Privacy in Crisis: Participants' Privacy Preferences for Health and Marketing Data during a Pandemic

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ABSTRACT

The severity of COVID-19 and the need for contact tracing has resulted in new urgency for investigating two mutually exclusive narratives about the importance of privacy. The assertion by some technology advocates that privacy is no longer an issue in the face of a pandemic has been repeatedly reported; while others advocated for its centrality. The rejection of contact tracing apps, in part because of privacy, has also been widely reported. Simultaneously, different tracing apps implement different conceptions of privacy. For any contact tracing app to function the technology must provide security and privacy implementations that are usable and acceptable. Towards that goal, we sought to better understand risk perceptions about data use during a public health crisis. To do this we conducted a between-subject online survey to identify participants' risk perceptions about their data being collected and shared during a public health crisis. The survey results do not support claims in prior work that people are comfortable with sharing their private information during a public health crisis; but instead offered nuanced responses depending on type of information, purpose of use, and recipient, thus reifying previous work rather than suggesting a fundamental difference. We note that participants' privacy risk perceptions remain similar whether data are to be used to address health risks or for traditional marketing. Finally, our findings show that device type, not just data type, should be taken into account when designing a tracing app that aligns with participants' privacy perceptions.

CCS CONCEPTS

• **Security and privacy** → **Social aspects of security and privacy**.

KEYWORDS

COVID-19, mobile privacy

ACM Reference Format:
Laura Calloway, Hilda Hadan, Shakthidhar Gopavaram, Shrirang Mare, and L Jean Camp. 2020. Privacy in Crisis: Participants' Privacy Preferences for Health and Marketing Data during a Pandemic. In *19th Workshop on Privacy in the Electronic Society (WPES '20), November 9, 2020, Virtual Event, USA.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3411497.3420223

ACM ISBN 978-1-4503-8086-7/20/11.
https://doi.org/10.1145/3411497.3420223

1 INTRODUCTION

Responding to a public health crisis on a national scale while balancing the need to collect data on citizens has again come to the forefront of public health and privacy research as COVID-19 spread across the nation.

There was an early burst of media assumptions that citizens' privacy might be eschewed in favor of digital surveillance to reduce the number of cases and the spread of the virus, e.g. [31]. The fundamental question is the degree to which people's privacy perceptions remain the same when data are to be used for marketing, general governance, or public health. If there are differences, what influences this beyond the purpose of data use: recipient, data type, device, or risk perception? To explore this we queried a range of recipients, both public and private sector, while varying the device type, data type, and purpose of use. Specifically, we surveyed a population of participants on Prolific that was representative of Americans in the United States. Of course, by definition this includes only Americans who are online.

Related Work and Research Questions

In this work we explore *what privacy concerns our participants' express during an on-going pandemic.* Previous studies suggest that people may give up their privacy not only when there is a public health crisis but literally for pennies [17]; while other research shows significant willingness to pay for privacy [7, 16]. Much of the media coverage has identified the horror and severity of the pandemic as a source of willingness to share information. The underlying assumption is likely protection-motivation theory, which has been applied to fear as a driver for security behaviors on the Internet [20, 22]. we address this possibility with queries about general risk perception and privacy concerns.

One cross-national study showed that contact tracing could be acceptable to all the populations studied, including the US [2]. The results from Altmann et al.'s survey of participants in France, Germany, Italy, the UK, and the US found the least acceptance in the US and Germany. The survey located a nexus of concern around trust of government, privacy, and security. We expanded upon this to evaluate trust in law enforcement and healthcare providers, as well as asking about trust in technology providers.

We evaluated privacy concerns by asking about health data and data for personalized services. In future work after the pandemic, we will be able to evaluate if participants' privacy perceptions remain the same after this public health crisis has ended.

Previous studies suggest that participants' privacy perceptions are based on the types of data being collected and shared [27, 29, 36]. Thus, we made explicit a hypothesis that is often assumed null; specifically in research on location data [5, 6, 28]. That hypothesis is that *H2: participants' privacy perceptions shift by data type, not device type*. That is, previous studies largely focus on participants' privacy perceptions based on the types of data being collected and shared without varying the mechanism of data sharing [27, 29]. We found significant variance in privacy perceptions when the same data was to be shared by different devices. In terms of data recipient, we found levels of trust in technology providers and trust in government vary significantly by device type.

In summary, to address the larger research question of location-sharing in a pandemic, we started with the following hypotheses:
H1: Participants' privacy perceptions remain the same whether information is for public health in the midst of a public health crisis (e.g., COVID-19)
H2: Participants' privacy perceptions shift by data type, not device type
H3: Participants' privacy perceptions are a function of risk perception.

2 METHODOLOGY

In this survey, we chose a quantitative approach to capture participants' perceived comfort with data collection and data sharing, as well as their risk perceptions about privacy and health. We adopted an *online survey* approach as our primary research methodology due to its flexibility, time efficiency, ease-of-launch, broader recruitment capability, and ease-of-analysis [8].

Survey Design We used vignettes to provide context to participants [3, 9]. In this survey, we used participants' comfort with data collection and sharing as an indicator of their privacy perceptions building on research from 2017 [26]. We presented participants with scenarios as shown in Table 1 and asked questions related to their comfort with data collection and sharing in each scenario. We followed these queries with further questions to measure their technical expertise, risk perceptions, understanding of infectious diseases (especially COVID-19), and for demographic information.

Participants in the study were randomly assigned to one of two groups, General or Health. In each group, they were shown 3 scenarios (see Table 1). Within the same scenario, the difference between 2 groups is the usage of data. Specifically, in the General group, the data usage is to "provide personalized services, recommendations, and conveniences" whereas the data usage in the Health Group is to help "contain the spread of an infectious disease'.' The 3 scenarios were developed based on 3 devices (Smartphone, Security Camera, and Fitness tracker). The devices in Scenario 1 and Scenario 3 collect the same data type (i.e., "your movement data"), whereas the security camera scenario has a different data type (i.e., video clips). This design allowed us to measure: 1) the difference between health vs. non-health contexts (*H1*); and 2) the difference between devices and data types (*H2*). To measure participants' risk perceptions, we relied on the standard 9-dimension risk perceptions scale by Fischhoff et al. [10] used in thousands of offline risk perception evaluations (*H3*). The survey was implemented on Qualtrics. Upon the approval of our University Institutional Review Board (IRB), we implemented the survey through Prolific, which provided a representative sample of the US population.

The study consisted of the study information sheet, then three scenarios. Each scenario was followed by questions about participants' comfort with data collection, sharing, and usage in the scenario. The next set of questions addressed perceptions of privacy risks. After querying about general risk perception, we evaluated participants' computer expertise. Here we leveraged the expertise measurement scale from Ravijan et al.'s work [30]. Then we repeated Fischhoff et al.'s 9-dimension scale to evaluate perceptions of health risk. In order to evaluate the participants' knowledge of health risk, we developed questions using the CDC's recommendations for preventing respiratory viral infections [11–13]. We ended the section of the survey by asking about participants' behaviors in terms of COVID-19. We specifically asked about the actions they took to protect themselves, and how the disease changed their life. We also included two moral agency questions about the value of protecting oneself versus others. We closed with demographics.

Participant recruitment Before the implementation of the survey, we conducted a pilot study with 10 university students to test the correctness and effectiveness of the questions. Then, we implemented the survey on Prolific on April 28th, 2020 with a payment of $3 for each participant. Upon setting up the recruitment criteria (i.e., a representative sample of US), Prolific sent out an invitation to qualified participants with a link to the survey. The welcome page (page 1) of the survey contained the study information which detailed confidentiality, anonymity, and withdrawal measures. Only participants that "agreed" with the information on the welcome page were allowed to complete the survey. The survey was live until May 2nd and we received responses from 291 participants. We rejected responses from 17 participants because they completed the survey in fewer than 5 minutes [25], and/or they had the exact same answers to all questions. In addition, we returned responses to 13 participants because they failed the attention check questions. We decided to exclude these 13 responses to ensure the quality of the results, but we paid these participants. In the end, we had valid responses from 262 participants, with an equal distribution of demographics in both groups.

Data Analysis We performed data analysis using Python. Our initial data analysis included data cleaning, data screening, and data reporting to resolve inconsistencies and errors, ensure data usability and reliability, and to capture general trends. This initial data analysis did not directly address the research questions but it ensured later statistical analysis could be performed efficiently and correctly [21]. Then, we conducted advanced statistical analysis based on the initial results of test *H1*, *H2*, and *H3*, and to identify additional patterns. We summarize our key findings in Section 3.

3 FINDINGS

Our data analysis reified some previous findings, but also contradicted previous studies. In this section, we present the preliminary results of the survey.

General Group (G)	Health Group (C)
Scenario 1 (G1): When you go outside (e.g., for a walk or run), your **smartphone** logs your movement data (including time, steps, and location). This data is used to provide personalized services, recommendations, and conveniences.	**Scenario 1 (C1):** When you go outside (e.g., for a walk or run), your **smartphone** logs your movement data (including time, steps, and location). This data is used to contain the spread of a contagious disease by tracing social encounters with people in the neighborhood who tested positive for the disease.
Scenario 2 (G2): At home, your **security camera** records the view of the street in front of your house. This data is used to provide personalized services, recommendations, and conveniences.	**Scenario 2 (C2):** At home, your **security camera** records the view of the street in front of your house. This data is used to contain the spread of a contagious disease by tracing social encounters with people in the neighborhood who tested positive for the disease
Scenario 3 (G3): When you go outside (e.g., for a walk or run), your **smartwatch/fitness tracker** logs your movement data (including time, steps, and location). This data is used to provide personalized services, recommendations, and conveniences.	**Scenario 3 (C3):** When you go outside (e.g., for a walk or run), your **smartwatch/fitness tracker** logs your movement data (including time, steps, and location). This data is used to contain the spread of a contagious disease by tracing social encounters with people in the neighborhood who tested positive for the disease.

Table 1: Scenarios used for all participants. Each participant saw the three scenarios associated with their experimental group.

Not Rejected H1: Participants' privacy perceptions remain the same whether information is for public health in the midst of a public health crisis (e.g., COVID-19)

As mentioned in Section 2, in this survey we used participants' comfort level with data collection and sharing as an indicator of their privacy perceptions. The visualization of the initial analysis shows a sizable difference between the General and Health group in Scenario 2 & 3 (see Figure 1).

We conducted a between group Wilcoxon rank-sum test to further explore the difference. Specifically, we tested the difference between the General group and Health group in each scenario. The null hypothesis (*H0*) of Wilcoxon rank-sum test assumes the two independent samples were selected from populations having the same distribution [23]. We used Holm-Bonferroni method [33] to reduce the family-wise error rate. The result of the Wilcoxon rank-sum test only led to the rejection of the *H0* in Scenario 3 (p=0.000; Scenario 1 p=0.767; Scenario 2 p=0.313). This indicates a significant difference in participants' comfort with data collection between the General and the Health group only in this scenario.

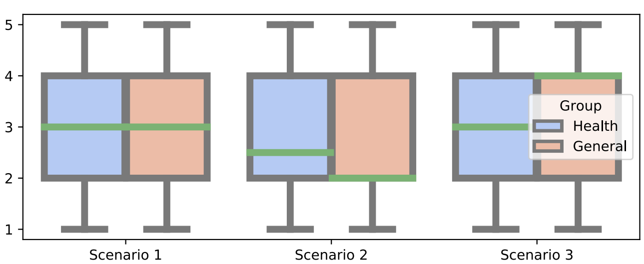

Figure 1: Participant comfort with data collection (1-very uncomfortable, 2-uncomfortable, 3-neutral, 4-comfortable, 5-very comfortable)

We queried participants' comfort with sharing their data with 5 entities: law enforcement, healthcare provider, health insurance company, third-party private company, and device manufacturer. We identified a sizable difference in comfort with sharing with healthcare provider and health insurance company in Scenario 1; law enforcement, healthcare provider, and third-party private companies in Scenario 2; and healthcare provider, health insurance company, device manufacturer, and third-party private companies in Scenario 3.

General Group vs. Health Group			
	Scenario 1	**Scenario 2**	**Scenario 3**
Law Enforcement	p = 0.332	p = 0.004 (reject H0)	p = 0.123
Healthcare provider	p = 0.126	p = 0.000 (reject H0)	p = 0.948
Health insurance company	p = 0.263	p = 0.061	p = 0.172
Device manufacturer	p = 0.371	p = 0.317	p = 0.073
Third-party private companies	p = 0.854	p = 0.680	p = 0.619

Table 2: Wilcoxon rank-sum test results show that *H0* could be rejected only in the second scenario

We conducted Wilcoxon rank-sum tests to further explore the between group difference. Specifically, in each scenario, we tested differences in comfort with data sharing between the General group and Health group for five entities. The result of the Wilcoxon rank-sum tests are shown in Table 2. We used the Holm-Bonferroni method [33] to reduce the family-wise error rate. Thus, the rejection of *H0* for law enforcement and healthcare provider in Scenario 2 indicate that there is a significant between group difference in these two entities. People in the Health group were *more* comfortable sharing information with healthcare providers and *less* comfortable with sharing information with law enforcement.

We also wanted to explore whether an ongoing public health crisis influenced participants' privacy risk perceptions. We conducted a Wilcoxon rank-sum test on the 9-dimensions of privacy risk perceptions to assess the between group difference in each of the 9-dimensions individually. No differences were significant.

Overall, the results from the visualization and from the Wilcoxon rank-sum tests imply that, although people's comfort with data collection and sharing differ slightly with or without a public health crisis, it did not shift their perceived privacy risks. This outcome contradicts results from previous work that suggest people have few privacy concerns when there is a public health crisis [2]. This may be due to the belief that the level of risk is over-stated. One participant wrote in the feedback: "I feel that the media and government is making more out of this than they should".

Rejected H2: Participants' privacy perceptions does not shift by device type

As described in Section 2, we used the same description of data collection and usage for Scenario 1 and Scenario 3. However, we found that participants' comfort with data collection and data sharing are very different in these 2 scenarios. In Figure 1, we can see an marked difference between the General group of Scenario 1 and Scenario 3. To further explore the significance of the difference, we conducted a within group analysis using a Wilcoxon signed-rank test. Specifically, we tested the difference between General groups and the difference between Health groups in these two scenarios. The null hypothesis (*H0*) of the Wilcoxon signed-rank test assumes that the two related paired samples come from the same distribution [35]. We used Holm-Bonferroni method [33] to reduce the family-wise error rate. The result of the Wilcoxon signed-rank test led to the rejection of *H0* in both the General groups (p=0.000) and Health groups (p=0.003). This indicates that the within group differences are significant in both groups, though the difference between the two groups is not obvious in Figure 1.

In addition, we also observed a difference in comfort with data sharing with different entities. Specifically, there were differences in comfort to share data with law enforcement, health insurance company, device manufacturer, and third-party private companies between Scenario 1 and Scenario 3. To confirm the significance of the difference, we conducted a within group analysis using a Wilcoxon signed-rank test. Specifically, we tested the difference between: comfort with data sharing with [law enforcement/healthcare provider/health insurance company/device manufacturer/third-party private companies] in Scenario 1 vs. in Scenario 3. We used the Holm-Bonferroni method [33] to reduce the family-wise error rate. The result of the Wilcoxon signed-rank tests is shown in Table 3, which has rejections of *H0* for healthcare provider, health insurance company, device manufacturer, and third-party private companies between General groups; and in health insurance company and third-party private companies between Health groups. This result indicates that the difference between these groups is significant.

Scenario 1 vs. Scenario 3		
	General Group	**Health Group**
Law Enforcement	p = 0.714	p = 0.108
Healthcare provider	p = 0.001	p = 0.601 (failed to reject H2)
Health insurance company	p = 0.033	p = 0.012
Device manufacturer	p = 0.006	p = 0.091 (failed to reject H2)
Third-party private companies	p = 0.036	p = 0.024

Table 3: Wilcoxon signed-rank test comparing comfort.

Overall, the results as illustrated in the visualization and evaluated in the Wilcoxon signed-rank tests imply that participants' privacy perceptions in Scenario 1 are significantly different than their perceptions in Scenario 3, even though both scenarios collect the exact same data type and use it in the exact same way. Thus, device type should be taken into account while measuring participants' privacy perceptions regarding data collection and sharing.

Rejected H3: Participants' privacy perceptions are a function of risk perception

Previous work on privacy and security has illustrated that users often do not see themselves as being at risk [15]. To evaluate the role of risk perception in both data risks and health risks, we leveraged Fischhoff's 9-dimensional scale. It is based on the psychometric paradigm of expressed preferences, and has been used extensively in health-related risk perception and communication studies. Previous work also provides evidence that it is effective for understanding risk perception in online environments [14]. However, other than a correlation with severity that did not withstand further testing, we did not find that individual components of risk perception provided explanatory power for other responses when used in standard Wilcoxon rank-sum. Future work will include multivariate regression, combinations of the dimensions using principle component analysis, and factor analysis as informed by previous work both in risk perception and in protection-motivation theory.

4 CONCLUSION AND FUTURE WORK

Our results reveal small but significant differences between participants' comfort with sharing data depending on its intended use, the recipients, and devices used for compilation when data are for public health versus other uses in the current pandemic. Specifically, the visualization (Figure 1) shows that the participants report greater comfort with sharing data in the General group, as opposed to the Health group, when data are collected with security cameras. Conversely the Health group show greater concern with data collection by wearable devices. However, that comfort level depends also on the data recipient. Significant research has focused on trust in government. Our results indicated that trust in technology providers deserves further exploration.

Our survey results also indicate participants' willingness to allow data collection and sharing varies depending not only on data type but also device type. This result indicates that device type should be used as an independent measurement when evaluating privacy perceptions, that identical location data may be perceived differently based on compilation. Privacy behavior research often focuses on a specific platform. [1, 16, 18, 19, 24, 32, 34]

Our participants include users and non-users of each device but only people who use the Internet. By assessing the difference between users and non-users, we may be able identify the correlation between device usage and privacy perceptions. The Oxford Internet Survey, for example, found significant differences between privacy perceptions of Internet users and non-users [4].

There were no significant correlations between the moral questions and the concern for privacy; however, we have not explored relationships between self-reports of behavior, risk perception, and these moral questions. In addition to more analysis of the risk perception questions, we will code the short answer responses. The perception that the risk is overblown was expressed in the qualitative responses. One participant mentioned COVID-19, "being spoonfed to everyone." Suspicion about the existence of a legitimate health crisis was expressed as well with the suggestion that COVID-19 is a "fake virus." We hope to discuss these nuances during WPES.

Participants uniformly indicated their neighbors were taking more health precautions than they themselves were. Fully 2.5% of participants reported that they do not have a safe place to stay. We will explore how this group differs from others in terms of privacy; however, the small sample size has limited statistical effect. For all participants, employment was the largest factor that made stay at home difficult.

This paper reports a preliminary analysis of our survey data results. WPES provides an excellent format for exploring additional avenues of research. We also plan to repeat the survey of privacy concerns after the end of this pandemic.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grant No. CNS 1565375 and CNS 1814518; support from a Cisco Research Award No. 1377239, and funds from the Comcast Innovation Fund.

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the NSF, Cisco, or Comcast.

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APPENDIX

Demographic Information

Gender		Age		Education		Income (annual)		Employment Status		People in the household	
Male	126 (48.28%)	Range	19-73	Less than a high school diploma	4	<$10K	20	Part-time/Full-time employed	39	with Kids (<18 years old)	81
Female	128 (49.04%)	Mean (SD)	37.00 (12.90)	High school degree or equivalent	72	10K−40K	72	Not in the labor force (e.g., retired, homemaker)	31	with Seniors (>65 years old)	261
Non-binary	6 (0.02%)	No answer	1	Associate's degree (e.g., AA, AS)	30	40K−70K	81	Unemployed looking for work	33		
No answer	1 (0.00%)			Bachelor's degree (e.g., BA, BS)	101	70K−100K	43	Student	30		
				Graduate or professional degree (e.g., MA, MD, PhD)	44	>$100K	41	Other (laid off, freelancer, furloughed, disabled, self-employed)	26		
				Other (Freelancer, self-employed)	9	Prefer not to say	4	Prefer not to say	2		
				Prefer not to say	1						

Table 4: Demographic Information of 261 participants

Survey Questionnaire

General Questions.

Q1. What is your Prolific ID?

Q2. We care about the quality of our data. In order for us to get the most accurate measures of your knowledge and opinions, it is important that you thoughtfully provide your best answers to each question in this study. Will you provide your best answer to each question in this study?
  (a) Yes; I will provide my best answers.
  (b) No; I will not provide my best answers.
  (c) I cannot promise either way.

Q3. Which of the following things do you use in your daily life? *(select all that apply.)*
  (a) Smartphone
  (b) Fitness Tracker (e.g., Fitbit, smartwatch)
  (c) Security Camera
  (d) none of above

Vignette 1. Consider the following scenario:

When you go outside (e.g., for a walk or run), your **smartphone** logs your movement data (including time, steps, and location). This data is used to provide personalized services, recommendations, and conveniences.

For this scenario, answer the following questions.

Q4. Please rate your level of agreement with each of the following statements [1 = Strongly disagree, 5 = Strongly agree]:
  (a) The use of my data in this scenario would be beneficial to me
  (b) The use of my data in this scenario would be beneficial to other people.
  (c) It's important that you pay attention to this study. Please select 'Strongly disagree.'

Q5. In your opinion, should other people allow or deny the collection and sharing of the data described in the scenario?
  (a) Allow
  (b) Deny
  (c) I am not sure

Q6. Please rate your level of comfort with the data collection in this scenario: [1 = Extremely uncomfortable, 5 = extremely comfortable]

Q7. How do you feel about sharing the data collected in this scenario with each of the following entities? *(assume that you would not be told how the entities would use your data).* [1 = Extremely uncomfortable, 5 = extremely comfortable]
  (a) Law enforcement
  (b) Healthcare provider
  (c) Health insurance company
  (d) Device Manufacturer
  (e) Third-party private companies

Q8. Who do you think should be responsible for storing and maintaining the data collected in this scenario? *(Select all that apply.)*
  (a) Law enforcement
  (b) Healthcare provider
  (c) Health insurance company
  (d) Device Manufacturer
  (e) Third-party private companies

Q9. How long do you think the data collected in this scenario should be stored?
  (a) For a fixed time (e.g., 14 days, 1 month)
  (b) Until the data is no longer needed
  (c) Until you ask to delete the data
  (d) Other, please specify:

Q10. Would such scenarios occur in real life?
  (a) They already happen today
  (b) They are likely to happen in the near future (within the next 2 years).
  (c) They are likely to happen at some point in the future (after 2 years)
  (d) They are unlikely to happen
  (e) I am not sure

Vignette 2. Consider the following scenario:

At home, your **security camera records** the view of the street in front of your house. This data is used to provide personalized services, recommendations, and conveniences.

For this scenario, answer the following questions:

[repeat the questions in Vignette 1]

Vignette 3. Consider the following scenario:

When you go outside (e.g., for a walk or run), your **fitness tracker** logs your movement data (including time, steps, and location). This data is used to provide personalized services, recommendations, and conveniences.

For this scenario, answer the following questions:

[repeat the questions in Vignette 1]

Perception of Privacy Risk. Now that you have responded to questions about the three scenarios, we would like to ask you about the **risks of privacy loss** due to the collection and sharing of your location data, as described in the previous scenarios.

Q11. Voluntary: Is your exposure to the risks of privacy loss in your control (voluntary risk), or out of your control (involuntary risk)?: 1 = voluntary; 5 = involuntary

Q12. Immediacy: Is the impact of exposing your private information immediate, or does it happen at a later point in time (delayed risk)?: 1 = immediate; 5 = delayed

Q13. Knowledge to exposed: To what extent do you understand the consequences of privacy loss?: 1 = understand completely; 5 = don't understand at all

Q14. Knowledge to science: To what extent do you think experts understand the conseuqnces of privacy loss?: 1 = understand completely; 5 = don't understand at all

Q15. Controllability: To what extent do you have control over the consequences of privacy loss?: 1 = complete control; 5 = no control

Q16. Newness: Are these risks new, novel ones, or old, familiar ones?: 1 = new; 5 = old

Q17. Chronic-catastrophic: Is this a risk that effects people one at a time (chronic risk), or a large number of people at once (catastrophic risk)?: 1 = chronic; 5 = catastrophic

Q18. Common-Dread: Is this a risk that you have learned to live with and can think about reasonable calmly (common risk), or is it one that you dread on the level of a gut reaction (dreadful risk)?: 1 = common; 5 = dreadful

Q19. Severity of Consequences: In your opinion, how severe are the consequences of privacy loss?: 1 = not severe; 5 = severe

Expertise Questions. Please tell us a bit about your experience with technology

Q20. Have you ever done any of the following? *(Select all that apply.)*
  (a) Written a computer program
  (b) Configured a firewall
  (c) Designed a website
  (d) Registered a domain name
  (e) Used SSH
  (f) Created a database
  (g) Installed a computer program
  (h) None of the above

Q21. Which of the following statements apply to you?*(Select all that apply.)*

(a) I have attended a computer security conference in the past year.
(b) I have a degree in an IT-related field (e.g. information technology, computer science, electrical engineering).
(c) Computer security is one of my primary job responsibilities.
(d) I have taken or taught a course on computer security.
(e) None of the above

Perceptions of Health Risk. Now, we would like to ask you questions about **health risks**. Consider the risks from infectious diseases, and please answer the following questions for those risks.

Q22. Voluntary: Is your exposure to the risks of infectious diseases in your control (voluntary risk), or out of your control (involuntary risk)?: 1 = voluntary; 5 = involuntary
Q23. Immediacy: Is the impact of being exposed to an infectious disease immediate, or does it happen at a later point in time (delayed risk)?: 1 = immediate; 5 = delayed
Q24. Knowledge to exposed: To what extent do you understand the consequences of infectious diseases?: 1 = understand completely; 5 = don't understand at all
Q25. Knowledge to science: To what extent do you think experts understand the conseuqnces of infectious diseases?: 1 = understand completely; 5 = don't understand at all
Q26. Controllability: To what extent do you have control over the consequences of infectious diseases?: 1 = complete control; 5 = no control
Q27. Newness: Are these risks new, novel ones, or old, familiar ones?: 1 = new; 5 = old
Q28. Chronic-catastrophic: Is this a risk that effects people one at a time (chronic risk), or a large number of people at once (catastrophic risk)?: 1 = chronic; 5 = catastrophic
Q29. Common-Dread: Is this a risk that you have learned to live with and can think about reasonable calmly (common risk), or is it one that you dread on the level of a gut reaction (dreadful risk)?: 1 = common; 5 = dreadful
Q30. Severity of Consequences: In your opinion, how severe are the consequences of infectious diseases?: 1 = not severe; 5 = severe

Infectious Disease Questions.

Q31. How concerned are you about getting an infectious disease? [1 = Not at all concerned, 5 = Extremely concerned]
Q32. How do infectious diseases (e.g., flu) spread? *(Select all that apply.)*
(a) Only by people who show symptoms
(b) From person to person
(c) Through touching frequently used surfaces such as doorknobs, shopping carts, phones, and faucets
(d) When an infected person coughs, sneezes, or talks
(e) I don't know
Q33. Which of the following habits help reduce your risk of exposure to an infectious disease? *(Select all that apply.)*
(a) Washing your hands with soap and water for at least 20 seconds
(b) Avoiding close contact with people who are sick
(c) Covering your mouth and nose with a cloth mask when around others
(d) Covering your coughs and sneezes with your elbow
(e) Cleaning and disinfecting frequently touched surfaces
(f) Putting distance between yourself and other people when out in public
(g) Avoiding touching your eyes, nose, and mouth with unwashed hands
(h) I don't know
Q34. Which of the following habits help reduce the risk of exposing others to an infectious disease? *(Select all that apply.)*
(a) Washing your hands with soap and water for at least 20 seconds
(b) Avoiding close contact with people who are sick
(c) Covering your mouth and nose with a cloth mask when around others
(d) Covering your coughs and sneezes with your elbow
(e) Cleaning and disinfecting frequently touched surfaces
(f) Putting distance between yourself and other people when out in public
(g) Avoiding touching your eyes, nose, and mouth with unwashed hands
(h) I don't know

COVID-19 Questions. Now that you have answered questions about infectious diseases in general, we would like to ask you questions related to COVID-19, the disease caused by the novel coronavirus.

Q35. How likely is another pandemic similar to COVID-19 in the next 10 years? [1 = Extremely unlikely, 5 = extremely likely]
Q36. Several states have imposed stay-at-home restrictions, asking people to stay home except for essential tasks. (NOTE: Stay-at-home restriction is also referred to as safer-at-home or shelter-in-place.) Please rate your level of agreement with the following statements regarding such restrictions: [1 = strongly disagree, 5 = strongly agree]
(a) I feel socially isolated due to the stay-at-home restrictions
(b) I felt socially isolated before the stay-at-home restrictions.
Q37. Please rate your level of agreement with the following statements: [1 = strongly disagree, 5 = strongly agree]
(a) Stay-at-home restrictions are beneficial to me.
(b) Stay-at-home restriction are beneficial to society.
Q38. Please answer the following questions: [1 = not at all strictly, 5 = extremely strictly]
(a) How strictly are the people in your neighborhood following the stay-at-home restrictions?
(b) How strictly are you following the stay-at-home restrictions?
Q39. What has made following the stay-at-home restrictions difficult? *(Select all that apply.)*
(a) I do not have a safe place to stay at home
(b) Stay-at-home restrictions are unnecessary
(c) I have care-giving responsibilities
(d) My work is classified as essential
(e) Other, please specify:
(f) There are no stay-at-home restrictions in my state.
Q40. When did you begin following the stay-at-home restrictions?
(a) Before my state imposed stay-at-home restrictions.
(b) When my state imposed stay-at-home restrictions.
(c) Some time after my state imposed stay-at-home restrictions
(d) There are no stay-at-home restrictions in my state, but I began following the restriction _ days ago. (Please enter an approximate number.)
Q41. Do you know anyone who has tested positive for COVID-19?
(a) Yes
(b) No
(c) Prefer not to answer
Q42. How has COVID-19 changed your life (e.g., daily routines, behaviors, and your food preferences)?

Demographic questions. Finally, please tell us a bit about yourself

Q43. Which is your gender?
(a) Male
(b) Female
(c) Non-binary
(d) Prefer to self-describe:
(e) Prefer not to disclose
Q44. How many people live in your household (including you)?
(a) Kids (under 18):

(b) Adults (18-65 years):
(c) Seniors (above 65 years):

Q45. What is the highest level of formal education you have completed?
(a) Less than a high school diploma
(b) High school degree or equivalent
(c) Associate's degree (e.g., AA, AS)
(d) Bachelor's degree (e.g., BA, BS)
(e) Graduate or professional degree (e.g., MA, MD, PhD)
(f) Other, please specify:
(g) Prefer not to answer

Q46. What is your employment status?
(a) Full-time employed
(b) Part-time employed
(c) Not in the labor force (e.g., retired, homemaker)
(d) Unemployed looking for work
(e) Student
(f) Other, please specify:
(g) Prefer not to answer

Q47. What is your occupation?

Q48. Approximately, how much was your household income before taxes in 2019?

Q49. What is your racial and ethnic background? *(Select all that apply.)*

Closing Questions.

Q50. Is there anything else you would like to tell us? Please feel free to include any questions, concerns, or suggestions.

Q51. Did you encounter any technical difficulties during this study?
(a) No
(b) Yes, please specify:

Q52. Enter your Prolific email address if you would you like to receive aggregate results of this survey.