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COVID-19 Apps as a Digital Intervention Policy: A Longitudinal Panel Data Analysis in South Korea

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ABSTRACT

Many countries have developed COVID-19 tracking apps that help individuals trace and detect “people” who are likely to have come in contact with confirmed patients. However, their adoption rates remain low. This study, therefore, investigated South Koreans’ adoption and usage behaviors of COVID-19 apps that detect the “place” where infectious people are found and alert people within 100m in dangerous zones. Our focus was on such apps’ impact on various facets of human life. Specifically, we analyzed mobile app usage data from 5,940 panelists at the start of the pandemic in South Korea and after the first major wave (January 6 to August 2, 2020). Findings showed that higher-income and more educated individuals were more likely to adopt COVID-19 apps early, and male and low-income people tended to use the COVID-19 tracking apps more frequently. In addition, this study offered empirical evidence of health protective behaviors, such as driving, shopping online, ordering food online, and avoiding travel and public transportation, and supported social- and religious-coping for people using COVID-19 apps. The implications are valuable for policy makers to implement a digital policy to motivate people to voluntarily engage in self-protective and coping behaviors through COVID-19 apps.

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1. INTRODUCTION

Governments around the world have implemented the various health policies and interventions in the face of infectious COVID-19 outbreaks. One of the popular tactics is to make use of mobile technologies, such as launching apps. Such COVID-19 apps are used to trace people who are likely to have come in contact with confirmed patients (e.g., apps in European countries, USA and Singapore) or alert people when they are within 100 m of dangerous zones where infectious people were found (e.g., apps in South Korea). This way, COVID-19 apps enable people to minimize their exposure to and the transmission of the virus, and the government can use this information to track down the history of any close contacts.

Despite this potential benefit as a digital intervention, several issues need to be resolved as adoption rates remain low; more importantly, the effectiveness of these apps has yet to be demonstrated. In this light, this study aims to resolve two problems of using COVID-19 apps as digital interventions. First, we investigate the adoption and usage behaviors of COVID-19 apps in South Korea to provide implications for policy makers about their target population regarding socio-demographic profiles. Second, we examine the impact of COVID-19 apps on various facets of human life such as health protective behaviors and coping behaviors which are inferred from mobile app usage, such as transportation, online shop-

ping, food delivery, entertainment, religion, and networking with others, and then offer theoretic explanations of the findings.

To investigate these important and imminent issues on COVID-19 apps as an intervention policy, we examine mobile users in South Korea at the start and after the first major wave of the pandemic (January 6 to August 2, 2020). To the best of our knowledge, this study is the first to empirically investigate COVID-19 apps using actual and longitudinal data.

As one of the first places where COVID-19 apps were rather successfully introduced early and given that the situation has been somewhat controlled, with cities reopening and functioning under relative normality, South Korea’s experience of using digital technology allows us to give timely recommendations to policy makers in places where COVID-19 apps were introduced late. In addition, as many countries are now also experiencing a second and even third wave of the pandemic, the study findings are valuable for policy makers to promote tracking apps to understand their outcome on people in everyday life and thus mitigate the devastating impact of the pandemic. In the following section, we present a literature review for this study.

1.1. Health protective behaviors

The COVID-19 crisis is a health crisis and a threat to well-being, security, and even life, with many people dying of this novel coro-

navirus. Thus, many people have been doing their best to reduce the threat and risks from pandemics by engaging in health protective behaviors [5,33].

This research is especially related to literature on the impact of a health threat warning on protective behavior. Leventhal's [21,40] parallel response model defines a reaction to a threat as the desire to avoid the danger and reduce fear. Thus, when people focus on the danger to health, they begin a process of danger control, such as taking self-protective measures. Specifically, given the drastic increase in the number of confirmed COVID-19 cases and deaths during the outbreak, the public's perceived susceptibility to the disease and its severity has surged to a high level. Furthermore, alerts and information from COVID-19 tracking apps heighten the ability to avoid such places where confirmed patients congregate with an emphasis on the threat of infectious situations. Thus, COVID-19 tracking apps engender higher arousal of the perception of the susceptibility to and severity of the threat, which motivates people to engage in health protective behaviors, such as avoiding crowds and social distancing.

1.2. Coping behaviors

The novel coronavirus has also brought a psychological impact, such as stress, feelings of isolation, and depression, to everyday life [2,35]. Especially when under a high threat condition, people are likely to engage more in various coping strategies [28,30,35]. According to the parallel response model, people engage in coping behaviors when exposed to threatening health information, and their reactions to specific information or instructions on a health threat can be alleviated by engaging in fear control [22]. Following this notion, we posit that the information and alert obtained from COVID-19 tracking apps as a health communication of the threat may accentuate various coping responses, such as emotion-, social-, and religious-oriented coping.

First, emotion-oriented coping refers to strategies intended to attenuate negative emotions caused by an event [10]. Thus, to cope with stress, anxiety, or depression caused by the COVID-19 outbreak, people may depend more on hedonic behaviors such as entertainment.

Second, a social coping strategy refers to the functional role of specific coping techniques that involve engaging in social activities with others. Prior research consistently finds that people with a supportive social network are better able to cope with stress, as social support plays a role in influencing health and well-being [14,15].

Third, religious coping refers to the functional role of religion as a coping mechanism. Various studies in medical research have shown that religion can be a source of hope, comfort and strength among diverse patient groups, such as those with hemodialysis, cancer, and HIV [12,17,25].

In summary, people may exercise various activities (i.e., health protective behaviors) to reduce the direct risk of contracting COVID-19 and alleviate psychological stress, depression, anxiety (i.e., coping behaviors), as predicted by health communication theory and coping theory. Our focus herein is on empirically investigating how COVID-19 tracking apps affect these behaviors in everyday life, thus indirectly measuring the effectiveness of the policy of releasing and promoting COVID-19 tracking apps.

2. MATERIALS AND METHODS

2.1. COVID-19 apps

COVID-19 apps are mobile applications to detect close contacts to collect the user's location data real time. The apps also alert users entering COVID-19 red zones where there are confirmed

COVID-19 cases. For example, Singapore's government launched a contact-tracing app, called TraceTogether, in March 2020. Some tracking apps were released relatively late in some counties where the situations were not well controlled. For example, the German government launched the app Corona-Warn-App, the Italian government released the app Immuni, and the Japanese government released the tracking app Cocoa, all in June 2020 [26]. In October 2020, the French government released TousAntiCovid, an updated version of the previous tracing app StopCovid. In November 2020, Hong Kong released its tracing apps, when it began experiencing the second wave of the pandemic after a mild first wave in February and March. In December 2020, the California government released a COVID-19 tracing app with the help of Apple and Google (for a comprehensive list, refer to "COVID-19 apps" in Wikipedia).

Although contact tracing is well understood to be one of the most effective and important responses to the COVID-19 pandemic, this intervention through use of mobile contact tracing apps may not literally be effective. For instance, based on Hinch et al.'s [16] simulation model, the pandemic would be suppressed if 80% of all smartphone users or 56% of the population use the apps. Similarly, Ferretti et al. [9] mathematically showed that tracking apps could reduce virus transmission only when a sufficiently high proportion of the population utilizes the apps. Recently, Rodríguez et al. [29] conducted an experiment in the Canary Islands, Spain, in a controlled environment and revealed potential effectiveness of tracing apps in identifying simulated contacts. To summarize, these studies discovered that COVID-19 tracing apps could be effective under two conditions: i) many people adopt and employ the apps, and ii) infectious people should register their status on the apps. However, these conditions were rarely met. For example, as of the summer of 2020, 21% downloaded the app in Germany; in Italy 14%; and in France, 3%. Moreover, as of June 2020, only 68 people had registered their infection status on the tracing apps in France; only three did so in Japan [24].

These low app adoption rates may be attributed to concerns over data protection, security, and privacy [36]. Several recent survey studies [1,7,37] found that privacy had a strong effect on one's app acceptance decision. As such, Braithwaite et al. [6] and Gardner [11] stressed that there is no empirical evidence of the effectiveness of automated contact tracing after reviewing recent studies on the COVID-19 pandemic.

As noted earlier, COVID-19 apps introduced in South Korea are different from other countries' tracing apps. The COVID-19 apps in South Korea help people identify the "places" where infectious individuals have been found in two weeks and warn users if they are within 100m from such dangerous places. Such location information of movement log of infectious people is collected by Korea Disease Control and Prevention Agency (Korea CDA) using smartphone GPS systems, CCTV and in-person interviews. Other nations' tracing apps addressed above help people identify "people" who are likely to be infectious within 15m. In this regard, interestingly, the COVID-19 apps in South Korea do not use any personal information transmitted directly from smartphones of infected people. More importantly, apps in other countries require an important condition that infectious people must keep using such tracing apps to ensure their effectiveness. However, this stipulation is not requisite with the COVID-19 apps in South Korea (for more details, see [39]).

These COVID-19 apps in South Korea were introduced first in early February and a million people had downloaded the apps in its first 17 days (ranked No.1 in Google Playstore's free apps during the first week of March 2020). Central and local governments also developed COVID-19 apps by collaborating with private app developers. These apps provide various functions, such as tracking where diagnosed COVID-19 patients were found with maps to warn users if they were in a high risk zone, and any govern-

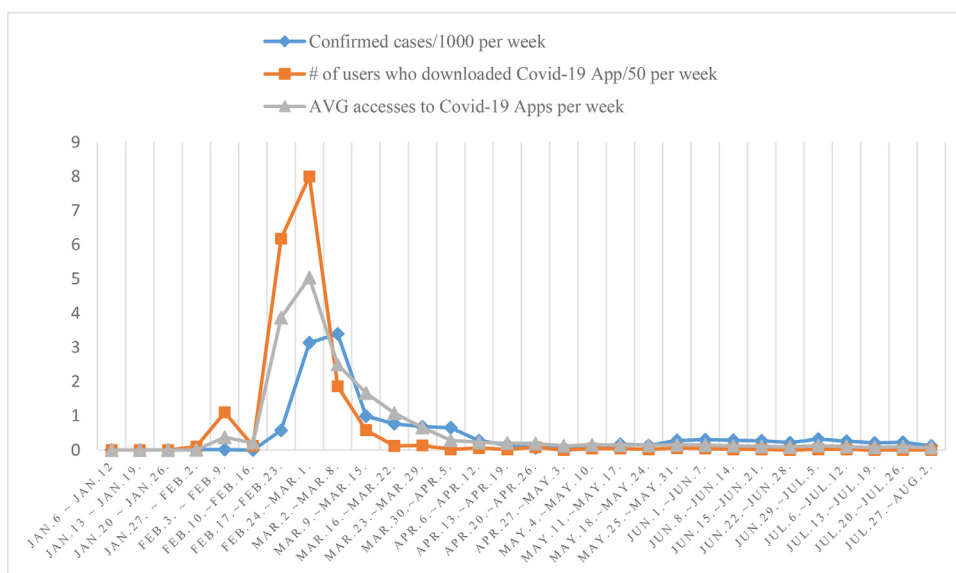
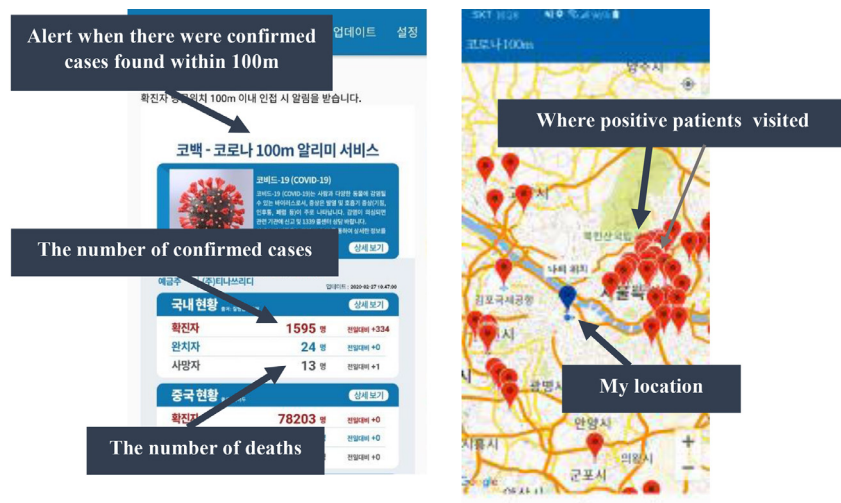


Figure 1. Examples of COVID-19 tracking apps, its adoption and usage trends and the weekly number of confirmed COVID-19 cases in South Korea in South Korea.

ment policies (e.g., lockdown of certain facilities, distribution of masks). Figure 1 provides examples of such apps (see the list in Appendix 1) and its download and usage trends along with COVID-19 trends in South Korea. According to Figure 1, of particular interest is that adoption and usage of COVID-19 apps decreased dramatically as the pandemic was alleviated. This may imply that people were showing signs of fatigue with the apps.

In summary, investigating digital intervention policies using mobile apps in a timely manner and verifying them empirically is essential. The implications of this study on South Korea are valuable for other countries where different types of tracing apps were released late.

2.2. COVID-19 Pandemic in South Korea

The first cases of COVID-19 in South Korea were found in late January 2020. However, that month experienced fewer than five weekly confirmed cases. About one month later, a sharp growth in the novel coronavirus occurred in the southern city of Daegu, mostly attributed to patients who attended a religious gathering. Afterward, the virus spread to the whole country. It reached a peak in late February and early March with more than 3,000 confirmed

cases found per week. After April 20, the pandemic was somewhat alleviated owing to large epidemic control programs such as early adoption of testing and contact tracing. South Korea has worked to control the spread of the coronavirus without imposing the kind of wide-scale economic shutdowns occurring in the United States, Europe, and many other parts of the world (for an overview for COVID-19 Pandemic in South Korea, see [41]). Figure 1 also illustrates the trends of COVID-19 development in South Korea.

2.3. Mobile app usage data in South Korea

We obtained mobile app usage data from Nielson Korea, an international research company in South Korea that collects panel data for people aged 7 to 69. Nielson Korea first aims at its statistical “population” as the entire population of South Korea. It then approximates the population distribution of mobile users by every quarter conducting computer-assisted telephone interviewing (CATI) surveys with 4,000 subjects. Based on the estimated population distribution of mobile users, it then sets the size of target population groups of mobile users using various demographic criteria. Finally, it randomly recruits panels to arrive at the target size of population groups and installs iTrack software into the re-

Table 1
Demographic summary of mobile app data.

		Total sample	Health protective behavior COVID-19							Social coping			Emotional coping			Religious coping
			App	Navigation	Taxi	Subway	Travel	Exercise	Food delivery	shopping	SNS	Messenger	Music	Game	Netflix	
# of panelists		5,940	933	4,081	1,491	1,071	601	2,443	2,639	4,902	4,369	3,954	4,772	3,577	988	919
Average # of weekly visits (SD)		-	0.6 (3.9)	8.3 (22.7)	0.69 (2.53)	1.76 (4.79)	0.77 (6.7)	2.5 (9.5)	3.2 (8.5)	29.0 (50.6)	26.2 (48.7)	146.6 (107)	8.1 (20.4)	26.3 (45.4)	3.4 (10.3)	6.5 (26.3)
% of users who also use COVID-19 tracking apps		15.7	-	19.2	21.5	20.5	26.1	21.5	19.8	17.7	18.4	15.2	17.7	18.2	19.7	20.5
Age (%)																
	~29	11.1	5.6	8.3	15.6	11.8	11.6	9.7	15.0	11.0	10.3	7.4	11.5	14.5	19.5	6.6
	30~39	14.2	15.9	16.1	25.7	18.0	29.5	15.1	24.2	15.1	15.2	9.8	15.0	18.0	26.8	11.1
	40~49	28.6	30.3	31.8	30.9	24.5	33.9	30.1	38.3	30.4	30.7	29.3	29.5	33.7	32.0	25.8
	50~59	24.8	25.2	25.6	17.8	23.4	19.0	25.1	17.0	24.9	24.8	28.2	24.4	19.8	16.1	25.9
	60~69	21.3	23.0	19.5	10.0	22.3	6.0	20.0	5.5	18.6	19.0	25.4	19.6	14.0	5.6	30.5
Gender (%)	Male	46.5	49.1	51.3	50.6	51.4	52.4	48.9	43.1	46.1	47.7	49.1	46.6	48.7	47.1	43.2
Single (%)		30.4	19.8	21.6	33.1	31.4	33.6	24.5	32.4	24.7	23.9	19.5	25.2	29.1	37.2	17.0
Education (%)	High school or less	32.7	30.6	30.7	27.0	26.8	14.8	31.0	26.0	34.0	34.0	39.3	35.0	34.6	25.5	35.0
	College graduate	67.3	69.4	69.3	73.0	73.2	85.2	68.9	74.0	66.0	66.0	60.7	65.0	65.4	74.5	65.0
Income level (%)	< 4.5K USD per month	68.5	61.9	63.7	62.6	61.2	58.8	61.9	62.6	65.0	64.6	67.7	63.5	65.2	61.9	66.0
	4.5K USD per month <	31.5	39.1	36.3	37.4	38.8	41.2	38.1	37.4	35.0	35.4	32.3	34.5	33.8	38.1	34.0

Table 2
Estimation results of who adopt COVID-19 apps, when and how much.

Model	Who adopts COVID-19 apps			How much they access COVID-19 apps	
		When they adopt COVID-19 apps	Before the peak	During the peak	After the peak
Intercept	-1.698** (0.091)	-2.834** (0.146)	-2.272** (0.123)	-4.554 (0.333)	-2.374** (0.182)
Sex (male = 1)	0.116 (0.072)	-0.056 (0.114)	0.190* (0.096)	0.395 (0.264)	0.254** (0.102)
Age					
~29	-0.802** (0.195)	-0.222 (0.281)	-1.135** (0.260)	-1.112** (0.679)	-0.011 (0.213)
30–39	-0.045 (0.130)	0.296 (0.197)	-0.190 (0.177)	-0.790* (0.471)	-0.217* (0.126)
40–49	-0.112 (0.103)	0.157 (0.162)	-0.214 (0.140)	-0.661* (0.365)	-0.160 (0.110)
50–59	-0.168 (0.103)	-0.066 (0.167)	-0.195 (0.140)	-0.307 (0.346)	-0.215* (0.106)
60–69 (base)	-	-	-	-	-
Income (+5,000 USD per month = 1)	0.207** (0.077)	0.137 (0.114)	0.256** (0.099)	0.038 (0.259)	-0.865** (0.066)
Marital (single = 1)	-0.090 (0.114)	-0.206 (0.163)	-0.048 (0.149)	0.142 (0.388)	-0.176 (0.117)
Education (college = 1)	0.203** (0.086)	0.242* (0.131)	0.101 (0.110)	0.632** (0.314)	0.094 (0.083)
COVID-19 confirmed cases	-	-	-	-	0.394** (0.055)
Children's and parents' days	-	-	-	-	-1.012 (1.512)
Random effects across users	-	-	-	-	1.801 (0.098)
Random effects across weeks	-	-	-	-	2.438 (0.699)

NOTE:

The significant and positive (negative) coefficient implies that people are more (less) likely to adopt apps (the first and second columns)/access the apps more (less) (the third column).

** indicates significance at the 95% level.

* indicates significance at the 90% level. Standard deviations are in parentheses.

cruited panels' smartphones; doing so affords electronically monitoring and collecting the log-activities on the phones (i.e., how many times a user accessed an app). In addition to electronic measures of media usage, Nielsen Korea collects information about panel members' characteristics, such as age, gender, education, and household income—if panel members have agreed to be in the panel.

Nielson Korea recruits new panels every quarter as panels are allowed to decide whether to remain in the sample pool or drop out each quarter. We obtained 5,940 mobile panelists who remained active without drop-out from January 6 to August 2, 2020—the period when the novel coronavirus was most severe (i.e., late February and early March)—and afterward. We then extracted various apps from the data, including COVID-19 apps, shopping apps (e.g., major domestic shopping apps), food delivery apps (e.g., major domestic delivery apps), social networking services (SNS) apps (e.g., Facebook, Instagram, Twitter), messenger apps (e.g., KakaoTalk), taxi apps (for making reservations), subway (metro) apps (for checking routes and time tables), navigation apps (for driving), exercise apps (e.g., Samsung Health, LG Health, step counters), travel apps (e.g., Expedia, Hotels.com), mobile game apps, video streaming apps (e.g., Netflix), music streaming apps (e.g., Google Music), and mobile bible/mass apps. In our data, approximately 20% of panelists downloaded at least one tracking app. Table 1 reports the summary statistics of the panelists for these mobile apps during the data period.

2.4. Who adopts COVID-19 apps?

We first model panelists' adoption decision of COVID-19 tracking apps to identify their profiles. To do so, we develop a logistic regression model, where the dependent variable, $Adopt_i = 1$ if per-

son i accessed the COVID-19 apps at least once during the data period and 0 otherwise. Our choice of independent variables is based on social-economic variables, such as age, gender, marital status, income level, and education level. Especially for studies on COVID-19, socio-economic positions such as economic and living conditions can be particularly important because they are directly or indirectly associated with risk such as disease and mortality rates [4,20]. The model is described in Appendix A2.

2.5. When do people adopt COVID-19 apps?

According to Figure 1, of particular interest is the result that a fairly large number of people adopted the COVID-19 apps before the pandemic reached the peak, while only a small number did so after the pandemic was alleviated. This singular finding necessitates analyzing the timing of adoptions. To do so, we divided the data periods into three phases of the pandemic: i) before the peak of the first wave (to February 23, 2020), ii) during the peak (from February 23 to March 8, 2020), and iii) after the peak (from March 9, 2020) (Figure 1). In our data, 375, 493, and 65 users accessed the COVID-19 apps for the first time in phases 1, 2 and 3, respectively. We estimated the adoption models in each phase in a similar manner to section 2.4 described above. The model is presented in Appendix A3.

2.6. How much do people access the COVID-19 apps?

We model how much users access the COVID-19 apps conditional on their adoption of the apps. To do so, we employ a Poisson regression model with mean λ_{it} , where the dependent variable, $Access_{it}$, indicates the number of times person i accesses the COVID-19 apps during week t . We then incorporate a set of inde-

pendent variables, such as socio-economic variables, the number of COVID-19 positive cases in week t and holidays. Last, we introduce normally distributed random effects across users and weeks to account for the over-dispersiveness of $Access_{it}$ (see Table 1). However, note that this access information does not indicate how many times users receive alerts as our data only records access and not specific app functions. The model is described in Appendix A4.

2.7. Spillovers from COVID-19 apps to behaviors in daily life

Last, we build a model to uncover how usage experience and information from the COVID-19 apps affect people's everyday lives, such as risk avoidance and coping behaviors as predicted by health communication theory and coping theory. In line with this aim, we use the Poisson regression model with mean λ_{it}^c , where the dependent variable, $Access_{it}^c$, indicates the number of times person i accesses apps in app category c (see examples in Table 1) during week t . As the same manner as Section 2.6., we incorporate a set of independent variables, such as socio-economic variables, the number of COVID-19 positive cases in week t and holidays. Importantly, to capture the spillover effect from usages of COVID-19 apps, we incorporate the number of times users accessed the COVID-19 apps in the previous period.

Note that not all panelists in our data adopted COVID-19 apps on their phones, but we incorporate the spillover from the apps in the models described above. The bias of panelists who adopted COVID-19 apps needs to be controlled for in our model. To resolve this selectivity bias, we introduce the inverse Mills ratio similar to [34] as an instrument in the estimation of the models. We present its model description in Appendix A5.

3. RESULTS

We estimated the models using the Markov Chain Monte Carlo (MCMC) Bayesian methods using a software, WinBUGS. We used the first 10,000 iterations as the burning period and the next 10,000 iterations to draw the posterior distributions of the parameters.

3.1. COVID-19 apps

Table 2 reports the estimation results of the adoption, timing, and usage models for the COVID-19 apps as described in Sections 2.4–2.6. First, we found significant estimates for age 20s, income, and education level for the adoption of COVID-19 apps. High-income and higher educated people tend to adopt the COVID-19 apps, while young people in 20s do not.

Interestingly, we found dissimilar results across the COVID-19 phases. Prior to the peak of the first wave, findings showed a high likelihood of adoption of the apps by higher educated people but no differences in age. During the peak, males and higher income people tended to adopt the apps, but individuals in their 20s did not. After the peak, we found a decreasing likelihood of adoption age groups in their 20s, 30s and 40s, and a greater likelihood of adoption of higher educated people. Last, turning to the usage model, the confirmed number of cases of COVID-19 was the main driver for people to adopt and use COVID-19 apps. Also, we ascertained that but people in their 30s and 50s employed them less than in other age groups. Interestingly, low income people who may be vulnerable to COVID-19 virus tend to adopt COVID-19 apps late but they were more prone to utilize COVID-19 apps more frequently.

3.2. Spillover from COVID-19 apps to other apps in daily life

We report the estimation results of the spillover models in Section 2.7. in Table 3. The results show a positive spillover from

COVID-19 apps to navigation, shopping, and food delivery apps and a negative spillover to travel, exercise and subway apps. This implies that people tend to avoid behaviors that may increase infection risk, as signaled by greater use of apps for navigation (i.e., driving), online shopping, food delivery services (i.e., avoid physical spaces and human contact), and by avoiding travel, public transportation such as subway (i.e., avoid human contact) and exercise (i.e., outdoor activity). Drawing on the theory of health protection, we infer that COVID-19 tracking apps help communicate the benefits of avoiding crowds and human contact to reduce the risk on health. These results showcase how COVID-19 apps may tilt people's behaviors toward health protection.

In addition, the increase in perceived risk after using COVID-19 apps may help people exercise various coping strategies to alleviate psychological fear and stress. The results reveal that the use of messenger apps increases after using COVID-19 apps, which implies that people exercise social coping strategies (e.g., messenger apps). However, the results for SNS do not show support for social coping strategies. We note that SNS such as Facebook, Twitter, and Instagram are not limited only to social interaction functions. SNS also provide functions such as news and entertainment (e.g., video clips, live broadcasting), so use of SNS apps may not imply only social coping. In addition, we found that people are more likely to access religion-oriented apps (e.g., mobile bible) after accessing COVID-19 apps, in support of religious coping exercise, while they are less likely to access entertainment apps such as video/music streaming and games.

However, it is important to note that this result may not guarantee “causality” as it is a finding through time- and cross-lagged correlation which is one of the most popular procedures for longitudinal panel data analysis [13]. We further address this limitation in the section that follows.

4. DISCUSSION

4.1. Implications for Academics

The importance of communication in health crisis has long been shown in the literature on health threat communication (for a comprehensive review, see [3,23]). The findings of this study contribute to the literature on health threat communication and coping strategies. The COVID-19 crisis is unique in that it has brought not only a threat to health, life, and security but also psychological stress and depression. Thus, the parallel response model [21,22,40] offers a useful framework to investigate the current COVID-19 pandemic, as it argues that people may engage in danger control (e.g., self-protective behaviors) and/or fear control (e.g., cope with emotional state). While this model conceptualizes health communications and suggests the switch between the processes of danger control and fear control, it has rarely been empirically tested.

This study is the first to provide the related pieces of empirical evidence that government interventions by releasing COVID-19 apps can stimulate voluntary health protective behaviors (e.g., avoiding crowds by driving, shopping online, delaying travel and avoiding public transportation) and threat-coping behaviors (e.g., communicate with others, religious exercise). Given that governments have been struggling to control the COVID-19 pandemic owing to limited resources and its devastating consequences, governments must motivate people to engage “voluntarily” in self-protective behaviors, as proposed in health communication theory.

4.2. Implications for Policy Makers

Since the COVID-19 pandemic began, public health officials and governments all over the world have tried to take advantage of big

Table 3
 Estimation results of spillover models from usage of COVID-19 apps to other apps in daily life.

App type Variable	Health protective behaviors					Food delivery	Shopping	Social coping		Emotional coping			Religious coping
	Navigation	Taxi	Subway	Travel	Exercise			SNS	Messenger	Music	Game	Netflix	
Intercept	-0.707** (0.038)	-0.933** (0.156)	0.215** (0.073)	0.360 (0.244)	-0.495** (0.125)	0.582** (0.063)	0.368** (0.030)	0.607** (0.135)	2.065** (0.045)	0.759** (0.080)	0.472** (0.054)	0.817** (0.088)	-0.672** (0.110)
Sex (male = 1)	0.732** (0.047)	-0.080* (0.056)	0.000 (0.084)	-0.018 (0.149)	0.025 (0.071)	-0.371** (0.052)	-0.747** (0.034)	-0.329** (0.052)	-0.218** (0.020)	-0.110* (0.060)	0.267** (0.042)	-0.212* (0.115)	-0.674** (0.095)
Age													
~29	0.971** (0.076)	0.003 (0.110)	-0.156 (0.149)	0.032 (0.168)	-0.053 (0.122)	0.340** (0.077)	1.308** (0.055)	-0.204** (0.078)	0.225** (0.038)	-0.190** (0.085)	-0.236** (0.045)	-0.846** (0.118)	0.155 (0.164)
30~39	0.606** (0.037)	-0.129 (0.109)	-0.782** (0.093)	-1.100** (0.175)	-0.144 (0.106)	-0.548** (0.062)	1.150** (0.056)	-1.003 (0.079)	0.188** (0.030)	-0.543** (0.112)	-0.345** (0.043)	-0.661** (0.098)	0.441** (0.120)
40~49	0.303** (0.069)	-0.366** (0.131)	-0.689** (0.132)	-1.017** (0.190)	-0.043 (0.096)	-1.183** (0.144)	0.525** (0.044)	-1.689** (0.087)	0.159** (0.033)	-1.034** (0.048)	-0.735** (0.052)	-1.332** (0.163)	0.643** (0.115)
50~59	-0.222** (0.074)	-0.586** (0.130)	-0.624** (0.125)	-1.489** (0.289)	0.395** (0.076)	-1.935** (0.134)	-0.374** (0.060)	-2.039** (0.082)	0.044* (0.028)	-1.402** (0.106)	-1.277** (0.069)	-1.567** (0.191)	1.046** (0.144)
60~69 (Base)	-	-	-	-	-	-	-	-	-	-	-	-	-
Income (+5K USD/month = 1)	0.111** (0.012)	0.038 (0.039)	-0.010 (0.033)	-0.209** (0.059)	0.192** (0.017)	0.071** (0.017)	0.082 (0.008)	-0.016 (0.010)	-0.015** (0.007)	-0.073** (0.007)	-0.013 (0.011)	0.152** (0.029)	-0.357** (0.022)
Marital (single = 1)	-0.058** (0.021)	0.205** (0.059)	-0.207** (0.065)	-1.385 (0.092)	-0.573** (0.045)	0.061** (0.026)	0.165 (0.013)	0.077** (0.014)	0.004 (0.010)	0.090** (0.014)	0.024 (0.021)	-0.747** (0.080)	0.163** (0.043)
Education (college = 1)	0.536** (0.027)	0.042 (0.051)	0.271** (0.036)	-0.559** (0.104)	-0.111** (0.021)	0.019 (0.015)	-0.020 (0.013)	0.069** (0.012)	0.027** (0.010)	0.126** (0.010)	0.041** ^v (0.012)	0.396** (0.047)	0.784** (0.033)
COVID-19 confirmed cases	-0.202** (0.015)	-0.125** (0.038)	-0.165** (0.029)	-0.176** (0.062)	-0.002 (0.027)	-0.005 (0.019)	0.044 (0.010)	0.511** (0.023)	0.251** (0.007)	0.284** (0.012)	0.132** (0.016)	0.039 (0.033)	0.015 (0.025)
Children's and Parents' days	-0.232 (0.238)	-0.339 (0.387)	-0.268 (0.283)	0.010 (0.488)	-0.040 (0.263)	-0.182 (0.275)	-0.364* (0.206)	0.011 (0.180)	0.337** (0.183)	0.421** (0.159)	0.543** (0.204)	-0.040 (0.326)	0.258 (0.423)
Lunar New Year holidays	-0.074 (0.212)	0.120 (0.367)	0.078 (0.326)	0.501 (0.434)	-0.221 (0.280)	-0.381* (0.210)	-0.071 (0.118)	0.565** (0.194)	0.408** (0.078)	1.092** (0.255)	0.558** (0.155)	-0.120 (0.259)	-0.350 (0.350)
Spillover from COVID-19 apps ²	0.022** (0.005)	0.025 (0.022)	-0.138** (0.019)	-0.362** (0.039)	-0.020** (0.007)	0.084** (0.007)	0.033** (0.004)	-0.001 (0.004)	0.016** (0.003)	-0.014** (0.004)	-0.015** (0.005)	-0.040** ^v (0.010)	0.077** (0.007)
Inverse Mills ratio	0.030** (0.010)	0.013 (0.020)	0.018 (0.027)	-0.061* (0.037)	0.027* (0.015)	-0.012 (0.013)	0.082** (0.010)	0.125** (0.012)	0.083** (0.006)	0.082** (0.011)	-0.015** (0.021)	0.012 (0.027)	0.103** (0.030)

NOTE:

The significant and positive (negative) coefficient of "Spillover from COVID-19 apps" implies that people access the apps more (less) after using COVID-19 apps.

** indicates significance at the 95% level.

* indicates significance at the 90% level. Standard deviations are in parentheses.

data, such as mobile technology, to help track and stop the transmission of the virus early on. However, some concerns for health policy makers remain unresolved in exercising such digital intervention policy.

4.2.1. Targeting strategies

First, given our evidence of the indirect effects of COVID-19 apps on health protective behaviors, policy makers must increase apps' adoption rates with effective targeting as the adoption rates have been low in most countries. According to our results in Section 3.1, although young people in their 20s tend to be technologically savvy and mobile friendly, the COVID-19 apps seemingly were not appealing to them as they may believe that they are invulnerable to the virus. Although young people may have low infection rates, they may be careless in their behaviors, which may affect other vulnerable groups. Thus, policy makers should particularly promote COVID-19 apps to young people (e.g., social media campaigns).

Also, low-income and less-educated people, who may also be vulnerable to the damages caused by the pandemic, are less likely to adopt COVID-19 apps. While COVID-19 apps may be useful for people to avoid personal visits to some dangerous places (e.g., restaurants), these apps may not be as useful for these low-income and less-educated people if they work outside or use public transportation. Thus, policy makers should pay particular attention to people of low socio-economic status as the pandemic has helped highlight the inequalities within societies [19,27,38]. For example, health officials may consider giving them incentives such as coupons to increase their adoption rates. More importantly, it would be helpful for such vulnerable people if governments were to promptly sterilize the places where infectious people are found.

4.2.2. Psychological recovery

The results in Section 3.2. imply that the usage of COVID-19 apps may cause people to perceive more anxiety and stress regarding the pandemic. To resolve such anxiety, people may increasingly exercise social and religious coping. However, note that this may not be a net effect only from coping exercise as the usage of religious apps and messaging apps may also exert some degree of health protective behaviors (i.e., avoiding face-to-face human contacts by using messaging apps and avoiding face-to-face religious gatherings).

Interestingly, we found negative spillover effects for mobile game apps, Netflix, and music streaming, which represent emotional coping, which is inconsistent with the results from social and religious coping. Given the limited time spent on mobile devices, people may be involved in activities, such as communicating with other people, and seek information first when the pandemic began to progress and delay activities for distraction (i.e., emotional coping), such as enjoying entertainment, for post-disaster recovery.

Coping is particularly important because the COVID-19 pandemic is a health crisis that can threaten life and has become a yearlong, psychologically stressful event. Importantly, policy makers need to be cognizant and aware that COVID-19 apps may arouse anxiety and stress in the pandemic. Thus, it is important to help people psychologically, especially in a long-term perspective (e.g., by embedding a link to counseling services for depression run by government clinics or non-profit organizations inside COVID-19 apps).

4.2.3. Privacy concern and legal support

Digital intervention using mobile apps inevitably leads to data security and privacy issues. Interestingly, though, the COVID-19

apps launched in South Korea do not use data directly transmitted from smartphones owned by infected people. Rather, they employ contact tracing information collected by the central government as explained in Section 2.1. The COVID-19 apps in South Korea may be a feasible option for other countries under two conditions.

First, it is of particular importance that governments have the ability and resources to perform high-quality contact tracing. KCDA tracks down everyone who has been in contact with an infected person. Once these individuals are contacted, KCDA can request that they get tested and quarantine, and their condition must be monitored. Health policy makers should note that contact tracing can make use of technology such as CCTV and smartphone GPS systems, but it is also a labor-intensive exercise as it is sometimes done by conducting in-person interviews with infected individuals and tracking down the infection chain.

Second, to make the contact tracing information public, compliance with relevant legal registration is required. South Korea, in 2015 after experiencing MERS, enacted a law which enables the collection and publication of anonymized public data, including travel histories of anonymous potential carriers organized by a timeline, to the public (without revealing any personal identifications, such as name, age, gender) in the case of a health crisis. However, this has been criticized for the release of detailed information of the movements of infected people (e.g., names of places they visited and when) through the media and COVID-19 apps [18]. It is still a huge challenge to maintain a balance between user privacy and societal benefit.

On the other hand, neo-liberal societies such as the USA, UK, France, and Germany may not replicate COVID-19 apps used in South Korea as they are very sensitive to privacy issues. For example, based on the European Data Protection Board, the use of COVID-19 apps must be strictly "voluntary" so that the data should come directly from smartphone users who willingly adopt COVID-19 apps and provide their personal information (e.g., whether they are infectious).

In this regard, it is important that governments in neo-liberal countries provide detailed guidance on the collection and use of personal data for contact tracing. People should be made aware as to what data is collected and when, how it will be used for public health purposes, and when it will be destroyed after the pandemic is over. Health officials or governments must take extra efforts to educate people on the societal benefits.

To summarize, COVID-19 apps may be a useful tool to battle the pandemic in some East Asian countries and regions, such as China, Singapore, Hong Kong and Taiwan that have conducted extensive and rapid contact tracing since the arrival of the pandemic (perhaps prior experience with SARS or MERS may have helped certain countries [32]) and where people consider privacy of less concern and, thus, perceive contact tracing information as a necessary trade-off for containing the virus.

Note that COVID-19 apps are not the only way to combat the spread of the novel coronavirus. The World Health Organization (WHO) recommends using digital proximity tracking only as a supplement to other measures, such as increased testing and manual contact tracing.¹ Even with COVID-19 apps, hand washing, social distancing, and wearing masks remain crucial.

¹ WHO, Ethical Considerations to Guide the Use of Digital Proximity Tracking Technologies for COVID-19 ContactTracing 1 (May 28, 2020), <https://perma.cc/5NRA-XUFA>.

Last, as shown in Figure 1, health officials should note that these app-based interventions may be effective only when the pandemic is severe (in our empirical study, at the first wave of the pandemic in South Korea). This implies that such technological tools may not be a long-term solution.

4.3. Limitations and Future Research Directions

As with any research, this study has limitations that could lead to further research. First, privacy concerns are a crucial issue in implementing policy for using mobile technologies and individual data [8,18,31]. However, from a policy standpoint, there is a trade-off between fast and effective control and privacy concerns. Future studies might investigate such a trade-off.

Second, this study sought to offer empirical evidence of the effectiveness of COVID-19 apps in South Korea. Its tracing apps are different from those in other countries. As such, future study may try to test our models for tracing apps in other countries.

Third, we did not investigate the impact of COVID-19 apps on the spread of the coronavirus and disease control. Doing so may require more confidential medical data on positive confirmed patients combined with behavioral data, such as app usage. Further research with medical data needs to be conducted to confirm the findings.

Last, our study employed cross- and time-lag correlation to identify the spillover effects on various facets in daily life. While we employed a fairly large sample of panelists, our study did not uncover the psychological underlying mechanisms to identify behavioral causal influence due to the urgency of COVID-19 research and the difficulty of measuring psychological status directly from the mobile app usage data. Future research could use a behavioral approach to conduct experiments to uncover the psychological underlying mechanisms of using COVID-19 tracking apps and to verify the behavioral causal mechanism to health protective and coping behaviors.

5. CONCLUSION

Launching COVID-19 tracking apps is an important intervention policy for governments to minimize additional exposure to the virus. Despite the importance of doing so, how these tracking apps provide benefit and shape people's everyday lives remains unclear. Drawing on health communication theory and coping theory, we examine the adoption and use of COVID-19 apps and the spillover impacts on various facets of human life in South Korea during and after the first major wave of the pandemic. Our study offers empirical evidence of the potential benefits of digital app-based health-care interventions (i.e., health protective behaviors and coping exercises). This present study provides important and timely recommendations to policy makers in countries where the governments have little experience with managing such tracking apps.

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Declaration of interest

The authors report no declarations of interest

APPENDIX

A1. List of COVID-19 Apps in South Korea

APP NAME (in Korean)	APP Name (in English translation)
코백-코로나맵100m근접알림	COVAC CORONA MAP 100m ALERT
코로나맵	CORONA MAP
코로나 닥터 - 코로나맵	CORONA DOCTOR CORONA MAP
코로나 100신 - 내 주변 확진자	CORONA VACINE INFECTIONS PEOPLE NEAR ME
코로나바이러스(우한페렴)	CORONA VIRUS
우한 코로나 정복	CORONA CONQUEST
우한 페렴 위험지도	CORONA DANGER ZONE MAP
코로나 알리미 - 코로나 맵	CORONA ALERT CORNA MAP
우한페렴예방 - 코로나맵/확진자	CORONA PREVENTION MAP/INFECTION
코로나맵 코로나 알리미	CORONA MAP CORONA ALERT
코로나 마이알림 - 내 주변 확진자	CORONA MY ALERT
코로나바이러스 알리미	CORONA VIRUS ALERT
신종 코로나 바이러스	NOVEL CORONA VIRUS
코로나앱 - 우한 페렴	CORONA APP CORONA VIRUS
코로나바이러스 알리미	CORONA VIRUS ALERT
코로나맵 코로나 알리미	CORONA MAP ALERT
코로나맵 - 코로나19 바이러스	CORONA MAP CORONA 19 VIRUS
우한 페렴 실시간 상황판	CORONA VIRUS REAL TIME ALERT

Note: We translated "Wu-han pneumonia" in app titles to "CORONA VIRUS".

A2. Logistic Regression Model in Section 2.4

$$P(Adopt_i = 1) = \frac{\exp(\alpha_0 + Demo_i\alpha_1)}{1 + \exp(\alpha_0 + Demo_i\alpha_1)} \tag{1}$$

Dependent variable

- $Adopt_i = 1$ if person i adopts COVID-19 apps (accessed COVID-19 apps at least once) during the data period and 0 otherwise.

Interdependent variables

- $Demo_i = [age_i, gender_i, income_i, single_i, education_i]$

where

age_i = a set of dummy variables [age ~29, 30~39, 40~49, 50~59], where the reference is age 60~69.

$gender_i = 1$, if person i is male and 0 female.

$income_i = 1$ if person i 's monthly income is greater than 5M KRW (4,500 USD) and 0 otherwise.

$single_i = 1$ if person i is not married and 0 if user i is married.

$education_i = 1$ if person i is a university student or graduated from a university and 0 otherwise.

A3. Logistic Regression Model in Section 2.5

$$P(Adopt_{it} = 1) = \frac{\exp(\alpha_0 + Demo_i\alpha_1)}{1 + \exp(\alpha_0 + Demo_i\alpha_1)} \tag{2}$$

Dependent variable

- **Model 1:** $t=1$ (before the peak: to February 23, 2020).

$Adopt_{it} = 1$ if person i adopts COVID-19 app (accessed COVID-19 apps for the first time) before the peak; 0 otherwise.

- **Model 2:** $t=2$ (during the peak: from February 23 to March 8, 2020).

Out of those people who had not adopted the COVID-19 app at $t=1$

$Adopt_{it} = 1$ if person i adopts COVID-19 apps (accessed COVID-19 apps for the first time) during the peak; 0 otherwise.

- **Model 3:** $t=3$ (after the peak: from March 9, 2020).

Out of those people who had not adopted the COVID-19 app at $t=1$ and 2

$Adopt_{it} = 1$ if person i adopts COVID-19 apps (accessed COVID-19 apps for the first time) after the peak; 0 otherwise.

Interdependent variables

- $Demo_i = [age_i, gender_i, income_i, single_i, education_i]$

where

age_i = a set of dummy variables [age ~29, 30~39, 40~49, 50~59], where the reference is age 60~69.

$gender_i = 1$, if person i is male and 0 female.

$income_i = 1$ if person i 's monthly income is greater than 5M KRW (4,500 USD) and 0 otherwise.

$single_i = 1$ if person i is not married and 0 if user i is married.

$education_i = 1$ if person i is a university student or graduated from a university and 0 otherwise.

A4. Poisson Regression Model in Section 2.6

$$Access_{it} \sim \text{Poisson}(\lambda_{it})$$

$$\ln(\lambda_{it}) = \alpha_0 + Demo_i\alpha_1 + \alpha_2 Covid19_t + Holidays_t\alpha_3 + \xi_i + \zeta_t. \tag{3}$$

Dependent variable

- $Access_{it}$ the number of times person i accesses the COVID-19 apps during week t .

Interdependent variables

- $Demo_i = [age_i, gender_i, income_i, single_i, education_i]$

where

age_i = a set of dummy variables [age ~29, 30~39, 40~49, 50~59], where the reference is age 60~69.

$gender_i = 1$, if person i is male and 0 female.

$income_i = 1$ if person i 's monthly income is greater than 5M KRW (4,500 USD) and 0 otherwise.

$single_i = 1$ if person i is not married and 0 if user i is married.

$education_i = 1$ if person i is a university student or graduated from a university and 0 otherwise.

- $Covid19_t$: logarithm of the number of COVID-19 confirmed cases on week t
- $Holidays_t = 1$ if Lunar New Year holidays in February, children's and parents' special days in April were in week t , 0 otherwise.
- $\xi_i \sim N(0, \sigma_\xi^2)$: normally distributed random effect across people
- $\zeta_t \sim N(0, \sigma_\zeta^2)$: normally distributed random effect across weeks

A5. Poisson Regression Model in Section 2.7

$$Access_{it}^c \sim \text{Poisson}(\lambda_{it}^c),$$

$$\ln(\lambda_{it}^c) = \alpha_0^c + Demo_i\alpha_1^c + \alpha_2^c Covid19_t + Holidays_t\alpha_3^c + \alpha_4^c Spillover_{it-1} + \alpha_5^c Mills_i + \xi_i + \zeta_t. \tag{4}$$

Dependent variable

- $Access_{it}^c$: the number of times person i accesses apps in app category c (see examples in Table 1) during week t

Interdependent variables

- $Demo_i = [age_i, gender_i, income_i, single_i, education_i]$

where

age_i = a set of dummy variables [age ~29, 30~39, 40~49, 50~59], where the reference is age 60~69.

$gender_i = 1$, if person i is male and 0 female.

$income_i = 1$ if person i 's monthly income is greater than 5M KRW (4,500 USD) and 0 otherwise.

$single_i = 1$ if person i is not married and 0 if user i is married.

$education_i = 1$ if person i is a university student or graduated from a university and 0 otherwise.

- $Covid19_t$: logarithm of the number of COVID-19 confirmed cases on week t
- $Holidays_t = 1$ if Lunar New Year holidays in February, children's and parents' special days in April were in week t , 0 otherwise.
- $Spillover_{it-1}$: logarithm of the number of times users accessed the COVID-19 apps in the previous period.
- $Mills_i = \frac{\phi(\theta_c + Demo_i\theta_{1c})}{\Phi(\theta_c + Demo_i\theta_{1c})}$ for person i if he or she adopted the COVID-19 apps, and $Mills_i = -\frac{\phi(\theta_c + Demo_i\theta_{1c})}{1 - \Phi(\theta_c + Demo_i\theta_{1c})}$ for person i if he or she did not adopt the COVID-19 apps, where ϕ and Φ indicate a standard normal distribution p.d.f. and c.d.f., respectively. The parameter θ_c in the inverse Mills ratio function can be estimated from a probit model, where the dependent variable is whether user i adopts the COVID-19 apps (0) or not (1). We incorporate demographic data of individual users into the inverse Mills ratio functions similar to Equation (1).

The inverse Mill's ratio works as an instrumental variable for a *spillover* variable (whether this variable is observed—that is, user i adopts and uses COVID-19 apps). In general, the interpretation of the coefficient of the inverse Mill's ratio, α_5^c , is described below. The major role of the inverse Mill's ratio is to correct for any selection bias. When the coefficient of the inverse Mill's ratio is positive, "positive selection" occurs (without the correction, the estimate of α_4^c would be upward-biased); when it is negative, "negative selection" occurs (without the correction, the estimate of α_4^c would be downward-biased). If the coefficient of the inverse Mill's ratio is not significant, there may not be a strong selection bias for the *spillover* variable.

- $\xi_i \sim N(0, \sigma_\xi^2)$: normally distributed random effect across people
- $\zeta_t \sim N(0, \sigma_\zeta^2)$: normally distributed random effect across weeks

References

- [1] Altmann S, Milsom L, Zillessen H, Blasone R, Gerdon F, Bach R, Kreuter F, Nosenzo D, Toussaert S, Abeler J. Acceptability of App-Based Contact Tracing for COVID-19: Cross-Country Survey Study. JMIR Mhealth Uhealth 2020;8(8):e19857. doi:10.2196/19857.
- [2] Barrett AM, Hogreve J, Brüggem EC. Coping With Governmental Restrictions The Relationship Between Stay-at-Home Orders, Resilience, and Functional, Social, Mental, Physical, and Financial Well-Being. Frontiers in Psychology 2021. doi:10.3389/fpsyg.2020.577972.
- [3] Beck KH, Frankel A. A conceptualization of threat communications and protective Health Behavior. Social Psychology Quarterly 1981;44(3):204–17.
- [4] Berger E, Castagne R, Chadeau-Hyam M, et al. Multi-cohort study identifies social determinants of systemic inflammation over the life course. Nature Communications 2019;10:773. doi:10.1038/s41467-019-08732-x.
- [5] Bish A, Michie S. Demographic and attitudinal determinants of protective behaviours during a pandemic: A review. British Journal of Health Psychology 2020;15(4):797–824.
- [6] Braithwaite I, Callender T, Bullock M, Aldridge RW. Automated and partly automated contact tracing: a systematic review to inform the control of COVID-19. The Lancet Digital Health, 2; 2020. p. e607–21. doi:10.1016/S2589-7500(20)30184-9.
- [7] Chan EY, Saqib NU. Privacy concerns can explain unwillingness to download and use contact tracing apps when COVID-19 concerns are high. Computers in Human Behavior 2021;119. doi:10.1016/j.chb.2021.106718.

- [8] Fahey RA, Hino A. COVID-19, digital privacy, and the social limits on data-focused public health responses. *International Journal of Information Management* 2020;55. <http://dx.doi.org/10.1016/j.ijinfomgt.2020.102181>.
- [9] Ferretti L, Wymant C, Kendall M, Zhao L, Nurtay A, Abeler-Dörner L, et al. Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science* 2020;368(6491):eabb6936 <http://dx.doi.org/10.1126/science.abb6936>.
- [10] Folkman S, Richard SL. An analysis of coping in a middle-aged community sample. *Journal of Health and Social Behavior* 1980;21:219–39.
- [11] Gardner A. There's No Evidence Contact-Tracing Apps Are Helping Stop COVID-19. *Science The Wire* 2020.
- [12] Gibbs HW, Achterberg-Lawlis J. Spiritual values and death anxiety: Implications for counseling with terminal cancer patients. *Journal of Counseling Psychology* 1978;25:563–9.
- [13] Granger CWJ. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 1969;37:424–38.
- [14] Greenglass E. The contribution of social support to coping strategies. *Applied Psychology: An International Review* 1993;42:323–40.
- [15] Greenglass ER. Proactive coping. In: Frydenberg E, editor. *Beyond coping: Meeting goals, vision and challenges*. London, UK: Oxford University Press; 2002. p. 37–62.
- [16] Hinch R, Probert W, Nurtay A, Kendall M, Wymant C, Hall M, Fraser C. Effective configurations of a digital contact tracing app: A report to NHSX (NHSX Report). The Conversation Trust (UK) Limited. 2020. https://cdn.theconversation.com/static_files/files/1009/Report_Effective_App_Configurations.pdf?1587531217.
- [17] Jenkins RA, Pargament KI. Religion and spirituality as resources for coping with cancer. *Journal of Psychosocial Oncology* 1995;13(5):1–74.
- [18] Jung G, Le H, Kim A, Lee U. Too much information: assessing privacy risks of contact trace data disclosure on people with COVID-19 in South Korea. *Frontiers in Public Health* 2020. doi:10.3389/fpubh.2020.00305.
- [19] Khalatbari-Soltani S, Cumming RC, Delpierre C, Kelly-Irving M. Importance of collecting data on socioeconomic determinants from the early stage of the COVID-19 outbreak onwards. *Journal of Epidemiology and Community Health* 2020;74:620–3.
- [20] Krieger NA glossary for social epidemiology. *Journal of Epidemiology and Community Health* 2001;55:693–700.
- [21] Leventhal H. Fear appeals and persuasion: The differentiation of a motivational construct. *American Journal of Public Health* 1970;61:1208–24.
- [22] Leventhal H, Safer MA, Panagis DM. The impact of communications on the self-regulation of health beliefs decisions and behavior. *Health Education Quarterly* 1983;10(1):3–29.
- [23] McComas KA. Defining moments in risk communication research: 1996–2005. *Journal of Health Communication* 2006;11(1):75–91.
- [24] Medical Express. French virus tracing app flops with only 14 Alerts. 2020. <https://medicalxpress.com/news/2020-06-french-virus-app-flops.html>.
- [25] Meyers MS, Altmaier EM, Bums CB. Religious orientation and coping with cancer. *Journal of Religion and Health* 1992;31:273–9.
- [26] Fulbright Norton Rose. Contact tracing apps: A new world for data privacy; 2020. <https://www.nortonrosefulbright.com/en-hk/knowledge/publications/d7a9a296/contact-tracing-apps-a-new-world-for-data-privacy>.
- [27] Patel JA, Nielsen FBH, Badiani AA, Assi S, Unadkat VA, Patel B, Ravindrane R, Wardle H. Poverty, inequality and COVID-19: the forgotten vulnerable. *Public Health* 2020;183:110–11.
- [28] Rippetoe PA, Rogers RW. Effects of components of protection-motivation theory on adaptive and maladaptive coping with a health threat. *Journal of Personality and Social Psychology* 1986;52(3):596–604.
- [29] Rodríguez P, Graña S, Alvarez-León EE, et al. A population-based controlled experiment assessing the epidemiological impact of digital contact tracing. *Nat Commun* 2021(587):12. doi:10.1038/s41467-020-20817-6.
- [30] Rogers RW. A protection motivation theory of fear appeals and attitudes change. *Journal of Psychology* 1975;91:93–114.
- [31] Rowe F. Contact tracing apps and values dilemmas: A privacy paradox in a neo-liberal world. *International Journal of Information Management* 2020;55. <http://dx.doi.org/10.1016/j.ijinfomgt.2020.102178>.
- [32] Ru H, Yang E, Zou K. Combating the COVID-19 Pandemic: The Role of the SARS Imprint. *Management Science* 2021 Forthcoming.
- [33] Savadori L, Lauriola M. Risk Perception and Protective Behaviors During the Rise of the COVID-19 Outbreak in Italy. *Frontiers in Psychology* 2021. doi:10.3389/fpsyg.2020.577331.
- [34] Semykina A, Wooldridge JM. Estimating panel data models in the presence of endogeneity and selection. *Journal of Econometrics* 2010;157(2):375–80.
- [35] Song S, Yang X, Yang H, Zhou P, Ma H, Teng C, Chen H, Ou H, Li J, Mathews CA, Nutley S, Liu N, Zhang X, Zhang N. Psychological resilience as a protective factor for depression and anxiety among the public during the outbreak of COVID-19. *Frontiers in Psychology* 2021. doi:10.3389/fpsyg.2020.618509.
- [36] Timberg C, Hendrix S, Kim MJ, Weber-Steinhaus F. Cell-phone apps designed to track covid-19 spread struggle worldwide amid privacy concerns. *The Washington Post*; 2020. <https://www.washingtonpost.com/technology/2020/08/17/covid-tracking-apps-cellphones/>.
- [37] Trang S, Trenz M, Weiger WH, Tarafdar M, Cheung CM. One app to trace them all? Examining app specifications for mass acceptance of contact-tracing apps. *European Journal of Information Systems* 2020;29(4):415–28.
- [38] Van Dorn A, Rebecca CE, Miriam SL. COVID-19 exacerbating inequalities in the US. *Lancet* 2020;395(10232):1243–4. doi:10.1016/S0140-6736(20)30893-X.
- [39] Meisenzahl M. Take a look at these Korean apps helping people avoid areas infected by the coronavirus. *Business Insider* 2020.
- [40] Witte K. Fear control and danger control: A test of the extended parallel process model (EPPM). *Communications Monographs* 1994;61(2):113–34.
- [41] Yoo KJ, Kwon S, Choi Y, Bishal DM. Systematic assessment of South Korea's capabilities to control COVID-19. *Health Policy* 2021. doi:10.1016/j.healthpol.2021.02.011.