International Journal of
Geo-Information

MDPI

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An Examination of People's Privacy Concerns, Perceptions of Social Benefits, and Acceptance of COVID-19 Mitigation Measures That Harness Location Information: A Comparative Study of the U.S. and South Korea

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Abstract: This paper examines people's privacy concerns, perceptions of social benefits, and acceptance of various COVID-19 control measures that harness location information using data collected through an online survey in the U.S. and South Korea. The results indicate that people have higher privacy concerns for methods that use more sensitive and private information. The results also reveal that people's perceptions of social benefits are low when their privacy concerns are high, indicating a trade-off relationship between privacy concerns and perceived social benefits. Moreover, the acceptance by South Koreans for most mitigation methods is significantly higher than that by people in the U.S. Lastly, the regression results indicate that South Koreans (compared to people in the U.S.) and people with a stronger collectivist orientation tend to have higher acceptance for the control measures because they have lower privacy concerns and perceive greater social benefits for the measures. These findings advance our understanding of the important role of geographic context and culture as well as people's experiences of the mitigation measures applied to control a previous pandemic.

Keywords: acceptance; comparative study; COVID-19; geoprivacy; location privacy; pandemic; perception; privacy; social benefits

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Citation: Kim, J.; Kwan, M.-P. An Examination of People's Privacy Concerns, Perceptions of Social Benefits, and Acceptance of COVID-19 Mitigation Measures That Harness Location Information: A Comparative Study of the U.S. and South Korea. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 25. https://doi.org/10.3390/ijgi10010025

Received: 25 November 2020
Accepted: 11 January 2021
Published: 12 January 2021

1. Introduction

Since December 2019, the COVID-19 (the novel coronavirus disease 2019) pandemic has become one of the unprecedented and critical global health issues [1,2]. As of mid-January 2021, there have been about 90.0 million total confirmed cases and 1.9 million deaths globally [3]. To control the COVID-19 pandemic, considerable research and policy efforts have been made, such as developing vaccines, increasing COVID-19 testing, and conducting epidemiological studies.

Among various COVID-19 mitigation methods, those that capture geographers' attention are methods that harness people's location data, which are private and often sensitive [4,5]. For example, some countries have obtained the location information of COVID-19 patients from their mobile phones (e.g., GPS trajectories records) to accurately find the close contacts of these patients (a practice called *contact tracing*). People's private location information has played an important role when implementing COVID-19 control measures [6–10] (Figure 1).

The first type consists of contact tracing methods. Contact tracing is an epidemiological survey method that public health authorities used to trace back the activities of patients to identify people who had been in close contact with the patients and might need to self-quarantine or get tested [11]. An in-depth interview with patients is the usual method for conducting contact tracing. However, the interviews are time-consuming and costly. For instance, it is estimated that 100,000 new contact tracers are needed in the U.S. to adequately track the close contacts of COVID-19 patients [12]. To address these limitations, some countries have obtained patients' location information by using geospatial technologies, such as GPS records in patients' mobile phones and their credit card usage records [13]. Similarly, other countries have adopted a proximity tracing approach, which utilizes a Bluetooth-based mobile phone application [14]. This application records the anonymized IDs of the people who were in close proximity to the application user over time. When the application user is diagnosed with COVID-19, the system sends an alarm message to people who were recorded as the close contacts of the application user. Using these technology-based methods, more efficient contact tracing can be achieved, which can potentially contribute to the social benefits of better control of the pandemic.

Despite the potential social benefits of these digital contact tracing methods, they may violate COVID-19 patients' geoprivacy. Geoprivacy entails "individual rights to prevent disclosure of the location of one's home, workplace, daily activities, or trips" ([15], p. 15). In the traditional interview method, COVID-19 patients may be able to control which location information they want to share and to what extent (although this is not a desirable situation). By doing so, they may be able to protect their geoprivacy. In the new digital contact tracing methods, however, people have very little control over the process to protect their geoprivacy because all location information that is gathered through various devices (e.g., mobile phones and applications) is automatically sent to public health agencies, and this may lead to some possibilities for geoprivacy violations. For example, public health officials obtain detailed information about certain patients (e.g., which store/café/restaurant patients visited, what items patients bought, and so on), as they can access patients' credit card usage history. When private information is not properly handled (e.g., breached by hackers), serious geoprivacy violations can occur because the data contain very detailed and comprehensive information about patients.

The second type of COVID-19 mitigation measure consists of methods that monitor how people properly practice self-quarantine. The rationale behind monitoring self-quarantine is to prevent non-compliance or violations, which may spread the virus [16,17]. In some countries, public health authorities randomly call people to check whether they are practicing self-quarantine properly [18]. Some countries have further implemented real-time monitoring methods that harness geospatial technologies, such as mobile phone GPS tracking or an e-wristband [19–21]. Some countries do not directly monitor self-quarantine but have implemented a travel certificate [19]. For example, people are required to show their valid travel certificates when visiting public spaces or entering buildings. People who are required to self-quarantine cannot have a valid travel certificate. Overall, by adopting these methods, self-quarantine can be managed more reliably, which can potentially contribute to the social benefits of disease control.

However, although these self-quarantine monitoring methods may benefit society at large, they may violate the geoprivacy of people who are required to self-quarantine. For instance, GPS tracking violates these people's geoprivacy because those who have access to this information would know the people's locations in real-time. Additionally, requesting people in self-quarantine to wear an e-wristband may trigger public controversy, as the e-wristband is usually applied to criminals. Moreover, although it is expected that the real-time location information from these devices is saved in a secured database, the database can be hacked and may lead to geoprivacy violations [22].

The third type includes COVID-19 mitigation methods that publicly disclose the locations where COVID-19 patients visited [23]. Although contact tracing can identify people who were in close contact with COVID-19 patients, it would not be possible to identify all the close contacts in public settings, such as grocery stores or public transit (e.g., people who sit right next to an infected person in the subway for 1 h). Since it is unclear whether those people are infected by the patient, one way to reduce the uncertainties is to release the information about locations where patients visited. By releasing such information to the public, people who visited those places can know that they might be infected and thus need to be tested. Moreover, during the pandemic, the general public would want to have more information about the disease [24]. In this light, disclosing such information may play an important role in satisfying people's right to know. This may potentially contribute to the social benefits of pandemic control.

Despite the potential social benefits, these methods may violate people's geoprivacy because the specific identity of a certain patient can be estimated through spatial reverse engineering. Spatial reverse engineering is the technique by which a specific identity of a certain person (e.g., name and home address) can be accurately estimated by linking detailed locational information to publicly available data, such as white pages or voter lists, which can lead to geoprivacy violations [25–27]. This would be particularly possible when patients' demographic information (e.g., age, gender, or occupation) is released along with their major locations because it becomes easier to estimate the identity of a certain patient with more information. Moreover, this would pose a serious geoprivacy issue because recent advances in AI and high-performance computing techniques may significantly increase the accuracy of spatial reverse engineering [28,29].

To sum up, although various COVID-19 mitigation methods that harness people's sensitive location information can potentially contribute to the social benefits of pandemic control, these methods have the potential for violating people's geoprivacy, as they utilize people's sensitive location information. Furthermore, some people may be more willing to accept certain mitigation methods, while others are less willing to accept them. Several factors may explain the variations in people's acceptance of COVID-19 mitigation measures.

First, a person's values regarding the trade-offs between his/her geoprivacy rights and the social benefits of disease control may influence his/her acceptance of these measures. Such value orientation may be assessed by people's individualist–collectivist orientation. A person with a collectivist orientation tends to prioritize the benefits for and welfare of his/her community at large and is less concerned about his/her privacy [30,31]. In this light, especially during the COVID-19 pandemic, when the community or society is at great risk, a person with a stronger collectivist orientation would be more willing to accept various COVID-19 mitigation measures than a person with a weaker collectivist orientation. This is because a person with a stronger collectivist orientation is more likely to think that these mitigation measures can control the disease and thus would benefit the community or society.

Second, a person's residing country and geographic context would play an important role in influencing his/her acceptance of these measures. Since people living in one country tend to share similar cultures and experiences, a person's reaction to a certain threat (e.g., the COVID-19 pandemic) may be similar to others in the same country. For example, it is widely known that South Korea (officially, the Republic of Korea) could implement COVID-19 control measures that harness sensitive location information without facing serious public opposition [23,24]. One of the reasons for being able to implement such policies is the country's painful lessons from its failure in dealing with the Middle East Respiratory Syndrome (MERS) in 2015 [32,33]. Since each country has its own specific experiences related to infectious disease outbreaks and control, a person's acceptance of various COVID-19 control measures is associated with his/her residing country and geographic context.

To date, however, empirical evidence of the relationships between people's acceptance, privacy concerns, and perceptions of social benefits regarding the COVID-19 mitigation methods and people's characteristics remains unclear. To fill this gap, this research aimed to examine people's acceptance, privacy concerns, and perceptions of social benefits for various COVID-19 mitigation measures that harness private location information by using data collected through an online survey.

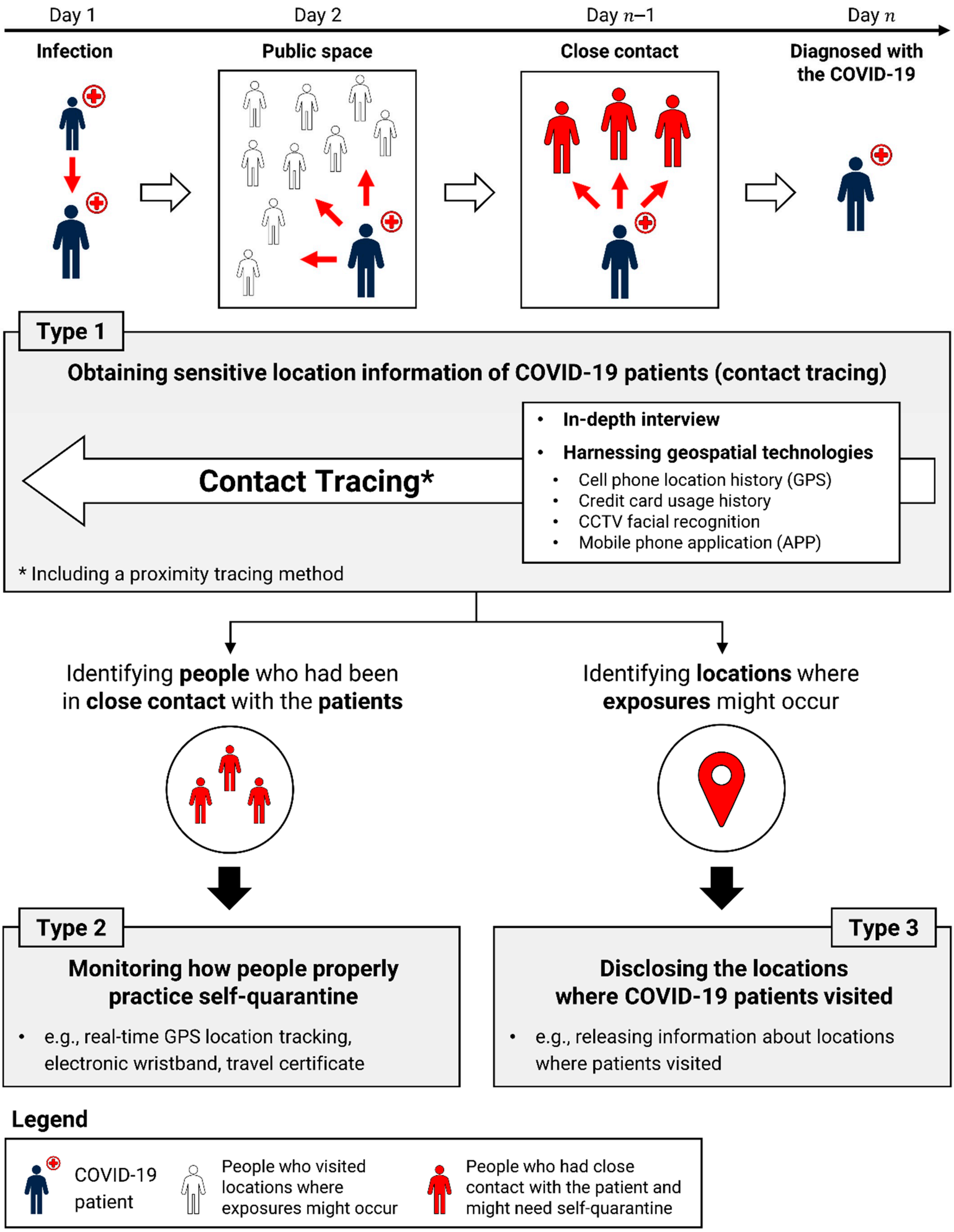

Figure 1. Three types of COVID-19 mitigation measures harnessing location information.

First, we investigated how people's acceptance, privacy concerns, and perceptions of social benefits were different in terms of COVID-19 mitigation methods. Second, we examined how an individual's acceptance of these methods was associated with his/her attributes, including sociodemographic characteristics, the residing country (i.e., geographic context), and their individualist–collectivist orientation. In terms of one's residing country, although it would be ideal to survey people from many countries in the world, it was practically difficult considering the limited budget. As a result, our research focused on two countries—the U.S. and South Korea—which are significantly different from one another in terms of culture (e.g., Eastern and Western culture) and experiences regarding the current COVID-19 pandemic and previous infectious diseases (e.g., MERS in 2015). Moreover, South Korea has implemented various powerful COVID-19 mitigation measures that harness sensitive location information, but the U.S. has focused on different types of measures, such as stay-at-home orders.

Understanding people's perception is significant, as it provides important insights into some of the reasons why some countries are more successful in implementing COVID-19 mitigation measures that utilize people's sensitive location information and balancing people's privacy concerns and the social benefits [19,21]. Furthermore, these insights are especially important because of the unabated and significant spread of COVID-19 in many countries at the time of writing (mid-December 2020) and the need for more effective mitigation measures. In this light, with a better understanding of people's acceptance of various COVID-19 mitigation measures, public health authorities can be informed to implement successful policies that would be highly acceptable to people.

Note that this research primarily sought to explain the difference in acceptance between South Korea and the United States while focusing on privacy concerns and perceptions of social benefits. Although other factors might also affect people's acceptance of various COVID-19 mitigation measures, such as the severity of COVID-19 and trust in government agencies, examining whether these factors affect acceptance was not the primary purpose of this paper.

2. Data and Methods

2.1. Data Collection

The data used for this research were collected via Qualtrics. Solicitations were distributed via the Facebook advertisement service. By using this service, one can advertise a solicitation Facebook post to target users (e.g., South Korean participants: adults 18+ years old living in South Korea; U.S. participants: adults 18+ years old living in the U.S.). In addition, solicitations were also distributed via the authors' Twitter accounts. We furthermore used a snowball sampling method to recruit more survey participants. Survey participants were recruited between 25 June 25 and 10 July 2020. Since the COVID-19 situation is changing rapidly, it is worth mentioning that the COVID-19 pandemic situations in South Korea and the U.S. were significantly different during the survey period (Figure 2); South Korea experienced relatively low daily new cases (compared to the peak in early March), while the U.S. experienced a second surge (Wave 2) in new cases starting from mid-June after several states re-opened.

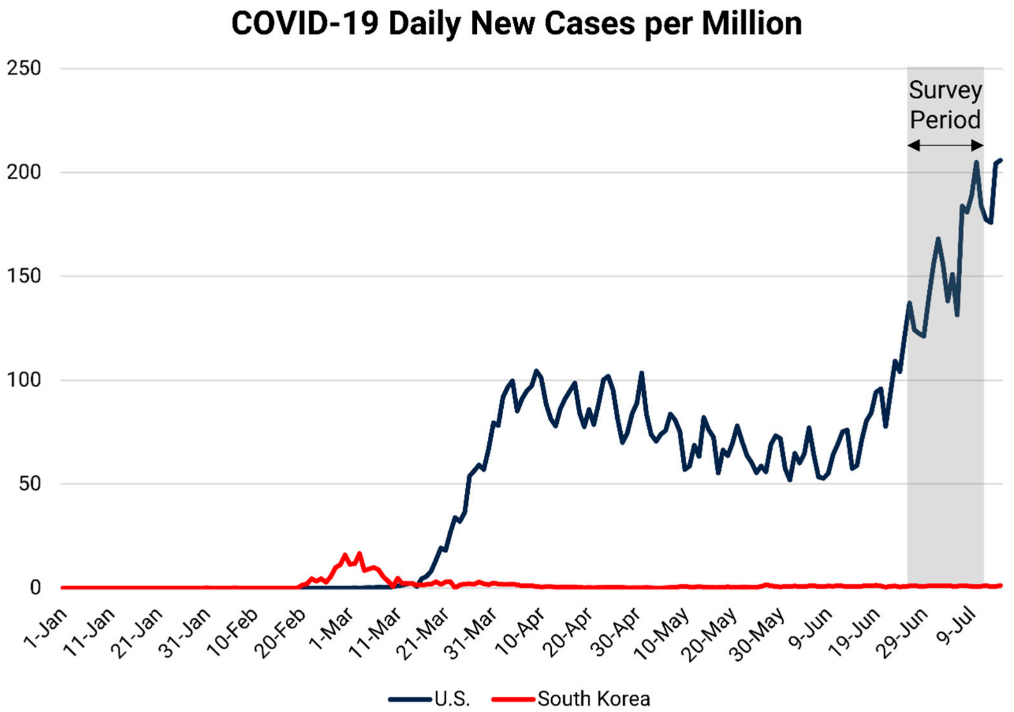

Figure 2. COVID-19: daily new cases per million in the U.S. and South Korea since January 2020 (data source: [34]).

In the end, 306 people participated in the online survey. Table 1 presents the descriptive statistics of the participants' sociodemographic attributes. Specifically, our sample in both countries consisted of higher percentages of young and highly educated people compared to each nationwide statistic. As one can expect, this is because of recruiting via Facebook and Twitter and the snowball sampling method [35,36]. Despite these discrepancies, the results of our survey can still provide some meaningful knowledge and public health policy suggestions. However, one needs to keep in mind this limitation when interpreting the results of our study. Lastly, since the survey was conducted in the U.S. and South Korea, the English version of the survey questionnaire was translated into the Korean language by a native South Korean. The Institutional Review Board (IRB) of the authors' university reviewed and approved the survey protocol and questionnaire.

Table 1. Sociodemographic characteristics of the U.S. (n = 188) and South Korea (n = 118) survey participants, and comparison with those of the national populations.

		U.S.		**South Korea**	
		Sample (n = 188)	**National Population [1]**	**Sample (n = 118)**	**National Population [2]**
Gender	Female	70%	51%	42%	50%
Age	18–24	26%	12%	30%	14%
	25–44	57%	34%	49%	33%
	45+	17%	53%	19%	53%
Race	White alone	55%	74%	N/A [3]	N/A [3]
Higher Education		88%	32% [4]	73%	33% [4]
Student		31%	N/A	41%	N/A

Notes: [1] ACS 2018 five-year estimate data (18+ years old). [2] 2015/2018 Statistics Korea data (15+ years old). [3] No race data. [4] Bachelor's degree or higher (U.S.: 25+ years old; South Korea: 20+ years old).

2.2. Survey Questionnaire

The survey questionnaire consisted of two parts. Part 1 examined people's opinions on 10 COVID-19 mitigation measures that harness location information. For each method, we asked questions on the following three things: (1) privacy concerns (i.e., the level of privacy concerns a person may have), (2) perceptions of social benefits (i.e., the level of social benefits a person thinks would be gained by providing the information requested by public health authorities), and (3) acceptance (i.e., to what extent the measure in question was acceptable to the respondent). Each item was measured on a 7-point scale (from 1 to 7). For example, regarding privacy concerns, "1" indicated "not concerned at all", and 4 indicated "neutral", while 7 indicated "very concerned". Regarding the perceptions of social benefits, "1" indicated "not beneficial at all", while "7" indicated "very beneficial". Regarding acceptance, "1" indicated "not acceptable at all", while "7" indicated "very acceptable".

Three types of COVID-19 mitigation measures were examined in the survey (Table 2). Appendix A Table A1 provides comprehensive survey instructions for each measure. The first type (M1–4) focused on contact tracing methods. The second type (M5–8) focused on self-quarantine monitoring methods. The third type (M9–10) focused on public disclosure of the locations of COVID-19 patients' major activities. Note that, in South Korea, most of these methods (except M4 and M8) have already been implemented. In the U.S., however, only one method (M1) is widely practiced. Recall that the primary goal of this paper was to compare people's acceptance of mitigation measures between the U.S. and South Korea. To achieve this, non-parametric tests (Mann–Whitney test) were utilized. We used non-parametric tests because the responses were measured on an ordinal scale and did not follow normal distributions, as the normality test (Shapiro–Wilk test) results reveal [37].

Table 2. A detailed description of the 10 COVID-19 mitigation methods harnessing location information used in the survey.

Method	Type	Description	Execution	
			U.S.	South Korea
M1	Contact Tracing	Obtaining location information by conducting conventional interviews	O	O
M2		Obtaining location information from patients' mobile phones (e.g., GPS trajectories)	△	O
M3		Obtaining location information from patients' credit card history	X	O
M4		Bluetooth-based proximity tracing method	△	X
M5	Self-Quarantine Monitoring	Monitoring people's self-quarantine by calling them at random times of day	△	O
M6		Monitoring people's self-quarantine by obtaining their real-time locations from their mobile phones (e.g., signal)	X	O
M7		Monitoring people's self-quarantine by requiring them to wear an e-wristband that reported their real-time locations to public health officers	X	□
M8		People were required to carry a valid travel certificate (i.e., not in self-quarantine) when using public places	X	X
M9	Location Disclosure	Publicly disclosing the locations of major activities of COVID-19 patients with their ages and genders	X	O
M10		Publicly disclosing the locations of major activities of COVID-19 patients (not disclosing age and gender)	X	O

Notes: The status of execution of each method is subject to change, as the COVID-19 pandemic situation is rapidly evolving. O: Being used (in most regions). X: Not being used. △: Some regions/institutions are employing this method. □: Only people who violate the self-quarantine mandate are required to wear an e-wristband.

Part 2 of the survey questionnaire asked about survey participants' various sociodemographic characteristics. Moreover, we used 16 survey items adopted from [38] to measure a person's collectivist–individualist orientation. Some of these 16 items were selected to calculate a factor score of a person's collectivist orientation score obtained from a confirmatory factor analysis (CFA). Although these survey items cover both individualist and collectivist orientations, we focused only on the collectivist orientation score because a stronger collectivist orientation is closely associated with a weaker individualist orientation. Individual sociodemographic attributes and estimated collectivist orientation scores were used in the analyses reported in the next section.

3. Results

3.1. Privacy Concerns, Perceptions of Social Benefits, and Acceptance of COVID-19 Contact Tracing Methods (M1–4)

In this subsection, we examine participants' privacy concerns, perceptions of social benefits, and acceptance regarding four contact tracing methods that harness location information (M1–4). Tables 3–5 and Figure 3 show the results. Table 5 focuses on the acceptance and disapproval rates. The acceptance rate (A) indicates the percentage of participants who chose 5, 6, and 7 for the acceptance question for each method (see Tables A2–A4 which present the frequency of responses for each method).

Table 3. Descriptive statistics of privacy concerns, perceptions of social benefits, and acceptance of the four contact tracing methods.

Methods	U.S.			South Korea		
	Privacy Concerns	Perceived Social Benefits	Acceptance	Privacy Concerns	Perceived Social Benefits	Acceptance
M1	3.1 (1.9)	5.7 (1.7)	5.6 (1.6)	3.6 (1.9)	5.7 (1.3)	5.7 (1.3)
M2	4.5 (2.0)	5.1 (1.9)	4.2 (2.0)	4.2 (1.9)	5.8 (1.4)	5.5 (1.4)
M3	5.0 (2.0)	4.1 (2.0)	3.5 (2.1)	4.0 (2.0)	5.5 (1.4)	5.6 (1.4)
M4	4.3 (2.1)	5.2 (1.8)	4.3 (2.0)	3.9 (1.9)	5.8 (1.2)	5.5 (1.5)

Notes: Standard deviation in parenthesis.

Table 4. Mann–Whitney test results for the four contact tracing methods (comparison between the U.S. and South Korea).

Methods	Privacy Concerns		Perceived Social Benefits		Acceptance	
	p-Value	$\lvert r \rvert$	*p*-Value	$\lvert r \rvert$	*p*-Value	$\lvert r \rvert$
M1	0.007 **	0.155	0.077	0.101	0.944	0.004
M2	0.188	0.076	0.006 **	0.158	0.000 ***	0.314
M3	0.000 ***	0.242	0.000 ***	0.340	0.000 ***	0.476
M4	0.123	0.088	0.031 *	0.123	0.000 ***	0.294

Notes: r denotes effect size. *** denotes $p < 0.001$. ** denotes $p < 0.01$. * denotes $p < 0.05$.

Table 5. Acceptance and disapproval rates for the four contact tracing methods.

Methods	U.S.		South Korea	
	Acceptance	Disapproval	Acceptance	Disapproval
M1	79%	10%	82%	6%
M2	48%	39%	78%	10%
M3	33%	56%	81%	8%
M4	53%	31%	75%	9%

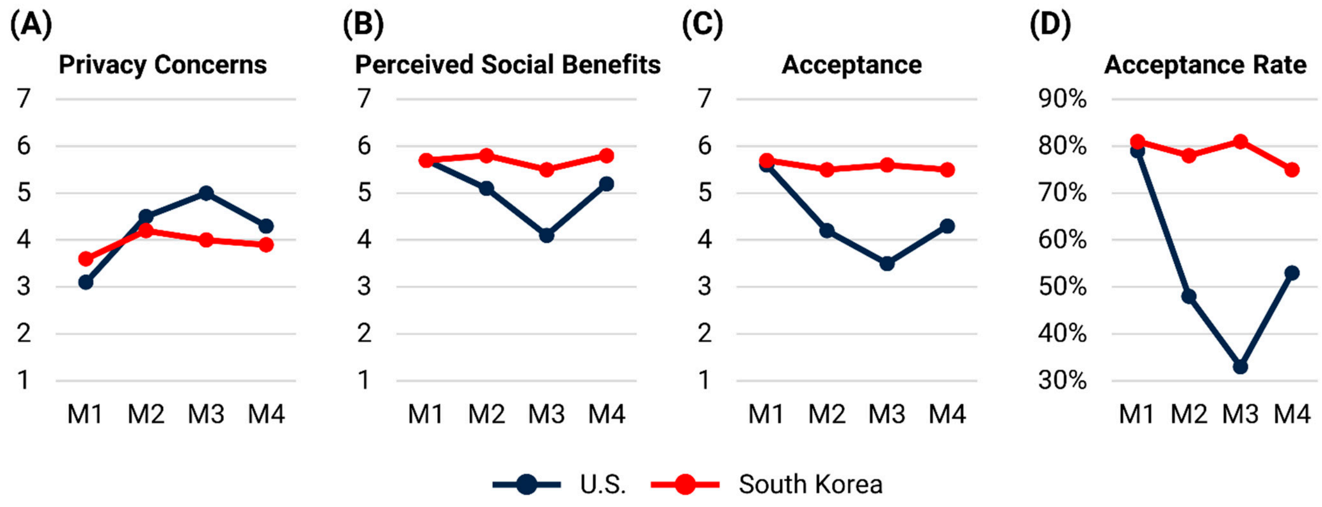

Figure 3. (**A**) Average privacy concerns; (**B**) Average perceived social benefits; (**C**) Average acceptance; (**D**) Acceptance rate (M1–4).

First, privacy concerns in both the U.S. and South Korea have similar patterns with regard to the four contact tracing methods. For instance, people have a higher privacy concern for methods that utilize more sensitive and private information (e.g., M2 and M3), which is in line with general expectations and previous findings [27]. Second, the results indicate a tendency that a method with a higher perceived social benefit has lower privacy concerns. These results indicate a trade-off relationship between privacy concerns and perceived social benefits, which aligns with previous findings and general expectations [15]. Lastly, focusing on the acceptance of the four contact tracing methods, Table 4 illustrates that all the differences between the two countries, except M1, are significant ($p < 0.001$), with medium effect sizes.

These results have several important public health policy implications when implementing contact tracing methods. First, contact tracing methods that utilize individuals' confidential location information, such as GPS records (M2) and credit card usage history (M3), may not be effective in the U.S. and other similar countries because of their lower acceptance rates. A possible reason for the low acceptance rate for M3 could be its higher privacy concerns and lower perceived social benefits. For instance, although authorized personnel can only access credit card usage history data to obtain location information for contact tracing, unnecessary sensitive information (e.g., what items the person purchased) can be improperly disclosed.

Second, although the conventional interview-based method (M1) is highly acceptable in the U.S. (80% of survey participants), this method is time-consuming and costly when new cases drastically surge because it heavily relies on human-to-human interviewing [12,39]. In this light, Bluetooth-based proximity tracing methods (M4) can be considered as one of the feasible options to partially overcome the limitations of M1. Our results indicate that about half of the U.S. participants consider these Bluetooth-based methods (M4) acceptable. This is in line with the results of a telephone-based survey of 1000 randomly selected U.S. adults in April 2020 [40]. According to that survey, about 50% of the participants who owned a smartphone were willing to use these methods (M4). However, the acceptance rate for M4 observed in our survey is lower than the threshold needed to achieve effective implementation and tracing (i.e., 80% of smartphone users need to implement the method), as proposed in a study based on epidemiological modeling [41]. Thus, proper public policy efforts, such as transparent communication with citizens, education, and campaigns, will be vital when countries aim to encourage more people to accept the method. Specifically, public health authorities should aim to minimize people's privacy concerns as well as convince them of the potential social benefits of implementing Bluetooth-based proximity tracing methods.

3.2. Privacy Concerns, Perceptions of Social Benefits, and Acceptance of Self-Quarantine Monitoring Methods (M5–8)

Next, we examine the privacy concerns, perceptions of social benefits, and acceptance for four self-quarantine monitoring methods utilizing location information (M5–8). Tables 6–8 and Figure 4 show the results of this analysis.

Table 6. Descriptive statistics of privacy concerns, perceptions of social benefits, and acceptance for the four self-quarantine monitoring methods.

Methods	U.S.			South Korea		
	Privacy Concerns	Perceived Social Benefits	Acceptance	Privacy Concerns	Perceived Social Benefits	Acceptance
M5	3.7 (2.1)	4.7 (2.0)	4.6 (2.1)	3.4 (1.9)	5.4 (1.5)	5.8 (1.4)
M6	5.1 (1.9)	4.5 (2.0)	3.5 (2.1)	4.0 (2.0)	5.9 (1.3)	5.6 (1.6)
M7	5.1 (2.0)	4.4 (2.1)	3.2 (2.0)	4.4 (2.1)	5.9 (1.2)	4.8 (1.9)
M8	4.0 (2.2)	4.7 (2.0)	4.2 (2.1)	3.5 (1.9)	5.3 (1.5)	5.0 (1.7)

Notes: Standard deviation in parenthesis.

Table 7. Mann–Whitney test results for the four self-quarantine monitoring methods (comparison between the U.S. and South Korea).

Methods	Privacy Concerns		Perceived Social Benefits		Acceptance	
	p-Value	$\lvert r \rvert$	*p*-Value	$\lvert r \rvert$	*p*-Value	$\lvert r \rvert$
M5	0.280	0.062	0.005 **	0.159	0.000 ***	0.285
M6	0.000 ***	0.270	0.000 ***	0.333	0.000 ***	0.472
M7	0.002 **	0.181	0.000 ***	0.350	0.000 ***	0.377
M8	0.036 *	0.120	0.030 *	0.125	0.001 **	0.194

Notes: r denotes effect size. *** denotes $p < 0.001$. ** denotes $p < 0.01$. * denotes $p < 0.05$.

Table 8. Acceptance and disapproval rates for the four self-quarantine monitoring methods.

Methods	U.S.		South Korea	
	Acceptance	Disapproval	Acceptance	Disapproval
M5	55%	27%	81%	10%
M6	34%	53%	80%	15%
M7	30%	59%	58%	28%
M8	47%	36%	60%	16%

First, the privacy concerns in both countries have similar patterns with regard to the four self-quarantine monitoring methods. For instance, people have a higher privacy concern for methods that obtain and utilize their real-time locations (e.g., M6–7), which is consistent with general expectations. Second, the trade-off relationship between privacy concerns and perceptions of social benefits is observed in the U.S. but not in South Korea (Figure 4A,B). For example, the South Korean participants have higher privacy concerns for M6–7 as well as reporting higher social benefits for them than for M5. In other words, they worry about their privacy, but they admit that those methods (M5–6) also have meaningful social benefits. Lastly, the differences in acceptance between the two countries are significant ($p < 0.01$), with small effect sizes for most of the four self-quarantine monitoring methods.

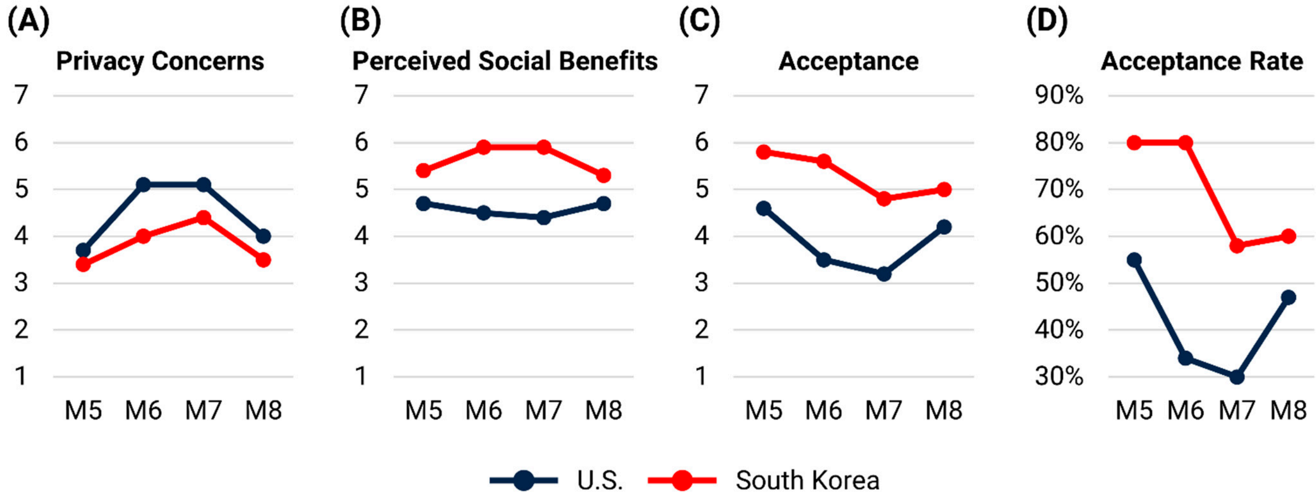

Figure 4. (**A**) Average privacy concerns; (**B**) Average perceived social benefits; (**C**) Average acceptance (**D**); Acceptance rate (M5–8).

These results have several important public health policy implications when implementing self-quarantine monitoring methods. First, self-quarantine monitoring by utilizing phone-based GPS tracking or e-wristbands (M6–7) would not be effective in the U.S. and other countries where people's acceptance of these methods is very low. For example, self-quarantine monitoring with an e-wristband has the lowest acceptance and highest privacy concerns among the 10 methods examined in our survey. One possible explanation is that these methods tend to involve involuntary or mandatory monitoring and people have very little control of how their information will be used. Moreover, because e-wristbands are often used for tracking criminals, people would be offended when required to wear an e-wristband even though it may contribute to mitigating the COVID-19 pandemic (by reducing possible self-quarantine violations).

Second, if public health authorities aim to monitor people's self-quarantine, monitoring methods based on random calling or travel certificates (M5 and M8) seem to be good starting points in the U.S. and other similar countries. For instance, some state governments in the U.S. have started monitoring the self-quarantine of people (M5) who enter their states from certain other states that are experiencing a surge in new COVID-19 cases [18]. Another example of M8 is the "Safer Illinois App" that has been developed by the University of Illinois [42]. To enter the university building, university members (e.g., faculty/staff and students) need to show that they have valid building access (Figure 5). A member's valid building access is granted only when he/she has a recent negative COVID-19 test result [42]. By utilizing this method, the University of Illinois could successfully mitigate the spread of the COVID-19 virus within the university community. These examples thus imply that using an approach that is similar to M5 and M8 may work well in the U.S. and other similar countries. However, our survey results indicate that only about 50% of people consider these methods acceptable, suggesting a relatively lower acceptance rate for them. Thus, more public health policy efforts, such as transparent communication with citizens, education, and campaigns, are needed to address people's privacy concerns. Especially, efforts should be made to better convince people about the need for and benefits of implementing self-quarantine monitoring measures.

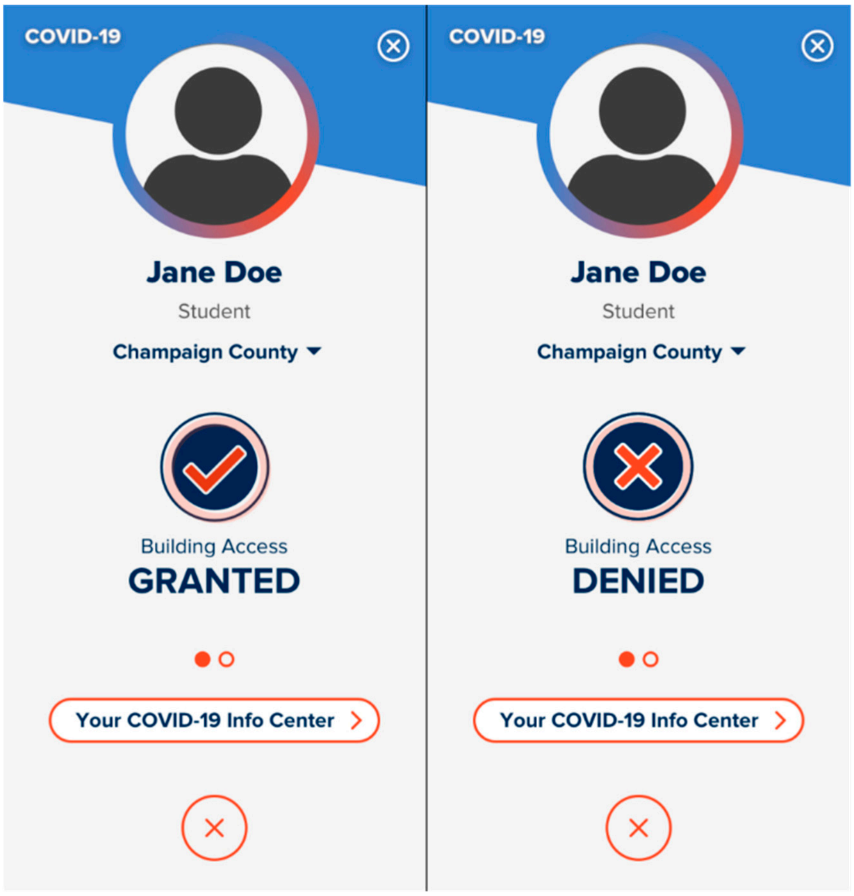

Figure 5. An example of M8 that has been utilized by a university institution in the U.S.: University of Illinois "Safer Illinois App" (source: [42]).

3.3. Privacy Concerns, Perceptions of Social Benefits, and Acceptance of Location Disclosure Methods (M9–10)

In what follows, we examine the privacy concerns, perceptions of social benefits, and acceptance of two location disclosure methods (M9–10). Tables 9–11 and Figure 6 show the results.

Table 9. Descriptive statistics of privacy concerns, perceptions of social benefits, and acceptance of the two location disclosure methods.

Methods	U.S.			South Korea		
	Privacy Concerns	Perceived Social Benefits	Acceptance	Privacy Concerns	Perceived Social Benefits	Acceptance
M9	5.1 (1.8)	4.6 (1.9)	3.6 (2.0)	4.9 (1.9)	5.3 (1.5)	4.7 (1.8)
M10	4.0 (1.9)	5.1 (1.8)	4.6 (1.9)	3.9 (1.9)	5.5 (1.2)	5.6 (1.4)

Notes: Standard deviation in parenthesis.

First, in both countries, participants' privacy concerns for M9 are higher than those for M10, indicating that people have higher privacy concerns when the probability of re-identifying certain people becomes higher through releasing more information [27]. Second, in both countries, the acceptance of M10 is higher than that of M9. Moreover, for both methods, the acceptance for South Korean participants is significantly higher than that for the U.S. participants ($p < 0.001$), with small effect sizes. The acceptance of these two methods in South Korea observed in our study is consistent with the results of a public survey of 1038 randomly selected South Korean adults in April 2020, where about 90% of the participants reported that M10 was acceptable [43].

Table 10. Mann–Whitney test results for the two location disclosure methods (comparison between the U.S. and South Korea).

Methods	Privacy Concerns		Perceived Social Benefits		Acceptance	
	p-Value	|*r*|	*p*-Value	|*r*|	*p*-Value	|*r*|
M9	0.384	0.050	0.004 **	0.163	0.000 ***	0.264
M10	0.693	0.023	0.167	0.079	0.000 ***	0.235

Notes: r denotes effect size. *** denotes $p < 0.001$. ** denotes $p < 0.01$.

Table 11. Acceptance and disapproval rates of the two location disclosure methods.

Methods	U.S.		South Korea	
	Acceptance	Disapproval	Acceptance	Disapproval
M9	36%	47%	59%	28%
M10	59%	28%	79%	9%

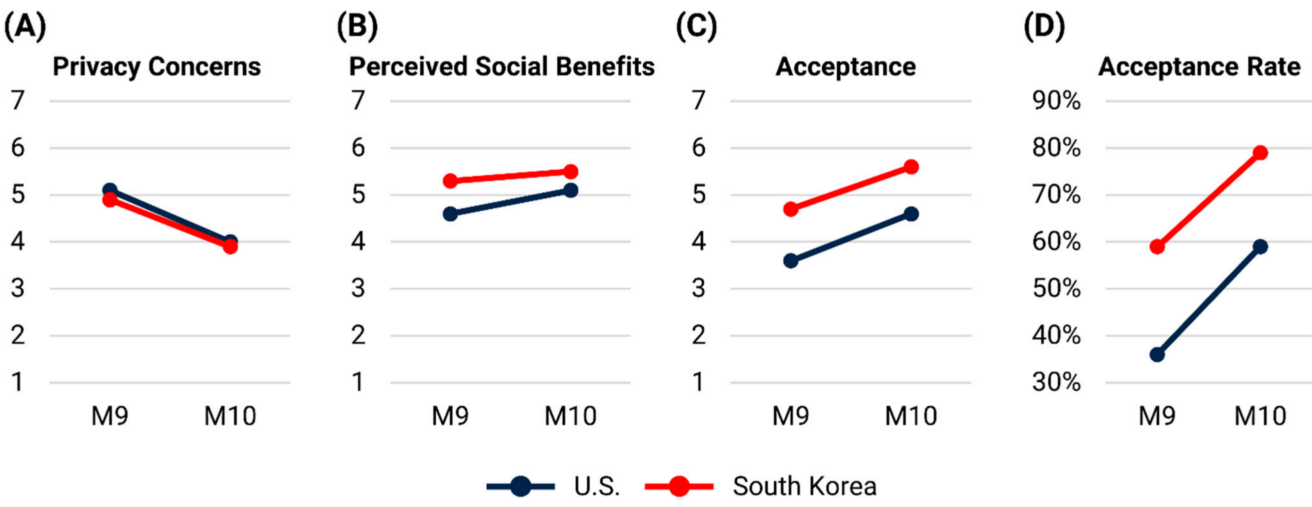

Figure 6. (**A**) Average privacy concerns; (**B**) Average perceived social benefits; (**C**) Average acceptance; (**D**) Acceptance rate (M9–10).

These results imply that, if public health authorities aim to publicly disclose the locations visited by COVID-19 patients, it is important not to release any demographic information about these patients. Releasing demographic information may increase people's privacy concerns because certain patients can be accurately re-identified through spatial reverse engineering [25–27]. For instance, our survey results indicate that only 36% of the U.S. participants think that M9 (that discloses COVID-19 patients' demographic information) is acceptable, while a considerably higher percentage of participants (59%) considered M10 (that does not disclose patients' demographic information) acceptable. However, we do not intend to argue that location disclosure methods can be directly applied in public health policies in the U.S. and other similar countries because about 30% of the participants still find them unacceptable. Furthermore, how and to what extent patients' location information can be disclosed should be discussed publicly before implementation. Besides, adequate privacy protection measures (e.g., geomasking) should be implemented to minimize the risk of privacy violations.

3.4. Acceptance with Respect to Sociodemographic Characteristics

In this subsection, we examine the association between an individual's acceptance of the COVID-19 mitigation measures and his/her sociodemographic characteristics using linear regression analysis (Model 1).

$$\begin{aligned} &\text{Combined Acceptance Score}_i \\ &= \beta_0 + \beta_1\text{Female}_i + \beta_2\text{Age1}_i + \beta_3\text{Age2}_i + \beta_4\text{Student}_i + \beta_5\text{Employed}_i + \beta_6\text{Highedu}_i \\ &+\beta_7\text{USA}_i + \beta_8\text{Collectivist}_i + \varepsilon_i \end{aligned} \quad (1)$$

The dependent variable of the regression model is a combined acceptance score, which was obtained by adding each of the acceptance response items of M1 through M10. The Cronbach's alpha of the 10 items is 0.9, meaning that these 10 items have a good internal consistency. A higher score indicates that a person is more willing to accept COVID-19 mitigation measures. Since each acceptance item was measured on a scale of 1 to 7, the minimum value of the combined acceptance score is 10 (10 items $\times$ 1), while the maximum value of the score is 70 (10 items $\times$ 7). The average score is 47.1, the median score is 48.0, and the standard deviation is 13.8.

The independent variables of the regression model include gender (female: 1; male: 0), age group 1 (18–24 years old: 1; 35–44 years old: 0), age group 2 (45+ years old: 1; 35–44 years old: 0), student (yes: 1; no: 0), employed (yes: 1; no: 0), higher education (yes: 1; no: 0), country (USA: 1; South Korea: 0), and the collectivist orientation score. To estimate an individual's collectivist orientation score, an individual factor score obtained from the confirmatory factor analysis (CFA) of three items was used: Item 1 (1.000, "If a coworker gets a prize, I would feel proud."), Item 2 (0.669, "The well-being of my coworkers is important to me."), and Item 3 (0.663, "I feel good when I cooperate with others."). A higher collectivist orientation score indicates that a person has a stronger collectivist orientation. The minimum value of the collectivist orientation score of the survey participants is 4.3, the maximum value is 16.3, and the average value is 12.9. To mitigate non-normality, standardized values of the dependent variable and the collectivist orientation score were used.

Table 12 shows the regression results for Model 1. Gender, age group, employment status, and having higher educational attainment are not significantly associated with the combined acceptance score. However, the residing country ($p < 0.001$) and the collectivist orientation score ($p < 0.01$) are associated with acceptance. Specifically, the acceptance of participants who live in South Korea is higher than that of participants who live in the U.S. when other covariates are controlled. Additionally, people who have a stronger collectivist orientation (i.e., a weaker individualist orientation) have higher acceptance for COVID-19 control measures.

To better understand the role of the residing country (U.S. and South Korea) and an individual's collectivist orientation, we investigated average acceptance in terms of the residing country and the collectivist orientation level (Figure 7). First, in both countries, people with high collectivist orientation scores (i.e., z-score ≥ 1.0) have higher acceptance of COVID-19 control measures than those with low collectivist orientation scores (i.e., z-score ≤ -10). Second, when the collectivist orientation score is the same, the average acceptance of COVID-19 control measures of the participants in South Korea is higher than that of the U.S. participants. Lastly, people's average acceptance of COVID-19 control measures in the U.S. who have high collectivist orientation scores is lower than that of people in South Korea who have low collectivist orientation scores. This indicates that the role of country can be more important than that of collectivist orientation in explaining people's acceptance of COVID-19 mitigation measures.

Table 12. Results of the linear regression model (Model 1) for the association between individual combined acceptance score and sociodemographic characteristics (n = 277).

Variables		Coefficient
Female		0.149 (0.116)
Age	Age1 (18–24)	−0.032 (0.145)
	Age2 (45+)	0.122 (0.154)
Employment Status	Student	0.017 (0.226)
	Employed	−0.048 (0.217)
High education		0.189 (0.154)
USA		−1.043 *** (0.123)
Collectivist orientation score		0.177 ** (0.059)
Intercept		0.399 (0.274)
R^2		0.225
$\overline{R}^2$		0.202
Cohen's f^2		0.290

Notes: Standard error in parenthesis. *** denotes $p < 0.001$. ** denotes $p < 0.01$.

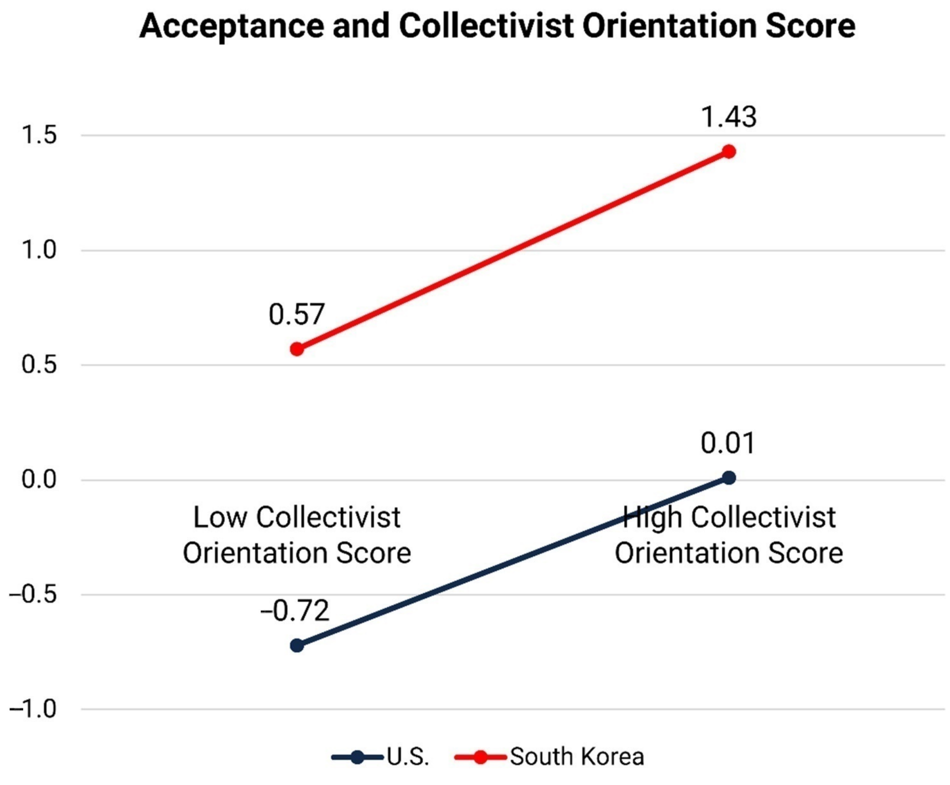

Figure 7. Average combined acceptance score (standardized) of people with low levels of collectivist orientation scores and high levels of collectivist orientation scores.

Furthermore, we explored why the residing country and the collectivist orientation are associated with acceptance. Because acceptance can be largely affected by privacy concerns and perceptions of social benefits, we hypothesize that people in South Korea (compared to those in the U.S.) and people with higher collectivist orientation scores are more likely to consider the control measures acceptable because they have lower privacy concerns and think that the control measures will bring forth a higher social benefit.

First, we examined whether an individual's combined acceptance score was associated with his/her privacy concerns and perceptions of social benefits. For this analysis, an individual composite privacy concern score and an individual composite perceived social benefit score were obtained by adding each participant's respective response items for M1 through M10. We estimated a linear regression model (Model 2) to examine the association between an individual's acceptance score (the dependent variable) and his/her composite privacy concern score and composite perceived social benefit score (the independent variables). To mitigate non-normality, standardized scores of the independent variables were used in the regression model. The results of Model 2 indicate that acceptance is negatively associated with participants' privacy concerns ($\hat{\beta} = -0.352,\ p < 0.001,$ SE = 0.037) and positively associated with the perceived social benefits of the control measures ($\hat{\beta} = 0.613,\ p < 0.001,\ SE = 0.037$), and the model has good explanatory power (R^2 = 0.702; $\overline{R}^2$ = 0.699; Cohen's f^2= 2.350). In other words, the results indicate that higher acceptance is associated with a higher level of perceived social benefit and a lower level of privacy concern, which is in line with the results of similar studies [44,45].

Second, we investigated whether participants' residing countries and collectivist orientations were associated with their privacy concerns and perceptions of social benefit by estimating two linear regression models (Models 3 and 4). Table 13 illustrates the results of these two models. The results of Model 3 show that people living in South Korea (compared to those living in the U.S.) and people with higher collectivist orientation scores tend to have statistically significantly lower privacy concerns ($p < 0.05$). The results of Model 4 indicate that people living in South Korea (compared to those living in the U.S.) and higher collectivist orientation scores are significantly associated with higher perceived social benefits ($p < 0.05$).

Table 13. Results of the linear regression models for the association between an individual's sociodemographic characteristics and privacy concerns (Model 3) and perceptions of social benefits (Model 4) (n = 277).

Variables		Model 3 (Privacy Concerns)	Model 4 (Perceived Social Benefits)
Female		0.162 (0.128)	0.113 (0.123)
Age	Age1 (18–24)	−0.093 (0.161)	0.115 (0.154)
	Age2 (45+)	−0.156 (0.171)	0.071 (0.164)
Employment Status	Student	−0.001 (0.250)	0.073 (0.240)
	Employed	0.163 (0.241)	0.111 (0.231)
Higher education		−0.281 (0.170)	0.413 * (0.163)
USA		0.302 * (0.136)	−0.749 *** (0.130)
Collectivist orientation score		−0.129 * (0.065)	0.138 * (0.063)
Intercept		−0.087 (0.304)	−0.085 (0.291)
R^2		0.052	0.132
$\overline{R}^2$		0.024	0.106
Cohen's f^2		0.055	0.152

Notes: Standard error in parenthesis. *** denotes $p < 0.001$. * denotes $p < 0.05$.

These results suggest the following two things. First, individuals with a stronger collectivist orientation have lower privacy concerns and higher perceptions of social benefits for COVID-19 mitigation methods, which is consistent with general expectations and findings from similar studies that have investigated people's privacy concerns in general [46–48]. Specifically, individuals with a stronger collectivist orientation tend to emphasize or prioritize the benefits and welfare of their communities, are less concerned about their privacy, and perceive much higher social benefits for the mitigation measures [30,31]. This would particularly be the case during a pandemic such as COVID-19 when people's communities and societies are at great risk.

Second, South Koreans have lower privacy concerns and higher perceptions of social benefits, compared to people in the U.S. One possible explanation for this is that people in South Korea have less concern about their privacy culturally. Specifically, because of the ongoing national security threat associated with the military conflicts with North Korea since the Korean War in the 1950s, South Koreans are familiar with pervasive technology-based surveillance systems, such as CCTV (closed-circuit television) and facial recognition technology, which are generally considered to be helpful for promoting national security. Moreover, since South Koreans have already experienced various COVID-19 mitigation measures [13,33] and witnessed the effectiveness of these measures in successfully controlling the COVID-19 pandemic, they may perceive considerable social benefits for these measures.

Based on these results, we conclude that people who live in South Korea (compared to people who live in the U.S.) and have higher collectivist orientation scores are more likely to consider COVID-19 mitigation measures that harness location information acceptable because they have lower privacy concerns and higher perceptions of social benefits for these measures.

4. Conclusions

This research examined people's privacy concerns, perceptions of social benefits, and acceptance of various COVID-19 mitigation measures that harness sensitive location information using data collected through an online survey in the U.S. and South Korea. The results indicate that people have higher privacy concerns for methods that use more sensitive and private information. The results also reveal that people's perceptions of social benefits are low when their privacy concerns are high, indicating a trade-off relationship between privacy concerns and social benefits. Moreover, the results reveal differences in people's acceptance of COVID-19 mitigation methods by people's residing countries. The regression results indicate that South Koreans (compared to people in the U.S.) and people with a stronger collectivist orientation are more likely to consider the control measures acceptable because they have lower privacy concerns and higher perceptions of social benefits.

Overall, our research is significant, as it is one of the first empirical studies to comprehensively survey people's privacy concerns, perceptions of social benefits, and acceptance regarding various COVID-19 mitigation measures that use sensitive individual location information. Although there are a few public surveys that have examined people's opinions [40,43], they have not investigated and compared multiple mitigation measures. On the contrary, we comprehensively surveyed people's opinions on 10 different COVID-19 mitigation methods. Our results provide important insights for understanding the patterns of acceptance for different methods.

Furthermore, this study is significant as it systematically compared the opinions on COVID-19 mitigation methods of people living in two different countries using a consistent survey instrument. Although some may think that the acceptance of these control measures in the U.S. is lower than that in South Korea based on their personal experiences, our research is significant because we empirically found such acceptance differences between the two countries. This finding advances our understanding of the important role of geographic context and culture as well as people's experiences of the mitigation measures that have been applied to control previous pandemics.

Lastly, our study is a timely contribution to the ongoing discussions about geoprivacy and geospatial ethics issues during the COVID-19 pandemic. Examples of these critical discussions include the *Location Tech Task Force* and *Ethical GEO Initiative* organized by the *American Geographical Society* (AGS) and online participatory forums (e.g., Ethical Research in the Age of COVID-19: A Participatory Forum) hosted by the *American Association of Geographers* (AAG) and the *American Association for the Advancement of Science* (AAAS) *Science and Human Rights Coalition* [49–51]. While participating in these activities, a diverse group of stakeholders, including geographers, urban and regional planners, public health researchers, private sectors, policymakers, and citizens, emphasized the importance of geoprivacy and geospatial ethics issues during the COVID-19 pandemic. Moreover, since there are no perfect or one-size-fits-all mitigation measures that completely guarantee people's geoprivacy, these ongoing discussions among various stakeholders will be invaluable for developing better measures that minimize people's privacy concerns (and thus maximize people's acceptance) as much as possible. In this light, our study provides important insights into and knowledge about geoprivacy and geospatial ethics issues that can nurture the sustainability of these important ongoing discussions.

However, our research has several limitations that future studies should address. First, the sample of our research was biased toward younger and highly educated people because of the recruitment method using Facebook, Twitter, and snowball sampling [35,36]. Although our results still provide meaningful insights into people's opinions on various COVID-19 mitigation measures, the results may not fully reflect the general public's opinions. Second, future studies could benefit from including survey participants from other countries to fully investigate the roles of geographic context, local culture, and previous experiences in the acceptance of pandemic control measures. Due to limited resources, our research only examined two countries: the U.S. (representing a Western culture) and South Korea (representing an Eastern culture). It would be significant to examine how acceptance is related to cultural differences and previous experiences by studying more countries e.g., [52,53]. Lastly, when modeling an individual's acceptance, future studies should measure and include other potentially important factors, such as trust in government (or other relevant agencies who handle sensitive information) and perceived COVID-19 risks e.g., [54,55]. Considering various factors will nurture our understanding of people's acceptance of pandemic mitigation measures that harness sensitive location information. Furthermore, it will lead to the effective implementation of those measures and, eventually, to the successful control of the future spread of the pandemic.

Author Contributions: Junghwan Kim conceived the idea; Junghwan Kim and Mei-Po Kwan designed and conducted the online surveys; Junghwan Kim analyzed the data and wrote and revised the paper; Mei-Po Kwan contributed to refining and revising the paper. All authors have read and agreed to the published version of the manuscript.

Funding: Junghwan Kim was supported by a Block Grant Fellowship from the University of Illinois at Urbana-Champaign (UIUC). Mei-Po Kwan was supported by a grant from the Research Committee on Research Sustainability of the Major RGC Funding Schemes of the Chinese University of Hong Kong. This research was supported by a grant from the U.S. National Science Foundation (BCS-2025783).

Acknowledgments: The authors would like to thank the University of Illinois at Urbana-Champaign (UIUC) Space-Time Analysis and Research (STAR) Lab members and Yonsei University Plan-It and Gateway to City (GTC) Society members for their helpful feedback during the study. The authors also thank the participants for their participation in the study and the anonymous reviewers for their helpful comments during the COVID-19 pandemic.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Detailed instructions of the 10 methods used in the survey.

Method	Type	Instructions
M1	Contact Tracing	Assume that you are diagnosed with COVID-19. Government agencies (e.g., public health authorities) conduct an in-depth interview with you to identify locations of your major activities in the past few days. The obtained information is only shared by public health authorities and other relevant government agencies and is NOT open or available to the public.
M2		Assume that you are diagnosed with COVID-19. Government agencies (e.g., public health authorities) obtain the location information in your mobile phone location history (e.g., based on cell-tower or GPS signals) to identify the locations of your main activities in the past few days. The obtained information is only shared by public health authorities and other relevant government agencies and is NOT open or available to the public.
M3		Assume that you are diagnosed with COVID-19. Government agencies (e.g., public health authorities) obtain the location information from your debit/credit card transaction history to identify the locations of your main activities in the past few days. The obtained information is only shared by public health authorities and other relevant government agencies and is NOT open or available to the public.
M4		Government agencies (e.g., public health authorities) launch a mobile phone application that records the anonymized ID of other application users who are in close contact (physical proximity) with you by using Bluetooth technology. The application does NOT collect your actual location (e.g., longitude and latitude). It also does NOT send real-time close-contact information to government agencies. Assume that government agencies request you (and other citizens as well) to install the application. Additionally, assume that you are diagnosed with COVID-19. In this case, your records of close contacts will be shared with government agencies so that the agencies can alert people who were in close contact with you. Please be advised that the government agencies do NOT share your identity (e.g., name) with other application users.
M5	Self-Quarantine Monitoring	Assume that you are required to self-quarantine at your home. Government agencies (e.g., public health authorities) monitor your location (i.e., whether you indeed are staying at your home) by calling you at a random time on some of the days of your self-quarantine period.
M6		Assume that you are required to self-quarantine at your home. Government agencies (e.g., public health authorities) monitor your real-time location (i.e., whether you indeed are staying at your home) by using the real-time location obtained from your mobile phone's wireless and GPS signals.
M7		Assume that you are required to self-quarantine at your home. Government agencies (e.g., public health authorities) monitor your real-time location (i.e., whether you indeed are staying at your home) by requesting you to wear an electronic wristband that sends your real-time location information to the government agencies. Note that you should keep wearing your electronic wristband during the self-quarantine period.
M8		Assume that government agencies (e.g., public health authorities) request you to install a mobile phone application that carries your travel certificate. Your travel certificate is valid only when you are NOT required to self-quarantine. However, if you are required to self-quarantine, your travel certificate becomes invalid. Specifically, you must display your valid travel certificate to the government agencies or other responsible agencies when using public transit or visiting public spaces (e.g., libraries, markets, etc.). Note that the travel certificate does NOT collect your real-time location data.
M9	Location Disclosure	Assume that you are diagnosed with COVID-19. Government agencies (e.g., public health authorities) disclose to the public the time and locations (e.g., street address) where COVID-19 patients (including you) have visited in the past few days as well as the patients' information on age and gender. However, the locations disclosed do NOT include patients' home addresses.
M10		Assume that you are diagnosed with COVID-19. Government agencies (e.g., public health authorities) disclose to the public the time and locations (e.g., street address) where COVID-19 patients (including you) have visited in the past few days. However, the locations disclosed do NOT include patients' home addresses. Additionally, patients' age and gender information are NOT disclosed.

Table A2. Frequency of the privacy concerns for 10 methods (U.S. and South Korea).

Methods	Country	Privacy Concerns						
		1	2	3	4	5	6	7
M1	U.S.	32%	14%	12%	19%	10%	5%	7%
	South Korea	18%	16%	14%	13%	21%	12%	6%
M2	U.S.	12%	9%	12%	15%	19%	10%	24%
	South Korea	11%	14%	13%	10%	26%	13%	13%
M3	U.S.	10%	5%	9%	13%	18%	15%	32%
	South Korea	15%	14%	9%	15%	17%	19%	9%
M4	U.S.	11%	13%	13%	15%	15%	9%	24%
	South Korea	14%	15%	12%	19%	15%	11%	14%
M5	U.S.	25%	9%	12%	20%	13%	7%	15%
	South Korea	23%	16%	16%	14%	12%	11%	8%
M6	U.S.	7%	6%	7%	12%	19%	13%	35%
	South Korea	17%	10%	15%	11%	20%	14%	13%
M7	U.S.	10%	4%	7%	13%	19%	8%	39%
	South Korea	14%	8%	14%	14%	10%	20%	19%
M8	U.S.	20%	12%	11%	14%	14%	9%	21%
	South Korea	19%	19%	18%	17%	8%	9%	10%
M9	U.S.	7%	2%	11%	10%	23%	14%	32%
	South Korea	8%	8%	5%	13%	18%	22%	25%
M10	U.S.	14%	11%	18%	16%	20%	6%	15%
	South Korea	16%	10%	14%	19%	19%	12%	8%

Notes: U.S. (n = 188). South Korea (n = 118). 1: not concerned at all; 4: neutral; 7: very concerned.

Table A3. Frequency of the perceived social benefits for 10 methods (U.S. and South Korea).

Methods	Country	Perceived Social Benefits						
		1	2	3	4	5	6	7
M1	U.S.	5%	4%	2%	8%	13%	17%	51%
	South Korea	2%	3%	1%	9%	22%	31%	33%
M2	U.S.	9%	5%	6%	11%	16%	20%	32%
	South Korea	1%	3%	5%	6%	15%	32%	38%
M3	U.S.	15%	10%	13%	12%	23%	9%	18%
	South Korea	1%	3%	3%	17%	14%	31%	31%
M4	U.S.	6%	4%	5%	16%	16%	19%	33%
	South Korea	0%	2%	3%	10%	21%	31%	33%
M5	U.S.	12%	7%	8%	14%	18%	16%	26%
	South Korea	1%	5%	7%	11%	19%	28%	29%
M6	U.S.	13%	10%	5%	19%	15%	18%	21%
	South Korea	1%	1%	6%	8%	10%	37%	37%
M7	U.S.	18%	3%	7%	17%	21%	15%	20%
	South Korea	1%	0%	4%	11%	14%	31%	39%
M8	U.S.	12%	5%	6%	18%	20%	15%	23%
	South Korea	0%	3%	10%	19%	19%	20%	28%
M9	U.S.	11%	7%	10%	14%	23%	13%	22%
	South Korea	2%	3%	7%	16%	21%	25%	25%
M10	U.S.	7%	4%	6%	13%	22%	18%	30%
	South Korea	0%	2%	3%	14%	27%	26%	27%

Notes: U.S. (n = 188). South Korea (n = 118). 1: not beneficial at all; 4: neutral; 7: very beneficial.

Table A4. Frequency of the acceptance levels for 10 methods (U.S. and South Korea).

Methods	Country	Acceptance						
		1	2	3	4	5	6	7
M1	U.S.	5%	1%	4%	11%	19%	20%	40%
	South Korea	1%	1%	4%	13%	19%	27%	36%
M2	U.S.	16%	7%	16%	13%	15%	17%	16%
	South Korea	1%	3%	6%	13%	22%	25%	31%
M3	U.S.	26%	10%	20%	12%	11%	8%	14%
	South Korea	1%	2%	5%	11%	26%	19%	36%
M4	U.S.	18%	6%	7%	16%	23%	14%	16%
	South Korea	2%	3%	4%	16%	18%	26%	31%
M5	U.S.	16%	4%	7%	18%	13%	17%	25%
	South Korea	0%	1%	9%	10%	8%	31%	42%
M6	U.S.	27%	10%	16%	13%	11%	10%	13%
	South Korea	0%	7%	8%	6%	14%	26%	40%
M7	U.S.	32%	12%	15%	11%	17%	4%	9%
	South Korea	6%	10%	12%	14%	13%	19%	26%
M8	U.S.	21%	5%	10%	17%	14%	14%	19%
	South Korea	3%	3%	10%	23%	16%	17%	27%
M9	U.S.	22%	12%	13%	17%	17%	7%	12%
	South Korea	6%	8%	14%	14%	21%	15%	23%
M10	U.S.	11%	7%	10%	13%	22%	14%	23%
	South Korea	1%	3%	5%	12%	21%	23%	35%

Notes: U.S. (n = 188). South Korea (n = 118). 1: not acceptable at all; 4: neutral; 7: very acceptable.

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