (Andreev et al., 2010), and this association held in this study. About 6% of the usual time spent outside was substituted by Internet use for work/study. Furthermore, the variable indicating that the workplace does not support telework was strongly related to the time spent outside. This variable is related to an increase in time spent outside by 9% over the study period. It implies that there are work that cannot be done on the Internet, and that even if work can be done on the Internet, it is necessary to go to work for some case. In Japan, there is a practice of putting a personal seal (Hanko) on documents when approving them, and people sometimes have to visit the office just for this purpose. The results seem to indicate the importance of whether the workplace supports telework, which may entail changes in this practice.

Binomial logistic regression analysis revealed the relationship between the purpose of Internet use and the destination respondents refrained from visiting. First, since the Japanese government's second declaration of a state of emergency in January 2021 placed more importance on restaurants than other facilities in controlling the spread of COVID-19 and requested a shortening of their opening hours, we focus on refraining from visiting restaurants.

In the findings of the binomial logistic regression analysis, as well as in the multilevel analysis, Internet use for socializing and leisure/entertainment are important variables. These two types of Internet use are strongly related to refraining from visiting restaurants. Based on its average marginal effect, Internet use for socializing increases the probability of refraining from visiting restaurants by 16 percentage points. Internet use for leisure/entertainment increases the probability of refraining from visiting restaurants by 13 percentage points. This leisure/entertainment variable is also related to refraining from visiting shopping malls that usually have restaurants in. In addition to these variables, Internet use for mail/messages increases the probability of refraining from visiting restaurants by 11 percentage points. Furthermore, the lack of a broadband connection is strongly related to an increase in visiting restaurants by 20 percentage points. These results suggest that face-to-face communication, which used to take place in restaurants, is being replaced by activities such as online drinking parties, gaming, and messages. In such cases, the broadband connection supports these online activities.

According to the results of the binomial logistic regression analysis, Internet use for daily shopping corresponds not only to refraining from outings to supermarkets and convenience stores but also to parks. In the Netherland, where relatively moderate restrictions on outings were imposed, outings for grocery shopping and touring/walking increased overall during the COVID-19 outbreak (de Haas et al., 2020). Google COVID-19 Community Mobility Reports also demonstrate that outings to the grocery/pharmacy and parks show similar trends in Japan, with relatively slower decreases compared to the decreases seen for retail/recreation or workplaces (Google, 2020). Since supermarkets and parks are often located in residents' neighborhoods, it is likely that a certain number of people will go to both destinations. According to the results of the binomial logistic regression analysis, it is possible that the group that visited both the supermarket and the park refrained from going out and used the Internet for daily shopping.

The policy implications based on the discussion thus far are as follows. The Japanese government's second declaration of a state of emergency stated that refraining from visiting restaurants is effective in controlling the number of infections, and requests were made to restaurants to reduce their business hours. To make this request more effective, Internet use for socializing and leisure/entertainment could be encouraged. In addition, the lack of a broadband connection was associated with an increase in visiting restaurants. Therefore, it would make sense to support consumers' use of broadband Internet for socializing and leisure/entertainment in combination with requesting restaurants shorten their business hours. For example, in Japan, at the request of the Ministry of Internal Affairs and Communications, major cell phone companies offered up to 50GB of free data per month to subscribers under 25 years old to support online classes when the state of emergency was declared in April 2020. This policy continued until the end of August 2020. The implementation of such policies that support Internet use, not only for the purpose of online classes, but also for a broader range of other purposes such as socializing and leisure/entertainment, will strongly promote the substitution relationship. Although, it is obviously necessary to address the digital divide while promoting the use of the Internet, this policy may be implemented at a relatively lower cost than compensating restaurants.

Restrictions on restaurants have also been imposed in other countries. The policy implications of this study may be applicable to countries and regions where the Internet environment is similar to that of Japan. This is because online drinking parties and gaming also occur in societies other than Japan. Therefore, it may be more effective to support consumers' use of the Internet in combination with the restriction of restaurants. However, for online video conferencing tools and games, it is better to have a broadband connection. The implications of this study are unlikely to be applicable to countries and regions where only the penetration of smartphones is high and wired broadband connections are not widely used.

In conclusion, this study confirms that Internet use substituted for outings during the first wave of COVID-19 in Japan. In particular, Internet use for socializing, exercise, and leisure/entertainment was strongly associated with decreasing time spent outside. These Internet uses contributed to reducing going out even in the absence of severe restrictions on outings. From Table 1, the number of respondents who refrain from going to restaurants and shopping malls is larger than that for other facilities. In addition, the number of respondents who increased their Internet use for leisure/entertainment purposes is the largest. When combined with the fact that these variables have strong relations in the analyses, the decline in outings during the survey period may first be attributed to the substitution of outings to restaurants and shopping malls with Internet use for leisure/entertainment purposes. Although telework tends to be an accepted focus of Internet use, it should not be overlooked that other purposes, such as leisure/entertainment and socializing, also supported the decline in outings.

This study has several limitations. First, in the multilevel analysis, the explanatory variable is Internet use, and the outcome is time spent outside. However, it is also possible to assume a relationship in which Internet use increases because people do not go out. The same can be said for the binomial logistic regression analysis. In this study, it is not possible to distinguish whether Internet use is a cause or effect. If we could determine when the use of the Internet increased during the study period, this problem might be solved using multilevel analysis. However, regardless of which is the cause and which is the effect, the fact remains that Internet use and outings are in a substitution relationship.

Regarding the second limitation, our sample was not collected via random sampling of the whole Japanese population. Because it is not a random sample, it is difficult to generalize the results immediately. In addition, since the survey was conducted on the web, the results are based on those who use the Internet a lot and have good Internet access. However, we adopted an online survey because it is an excellent method for rapid and non-face-to-face data collection in the midst of the COVID-19 outbreak. As a future task, it is desirable to conduct surveys other than online. Furthermore, socioeconomic attributes of the respondents, such as income and education, were not used in this study. Although including these variables did not substantially change the results of the current study, further studies should consider the socioeconomic digital divide in exploring the substitution relationship between Internet use and outings.

Another limitation of this study is that time spent outside was measured by relying on the respondent's subjective memory. To combat this issue, characteristic events in each time period were described in the survey to reduce recall bias. Nevertheless, when collecting longitudinal data using retrospective methods, it is necessary to carefully consider the method to ensure the reliability of the data.

In addition, Internet use was not the only factor that supported the decline in outings. There may have been other factors related to the decline in outings, such as peer pressure, fear of infection, store closure, and socioeconomic attributes. This study is a rather simple, preliminary consideration, and future research is needed to ascertain more complex relationships between the related variables.

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Author contributions statement

Naoto Yabe conducted the data analysis, interpretation, and manuscript writing. Tomoya Hanibuchi contributed to the study design and funding acquisition. Hiroki M. Adachi conducted the coding. Shohei Nagata contributed to the survey design. Tomoki Nakaya contributed to the study design and supervision. All authors reviewed and approved the final version of the manuscript.

Declarations of competing interests

The authors declare no competing interests.

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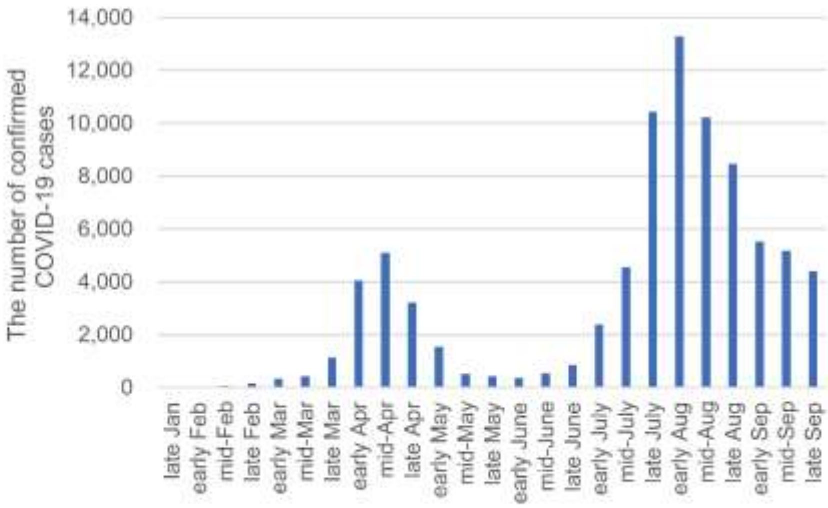

Fig. 1. The number of confirmed COVID-19 cases in Japan

Source: Ministry of Health, Labor and Welfare (https://www.mhlw.go.jp/stf/covid-19/open-data.html)

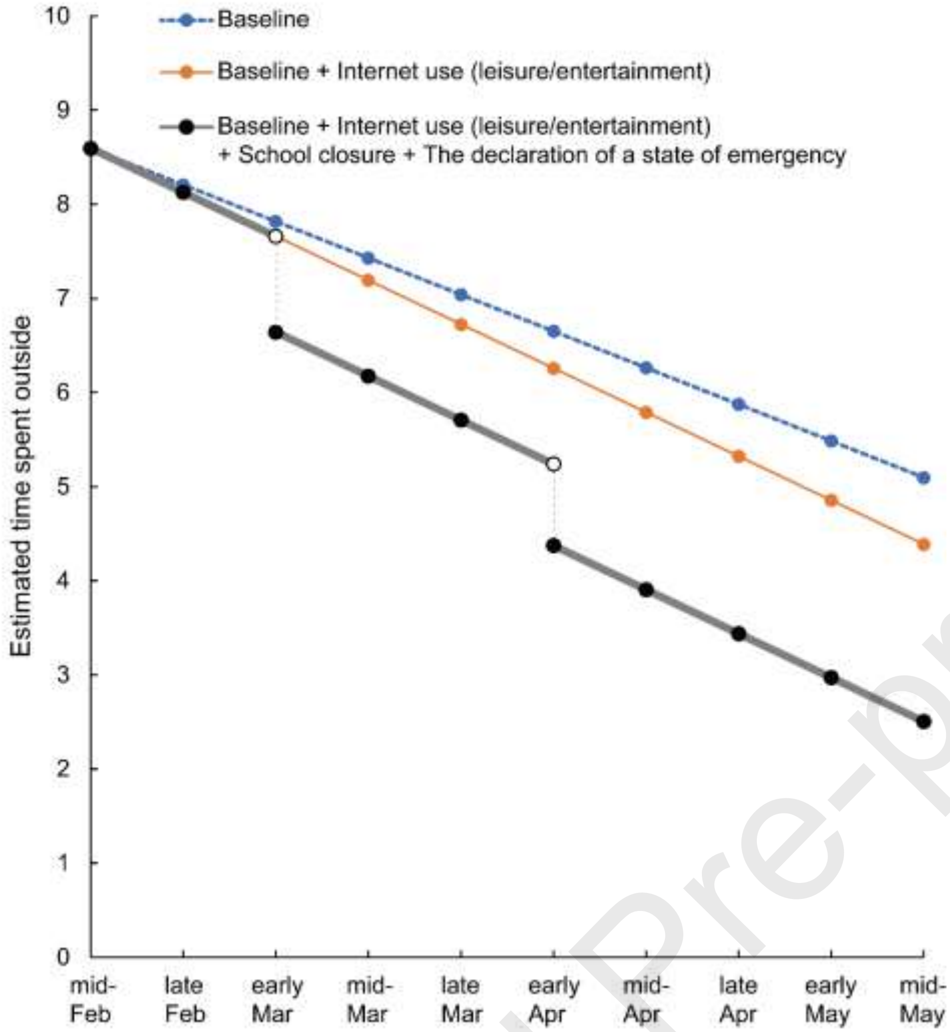

Fig. 2. Estimated time spent outside based on the multilevel analysis

Note: The number on the y-axis is the estimated time spent outside, and 10 points refers to the usual time spent outside before the outbreak. A decrease of 1 point means that the time spent outside decreased by 10% compared to that before the outbreak.

Table 1. Descriptive statistics of the variables

		Sample used in analyses		All sample	
		Number	%	Number	%
Personal attributes	Age 20s	172	19.0	186	20.0
	Age 30s	231	25.5	235	25.3
	Age 40s	273	30.1	276	29.7
	Age 50s	230	25.4	231	24.9
	Gender male	458	50.6	468	50.4
	Gender female	448	49.4	460	49.6
	Residence metropolitan area	494	54.5	503	54.2
	Residence nonmetropolitan area	412	45.5	425	45.8
Internet use	Daily shopping	299	33.0	307	33.1
	Non-daily shopping	87	9.6	88	9.5
	Mail/Messages	311	34.3	318	34.3
	Socializing	104	11.5	105	11.3
	Exercise	178	19.6	180	19.4
	Leisure/Entertainment	420	46.4	429	46.2
	Work/Study	185	20.4	188	20.3
Internet access	Don't have a broadband connection	59	6.5	60	6.5
	Have traffic volume limit	79	8.7	79	8.5
	Don't know how to shop online	12	1.3	12	1.3
	Workplace doesn't support telework	133	14.7	134	14.4
	Don't have a personal computer	65	7.2	65	7.0
Commercial district	Living within commercial district	68	7.5	68	7.3
Less visited destinations	Supermarket	247	27.3	251	27.0
	Convenience store	175	19.3	177	19.1
	Park	219	24.2	224	24.1
	Shopping mall	657	72.5	673	72.5
	Restaurant	660	72.8	676	72.8
	Workplace/School	237	26.2	240	25.9
Time spent outside		Mean	SD	Mean	SD
	Mid-February	8.6	2.4	8.9	5.0
	Late February	8.2	2.5	8.4	5.0
	Early March	7.1	2.8	7.4	5.3
	Mid-March	6.4	2.9	6.7	5.3
	Late March	5.7	2.9	6.0	4.6
	Early April	4.5	2.8	4.7	3.9
	Mid-April	3.9	2.8	4.0	3.7
	Late April	3.5	2.7	3.7	3.7
	Early May	3.3	2.6	3.5	3.5
	Mid-May	3.9	2.8	4.0	4.1
Number of samples		906		928	

Table 2. Results of the multilevel linear regression analysis

	Fixed effects	Model 1	p-value	Model 2	p-value
β_{0j}	γ_{00}	5.509	p<0.001	8.593	p<0.001
	School closure			-1.016	p<0.001
	The declaration of a state of emergency			-0.867	p<0.001
	Confirmed COVID-19 cases			-0.001	p<0.001
β_{1j}	γ_{10}			-0.389	p<0.001
	Internet use				
	Daily shopping			-0.031	0.174
	Non-daily shopping			-0.058	0.109
	Mail/Messages			-0.028	0.236
	Socializing			-0.112	0.001
	Exercise			-0.080	0.004
	Leisure/Entertainment			-0.079	p<0.001
	Work/Study			-0.061	0.022
	Internet access				
	Don’t have a broadband connection			-3.94×10^{-4}	0.993
	Have traffic volume limit			-0.041	0.277
	Don’t know how to shop online			0.093	0.331
	Workplace doesn’t support telework			0.100	p<0.001
	Don’t have a personal computer			-0.007	0.876
	Personal attributes				
	Male (Ref. Female)			0.068	0.001
	Age 30s (Ref. Age 20s)			0.049	0.113
	Age 40s (Ref. Age 20s)			0.054	0.077
	Age 50s (Ref. Age 20s)			0.047	0.138
	Commercial district			0.107	0.006
Variance	r_{ij}	6.871		1.711	
	u_{0j}	4.012		6.405	
	u_{1j}			0.128	
	AIC	44920.88		35353.80	
	Number of Sample	906		906	

Table 3. Results of the binomial logistic regression analysis

	Dependent Variable: Less visited destination					
	Supermarket		Convenience Store		Park	
	Average Marginal Effect	p-value	Average Marginal Effect	p-value	Average Marginal Effect	p-value
Internet use						
Daily shopping	0.132	p<0.001	0.057	0.040	0.113	p<0.001
Non-daily shopping	-0.043	0.408	-0.062	0.205	-0.014	0.766
Mail/Messages	0.034	0.311	0.050	0.088	0.068	0.029
Socializing	-0.026	0.598	0.018	0.660	-0.026	0.570
Exercise	0.005	0.900	-0.002	0.949	-0.052	0.159
Leisure/Entertainment	0.017	0.589	0.033	0.236	0.040	0.177
Work/Study	0.008	0.838	0.036	0.268	0.022	0.536
Internet access						
Don’t have a broadband connection	0.023	0.700	0.043	0.411	-0.029	0.637
Have traffic volume limit	0.033	0.527	-0.021	0.656	-0.055	0.313
Don’t know how to shop online	0.137	0.273	0.029	0.798	0.088	0.494
Workplace doesn’t support telework	-0.074	0.092	-0.030	0.430	-0.028	0.501
Don’t have a personal computer	0.034	0.556	0.073	0.132	-0.007	0.901
Personal attributes						
Male (Ref. Female)	-0.039	0.194	-0.009	0.741	-0.065	0.022
Age 30s (Ref. Age 20s)	0.073	0.110	-0.037	0.370	0.111	0.014
Age 40s (Ref. Age 20s)	0.032	0.486	0.024	0.532	0.143	0.001
Age 50s (Ref. Age 20s)	0.140	0.002	0.029	0.471	0.053	0.264
Commercial district	0.062	0.239	0.067	0.138	0.053	0.289
Confirmed COVID-19 cases	2.73×10^{-6}	0.756	-2.41×10^{-6}	0.760	7.26×10^{-6}	0.375
Nagelkerke R^2	0.068		0.043		0.088	
Number of Sample	906		906		906	

Note: Average marginal effects are calculated from the average of 906 samples.

Table 3. Results of the binomial logistic regression analysis (continued)

	Dependent variable: Less visited destination					
	Shopping mall		Restaurant		Workplace/School	
	Average Marginal Effect	p-value	Average Marginal Effect	p-value	Average Marginal Effect	p-value
Internet use						
Daily shopping	-0.057	0.071	0.011	0.718	0.039	0.177
Non-daily shopping	0.072	0.193	0.062	0.254	0.001	0.982
Mail/Messages	0.110	0.002	0.108	0.002	0.002	0.961
Socializing	0.070	0.178	0.159	0.006	0.140	p<0.001
Exercise	0.057	0.169	0.032	0.427	0.013	0.711
Leisure/Entertainment	0.064	0.037	0.130	p<0.001	-0.041	0.163
Work/Study	-0.023	0.545	-0.015	0.695	0.228	p<0.001
Internet access						
Don't have a broadband connection	-0.068	0.229	-0.198	p<0.001	-0.003	0.957
Have traffic volume limit	-0.017	0.743	-0.024	0.629	-0.003	0.944
Don't know how to shop online	-0.039	0.752	-0.143	0.226	0.109	0.340
Workplace doesn't support telework	0.036	0.403	-0.029	0.473	-0.049	0.250
Don't have a personal computer	-0.036	0.538	0.053	0.365	0.006	0.914
Personal attributes						
Male (Ref. Female)	-0.120	p<0.001	-0.105	p<0.001	0.024	0.382
Age 30s (Ref. Age 20s)	0.075	0.073	0.127	0.001	0.018	0.656
Age 40s (Ref. Age 20s)	0.144	p<0.001	0.199	p<0.001	-0.030	0.449
Age 50s (Ref. Age 20s)	0.121	0.005	0.184	p<0.001	-0.047	0.270
Commercial district	-0.038	0.477	0.074	0.212	0.102	0.029
Confirmed COVID-19 cases	-1.20×10^{-5}	0.151	1.20×10^{-5}	0.171	2.36×10^{-5}	0.002
Nagelkerke R^2	0.107		0.190		0.189	
Number of Sample	906		906		906	

Note: Average marginal effects are calculated from the average of 906 samples.