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The bright and dark sides of social media usage during the COVID-19 pandemic: Survey evidence from Japan

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ABSTRACT

The spread of misinformation on the internet regarding the COVID-19 pandemic, such as unproven or fake cures, has been a serious concern. However, the extent to which social media usage affects individuals' health behavior, particularly when reliable information is scarce, is not well understood. This study evaluates the impact of social media usage on individuals' responses to the COVID-19 pandemic, such as demand for necessities and social distancing. We conduct an original online survey of 1804 Japanese respondents in March 2020. Japan is suitable because it confirmed COVID-19 cases earlier than most other countries. Scientific evidence about the coronavirus and protective measures was scarce in the initial pandemic phase, despite the spread of unconfirmed rumors. Our analysis focuses on the usage of Twitter, Facebook, and Instagram. We use the entropy balancing method to control for heterogeneity in observed characteristics between social media users and non-users. The results show that while users are more likely to maintain social distancing practices, they are also more likely to take measures whose reliability is not scientifically confirmed, such as eating fermented soybeans. Although previous studies emphasize the negative effects of social media, our results suggest that it has both bright and dark sides.

1. Introduction

The lack of reliable information can complicate effective responses to crises [1–5]. This is particularly problematic when crisis management requires the large-scale coordination of individual behavior, as seen strikingly in the case of the COVID-19 pandemic [6]. Although the diffusion of internet and social media in recent years has made it easier to obtain a wider variety of information, this has also raised the new issue of *infodemics* [7,8]. An infodemic is defined as an over-abundance of information—some accurate and some not—that makes it difficult for people to find trustworthy sources and reliable guidance when they need it [9]. Because the spread of misinformation can engender counterproductive individual and social behavior that exacerbates crises, including the COVID-19 pandemic, it is also important to control infodemics [9,10].

Existing studies suggest that social media can be a key driver of the COVID-19 infodemic. Unsurprisingly, people have actively used the internet to search for information about the symptoms of and protective measures against COVID-19, as well as the availability of necessities such as food and drink [11,12]. However, information on the internet also includes misinformation[1]; out of the 12 most popular YouTube videos related to COVID-19, one-quarter of them contained misinformation [13]. Around 16.1% of tweets with a hashtag related to COVID-19 actually exploit the context for advertisement and redirect users to irrelevant topics [14]. Furthermore, due to the misinformation that drinking highly concentrated alcohol could disinfect the body and kill the coronavirus, 800 people have died and 6000 have been hospitalized around the world [15]. The WHO [9] states that "*the infodemic is exacerbated by the global scale of the emergency, and propagated by the interconnected way that information is disseminated and consumed through social media platforms and other channels.*"

That said, the extent to which the usage of social media affects individuals' health behavior is not well understood. This linkage is crucial, because social media can have both socially desirable and undesirable effects. On the one hand, it can raise individuals' risk perception and perceived coping ability, and encourage protective behavior, such as

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[1] The fake news on social media is not new: evidence of this was confirmed during the Great East Japan Earthquake in 2011 [52].

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social distancing. On the other hand, if social media exposes the users to misinformation, such as fake cures, it can cause excessive or misguided responses. While some studies have examined the behavioral and psychological impacts of social media usage during the COVID-19 pandemic [16–19], they mostly rely on statistical methods prone to problems of misspecification.

This study bridges this knowledge gap by examining the case of Japan during the initial phase of the COVID-19 pandemic. Specifically, it uses original online survey data collected in March 2020 to analyze the impact of social media usage on individual behavior. This includes the adoption of protective measures encouraged by the government, such as maintaining social distancing, using disinfectant, and wearing facemasks, as well as engagement in activities not encouraged by the government, such as increased purchasing of fermented soybeans and toilet paper rolls. To control for heterogeneity in observed respondent characteristics between social media users and non-users, such as pre-pandemic behavioral patterns, socio-economic status, and personality traits, we use the entropy balancing model. Its key advantage over more common models, such as linear regression and propensity score models, is that it is less prone to estimation biases driven by misspecifications.

Japan has two suitable features for the analysis of COVID-19-related infodemics. First, it was one of the earliest countries to confirm COVID-19 cases outside of China, following Thailand [20]. Compared to countries that confirmed cases later, scientific evidence about effective protective measures and the socio-economic consequences of the pandemic was scarce in Japan at that time, exacerbating the spread of scientifically unconfirmed rumors. Social media propagated unsubstantiated information that some foods, such as fermented soybeans, reduced infection risks and that some necessities, such as toilet paper rolls, were running out of stock. The uncertainty surrounding the COVID-19 pandemic in these early stages could complicate people's ability to assess the reliability of each rumor. Second, it can be challenging to define a suitable comparison group to evaluate the impact of social media if its diffusion rate is too high. However, the proportion of social media users in Japan is still moderate compared to other developed countries.[2]

2. Background

2.1. The spread of information during the COVID-19 pandemic

During the initial phase of the pandemic, both scientifically confirmed and unconfirmed information about COVID-19 spread on social media, particularly Twitter, Facebook, and Instagram. Scientifically confirmed information included protective measures officially encouraged by the government, such as maintaining social distance, wearing face masks, and using disinfectant. However, social media also spread unconfirmed information about the causes and consequences of the infection spread. In particular, it was rumored in late February 2020 that a popular traditional food, fermented soybeans *(natto)* could boost immune systems and reduce infection risks,[3] causing a sizable boost in sales and stock exhaust. Despite the absence of scientific evidence, some people believed this information because it was commonly known that the consumption of fermented soybeans was higher in particular regions of Japan, and those regions coincidentally had fewer confirmed cases.

Another type of unsubstantiated information relates to the consequences of infection spread. In late February, people rumored on social media that some necessities, such as toilet paper rolls, would run out of stock, because they were mostly produced in China, where many factories had been closed since the end of January.[4] This rumor was even repeated in newspapers and on television, causing panic buying and hoarding. As a result, sales of toilet paper rolls increased by 134.5% in February compared to the same month in 2019, and they were out of stock in many shops until the end of March.

Importantly, both rumors spread despite the absence of evidence. The Consumer Affairs Agency issued a statement on false and exaggerated labeling of food products, including fermented soybeans, on March 10th. Regarding toilet paper rolls, the Japan Paper Association stated on February 28th that approximately 98% of the rolls were produced domestically. Even their key ingredient, pulp, does not depend on imports from China. The Ministry of Economy, Trade and Industry also announced on the same day that there were no problems with the supply chain.

2.2. Conceptual framework

How does social media influence users' behavior? Among various psychological models, the Protection Motivation Theory proposes that high risk perceptions and perceived coping abilities are essential to prompt individuals to take protective measures against health risks [21,22]. Risk perception describes how a person assesses the probability of and potential damage from a threat if he/she does not change their behavior. It is determined based on the perceived probability, severity, fear, and reward from a maladapted response.[5] Perceived coping ability is characterized by three subcomponents. The first, response efficacy, refers to perceptions of the effectiveness of a protective response. The second subcomponent is self-efficacy, that is, individuals' perceived ability to perform or carry out protective responses. The last is protective response cost, that is, the cost of taking the response including monetary, time, and effort factors.

Previous empirical studies demonstrate that this theory well explains the adoption of protective behaviors against infectious diseases, such as social distancing and vaccination [23–28].[6] Early research also shows that policy interventions to inform the public of the effectiveness of protective behaviors, such as good hygiene practices, increase the diffusion of such measures [29,30].

Social media can affect users' behavior by changing both perceptions. First, it can expose users to information about COVID-19 and make them more aware of the probability and severity of infection risks. Second, social media usage can also affect perceived coping ability by informing users about the effectiveness of protective measures, such as social distancing and wearing facemasks.

However, the behavioral impact of social media depends on the quantity and quality of exposed information. On the one hand, social media can raise users' risk perception and encourage protective behaviors, such as social distancing, if better information access mitigates their normalcy bias, i.e. the optimistic underestimation of risk perception [31]. On the other hand, it can also have the opposite effect by inundating users with an over-abundance of information that makes it difficult to find trustworthy sources and reliable guidance. This can cause cognitive overload that exacerbates the normalcy bias. Finally, if users are exposed to false information, they may take excessive or misguided protective measures.

[2] For example, the proportion of Facebook users are 43% in Japan, while it is 89% in the U.S [32]. (p160).

[3] See *IT Media Business Online*, March 19, 2020 (https://www.itmedia.co.jp/business/articles/2003/19/news053.html, accessed on June 24, 2020), and *The Mainichi*, March 2, 2020 (https://mainichi.jp/english/articles/20200302/p2a/00m/0na/004000c, accessed on June 24, 2020) for details.

[4] See *True Data*, March 27, 2020 (https://www.truedata.co.jp/news/release20200327, accessed on May 7, 2020) for details.

[5] Maladaptive responses, including ignoring an evacuation order and staying home, can generate intrinsic and extrinsic rewards such as physical pleasure and approval from community members.

[6] This theory has been widely applied in the literature on health behavior, including for disaster evacuations [53,54].

3. Methodologies

3.1. Survey design

This study uses data from an original, nationwide online survey.[7] Our survey was designed to collect data from around 2500 people in their 30s and 40s, the generation whose internet diffusion is among the highest [32] (p156). In the sampling process, 50,000 people were selected from the members of Rakuten Insight, one of the largest survey companies in Japan (2.2 million registrations). They were randomly selected based on quota sampling with regard to gender (two categories), age group (four 5-year categories), and location of residence (10 categories), so that the expected distribution of these characteristics among respondents was comparable to that of the Japanese population.

On March 25th, 2020, the invitation for the first wave of the survey was sent to 50,000 members by email. They were informed that participants would receive tokens for shopping at Rakuten.com as financial incentive, and that the survey would be closed once the required sample size was obtained. This first wave was closed on March 27th, 50 h after sending the invitation. Out of those who received the invitation, 3336 browsed the survey website, 2822 participated, and 2262 respondents answered all questions related to this study.[8] The first round of the survey collected information on socio-economic behaviors including social-distancing, demand for food and necessities, and use of social media.

On April 27th to May 7th, we re-surveyed the first-wave participants to collect further information on their social and psychological traits. A total of 1823 individuals participated in both waves, of which 1804 answered all questions related to this study. The attrition in the second wave is uncorrelated with social media usage. Table A1 presents the summary statistics of respondent characteristics.

3.2. Measures

3.2.1. Changes in social-distancing behavior

Our survey's first wave contains data on three social-distancing behaviors: frequency of face-to-face conversations per day, frequency of having lunch outside per week, and frequency of having dinner outside per week.[9] The transmission risk from these activities may depend on various factors, such as the use of masks and maintaining physical distance from others. However, we did not ask such detailed questions to mitigate the respondents' burdens and ensure a higher response rate. Information for each month since January to March 2020 was collected, based on recall. The dependent variables take unity if the respondents engaged in these activities less frequently in March than in January 2020.

3.2.2. Changes in demand for necessities and food

In the first wave, we inquired about changes in demand for eight products, such as toilet paper, fresh food, rice, and face masks, using the following question: "Did you change how much you sought to buy this item, compared to usual?" The answer options included (1) Less than usual, (2) Comparable, and (3) More than usual. Because only a few respondents answered (1), the dependent variable takes unity if the respondent answered (3), and zero otherwise. Importantly, we do not examine whether they successfully bought the items they sought, because of unobserved variation in the availability of these items due to stock shortages.

Among these, we use changes in demand for five items in our main analysis: face masks, disinfectant, books/games, toilet paper, and fermented soybeans. The first two items were officially endorsed by the government and frequently mentioned in social media. Books and games were neither officially encouraged nor widespread on social media. However, we include them in our analysis, because if social media spurred social distancing and time at home, then people may have demanded them more than usual. The last two items are included to examine responses to unconfirmed rumors spread on social media.

Regarding the remaining three items from our survey, that is, rice, fresh food, and preservative food, we use them for a falsification test. These items were less frequently mentioned on social media, and their demand should not differ between social media users and non-users.

3.2.3. Use of social media

Our independent variable of interest is the usage of social media. Our survey contains data on nine social media platforms, and we define that a respondent is a user of a particular platform if he/she uses it at least once a week in a typical week.[10] According to this definition, LINE (83%), Twitter (45%), Instagram (41%), and Facebook (36%) are particularly widespread among respondents (Figure A1). Although LINE, a Japanese app, is the most popular, people use it mainly to send personal messages to their family, friends, and colleagues, rather than sharing information [32] (p165). Therefore, we do not use it in the empirical analysis. The diffusion rates of the remaining five platforms are less than 10%, and therefore, we do not use them in our analysis either. Hence, we construct three binary variables for the users of Twitter, Facebook, and Instagram.

3.2.4. Personality traits

Two types of personality variables are used as covariates to control for heterogeneity in individual characteristics. The first is the Big 5 personality traits, which quantifies individuals' neuroticism, extraversion, openness, agreeableness, and conscientiousness. We employ the Ten Item Personality Inventory to elicit these traits from 10 questions. This test was originally developed by Gosling et al. [33] and modified into a Japanese version by Oshio et al. [34].

Second, we measure attitudes towards risk with the following question: which of the following two sayings characterizes you better, "A: *nothing ventured, nothing gained*" or "B: *a wise man never courts danger*"? The answer options include (1) B, (2) Lean B, (3) Neutral, (4) Lean A, and (5) A. A lower score indicates greater risk aversion. This question is frequently used in the social survey literature [35,36] (p142) and draws from earlier work in the United States.

3.3. Estimation model

We employ Hainmueller's [37] entropy balancing model to eliminate the effects of differences in observed characteristics between social media users and non-users. An advantage of this model is that, in contrast to similar approaches such as propensity score methods, it is less prone to misspecifications of the propensity score model.

[7] A potential drawback to the use of online survey data is sample selection. However, we chose this approach because it was difficult to conduct either a paper-and-pencil mail survey or an in-person survey in a timely manner, due to the spread of COVID-19.

[8] See Shoji et al. [40] for discussion about the representativeness of the sample.

[9] For conversations, we asked the following question: "On a typical day, with how many people do you have face-to-face conversation in your daily life and job?" The answer options included: (1) Rarely, (2) 1 to 2, (3) 3 to 5, (4) 5 to 10, (5) 11 or more, (6) do not want to answer. For eating out, we asked: "On a typical week, how often do you dine out for lunch/dinner per week?" The answer options included: (1) Rarely, (2) 1 to 3, (3) 4 to 6, (4) everyday, (5) do not want to answer.

[10] Although exposure to information related to COVID-19 can vary even among social media users, due to their frequency of usage and type of information searched, we examine the average impact of having a social media account, given the difficulty in collecting such detailed information. To exclude inactive users, we consider those who use social media less than once a week as a non-user.

Specifically, we estimate the following weighted least square model:

$$\Delta Y_{ip} = \beta_0 + \beta_1 SMU_{ip} + \beta_2 X_{ip} + \delta_p + \varepsilon_{ip}, \quad (1)$$

where ΔY_{ip} denotes the changes in demand for necessities and social-distancing behavior of individual i in prefecture p.[11] SMU_{ip} takes unity if i uses a social media platform at least once a week, and zero otherwise. X_{ip} denotes the pre-pandemic respondent characteristics listed in Table A1, such as demographics, socio-economic status, social-distancing behavior in January 2020, and socio-psychological traits. Finally, δ_p denotes the prefecture fixed effects. Standard errors are clustered at the prefecture level to correct for the correlation of residuals. We estimate this model to examine each of Twitter, Instagram, and Facebook separately.

In this model, the observations are weighted by 1 for social media users. The weight for non-users is computed non-parametrically, so that the first and second moments of all pre-pandemic observed characteristics (Table A1) are balanced between users and non-users. In this method, coefficient β_1 estimates the average treatment effect on the treated (ATT), i.e. social media users.

An underlying assumption of the model is selection-on-observables. Put differently, unobserved determinants of social media use that are correlated with the outcomes will cause the estimation results to be biased. In particular, individuals' social network size and socio-economic status may affect both social media use and behavioral patterns. However, because our dependent variables are first differenced, the impact of unobserved characteristics on pre-pandemic product demand and social-distancing levels is cancelled out. Furthermore, because the covariates include the respondents' personality traits (Big 5), such as extraversion and agreeableness, as well as their pre-pandemic income and occupation, our model controls for their effects on behavioral changes during the pandemic. Finally, to test the severity of potential bias, we conduct a falsification test in the next section. Therefore, the bias driven by selection-on-unobservables should play a limited role, if any.

4. Results

4.1. Summary statistics

Fig. 1 presents the summary statistics of social-distancing behavior. Because the Japanese government did not legally restrict or monitor individuals' activities, only 10–15% of respondents voluntarily took social-distancing behavior as of March 2020. Fig. 2 presents the increases in demand for necessities and food. Although around 50% and 30% of respondents tried to buy more face masks and disinfectant, respectively, changes in demand for other products were smaller. An intriguing pattern is that compared to other goods, the demand for toilet paper rose strikingly.

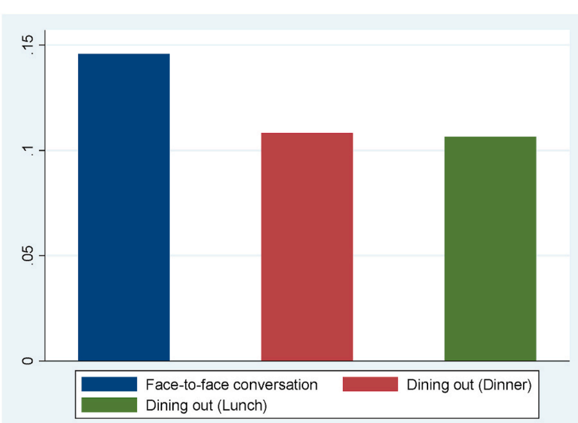

Fig. 1. Proportion of respondents who reduced social activities from January 2020 to March 2020.

4.2. Behavioral impact of social media

In this subsection, we present the results of the entropy balancing model. Figure A2 depicts the Kernel densities of entropy balancing weights for each social media platform. They mostly range from zero to three, suggesting that our results are not sensitive to outliers whose weight is too high. After conducting the weighting, the first and second moments of all covariates are balanced, supporting the validity of our approach (Table A1).

Table 1 shows the impact of using Twitter, Instagram, and Facebook. The dependent variables consist of activities encouraged by the government, such as social distancing, using disinfectant, and wearing face masks, and activities that were not encouraged by the government, namely purchases of fermented soybeans and toilet paper. First, social media usage has positive effects on the protective measures encouraged by the government. Columns (1) and (3) show that Twitter users are more likely to reduce the frequency of face-to-face conversation during the infection spread by 4.0% points and lunching out by 2.8% points. Given the low means of the dependent variables, these effects are large in magnitude. For example, Column (1) suggests that 16.7% of Twitter users reduced the frequency of face-to-face conversation in March. Had they not used social media, this would have been only 12.7%. Twitter usage also increases demand for books and games (Column 4). This is presumably because of the increase in time spent at home, although the purchase of books and games were not directly encouraged by the government. Furthermore, Twitter usage increases demand for disinfectants (Column 5). The results do not change qualitatively in the analyses of Facebook and Instagram (Panels B and C). Finally, in contrast to these positive and significant effects, the impact on face masks is mixed. (We explore this point further in the Conclusion section.)

Second, we find that social media users respond to unconfirmed rumors as well. They are more likely to increase demand for fermented soybeans during the infection spread. In particular, the impact of Instagram is as large as 5.3% points (Column 15). While 11.6% of Instagram users increased demand, this would have been only 6.3% had they not used it. By contrast, the impact on toilet paper is unstable across columns.

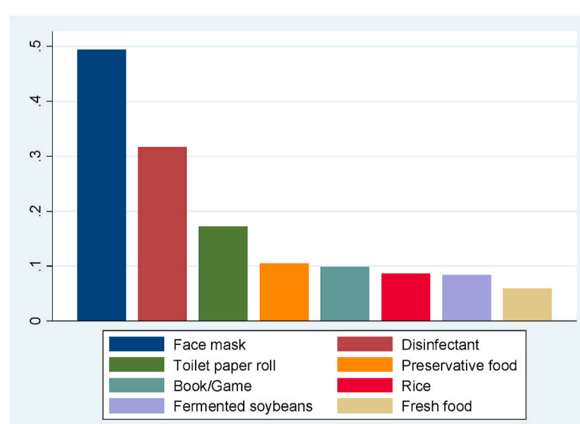

Fig. 2. Proportion of respondents whose demand for products increased from January 2020 to March 2020.

[11] Prefectures are the main unit of subnational government in Japan.

Table 1
Behavioral impact of social media use.

	Reducing the frequency of:			Increasing the demand for:				
	Face-to-face conversation	Dining out: dinner	Dining out: lunch	Books/ games	Disinfectant	Face mask	Fermented soybeans	Toilet paper rolls
Encouraged by the government?	Yes	Yes	Yes	No	Yes	Yes	No	No
Panel A:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Twitter	0.040**	0.022	0.028**	0.058***	0.049***	0.019	0.024*	0.027*
	(0.018)	(0.015)	(0.013)	(0.019)	(0.016)	(0.021)	(0.014)	(0.015)
Mean Dep. Var. among users	0.167	0.126	0.127	0.138	0.337	0.504	0.096	0.192
Counterfactual	0.127	0.104	0.099	0.080	0.288	0.485	0.072	0.165
Observations	1804	1804	1804	1804	1804	1804	1804	1804
Panel B:	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Instagram	0.046**	0.037**	0.043***	0.044***	0.081**	0.067**	0.053***	0.033
	(0.019)	(0.016)	(0.015)	(0.015)	(0.031)	(0.031)	(0.014)	(0.023)
Mean Dep. Var. among users	0.182	0.145	0.130	0.130	0.395	0.565	0.116	0.219
Counterfactual	0.136	0.108	0.087	0.086	0.314	0.498	0.063	0.186
Observations	1804	1804	1804	1804	1804	1804	1804	1804
Panel C:	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Facebook	0.044	0.030**	0.008	0.032*	−0.013	−0.011	0.039***	−0.038*
	(0.027)	(0.014)	(0.023)	(0.017)	(0.023)	(0.028)	(0.014)	(0.022)
Mean Dep. Var. among users	0.197	0.148	0.140	0.129	0.332	0.512	0.109	0.167
Counterfactual	0.153	0.118	0.132	0.097	0.345	0.523	0.070	0.205
Observations	1804	1804	1804	1804	1804	1804	1804	1804

The coefficients from the entropy balancing model are reported. All specifications control for the covariates used to estimate the entropy balancing weights. The counterfactual is defined as the difference between the mean dependent variable and the average treatment effect. Standard errors clustered at the prefecture level are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.3. Falsification test

One possible concern is that the increase in demand for fermented soybeans simply captures the effect of greater time spent—and thus food consumed—at home. Another potential issue is that the results may be driven by selection-on-unobservables. To test the severity of these effects, we estimate the impact of social media on demand for rice, fresh food, and preserved food. These items were less frequently mentioned in social media, but their demand should also rise with time spent at home. Therefore, if the estimated impact on fermented soybeans is indeed attributed to social media, the impact on these items should be zero. Table A2 confirms that the coefficient of social media use is small in magnitude and statistically insignificant.

5. Discussion

Using original online survey data and the entropy balancing model, we evaluated the impact of social media usage on individual behavior during the initial phase of the COVID-19 pandemic in Japan. We find that there are both bright and dark sides to information dissemination on social media. The bright side is that it encourages users to take protective measures officially endorsed by the government based on scientific evidence, such as social distancing and use of disinfectants. A likely mediator underlying our results is the increase in perceptions of infection risks and coping ability. This is in line with earlier studies which have provided evidence on the relationship between information, risk perception, and health behavior during the COVID-19 pandemic [38–41].

However, social media also has a dark side. Users take measures which are not grounded in scientific evidence, such as eating fermented soybeans. Admittedly, the negative consequences of this reaction may be small, as fermented soybeans are neither costly nor harmful to health. However, policymakers should be still mindful that the spread of rumors on social media may trigger panic buying and abrupt product shortages. In fact, around 30% and 20% of our respondents reported that they could not buy toilet paper rolls and fermented soybeans as much as they wanted, respectively. There is a long history of societies suffering from the spread of rumors and panic buying during emergencies, such as the 1943 Bengal famine and the 1923 Great Kanto (Japanese) earthquake [42,43]. Our study suggests that these problems still exist today, and that they may become exacerbated in the future with the continuing diffusion of social media.

Our findings make the following contributions to the literature on disaster communication. Previous studies have argued that the lack of reliable information is the central driver of both non-responses and wrong responses to emergencies [1–4]. However, the diffusion of the internet and social media worldwide may make this issue less salient in explaining current/future individual behavior, particularly in developed countries. Instead, we show that the increase in information access through social media has potential drawbacks. Social media users are exposed not only to information grounded in scientific evidence, but also to rumors from unreliable sources that contain misinformation, presenting an obstacle to appropriate responses. As such, researchers should be cognizant of the divergent effects of information access on emergency responses before and after the diffusion of social media. In addition, a new decision-making theory incorporating this change is also required.

6. Conclusion

The following policy implications can be derived. First, social distancing can be an effective tool to reduce risks of infectious diseases [44–47]. However, it is difficult to achieve sufficient levels of distancing in general [48], and the level of distancing can vary with individuals' socio-economic status, personality, and cultural and religious backgrounds [49–51]. This raises a new question about which policy interventions encourage social distancing effectively. This study contributes to this argument by showing that individuals' social-distancing behavior changes with their information exposure.

Second, despite the importance of information exposure in encouraging protective behavior, previous studies have emphasized the negative impact of social media on users' responses to COVID-19. Using data collected in Ireland, the U.K., and the U.S., Allington et al. [17] and Roozenbeek et al. [19] find a significant relationship between social media usage and susceptibility to misinformation about COVID-19. Islam et al. [18] show that it is also associated with panic buying in the U.S., China, India, and Pakistan. In Iraq, social media is found to have spread fear and panic, generating a potential negative effect on users' mental health [16]. However, policymakers should not conclude that social media is inherently harmful. As shown in this study, it has both bright and dark sides. Policy interventions should seek to minimize the impact of the dark side and maximize that of bright side, rather than limiting social media interactions generally.

Third, the behavioral impact of exposure to unreliable information is often seen as depending on the information receiver's sense of judgement. However, this study has shown that people respond to scientifically unconfirmed rumors even in Japan, where internet diffusion is among the highest, suggesting that it may be a challenge to rely on the receivers' judgement. Therefore, to mitigate the negative impact of information exposure, it is essential for policymakers to control the spread of unreliable information, while encouraging the diffusion of reliable information. For example, the WHO has been managing the infodemic through a wide range of methods, including active engagement on social media platforms [9]. These efforts may be effective.

This study is subject to the following two limitations. First, our results show that demand for face masks and toilet paper did not change with social media use, but we fail to provide a clear explanation for this. There are three potential interpretations. First, since the unavailability of face masks and toilet paper was reported even in the mass media, both social media users and non-users may have reacted symmetrically. Second, some social-media users were suspicious of the effectiveness of face masks, and so demand for them may have been less than that for disinfectants. The third interpretation is that government responses to these items were quicker than that for disinfectants and fermented soybeans. Face masks and disinfectant were running out of stock in many shops, and some people resold them at a higher price on the internet. To address this problem, the government prohibited the reselling of face masks on March 5th, but the proscription on reselling disinfectant came as late as March 22nd. Similarly, rumors regarding both fermented soybeans and toilet paper shortages started to spread around the same time in late February, but the announcement by the government regarding toilet paper was on February 28th, while that for fermented soybeans was on March 10th. Early responses regarding face masks and toilet paper may have corrected individuals' perceptions about the availability of items promptly, reducing speculative, precautionary purchases. Although it would be insightful to test which of these interpretations best explains the observed pattern, this is beyond the scope of this study. Addressing this question requires further research to uncover detailed information about the content and timing of information that people obtained from social and mass medias.

The second limitation is that our data does not cover those aged over 50 with higher mortality risks. Given that their behavioral patterns could differ from younger individuals, we should be careful in generalizing our findings to other generations or other regions. Further studies using data collected from older demographics and other countries are encouraged to clarify these points.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2020.102034.

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