



# The role of nudge-based messages on the acceptability and download of COVID-19 contact tracing apps: survey experiments

Hirofumi Kurokawa<sup>1</sup> · Shusaku Sasaki<sup>2</sup> · Fumio Ohtake<sup>2,3</sup>

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## Abstract

We investigated the effectiveness of nudge-based messages in promoting the download of contact tracing apps, particularly in the context of low uptake due to serious distrust in the product. Even in the presence of distrust towards the app, promoting downloads can be a beneficial means of preventing infection spread at a stage before pharmacological interventions, such as vaccines or therapeutic drugs, are established. Two studies were conducted with Japanese residents who had not yet downloaded any contact tracing apps. Study 1, based on smartphone location data, targeted 2690 individuals who had gone out despite public instructions to stay at home. Study 2 targeted 4126 individuals whose web-search behavior could be tracked. Nudge-based messages did not increase app downloads in either study. In Study 1, where participants were considered non-cooperative, these messages also did not enhance acceptability such as willingness to accept and intention to download the apps. Conversely, in Study 2, a more representative sample, nudge-based messages emphasizing altruism, economic losses, and medical losses increased app acceptability, although they did not increase searches related to the app's keywords.

**Keywords** Nudge · Contact tracing apps · COVID-19 · Survey experiment

**JEL Classification** C93 · D01 · D91 · I12

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✉ Hirofumi Kurokawa  
kurokawa@kwansei.ac.jp

<sup>1</sup> School of Economics, Kwansai Gakuin University, 1-155 Uegahara Ichiban-cho, Nishinomiya, Hyogo 662-8501, Japan

<sup>2</sup> Center for Infectious Disease Education and Research (CiDER), Osaka University, 2-8 Yamadaoka, Suita City, Osaka 565-0871, Japan

<sup>3</sup> Graduate School of Economics, Osaka University, 1-7, Machikaneyama, Toyonaka, Osaka 560-0043, Japan

## 1 Introduction

During the coronavirus disease 2019 (COVID-19) pandemic, non-pharmacological interventions played a pivotal role in reducing the spread of the virus before the development of vaccines and therapeutic drugs. Beyond mandatory measures like lockdowns aimed at reducing interpersonal contact, individuals were encouraged to voluntarily adopt infection-prevention behaviors such as maintaining a social distance from others, wearing masks, and practicing hand hygiene. Additionally, many countries sought the development of contact tracing apps to facilitate the early detection of contact with infected individuals, encouraging testing and self-isolation after such contact was detected. In the early stages of the pandemic, Ferretti et al. (2020) estimated that COVID-19 transmission could be restricted if at least 60% of the population downloaded contact tracing apps. In the United Kingdom, an increase of 1% in the number of app users was estimated to reduce infections by 2.3% (Wymant et al., 2021). However, as app downloads are voluntary, rather than mandatory, download rates were low in many countries. As of October 2022, only 46.8% (National Health Service, 2022), 41.3% (Robert Koch Institute, 2022), and 32.6% (Ministry of Health, Labour and Welfare [MHLW], 2022) of the populations of the United Kingdom, Germany, and Japan, respectively, had downloaded a contact-tracing app.

Acceptance of the app is associated with a variety of factors (Villius Zetterholm et al., 2021; Oyibo et al., 2022). Distrust is a factor contributing to the low download rate, related not only to privacy concerns (Altmann et al., 2020; Kostka & Habich-Sobiegalla, 2022; Walrave et al., 2021; Williams et al., 2021) but also extending to concerns about the app's accuracy (Thomas et al., 2020; Sharma et al., 2020). Due to the rapid development of contact tracing apps, frequent flaws have occurred. For instance, in Japan, a flaw in February 2021 resulted in users of Android devices not being notified even if they had been in contact with a confirmed positive case (Digital Agency, 2023a, b). In a situation where pharmaceutical interventions such as vaccines and therapeutic drugs are not available, encouraging as many people as possible to download the app, despite low public trust, can be effective in mitigating the spread of the infection. Nudge-based messages have been utilized to promote voluntary infection-prevention behaviors (Jordan et al., 2021; Lunn et al., 2020; Sasaki et al., 2021), and vaccination (Dai et al., 2021; Sasaki et al., 2022; Volpp et al., 2021), but the question of whether such messages can also be effective in promoting the download of contact tracing apps in situations where there is a low download rate due to distrust has yet to be examined. This study aims to verify whether nudge-based messages can promote the download of contact tracing apps even in situations where there is a low download rate due to distrust in the app.

We conducted two survey experiments in March 2021 following the occurrence of the flaws. Data were collected from people who had not downloaded contact tracing apps. The first group consisted of individuals not complying with the Japanese government's stay-at-home orders (Study 1), visiting shopping districts and putting themselves at risk of contracting and spreading the disease.

For such a group, downloading contact tracing apps could help reduce the overall spread of the disease. The second group included individuals who were traceable through their web-searching behavior (Study 2). We assessed whether nudges were linked to app downloads and whether they affected the process of information collection. This may clarify the mechanism by which nudges lead to app downloads based on information collection.

In this study, messages emphasizing altruism, monetary incentives, health-care system losses, and economic losses were prepared, and their impact on promoting app downloads was examined. However, no message was found to have a significant effect on promoting downloads in Studies 1 or 2. Furthermore, in Study 1, which focused on individuals who were non-compliant with stay-at-home orders, there was no impact on acceptability measures such as willingness to accept and intention to download the apps. In Study 2, targeting a more general population, messages highlighting altruism, economic losses, and health-care losses increased acceptability of apps download, though these messages did not contribute to an increase in searches for keywords associated with the app.

This study contributes to the literature on the acceptance of contact tracing apps in the COVID-19 pandemic. Acceptability of contact tracing apps is correlated with attitudes such as perceived health threat (Altmann et al., 2020), experience of and access to technologies (Altmann et al., 2020; Von Wyl et al., 2021), performance expectancy (Walrave et al., 2021), perceived benefits (Kostla & Habich-Sobiegalla, 2022), as well as understanding (Thomas et al., 2020; Williams et al., 2021). Sociodemographic characteristics such as age and gender (Altmann et al., 2020; Von Wyl et al., 2021) and personality traits such as pro-sociality (Li et al., 2021) have also been considered. Motivations for downloading apps differ across generations (Shoji et al., 2021). Shoji et al. (2022) suggested a correlation between lower levels of self-control and increased app downloads, implying the potential use of the app as a commitment device.

However, few studies have experimentally tested whether nudges can effectively promote the download of contact tracing apps. Videos containing self-interest or altruistic messages were found to be effective in transmitting knowledge but less effective in promoting the download of contact tracing apps (Munzert et al., 2021). Messages emphasizing a combination of self-interest and altruism stimulated more interest in contact tracing apps than messages emphasizing self-interest alone or altruism alone (Jordan et al., 2021). Additionally, an altruistic message without an emphasis on social norms increased click-through rates to contact-tracing app sites (Sharif et al., 2021). Amid numerous studies exploring factors correlated with acceptability, we provide one of the scarce pieces of evidence examining the potential for nudges to promote acceptance of such apps.

The remainder of this paper is organized as follows: Sect. 2 provides background information on contact tracing apps in Japan and outlines the experimental design of this study. Section 3 reports the results, while Sect. 4 discusses our findings, the study's implications, and our conclusions.

## 2 Methods

### 2.1 COVID-19 contact-confirming application (COCOA)

The Japanese contact tracing app, COCOA, was launched on June 19, 2020 (Digital Agency, 2023a). With user consent, the app utilizes the smartphone's Bluetooth sensor to detect and record the app IDs of other users within 1 meter for more than 15 minutes (MHLW, 2021). Bluetooth functionality must be enabled to use COCOA. The app's primary functions include confirming contact with a COVID-positive person and recording when a user tests positive for COVID-19. Privacy is maintained, as the app does not disclose details of when and with whom one has been in contact. Unlike location-based contact verification apps in India and Israel, COCOA is a Bluetooth-based contact verification app (Digital Agency, 2023b). Among Bluetooth-based apps, COCOA is anonymous, similar to those used in European countries, in contrast to personally identifiable apps in Singapore and Australia. In the event of a user confirming a COVID-19 infection and voluntarily reporting it through the app, other users in close contact within the previous 14 days receive a warning message about the user's infection. Recipients of the message are eligible for a free reverse-transcription polymerase chain reaction test.

The app achieved 17 million downloads (13.5% of the total population) within three months of its initial release in June 2020, surpassing the download rates of apps from private companies. The download numbers continued to steadily increase, reaching approximately 25 million downloads (20.0% of the total population) by February to March 2021 when this study was conducted. On February 3, 2021, the MHLW announced a notification issue affecting Android devices; a new version released on February 18 resolved this problem. In September 2022, a comprehensive review of the registration of positive cases was conducted, resulting in a modification where only individuals at high risk of severe outcomes, such as older adults, were registered as positive cases. Consequently, the number of registered positive cases was restricted, and COCOA was scheduled to cease functioning in November 2022. As of November 16, 2022, the day before the final updated version was released, COCOA recorded 41,287,054 downloads (32.8% of the total population) and 3,694,068 reported positive cases of COVID-19.

### 2.2 Experimental design

In this study, we conducted two survey experiments targeting individuals who had not downloaded the COCOA app. As the study was an online survey, informed consent was obtained in an electronic format, and only those who agreed proceeded to complete the survey. In the first survey, participants were randomly assigned to either the control message group or the nudge-based message group. Participants in Study 1 were randomly assigned and stratified based on age, sex, and area, while participants in Study 2 were randomly assigned and stratified based on age and sex. The survey included questions related to contact tracing apps, such as the intention

to download, willingness to accept app downloads, and knowledge about contact tracing apps, along with socioeconomic variables like education and income. Following these questions, participants in each group were exposed to different messages. Subsequently, participants were re-evaluated on their intention and willingness to download the app after exposure to the messages. We investigated whether participants' attitudes changed after receiving the nudge-based messages. A follow-up survey was conducted approximately one week later to confirm the app download status. Only participants responding to the follow-up were included in the analysis. The survey flow was consistent between Studies 1 and 2, but the participant pools were distinct.

In Study 1, participants were recruited through a smartphone research company. GPS data obtained from this company allowed us to identify individuals aged 20 to 59, who were outside their homes in Tokyo (Shinjuku, Shibuya, and Ikebukuro) and Osaka (Kita and Minami) shopping districts at 8 p.m. or later between February 3 and 23, 2021, during a state of emergency in Japan (Fig. 1). Participants were selected from those at high risk of contracting and spreading the disease and who agreed to provide GPS data and participate in a GPS-based survey when registering with the research company. The first survey took place from March 2 to 15, 2021, generating 3115 responses, and the follow-up survey occurred from March 22 to 23, 2021, with 2690 respondents included in the main analysis. The attrition rate was approximately 13.6% (see Sect. 2.5 for details on the attrition).

In Study 2, participants were recruited through Rakuten Insight, a research company, from a sample pool of 2.2 million individuals aged 20 years or older with a recorded Internet search history. The first survey was conducted between February 26 and March 2, 2021, resulting in 5000 responses, and the follow-up survey occurred from March 5 to 15, 2021, with 4126 respondents included in the main analysis. The attrition rate was approximately 17.5% (see Sect. 2.5 for details on the attrition).

Here, to gain insights into the background characteristics of our sample regarding the contact tracing app, we provide an overview of the app's understanding and the reasons for not downloading it in the samples from Studies 1 and 2 (see Appendix A for detail). The average understanding of the contact tracing app did not differ between Studies 1 and 2, with a 41% correct response rate out of six questions. However, in Study 1, 90% of the participants misunderstood that GPS-based location information was being obtained. The primary reasons for not downloading the app included the perception that it was not mandatory and concerns about the app's reliability.

### 2.3 Nudge-based messages

In the final section of the first survey, participants were presented with nudge-based messages. These messages varied based on the assigned group, comprising one control message and four distinct nudge messages (Fig. 2). For all messages, the following text was displayed:

“The early detection of infected people is important to prevent the spread of COVID-19. An increase in the number of users of the contact-tracing app COCOA is expected to help prevent the spread of infection.”

While the common message remained constant, specific messages were tailored for each group. The control group received the following message utilized by the MHLW, the entity operating COCOA:

### 2.3.1 Control message

“Let us install the contact-tracing app COCOA to protect you, your loved ones, and your community.”

The control message already included elements of the first type of nudge, “emphasis on altruistic interest.” Although altruistic messages have proven effective in promoting infection-prevention behaviors and vaccination (Dai et al., 2021; Jordan et al., 2021; Lunn et al., 2020; Sasaki et al., 2021, 2022; Volpp et al., 2021), this control message also emphasized self-interest, potentially crowd out the motivation to assist others (Gneezy & Rustichini, 2000) and hindering downloads. Therefore, in the altruistic message, we solely emphasized altruistic benefits to explore their effectiveness while eliminating concerns about crowding out the motivation to help others.

### 2.3.2 Altruistic message

“Installing the contact tracing app COCOA can help protect the lives of those you come across.”

The financial incentive message concentrated on individual economic benefits that might make people more willing to download the app (Frimpong & Hellinger, 2021; Jonker et al., 2020). In fact, downloads increased when financial incentives were offered (Munzert et al., 2021). While Japan lacks direct financial incentives for contact tracing app downloads, some local governments and businesses provide discounts on vaccinations and benefits for app downloads (Liquor Mountain 2022; @Press, 2020). Thus, a message highlighting indirect financial incentives was prepared.

### 2.3.3 Financial incentive message

“Install the contact tracing app COCOA and receive discounts, privileges, and other benefits at restaurants, hotels, etc.”

The medical-loss and economic-loss messages focused solely on the impact on healthcare services and the economy, respectively. During a pandemic, the trade-off between healthcare and the economy is a predominant subject of debates (Carrieri et al., 2021). Enforcing strict restrictions on physical contact, such as through lockdowns, can effectively curb the spread of infection and alleviate the burden on healthcare services

during a pandemic. However, these measures may inflict substantial economic damage. Conversely, if efforts are made to support the economy without restricting the movement of people, the infection may persist, leading to strain on healthcare services. Hence, early detection of infections can aid in preventing the spread of the disease and mitigating adverse impacts on both healthcare services and the economy. Contact tracing apps play a pivotal role in promptly identifying infected individuals. By utilizing a loss frame that emphasizes the negative consequences of not using contact tracing apps, we aimed to tap into loss aversion (Tversky & Kahneman, 1981), where individuals perceive a loss approximately twice as much as a gain. This study does not solely focus on the framing effect but rather on whether emphasizing medical or economic losses is more effective given loss aversion. Similar studies have explored nudge-based messages using medical and economic losses (Moriwaki et al., 2020).

### 2.3.4 Medical-loss message

“With fewer people installing the contact tracing app COCOA, the infection spread will continue, and some people will be at risk of death due to the lack of hospital beds.”

### 2.3.5 Economic-loss message

“Currently, owing to the spread of the disease, economic conditions are deteriorating, and the number of unemployed people is increasing. With fewer people installing the contact tracing app COCOA, the spread of infection will continue, and economic conditions may further deteriorate.”

## 2.4 Outcomes

### 2.4.1 Downloads

The primary outcome of this study was ascertaining whether contact tracing apps have been downloaded. The Japanese contact tracing app COCOA was launched on June 19, 2020, and as of February 1, 2021, approximately 24.56 million (19.5%) of Japan's total population of 125.9 million had downloaded the app. The first survey targeted individuals who had not downloaded the app, and a subsequent follow-up survey, conducted about one week later, aimed to verify participants' app downloads. Given the self-reported nature of these surveys, there was a potential for upward bias associated with social desirability. However, this bias was considered minimal, as we recruited participants who had not yet downloaded the app in the first survey.

### 2.4.2 Acceptability

The secondary outcome of this study was determining the acceptability of contact tracing apps, based on participants' download intention and willingness to accept the use of contact tracing apps. Acceptability was evaluated both before and after

the presentation of nudge-based messages. Consequently, the primary outcome, downloading, was action-oriented, while the secondary outcome, acceptability, was awareness-based. We hypothesized a decision-making process where acceptability, influenced by nudge-based messages, subsequently translates into the concrete action of downloading. The first survey included nudge-based messages and inquired about the app's acceptability. Approximately one week later, in a follow-up survey, participants were asked whether they had downloaded the app. This design aimed to verify whether the nudge impacted awareness before driving a specific behavior. Even if the nudge did not prompt downloading behavior, it might have influenced the acceptability of contact tracing apps. Identifying the effective nudges on acceptability contributes to refining messaging strategies.

Download intention was subjectively assessed through participants' responses to the question, "Currently, how willing are you to install COCOA in the near future?" using a five-point scale (0 = "I definitely do not want to install it," 1 = "I may not want to install it," 2 = "I cannot say either way," 3 = "I may install it," and 4 = "I definitely want to install it"). This question format aligns with established approaches (Altmann et al., 2020; Villius Zetterholm et al., 2021).

Concerning participants' willingness to accept downloading the app, participants were prompted to imagine a scenario in which they would receive a financial incentive by showing evidence of app download at a government office. The survey then gauged participants' willingness to download the app under such incentivized conditions. Financial incentives are known to be directly correlated with downloads (Frimpong & Helleringer, 2021; Jonker et al., 2020; Munzert et al., 2021) and are anticipated to be influential in driving public implementation. The results of the willingness to accept (WTA) variable in this study provide insights into determining appropriate financial incentive amounts.

The question formats varied between Studies 1 and 2 due to differences in the specifications of the research companies employed. In Study 1, participants were asked about the minimum financial incentive that would motivate them to install the app, with response options ranging from "0 yen" to "more than 5000 yen" or "regardless of the amount, I will not install the app." The lowest selected amount was considered participants' WTA, and for simplicity, "more than 5000 yen" and "regardless of the amount" were both categorized as 6000 yen. In Study 2, participants were presented with various incentive amounts ("0 yen" to "5000 yen") and asked whether they would install the app for each amount. The threshold at which their response changed from "will not install" to "will install" was defined as their WTA. Essentially, those who would not install the app for any incentive amount in Study 2 fell into the categories of "higher than 5000 yen" and "regardless of the amount" in Study 1. Despite slight differences in question formats, these variables can be considered similar.

### 2.4.3 Search behavior (only in study 2)

Study 2 also set search behavior as a secondary outcome. While acceptability evaluated awareness leading to app downloads, search behavior assessed the decision-making process of information search preceding such downloads. Some studies have



used website clicks about contact tracing apps as an outcome to explore the impact of nudges on app interest (Jordan et al., 2021; Sharif et al., 2021). Search behavior serves as an alternative indicator of interest in the apps. We determined whether individuals searched for keywords such as “COCOA,” “COCOA app,” “contact-confirming app,” “contact app,” “contact confirmation app,” and “corona app,” which are related to contact-tracing apps. Data on search behavior were collected during two periods: two weeks before the first survey (February 12, 2021, to February 25, 2021) and one week after the first survey (February 26, 2021, to March 4, 2021). We created a dummy variable, coded as 1 if these keywords were searched and 0 if not. As search behavior data could only be obtained when a user logged into the web search page operated by the company in the research company’s group, the search behavior evaluated here may have been underestimated, as users might have searched for these keywords without logging in or using other search pages.

## 2.5 Descriptive statistics

Tables 7 and 8 present descriptive statistics across groups. Individual characteristics were largely balanced across the groups in both Studies 1 and 2. However, while we verified the balance of all individual characteristics in the first survey (Tables 9 and 10), income was not balanced across the groups in Study 2. The following paragraph provides a detailed examination of the attrition occurring in both Studies 1 and 2.

In Study 1, attrition rates were 13.8% in the control group, 15.5% in the altruistic group, and 11.6% in the incentive group, with these rates differing across the groups ( $p = 0.04$ ). Table 11 compares the characteristics of the sample that completed both surveys with those of the drop-out sample that only responded to the first survey. While no differences in many individual characteristics were observed, women were more frequently included in the drop-out sample in the control and incentive groups. In the altruism group, those with lower incomes were more frequently included in the drop-out sample. Despite differences in drop-out rates between groups, the sample used in the main analysis remained balanced, as indicated in Table 7. The full sample responding to the first survey was also balanced (Table 9).

In Study 2, attrition rates were 17.1% in the control group, 18.9% in the altruistic group, 17.9% in the incentive group, 17.3% in the medical-loss group, and 16.2% in the economic-loss group, with these rates not differing across the groups ( $p = 0.60$ ). The attrition rates did not differ significantly between groups, but as in Study 1, we compared the characteristics of the sample that completed the two surveys with those of the drop-out sample (Table 12). Women were less likely to drop out in the control group and more likely in the medical-loss group. In many groups, those who did not respond to income were more likely to drop out. People with lower incomes were more likely to drop out in the control group, whereas people with higher incomes were more likely to drop out in the incentive and medical-loss groups. Therefore, as shown in Tables 8, income was unbalanced between groups in the sample used for the main analysis. However, we confirmed that the entire sample responding to the first survey was balanced (Table 10).

In summary, random assignment in the first survey was successful in both Studies 1 and 2, but attrition rates differed between groups in Study 1, and the main sample in Study 2 was unbalanced regarding income. To ensure the robustness of our results, we addressed these imbalances and attrition rates.

## 2.6 Statistical analysis

We conducted the analysis using a difference-in-differences fixed-effects model, as we have data from two time points. For downloads, the two time points are the first survey and the follow-up survey. Not all individuals reported downloading the app in the first survey; some did so in the follow-up survey. Information on download intention and willingness to accept were collected twice, before and after participants were presented with nudge-based messages in the first survey. We applied multivariate regression analysis (using ordinary least squares for “download intention” and “WTA” and a linear probability model for “download” and “search behavior”) to investigate the impact of nudges on downloads, acceptability, and search behavior.

In addition to presenting results for the full sample, we also provide age-specific analyses to illustrate the heterogeneity of effects by age. Finally, a robustness check was conducted by directly controlling for covariates through regression analysis with the subsequent lags instead of panel data analysis. Given the income imbalance in Study 2, this approach aimed to confirm that directly controlling for covariates, including income, did not alter the primary results. In this specification, we employed the full sample and evaluated the effect of nudge-based messages on the app’s acceptability. As we had inquired about acceptability in the first survey, attrition was not a concern.

## 3 Results

### 3.1 Study 1

Table 1 presents the results of the difference-in-differences analysis with panel fixed effects. In Column 1, where the download dummy serves as the dependent variable, it is observed that, on average, 3.9% of the participants downloaded the app during the follow-up survey. However, it was not determined whether downloading was further encouraged in groups that (a) received nudge messages emphasizing altruism or (b) messages emphasizing financial incentives. On average, there was an increase in the intention to download the app following the presentation of the message, but the impact of nudges did not enhance participants’ intention to download (Column 2). There was no observable change in willingness to accept downloading the app before and after the message delivery (Column 3). To examine the connection between downloads and acceptability, Column 4 employs downloads as the dependent variable and considers WTA and intention as the independent variables. Interpreting the treatment effect becomes challenging when acceptability is included

**Table 1** Effect of nudges on the download and acceptability of contact tracing apps in Study 1

	Download (1)	Intention (2)	WTA (3)	Download (4)
Follow-up	0.039*** (0.006)	0.133*** (0.029)	- 9.101 (31.524)	0.040*** (0.007)
Follow-up × Altruism	0.009 (0.010)	0.009 (0.041)	- 9.525 (42.029)	0.009 (0.010)
Follow-up × Incentive	0.009 (0.010)	- 0.031 (0.040)	35.216 (41.523)	0.010 (0.010)
Intention				- 0.001 (0.005)
WTA				- 0.000 (0.000)
Constant	0.000 (0.002)	1.587*** (0.008)	3,527.286*** (8.341)	0.018 (0.022)
Number of participants	2690	2690	2690	2690
Number of observations	5380	5380	5380	5380

Robust standard errors are in parentheses

WTA means willingness to accept

\*\*\*denotes  $p < 0.01$ ; \*\*,  $p < 0.05$ ; and \*,  $p < 0.1$

in the estimation equation, as it introduces post-treatment bias. Nonetheless, it is beneficial to assess whether the relationship between acceptability and download aligns with expectations. Contrary to expectations, the relationship between intention and downloads was negative; in addition, the relationship between WTA and downloads was negative, as anticipated. However, neither relationship was statistically significant.

Table 2 presents the results of the analysis, dividing the sample into participants in their 20s and 30s and those in their 40s and 50s. The app downloading rates during the follow-up survey increased regardless of age (3.5% for participants in their 20s and 30s and 4.6% for those in their 40s and 50s). However, no additional promotional effects with nudges were observed in either age group. Following the presentation of the message, the download intentions of participants in their 20s and 30s increased on average, while there was no change in the download intentions of those in their 40s and 50s.

Table 3 displays an alternative specification of the estimation results as a robustness check. In this specification, we treated the data as cross-sectional rather than panel data. Consistent with Table 2, where a panel analysis was conducted, the relationship between nudge-based messages and the number of downloads was positive but not statistically significant (Column 1). Similarly, no evidence was found that nudge-based messages influenced download intention (Column 2) or willingness to accept (Column 3). Columns 4 and 5 were analyzed similarly using the full samples. In line with previous results, no significant effect of nudge-based messages on acceptability was observed.

**Table 2** Effect of nudges on the download and acceptability of contact tracing apps by age group (Study 1)

	Download		Intention		WTA	
	20–39	40–59	20–39	40–59	20–39	40–59
	(1)	(2)	(3)	(4)	(5)	(6)
Follow-up	0.035*** (0.008)	0.046*** (0.011)	0.173*** (0.035)	0.066 (0.049)	– 17.138 (40.204)	4.046 (50.840)
Follow-up × Altruism	0.018 (0.013)	– 0.005 (0.016)	0.030 (0.051)	– 0.019 (0.067)	1.046 (52.982)	– 26.598 (68.939)
Follow-up × Incentive	0.017 (0.012)	– 0.003 (0.016)	0.005 (0.050)	– 0.093 (0.068)	27.068 (55.277)	48.997 (61.513)
Constant	– 0.000 (0.003)	0.000 (0.003)	1.606*** (0.010)	1.556*** (0.014)	3,334.055*** (10.915)	3,839.689*** (12.853)
Number of participants	1662	1028	1662	1028	1662	1028
Number of observations	3324	2056	3324	2056	3324	2056

Robust standard errors are in parentheses

WTA means willingness to accept

\*\*\* denotes  $p < 0.01$ ; \*\*,  $p < 0.05$ ; and \*,  $p < 0.1$

**Table 3** Robustness check of the effect of nudges on the download and acceptability of contact tracing apps in Study 1

	Main sample			Full sample	
	Download	Intention	WTA	Intention	WTA
	(1)	(2)	(3)	(4)	(5)
Altruism	0.010 (0.010)	0.044 (0.036)	– 17.115 (41.070)	0.033 (0.033)	5.429 (37.045)
Incentive	0.009 (0.010)	– 0.001 (0.035)	30.138 (40.268)	– 0.001 (0.032)	34.949 (36.539)
Intention (pre-treatment)		0.478*** (0.020)		0.474*** (0.019)	
WTA (pre-treatment)			0.902*** (0.011)		0.902*** (0.010)
Constant	0.091** (0.039)	1.081*** (0.141)	552.256*** (163.347)	1.050*** (0.130)	468.514*** (148.572)
Individual characteristics	Yes	Yes	Yes	Yes	Yes
Number of observations	2690	2690	2690	3115	3115

Robust standard errors are in parentheses. Individual characteristics includes age, female dummy, income, schooling, married dummy, divorce dummy, and working status. \*\*\* denotes  $p < 0.01$ ; \*\*,  $p < 0.05$ ; and \*,  $p < 0.1$ . WTA means willingness to accept

### 3.2 Study 2

Table 4 displays the results of the difference-in-differences analysis with panel fixed effects. While we confirmed that 6.3% of participants downloaded the app during the follow-up survey, the impact of nudge-based messages on promoting downloads could not be verified (Column 1). Although the intention to download increased after message presentation, no additional nudge effect was identified (Column 2). However, in terms of willingness to accept, we observed a significant effect of nudges in further enhancing acceptability (Column 3). Following the message presentation, WTA decreased by 46.6 yen, on average. Moreover, altruistic, medical-loss, and economic-loss nudges resulted in reductions of 71.2 yen, 67.6 yen, and 65.2 yen, respectively. Financial incentive nudges exhibited additional acceptability-enhancing effects. Nevertheless, with regard to search behavior, there was no observed promotion of search behavior through surveys and nudge-based messages on contact tracing apps (Column 4). As anticipated, the relationship between willingness to accept and downloads was negative, while

**Table 4** Effect of nudges on the download and acceptability of contact tracing apps in Study 2

	Download (1)	Intention (2)	WTA (3)	Search (4)	Download (5)
Follow-up	0.063*** (0.008)	0.223*** (0.022)	- 46.562* (27.560)	- 0.000 (0.002)	0.060*** (0.008)
Follow-up × Altruism	0.000 (0.012)	0.037 (0.034)	- 71.194* (40.958)	- 0.004 (0.005)	- 0.001 (0.012)
Follow-up × Incentive	- 0.014 (0.011)	0.001 (0.036)	14.163 (35.952)	- 0.002 (0.003)	- 0.014 (0.011)
Follow-up × Medical	- 0.016 (0.011)	- 0.009 (0.033)	- 67.585* (36.523)	- 0.001 (0.004)	- 0.016 (0.011)
Follow-up × Economic	- 0.009 (0.011)	- 0.043 (0.034)	- 65.192* (37.883)	- 0.005 (0.004)	- 0.009 (0.011)
Intention					0.010* (0.006)
WTA					- 0.000 (0.000)
Search					0.073* (0.037)
Constant	0.000 (0.002)	1.590*** (0.006)	2799.200*** (5.877)	0.008*** (0.001)	0.005 (0.021)
Number of participants	4126	4126	4126	4126	4126
Number of observations	8252	8252	8252	8252	8252

Robust standard errors are in parentheses. \*\*\* denotes  $p < 0.01$ ; \*\*,  $p < 0.05$ ; and \*,  $p < 0.1$ . WTA means willingness to accept.

the relationship between intention to download, search behavior, and downloads was significantly positive (Column 5).

The samples were divided into age groups of 20–39 years old, 40–59 years old, and 60 years and older, and the results are presented in Table 5. No age-related differences were found for downloads, but age-related heterogeneity was observed for other outcomes. Economic-loss nudges had a counterproductive effect in promoting download intentions among those in their 20s and 30s, while financial incentive nudges had a counterproductive effect in promoting download intentions among those aged 60 and older. Similarly, altruistic and economic-loss nudges were counterproductive in promoting search behavior among individuals in their 20s and 30s. Although the value of WTA was highest for those aged 60 and older, and the value of intention to download was also highest, examining the correlations within age groups revealed the expected negative correlation between WTA and intention to download ( $r = -0.34$  for 20–39 years old,  $r = -0.41$  for 40–59 years old, and  $r = -0.44$  for 60 years and older). As both WTA and intention are subjective variables, between-group comparisons are not suitable. In within-group comparisons, WTA and intention were negatively correlated, as hypothesized.

Table 6 presents the estimation results with cross-sectional data as a robustness check. In line with Table 4, there was no evidence that any of the nudge messages promoted downloads (Column 1). This specification confirmed that nudge messages emphasizing altruism tended to increase download intention (Column 2). Messages of altruism, medical loss, and economic loss were confirmed to have a reducing effect on the amount of WTA, similar to the main results (Column 3). Column 4 shows that nudge messages had no effect on search behavior. The main results remained consistent even when the analysis was based on cross-sectional data rather than panel data. Columns 5–6 were analyzed similarly using the full samples. The analysis with fully balanced data without attrition confirmed the same results as before. Therefore, the primary finding is robust: Although nudge messages can increase download intention, they do not lead to downloads.

## 4 Discussion and conclusions

While some participants had downloaded the app during the follow-up survey, nudge-based messages had no observed effect in promoting downloads. In Study 1, which targeted individuals who did not comply with stay-at-home orders, nudges did not impact their download intention or willingness to accept downloads. However, Study 2 revealed the effectiveness of nudging in lowering the financial incentives required to promote participants' WTA, specifically for altruistic, economic, and medical-loss messages. However, for individuals aged 60 and above, nudges emphasizing financial incentives had an inverse effect on their intention to download and WTA. The promotion of web search behavior through nudges was not ascertained.

The finding that some participants downloaded the app during the follow-up survey suggests that the survey itself may have raised awareness about contact tracing apps, potentially promoting their downloads. While no additional download-promotion effects were observed for nudge-based messages, approximately

**Table 5** Effect of nudges on the download and acceptability of contact tracing apps by age group (Study 2)

	Download			Intention			WTA			Search		
	20-39	40-59	60-	20-39	40-59	60-	20-39	40-59	60-	20-39	40-59	60-
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Follow-up	0.083*** (0.015)	0.041*** (0.011)	0.049*** (0.017)	0.210*** (0.033)	0.159*** (0.037)	0.354*** (0.056)	- 7.716 (41.106)	- 54.140 (47.916)	- 130.183** (63.469)	0.003 (0.003)	- 0.003 (0.006)	- 0.000 (0.000)
Follow-up x Altruism	0.002 (0.022)	0.007 (0.017)	- 0.009 (0.022)	0.052 (0.055)	0.068 (0.054)	- 0.022 (0.077)	- 78.677 (58.909)	- 34.009 (66.938)	- 85.246 (96.017)	- 0.010* (0.006)	- 0.000 (0.008)	0.000 (0.014)
Follow-up x Incentive	- 0.016 (0.021)	- 0.013 (0.015)	- 0.019 (0.021)	0.119* (0.063)	0.036 (0.058)	- 0.241*** (0.075)	- 81.881 (55.773)	16.121 (56.458)	173.082* (89.121)	- 0.006 (0.005)	- 0.003 (0.007)	0.006 (0.006)
Follow-up x Medical	- 0.023 (0.020)	- 0.008 (0.015)	- 0.007 (0.023)	- 0.012 (0.050)	0.005 (0.052)	- 0.018 (0.077)	- 69.513 (47.904)	- 84.462 (64.424)	- 26.703 (80.550)	0.000 (0.004)	0.000 (0.009)	- 0.006 (0.010)
Follow-up x Economic	- 0.034* (0.020)	0.004 (0.016)	0.014 (0.025)	- 0.106** (0.053)	0.025 (0.053)	- 0.068 (0.076)	- 91.795 (57.812)	- 22.597 (60.130)	- 85.531 (88.406)	- 0.010* (0.006)	0.000 (0.008)	- 0.006 (0.006)
Constant	0.000 (0.003)	- 0.000 (0.002)	- 0.000 (0.004)	1.594*** (0.009)	1.558*** (0.009)	1.633*** (0.012)	2,452.261*** (8.451)	2,999.812*** (9.227)	3,043.529*** (13.966)	0.004*** (0.001)	0.010*** (0.001)	0.011*** (0.002)
Number of par- ticipants	1637	1634	855	1637	1634	855	1637	1634	855	1637	1634	855
Number of obser- vations	3274	3268	1710	3274	3268	1710	3274	3268	1710	3274	3,268	1,710

Robust standard errors are in parentheses

WTA means willingness to accept

\*\*\*denotes  $p < 0.01$ ; \*\*,  $p < 0.05$ ; and \*,  $p < 0.1$

**Table 6** Robustness check of the effect of nudges on the download and acceptability of contact tracing apps in Study 2

	Main sample				Full sample		
	Download	Intention	WTA	Search	Intention	WTA	Search
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Altruism	0.000 (0.012)	0.054* (0.032)	- 69.882* (40.218)	0.001 (0.003)	0.053* (0.029)	- 91.732** (37.001)	0.001 (0.003)
Incentive	- 0.015 (0.011)	0.025 (0.034)	23.498 (35.484)	0.000 (0.003)	0.031 (0.031)	- 0.448 (33.272)	- 0.001 (0.003)
Medical	- 0.017 (0.011)	0.011 (0.031)	- 71.283** (35.879)	0.004 (0.004)	0.022 (0.028)	- 79.776** (34.250)	0.004 (0.003)
Economic	- 0.009 (0.011)	- 0.030 (0.032)	- 61.427* (37.191)	- 0.003 (0.002)	- 0.021 (0.029)	- 82.089** (34.530)	- 0.003 (0.002)
Intention (pre-treatment)		0.710*** (0.013)			0.716*** (0.011)		
WTA (pre-treatment)			0.934*** (0.006)			0.934*** (0.006)	
Search (pre-treatment)				0.286*** (0.081)			0.288*** (0.071)
Constant	0.165*** (0.032)	0.469*** (0.091)	67.767 (96.311)	0.002 (0.008)	0.458*** (0.083)	168.314* (93.121)	0.001 (0.007)
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4126	4126	4126	4126	5000	5000	5000

Robust standard errors are in parentheses. Individual characteristics includes age, female dummy, income, schooling, married dummy, divorce dummy, and working status

WTA means willingness to accept

\*\*\*denotes  $p < 0.01$ ; \*\*,  $p < 0.05$ ; and \*,  $p < 0.1$

4–6% of participants had downloaded the app during the survey period. During the survey period, the download increase rate for Japan was 0.81% (from 20.00% on February 12, 2021 to 20.81% on March 19, 2021). Notably, this download increase rate for those surveyed exceeded the average rate in Japan, implying that the survey might have effectively increased awareness and facilitated downloads. Similar to Dai et al. (2021), who found that even reminders without nudge-based messages increased vaccination rates, our survey might have served as a reminder, contributing to increased downloads. Through media campaigns, there is still some potential for increasing awareness regarding contact tracing apps and promoting their downloads.



In contrast to the successful promotion effects of nudge-based messages on COVID-19 vaccination and infection-prevention behavior (Sasaki et al., 2021, 2022), such messages did not stimulate the downloading of contact tracing apps. Trust has emerged as a crucial factor in accepting contact tracing apps (Altmann et al., 2020; Von Wyl et al., 2021), with our results highlighting unreliability as the primary reason for not downloading the app. This unreliability may hinder download-promotion efforts. Furthermore, as our experiment occurred more than six months after the app's release, participants generally belonged to the group unwilling to download the app voluntarily, making it unlikely for nudge-based messages to encourage downloads. A similar result was also observed in the context of COVID-19 vaccine-intake promotion (Rabb et al., 2022).

The outcome that message-based nudges are not linked to downloads aligns with Munzert et al. (2021), demonstrating that message videos incorporating self-interest and others' interests can enhance knowledge sharing about contact tracing apps but are insufficient to boost app downloads. Our findings indicate that messages emphasizing altruism, economic losses, and medical losses increased app acceptability. However, nudge-based messages alone are insufficient to drive app downloads, despite their ability to enhance acceptability. Nevertheless, for individuals not complying with government stay-at-home orders, nudge-based messages have no effect on increasing acceptability. Additionally, while providing financial incentives directly encourages app downloads (Munzert et al., 2021), conveying messages about financial incentives, such as discounts for downloading contact tracing apps, proves insufficient to drive downloads.

Based on these findings, three potential strategies can be considered to enhance the download of contact tracing apps. First, proactive media campaigns should be implemented to improve the public's comprehension of contact tracing apps. A survey on these apps could contribute to increased downloads, given the evident low level of understanding among participants in our study. Survey results indicated that a significant percentage of respondents provided incorrect answers about the app, with many erroneously believing that their mobile GPS was being utilized. Additionally, privacy concerns were prevalent. Addressing these apprehensions through informative measures, coupled with the incorporation of nudge-based messages emphasizing altruism, economic loss, and medical loss, could bolster acceptability. Ensuring the reliability and accuracy of contact tracing apps is paramount, as system failures leading to poor reliability may deter downloads.

Second, the download and acceptability of apps may benefit from direct financial incentives. While messages emphasizing access to financial incentives did not directly correlate with increased downloads, we propose that offering direct incentives for downloads could be a more effective approach (Munzert et al., 2021). One way of implementing this is by increasing the number of places where people can receive financial incentives. Our findings indicate that the average minimum financial incentive for accepting and downloading such apps is 3000 yen. Offering a financial incentive, even a small amount, could encourage further downloads. Some nudge-based messages were found to reduce the perceived cost of financial incentives. However, careful consideration is needed to design an incentive system that promotes sustained app usage, as users might uninstall the app after receiving incentives.

Third, rather than relying solely on message-based nudges, employing default nudges that pre-install contact tracing apps could elevate download rates (Johnson

& Goldstein, 2003). With this approach, contact tracing apps would be pre-installed, shifting from the current opt-in regime where users voluntarily download them. This method may be particularly advantageous for those who have contemplated downloading the app but have postponed doing so. Although message-based nudges were not deemed effective, default nudges within an opt-out regime are considered more potent (Hummel & Maedche, 2019). Nevertheless, concerns about autonomy must be noted, and it will be crucial to address trust issues, with some evidence suggesting a preference for the opt-in regime among those lacking trust in the government (Altmann et al., 2020). If transitioning to an opt-out regime is undertaken, transparent communication about the reasons for the change is imperative (Sunstein & Reisch, 2019).

In the current pandemic scenario, the swift development of pharmacological treatments such as vaccines has diminished the immediate significance of non-pharmacological interventions like contact tracing apps, social distancing, and lockdowns. However, considering that pharmacological treatments may not always be rapidly available in future pandemics, non-pharmacological interventions could become vital alternatives. Nudges, with their demonstrated positive impact on awareness, can serve as an effective policy tool in such circumstances. While nudges alone are insufficient, complementary policy instruments, including opt-out pre-installation and financial incentives, should be integrated into comprehensive strategies.

Our study has four limitations. First, both Studies 1 and 2 utilized non-nationally representative data, limiting the generalizability of our findings to the entire Japanese population. In Study 1, the sample was drawn from people in Tokyo and Osaka shopping districts who did not comply with the stay-at-home order. While not nationally representative, this targeted group represents individuals at higher risk of contracting and spreading the disease, making it crucial to understand effective messaging for this demographic. Although it is not a fully representative sample, it provides valuable insights into effective communication strategies for those at a high risk. Additionally, Study 2, aimed at understanding search behavior, also lacks national representativity, but it offers insights into the process by which nudges lead to action among identifiable search behavior participants.

Second, Study 2's scope of capturing search behaviors was limited due to constraints in data extraction by the research company, collecting data only when users accessed the web search page of the group company. Future research should explore experimental designs, such as randomly displaying messages in platforms like Facebook ads, to analyze subsequent behavior more reliably (Blanco & Rodriguez, 2020; Subasinghe et al., 2016).

Third, self-report surveys assessing app downloads introduce potential biases. Participants might inaccurately report their app downloads, leading to a potential upward bias. Studies combining self-report and mobile tracking data have shown discrepancies, with some individuals reporting app usage despite not actually using it (Munzert et al., 2021). Attrition issues also emerged as not all participants took part in the follow-up survey, potentially affecting the estimation results. While robustness checks with only first survey data yielded similar results, caution is warranted, recognizing that the outcome may have been overestimated due to the self-selection bias of participants who already had an interest in contact tracing apps.

Fourth, caution is advised when generalizing experimental results. The experiment took place around six months after the app's release, excluding those already willing to download the app before the study. In addition, the survey occurred immediately after the app experienced a system error, influencing public perceptions of app reliability. This unique experimental timing requires caution in generalizing the findings. Despite these circumstances, nudges demonstrated a slight improvement in acceptability, emphasizing their partial effectiveness even under conditions of low reliability perception.

While nudges increased the acceptability of contact tracing apps, they were not enough to encourage the prompt download of these apps. Relying solely on nudges is not advisable; instead, they should complement traditional policy measures like information provision and financial incentives to boost downloads of contact tracing apps.

## Appendix A. Statistics on the understanding of contact tracing apps and reasons for not downloading the apps

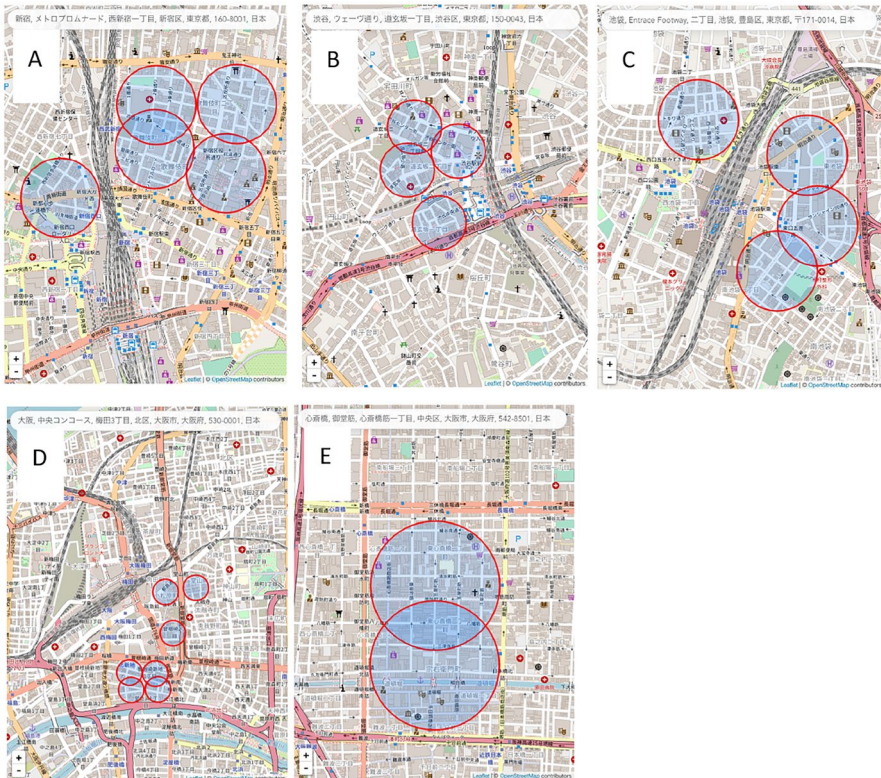
Here, to grasp the background characteristics of our sample regarding the contact tracing app, we present statistics on the understanding of contact tracing apps and participants' reasons for not downloading the apps, as obtained from the first survey (Table 13). To assess the participants' comprehension, a quiz was administered to determine the accuracy of six items: (i) not using GPS-based location information (*GPS*), (ii) no requirement for user registration such as an email address (*registration*), (iii) effectiveness in preventing infection spread even if used by less than 60% of the population (*60% or more*), (iv) insignificant increase in power consumption when using the app (*battery*), (v) app installation not imposing a significant burden on cellphone data capacity (*data*), and (vi) the number of COCOA downloads exceeding approximately 25 million at the survey time (*number of downloads*). The correct response rate for all six questions was 41% in both Studies 1 and 2, although individual question correctness varied between the two studies. Notably, in Study 1, which targeted individuals who disregarded the government's stay-at-home orders, 90% of participants held the misconception that GPS-based location information was collected.

For understanding the reasons for not downloading the app, participants rated four items on a five-point scale (ranging from 1 = "strongly disagree" to 5 = "strongly agree"): 1 "because I do not like revealing my personal information" (*privacy*), 2 "because the app is defective and therefore unreliable" (*unreliable*), 3 "because installation is not mandatory" (*non-mandatory*), and 4 "because I am scared to receive a notification confirming contact with an infected person" (*fear*). While various factors inhibit downloading (Villius Zetterholm et al., 2021), our focus here is on privacy (Chan & Saqib, 2021), system quality (Suh & Li, 2021), compulsion (Abuhammad et al., 2020; Zimmermann et al., 2021), and fear of notifications (Altmann et al., 2020). Participants may assess the app system's quality and reliability as low in Japan due to numerous reported flaws (NTV News, 2020a, b; NHK News, 2020a, b), particularly the flaw reported by the MHLW just before the first survey (Digital Agency, 2023a). In both studies, the primary reasons for not downloading the contact tracing app were its


non-mandatory nature and perceived unreliability. Additionally, privacy concerns were prevalent in both studies.

## Appendix B. Appendix figures and tables


See Figs. 1 and 2. Tables 7, 8, 9, 10, 11, 12, 13




**Fig. 1** Screening range of participants in Study 1. **A.** Shinjuku (specified within a radius of 150 m); **B.** Shibuya (specified within a radius of 100 m); **C.** Ikebukuro (specified within a radius of 150 m); **D.** Kita (specified within a radius of 100 m); **E.** Minami (specified within a radius of 250 m)

 The early detection of infected people is important to prevent the spread of COVID-19.  
An increase in the number of users of the contact-tracing app COCOA is expected to help prevent the spread of infection.


Let us install the contact-tracing app COCOA to protect you, your loved ones, and your community.




### A Control message

 The early detection of infected people is important to prevent the spread of COVID-19.  
An increase in the number of users of the contact-tracing app COCOA is expected to help prevent the spread of infection.


Installing the contact-tracing app COCOA can help protect the lives of those you come across.




### B Altruistic message

 The early detection of infected people is important to prevent the spread of COVID-19.  
An increase in the number of users of the contact-tracing app COCOA is expected to help prevent the spread of infection.


Install the contact-tracing app COCOA, and receive discounts, privileges, and other benefits at restaurants, hotels, etc.




### C Incentive message

 The early detection of infected people is important to prevent the spread of COVID-19.  
An increase in the number of users of the contact-tracing app COCOA is expected to help prevent the spread of infection.


With fewer people installing the contact-tracing app COCOA, the infection spread will continue, and some people will be at risk of death due to the lack of hospital beds.



### D Medical-loss message

 The early detection of infected people is important to prevent the spread of COVID-19.  
An increase in the number of users of the contact-tracing app COCOA is expected to help prevent the spread of infection.

Currently, owing to the spread of the disease, the economic conditions are deteriorating, and the number of unemployed people is increasing. With fewer people installing the contact-tracing app COCOA, the spread of infection will continue and the economic conditions may further deteriorate.



### E Economic-loss message

**Fig. 2** Nudge messages. The icons were designed by Freepik and distributed by Flaticon (<https://www.flaticon.com/>).

**Table 7** Balance check in study 1

	Control	Altruism	Incentive	p-value from joint orthogonality test of treatment arms
Age	35.934 (0.386)	36.142 (0.399)	35.620 (0.378)	0.633
Female	0.575 (0.016)	0.559 (0.017)	0.557 (0.016)	0.711
Income	617.404 (13.375)	599.386 (13.132)	614.740 (12.506)	0.579
No income	0.178 (0.013)	0.204 (0.014)	0.197 (0.013)	0.348
Schooling	14.652 (0.063)	14.599 (0.065)	14.588 (0.063)	0.745
No schooling	0.020 (0.005)	0.021 (0.005)	0.032 (0.006)	0.196
Married	0.298 (0.015)	0.295 (0.016)	0.309 (0.015)	0.785
Divorced	0.083 (0.009)	0.085 (0.010)	0.083 (0.009)	0.984
Working	0.690 (0.015)	0.698 (0.016)	0.681 (0.015)	0.733
Number of participants	912	859	919	

The figures in parentheses show the standard error. “No income” denotes the percentage of respondents who did not reveal their income. The average income was assigned to those who did not reveal their income. “No schooling” denotes the percentage of respondents who did not reveal their years of schooling. The average number of years of education was assigned to those who did not reveal their years of schooling.

**Table 8** Balance check in Study 2

	Control	Altruism	Incentive	Medical	Economic	p-value from joint orthogonality test of treatment arms
Age	44.947 (0.502)	45.454 (0.519)	45.389 (0.512)	45.160 (0.505)	45.606 (0.504)	0.902
Female	0.524 (0.017)	0.512 (0.018)	0.509 (0.017)	0.487 (0.017)	0.496 (0.017)	0.624
Income	617.093 (12.962)	598.330 (12.000)	565.455 (11.642)	586.814 (11.989)	585.727 (11.767)	0.044
No income	0.170 (0.013)	0.199 (0.014)	0.149 (0.012)	0.166 (0.013)	0.165 (0.013)	0.106
Schooling	14.474 (0.074)	14.499 (0.074)	14.454 (0.073)	14.497 (0.072)	14.400 (0.074)	0.874
Married	0.563 (0.017)	0.577 (0.017)	0.559 (0.017)	0.589 (0.017)	0.587 (0.017)	0.648
Divorced	0.084 (0.010)	0.092 (0.010)	0.090 (0.010)	0.099 (0.010)	0.072 (0.009)	0.345
Working	0.717 (0.016)	0.684 (0.016)	0.698 (0.016)	0.712 (0.016)	0.695 (0.016)	0.604
Number of participants	829	811	821	827	838	

The figures in parentheses show the standard error. “No income” denotes the percentage of respondents who did not reveal their income. The average income was assigned to those who did not reveal their income

**Table 9** Balance check for the full sample in Study 1

	Control	Altruism	Incentive	p-value from joint orthogonality test of treatment arms
Age	35.762 (0.357)	36.064 (0.361)	35.726 (0.356)	0.767
Female	0.590 (0.015)	0.568 (0.016)	0.572 (0.015)	0.570
Income	611.542 (12.438)	590.103 (11.907)	609.452 (11.695)	0.384
No income	0.175 (0.012)	0.201 (0.013)	0.195 (0.012)	0.287
Schooling	14.623 (0.060)	14.584 (0.062)	14.563 (0.061)	0.778
No schooling	0.018 (0.004)	0.022 (0.005)	0.030 (0.005)	0.182
Married	0.292 (0.014)	0.291 (0.014)	0.314 (0.014)	0.422
Divorced	0.087 (0.009)	0.088 (0.009)	0.087 (0.009)	0.997
Working	0.695 (0.014)	0.696 (0.014)	0.685 (0.014)	0.825
Number of participants	1058	1017	1040	

The figures in parentheses show the standard error. “No income” denotes the percentage of respondents who did not reveal their income. The average income was assigned to those who did not reveal their income. “No schooling” denotes the percentage of respondents who did not reveal their years of schooling. The average number of years of education was assigned to those who did not reveal their years of schooling.



**Table 10** Balance check of the full sample in Study 2

	Control	Altruism	Incentive	Medical	Economic	p-value from joint orthogonality test of treatment arms
Age	45.145 (0.458)	45.048 (0.459)	45.137 (0.458)	45.158 (0.457)	45.187 (0.459)	1.000
Female	0.500 (0.016)	0.500 (0.016)	0.500 (0.016)	0.500 (0.016)	0.500 (0.016)	1.000
Income	606.383 (11.459)	598.565 (10.816)	573.883 (10.893)	597.877 (11.238)	592.096 (10.680)	0.296
No income	0.187 (0.012)	0.206 (0.013)	0.163 (0.012)	0.180 (0.012)	0.185 (0.012)	0.176
Schooling	14.375 (0.068)	14.498 (0.068)	14.429 (0.066)	14.457 (0.065)	14.380 (0.067)	0.658
Married	0.561 (0.016)	0.569 (0.016)	0.568 (0.016)	0.590 (0.016)	0.590 (0.016)	0.561
Divorced	0.086 (0.009)	0.096 (0.009)	0.086 (0.009)	0.097 (0.009)	0.071 (0.008)	0.239
Working	0.718 (0.014)	0.686 (0.015)	0.705 (0.014)	0.706 (0.014)	0.692 (0.015)	0.553
Number of participants	1000	1000	1000	1000	1000	

The figures in parentheses show the standard error. “No income” denotes the percentage of respondents who did not reveal their income. The average income was assigned to those who did not reveal their income

Table 11 Checks for attrition bias in Study 1

	Control			Altruism			Incentive		
	Main	Drop-out	p-value	Main	Drop-out	p-value	Main	Drop-out	p-value
	Age	35.934 (0.386)	34.685 (0.928)	0.227	36.142 (0.399)	35.639 (0.833)	0.614	35.620 (0.378)	36.529 (1.057)
Female	0.575 (0.016)	0.685 (0.039)	0.012	0.559 (0.017)	0.620 (0.039)	0.152	0.557 (0.016)	0.686 (0.042)	0.007
Income	617.404 (13.375)	574.921 (33.772)	0.239	599.386 (13.132)	539.630 (27.608)	0.069	614.740 (12.506)	569.294 (32.790)	0.213
No income	0.178 (0.013)	0.158 (0.030)	0.553	0.204 (0.014)	0.184 (0.031)	0.561	0.197 (0.013)	0.182 (0.035)	0.693
Schooling	14.652 (0.063)	14.436 (0.161)	0.204	14.599 (0.065)	14.502 (0.156)	0.561	14.588 (0.063)	14.382 (0.188)	0.267
No schooling	0.020 (0.005)	0.007 (0.007)	0.277	0.021 (0.005)	0.025 (0.013)	0.729	0.032 (0.006)	0.017 (0.012)	0.361
Married	0.298 (0.015)	0.253 (0.036)	0.269	0.295 (0.016)	0.272 (0.036)	0.570	0.309 (0.015)	0.355 (0.044)	0.302
Divorced	0.083 (0.009)	0.110 (0.026)	0.296	0.085 (0.010)	0.101 (0.024)	0.506	0.083 (0.009)	0.116 (0.029)	0.225
Working	0.690 (0.015)	0.726 (0.037)	0.377	0.698 (0.016)	0.684 (0.037)	0.708	0.681 (0.015)	0.711 (0.041)	0.511
Number of observations	912	146		859	158		919	121	

The figures in parentheses show the standard error. "No income" denotes the percentage of respondents who did not reveal their income. The average income was assigned to those who did not reveal their income. "No schooling" denotes the percentage of respondents who did not reveal their years of schooling. The average number of years of education was assigned to those who did not reveal their years of schooling

**Table 12** Checks for attrition bias in Study 2

	Control			Altruism			Incentive			Medical			Economic		
	Main	Drop-out	p-value	Main	Drop-out	p-value	Main	Drop-out	p-value	Main	Drop-out	p-value	Main	Drop-out	p-value
Age	44.947 (0.502)	46.105 (1.120)	0.341	45.454 (0.519)	43.307 (0.965)	0.067	45.389 (0.512)	43.983 (1.008)	0.239	45.160 (0.505)	45.150 (1.078)	0.994	45.606 (0.504)	43.019 (1.101)	0.038
Female	0.524 (0.017)	0.386 (0.037)	0.001	0.512 (0.018)	0.450 (0.036)	0.125	0.509 (0.017)	0.458 (0.037)	0.216	0.487 (0.017)	0.561 (0.038)	0.079	0.496 (0.017)	0.519 (0.039)	0.607
Income	617.093 (12.962)	554.462 (22.939)	0.040	598.330 (12.000)	599.573 (25.042)	0.964	565.455 (11.642)	612.537 (29.096)	0.098	586.814 (11.989)	650.761 (30.347)	0.031	585.727 (11.767)	625.042 (25.242)	0.175
No income	0.170 (0.013)	0.269 (0.034)	0.002	0.199 (0.014)	0.238 (0.031)	0.226	0.149 (0.012)	0.229 (0.031)	0.008	0.166 (0.013)	0.249 (0.033)	0.010	0.165 (0.013)	0.290 (0.036)	0.000
Schooling	14.474 (0.074)	13.892 (0.169)	0.001	14.499 (0.074)	14.489 (0.162)	0.954	14.454 (0.073)	14.318 (0.160)	0.434	14.497 (0.072)	14.263 (0.151)	0.174	14.400 (0.074)	14.272 (0.149)	0.478
Married	0.563 (0.017)	0.550 (0.038)	0.744	0.577 (0.017)	0.534 (0.036)	0.287	0.559 (0.017)	0.609 (0.037)	0.223	0.589 (0.017)	0.595 (0.037)	0.875	0.587 (0.017)	0.605 (0.039)	0.673
Divorced	0.084 (0.010)	0.094 (0.022)	0.699	0.092 (0.010)	0.111 (0.023)	0.434	0.090 (0.010)	0.067 (0.019)	0.318	0.099 (0.010)	0.087 (0.021)	0.615	0.072 (0.009)	0.068 (0.020)	0.867
Working	0.717 (0.016)	0.725 (0.034)	0.820	0.684 (0.016)	0.693 (0.034)	0.815	0.698 (0.016)	0.737 (0.033)	0.294	0.712 (0.016)	0.676 (0.036)	0.346	0.695 (0.016)	0.679 (0.037)	0.696
Number of observations	829	171		811	189		821	179		827	173		838	162	

The figures in parentheses show the standard error. "No income" denotes the percentage of respondents who did not reveal their income. The average income was assigned to those who did not reveal their income

**Table 13** Participants' understanding of and reasons for not downloading contact tracing apps

	Study 1	Study 2
Quiz: GPS	0.099 (0.299)	0.326 (0.469)
Quiz: registration	0.644 (0.479)	0.276 (0.447)
Quiz: 60% or more	0.534 (0.500)	0.337 (0.473)
Quiz: battery	0.849 (0.359)	0.597 (0.491)
Quiz: data	0.246 (0.431)	0.594 (0.491)
Quiz: no. of downloads	0.096 (0.294)	0.327 (0.470)
Quiz: accuracy rate	0.411 (0.172)	0.410 (0.222)
Reason: privacy	3.079 (1.331)	3.372 (1.180)
Reason: unreliable	3.324 (1.300)	3.905 (1.093)
Reason: non-mandatory	3.865 (1.144)	3.747 (1.054)
Reason: fear	2.307 (1.205)	2.571 (1.171)
Number of observations	2690	4126

Standard deviations are in parentheses

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## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethical approval** This study was approved by the Ethics Committee of Osaka University's Faculty of Economics (approval number: R030216) and preregistered in AEA RCT Registry (AEARCTR-0007237).

**Informed Consent** Informed consent was obtained from all the participants prior to their participation.

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