How Mass surveillance Crowds Out Installations of COVID-19 Contact Tracing Applications

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During the COVID-19 pandemic, many countries have developed contact tracing technologies to curb the spread of the disease by locating and isolating people who have been in contact with coronavirus carriers. Subsequently, understanding why people install and use contact tracing applications is becoming central to their effectiveness and impact. However, involuntary systems can crowd out the use of voluntary applications when several contact tracing initiatives are employed simultaneously. To investigate this hypothesis, we analyze the concurrent deployment of two contact tracing technologies in Israel: centralized mass surveillance technologies and a voluntary contact tracing mobile app. Based on a representative survey of Israelis (n=519), our findings show that positive attitudes toward mass surveillance were related to a reduced likelihood of installing contact tracing apps and an increased likelihood of uninstalling them. These results also hold when controlling for privacy concerns, attitudes toward the app, trust in authorities, and demographic properties. We conclude the paper by suggesting a broader framework for analyzing crowding out effects in ecosystems that combine involuntary surveillance and voluntary participation.

CCS Concepts: • **Human-centered computing** → **Collaborative and social computing**; • **Security and privacy** → **Social aspects of security and privacy**; • **Applied computing** → **Health informatics**.

Additional Key Words and Phrases: COVID-19, contact tracing, mass surveillance, crowding out, privacy, government policy

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1 INTRODUCTION

The COVID-19 pandemic is an unprecedented global crisis that poses a severe threat to the health and well-being of every person on the planet. Even with the availability of vaccines and treatments, isolating people who were in contact with the virus remains one of the main tools to curb the spread of the pandemic. For decades, contact tracing has been used as an effective public health response in the face of infectious disease outbreaks. Successful contact tracing is based on identifying people who have come in contact with infected people and then quarantining them to interrupt further transmission of the epidemic [59]. COVID-19 presents a severe challenge to traditional contact tracing because many transmissions happen early in the infection cycle, before the onset of symptoms, and before test results are received. Therefore, many countries have taken advantage of the advancements in mobile computing platforms to develop digital technologies systems that

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capture “proximity events”, in which two mobile phones are close enough for sufficient time for the risk of infection to be inferred [3].

Digital contact tracing technologies have been regarded as a particularly important tool for managing the of COVID-19, since they were shown to be effective in rapid identification and notification of exposures to the virus [27]. Empirical studies have shown that contact tracing applications can be effective in slowing down the rate of the spread curbing the spread of COVID-19, based on administrative health data analysis [93] and natural experiments [28]. However, the effectiveness of contact tracing applications is tied to the proportion of people who use them. If the adoption rates are high enough, the combination of isolation and contact tracing could bring the effective reproduction number of the virus, below 1 and, therefore, effectively control the epidemic [27, 36, 38]. However, contact tracing interventions can be useful and reduce the number of transmissions with any uptake in the adoption rates [78]. Based on the actual installation rates of apps around the world at the height of the pandemic, the attention of many public health scholars has turned to understand the reasons behind installing contact tracing applications, many times with the motivation of raising installation rates [7].

Several recurring motivations shape people’s willingness to install contact tracing applications. A recurring one is the perceptions of the health benefits that it offers to individuals or to the people around them [5, 16, 29]. Surveys also found a link between trust in health authorities and acceptance of contact tracing applications [29, 32] and practical concerns about battery consumption [56, 73]. Several surveys have found a connection between more significant privacy concerns and lower acceptance of contact tracing applications. However, the strength of these relations varies widely between strong correlations [5, 16, 96] and weak ones [29, 56].

Unpacking the context of contact tracing applications requires understanding the ecosystem in which the technologies are operated. Many countries have deployed various types of contact tracing operations, with different architectures and processes that interact with other parts of epidemic control efforts [7, 38, 43]). For example, China, Thailand [2], South Korea [79] and Israel [8, 47] use cellular traces from mobile carriers for tracking contacts through cellular traces. There are multiple contact tracing operations in other countries, through a manual process by health authorities or through applications operated by private companies [3]. As Chen argues, technological fragmentation can negatively impact the public health response [18]. However, the current literature looks at contact tracing applications as an isolated phenomenon, missing potential important factors that can help us understand how it can be effectively deployed and serve people’s well-being.

Many COVID-19 public health interventions share the fundamental dilemma of voluntary versus involuntary measures. While involuntary measures may be more effective because they do not require the active cooperation of citizens, there is a basis for suspecting that they may crowd out motivations for voluntary behaviors. In the context of the COVID-19 pandemic, studies have documented the impact of crowding out on social distance measures [94] and on people’s acceptance of different types of countermeasures [75]. Multiple behavioral experiments show that enforcement can reduce intrinsic motivation, a phenomenon termed “motivational crowding out” [14]. As the number of spread of involuntary measures increase, voluntary contributions are increasingly crowded out, even when participation is a personal benefit.

This paper explores the spillover effects of involuntary mass surveillance systems on voluntary contact tracing app installations. To operationalize this hypothesis in the context of the rapidly evolving COVID-19 pandemic, we empirically examine whether attitudes toward the involuntary system are associated with the likelihood of installing the official Israeli contact tracing apps. We use Israel’s deployment of two contact tracing technologies in the spring of 2020 as a natural experiment for assessing the adoption of existing contact tracing applications and attitudes toward variants of contact tracing technologies. The first is *HaMagen* ("The Shield", in Hebrew), a privacy-preserving contact tracing mobile application that the Ministry of Health developed. The second is mass surveillance technology-based cellular tracking technology operated by Israel's General Security Services (GSS), dubbed "The Tool." [47, 80] The tool uses a mixture of GPS locations transmitted through cellular protocols and cellular antenna triangulation to track the location of the whole population [20].

The paper contributes to a growing literature on the intersection of privacy, government health technologies, and the interplay of mass surveillance and voluntary participation. We operationalize this general research inquiry to ask about the effect of attitudes toward mass surveillance on people's installation and uninstallation of contact tracing applications. Given the theory on motivational crowding out, we ask whether the deployment of involuntary mass surveillance can interfere with voluntary technologies and reduce the installation of contact tracing apps. Our findings suggest that mass surveillance has a strong negative effect on installations and a positive effect on uninstallations, even when controlling for attitudes toward contact tracing privacy, utility, and demographics.

2 BACKGROUND

2.1 Contact Tracing Technologies

In the months that followed the pandemic's outbreak, many countries introduced contact tracing mobile applications, which detect proximity through Bluetooth connections or co-location through device positioning. While the focus of the research community in human-computer interaction was on contact tracing applications [4, 44, 77], the scope of contact tracing technologies is wider than mobile applications. A fundamental difference between contact tracing technologies is between voluntary and non-voluntary designs. Voluntary design requires individuals to take an active step to participate in the contact tracing process, such as installing a contact tracing application (e.g., Singapore's TraceTogether [30], or Israel's HaMagen (Shield) App [69]). Non-voluntary systems rely on mass surveillance to infer contacts without asking the user to install a dedicated technology. Non-voluntary solutions often rely on cellular providers' centralized acquisition of cellphone location data. For example, China, Thailand, South Korea [79], and Israel [8] use cellular traces from mobile carriers for tracking contacts through cellular traces.

Voluntary contact tracing applications offer many advantages regarding privacy: they protect users' private information (such as locations and contacts) and avoid mass tracking. Moreover, they give users control of the app's various functions. However, for health authorities, voluntary solutions also present some severe limitations [7]. First, it is possible to trace contacts and notify only those who have installed the app, not the population. Second, as data is not uploaded to a central server, health authorities lack oversight over infection events and over compliance.

The architecture and contact tracing technologies' design have ethical and practical implications. Contact tracing requires fine-grained information about people's whereabouts, contacts, and health status. To ethically design these applications, designers need to balance the benefits and harms of data collection [70] and ensure the benefits of contact tracing are distributed fairly [54]. Privacy-by-design principles were applied to the design and deployment of contact tracing, including data minimization, consent, proper oversight, and due processes. These principles include recommendations that the technology has an expiry date and is accompanied by proper oversight that would ensure that the extraordinary measures of contact tracing will not be used for purposes other than restricting the spread of the pandemic [53].

2.2 People's Attitudes towards Contact Tracing

The effectiveness of contact tracing applications depends heavily on the proportion of people who install and use the technology. Effective use of voluntary contact tracing requires enough people to download, authorize, and configure the applications [36, 38]. The greater the number of people who install the app, the more potential contacts can be identified and the easier it is to control the epidemic [50] effectively. Significantly, installation rates among the general population can indirectly benefit more vulnerable people, such as the elderly [59]. Since the beginning of the COVID-19 pandemic, many studies have surveyed people's attitudes toward contact tracing. Surveys were carried out in multiple countries (e.g., [5, 12, 16, 16, 67, 86]) or in specific countries, including Australia [84], France [32], Germany [11, 66], Ireland [29], Japan [44, 62], The Netherlands [46], Saudi Arabia [4], South Korea [52], Switzerland [89], The United Kingdom [90], and The United States [22, 35, 48, 56, 77, 81, 96].

The existing literature portrays a contradictory picture of user attitudes towards contact tracing technologies. In a survey carried out in the U.K., the U.S., France, Germany, and Italy, Milsom et al. have shown that 75% of all respondents have declared that they would "definitely install" contact tracing apps [67]. On the other hand, a representative sample of 2,000 people in the U.S. shows that just over 30% of Americans indicated they would download and use a mobile contact tracing application [96]. While the studies agree that trust in health authorities is an essential factor in their adoptions [29, 32], contradictions also occur in the results of studies that evaluated the effect of privacy designs on user approaches. Li et al. have used a vignette study design to test people's willingness to install various designs of contact tracing apps [57]. Participants have preferred to install apps that use a centralized server for contact tracing rather than designs that provide more privacy protection through decentralized architectures. However, Zhang et al. [96] and Kaptchuk et al. [48] found significantly higher levels of support for apps that offer privacy protections.

The confusion over the willingness to install apps and the effect of privacy controls push us to ask how we can accurately describe the factors that contribute to the adoption and related behaviors. First, it is crucial to measure actual behavior rather than attitudes. We know that there is a considerable distance between people's stated privacy attitudes and their actual behavior, a phenomenon sometimes referred to as the "privacy paradox" [74]. In contrast, concern does not seemingly affect actual behaviors. Specifically, relatively high privacy concerns do not affect people's use of mobile apps that require access to sensitive data [71]. Keeping this in mind brings some skepticism to the current literature. While surveys show that 75% of respondents say they would install or be willing to install contact tracing apps, actual installation ranges between 15% and 40% in countries that actually rolled out apps [45]. Furthermore, the studies ignored other contact tracing technologies and other COVID-19 interventions that may intervene with people's motivation to install the application.

2.3 Surveillance and Contact Tracing

The COVID-19 crisis has led to the rapid development of surveillance mechanisms in both democratic and authoritarian governments. The arguments against non-voluntary technologies mainly concentrate on the immediate and substantial negative impact on citizens' privacy and on the involvement of security forces in what is, essentially, a health challenge [64]. This type of criticism allows proponents of non-voluntary people's behavior to argue that normative arguments cannot stand in the way of life-saving interventions, as was the defense of the GSS Cellular Tracking technology in Israel's Supreme Court [65].

However, research in the fields of Human-Computer Interaction and Collaborative Systems pointed to negative externalities, for example, in surveillance in health tracking [10, 49]. Bhat and

Kumar analyze the adverse effects of personal health tracking, pointing to the negative effect of surveillance when using health monitoring [10]. People may abandon tracking when the cost of tracking is too high or when they may feel discomfort in revealing the information to themselves, or others [25]. This objection to surveillance extends to other types of increasingly digitized spaces, such as the classroom [60].

Mass surveillance went beyond traditional monitoring and tracking and was studied mainly by the Surveillance Studies community. Mass surveillance creates a culture in which being watched becomes so normalized that we may be unaware of the effects [61]. In this culture, our actions and expectations are carried out in "surveillance imaginaries," which have *"to do with shared understandings about certain aspects of visibility in daily life and in social relationships, expectations, and normative commitments. They provide a capacity to act, engage in, and legitimate surveillance practices. In turn, surveillance practices help to carry surveillance imaginaries and to contribute to their reproduction" (p. 41)[61].* Draper and Turow describe how mass surveillance leads to "digital resignation", people's feelings of futility in understanding and committing to action regarding their digital rights [24].

2.4 Motivational Crowding Out

Deploying mass surveillance systems as a measure against COVID-19 can have unexpected consequences. Specifically, it may reduce the public's motivation to take voluntary steps to combat the COVID-19 pandemic. While compulsory methods may be more effective, there is evidence that they may also crowd out voluntary participation and user engagement. In the context of COVID-19, Schmelz has shown that people state that they agree more to follow COVID-19 measures if the regulation is strongly advised by the government rather than if it is enforced [75, 76].

Enforcement can reduce intrinsic motivation, a phenomenon termed "motivational crowding out." When analyzing motivations, long-held evidence points to the difference between autonomous and controlled motivation [21]. More recently, this phenomenon has also been found in behavioral experiments by economists [14]. One of the underlying behaviors that cause motivational crowding out is termed "control aversion", which is a negative response to control over one's decisions [26, 97]. Control aversion can be caused by control over people's decisions or over-monitoring their behavior, as several field experiments have shown [9, 37]. The effect of monitoring on intrinsic motivation draws us to ask about the possible negative externalities of using mass surveillance for contact tracing on the willingness of people to install and use contact tracing applications.

2.5 Contact Tracing Technologies in Israel

In Israel, two contact tracing technologies were operable the spring of 2020: *HaMagen* ("the Shield", in Hebrew), a contact tracing application that the Ministry of Health developed and a centralized cellular tracking technology that is operated by Israel's internal security bureau, the General Security Services (GSS), dubbed *"The Tool"*. HaMagen is a contact tracing application that was developed by the Ministry of Health and was deployed on March 22, 2020 [83] (a full timeline of the deployment of the tools is depicted in Figure 1). The first version, HaMagen 1.0, was based on the ongoing local storage of users' location data and local matching with official data about infected people's whereabouts. The government provided links to downloading the application were on the Health Ministry Website but was not widely promoted in the media. Even with the limited exposure, about 1.5 million people have downloaded it, and 400,000 people have uninstalled it [31].

The Tool is based on centralized cellular tracking, which tracks all of the cellular phones operating in Israel [47, 80]. The Tool traces contacts with constant location tracking through Israel's cellular companies. Cell phone's location is tracked using a mixture of GPS locations transmitted through

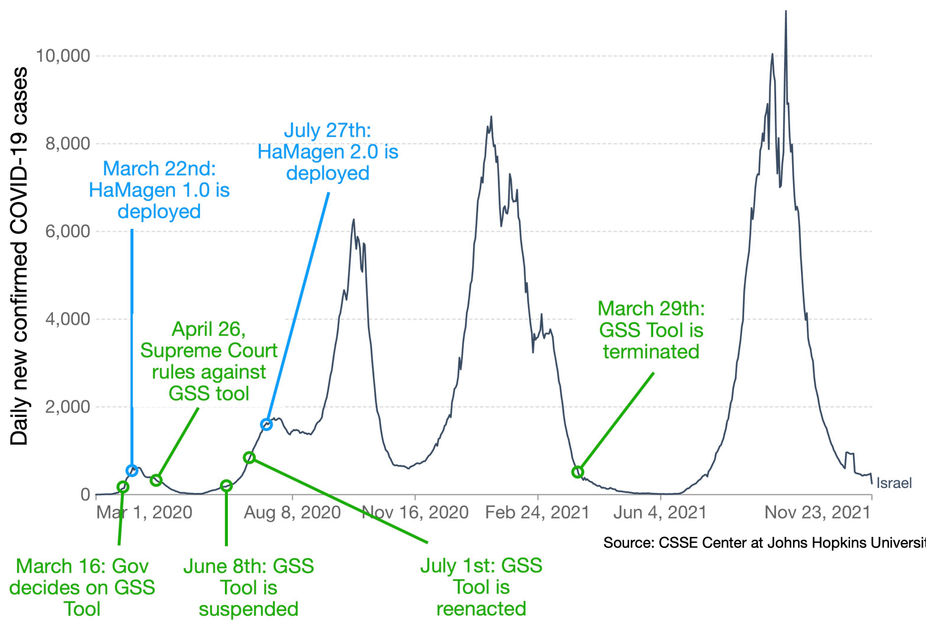


Fig. 1. A timeline of the implementation of Contact Tracing Technologies in Israel

cellular protocols and cellular antenna triangulation [20]. Routinely, The Tool is used for counter-terrorism and can be authorized only with a court order [42] [47]. However, on March 16, 2020, the Israeli government authorized the use of this technology for contact tracing [20].

When the epidemiological investigation teams briefed COVID-19-positive individuals, they fed the locations visited during the previous two weeks were into The Tool. The system analyzed the location data and pinpointed individuals close to the COVID-positive case. Contact details for individuals identified by The Tool are then sent to the health authorities, which notify them via text message that they have to self-quarantine (see Figure 6 in the Appendix for a depiction and the full text of the text message). The system did not let people know the location or the exact time of their interaction with the infected individual. Due to petitions to Israel's high court, the government suspended use of The Tool on June 8, but then reinstated it under temporary statutory provisions on July 1, 2020 [7]. On July 20, a supplementary bill was enacted that authorized the GSS to use The Tool as long as the number of new confirmed cases is higher than 200, and at the end of March 2021, the Tool's activity for contact tracing was officially terminated [95].

HaMagen mobile application collected information about the visited locations using the mobile phone's GPS and Wi-Fi positioning capabilities [6]. See Figure 7 for screenshots of the app and the texts displayed for users. Beginning with the second version of HaMagen, the application also received messages from nearby phones through Bluetooth Low Energy (BLE) protocol. These messages contained randomly assigned IDs and cannot be used to identify the nearby telephone. When an individual is identified as COVID-19 positive, they are briefed by an epidemiological investigation team. The locations users visited within the past two weeks were fed into simple centralized file storage. If the individual had the HaMagen application installed, health authorities could upload the locations and BLE messages to the server. Each application regularly retrieves the list of places and message IDs. If there was a match with the places or the messages received from a COVID-19 positive person, the user was notified and was asked to contact the health authorities.

Based on the theory on crowding out, we ask whether the deployment of involuntary mass surveillance can interfere with the deployment of voluntary technologies and reduce the installations of contact tracing apps. We operationalize this general research inquiry to two specific questions: What is the effect of attitudes toward mass surveillance on people's (1) installation of the contact tracing app and the (2) uninstallation of the app?

3 METHOD

To study the possibility that involuntary contact tracing may crowd out voluntary contact tracing, we conducted a representative online survey of Israelis between May 4 and May 7, 2020. The survey was conducted 49 days after the mass surveillance technology was deployed in Israel and 43 days after the contact tracing application was deployed. Participants were presented with questions about the contact tracing application and mass surveillance technology[1]. For each technology, we asked the participants to read a short excerpt from a daily newspaper that describes the technology and answer several questions about their attitudes toward it (we have randomized the order of the questionnaire sections regarding the two technologies.)

3.1 Questions

The survey instrument included several questions about voluntary and involuntary contact tracing technologies. The questions and summary statistics are available in Table 2 and Table 3 in the Appendix. We asked participants to indicate on a 5-point Likert scale their level of agreement with the questions (the markers were 'Strongly Disagree', 'Disagree', 'Neutral', 'Agree', 'Strongly Agree'). The participants were first presented with general questions about their attitudes toward the COVID-19 crisis (GA1-7) and some risk factors (RF1-6). To assess the basic attitudes about the two technologies, we used four identical questions: application utility questions were based on the World Health Organization (WHO) guidelines for COVID-19 survey tools [92] and asked about the perceived utility of the app. Two other questions measure the perceived privacy concerns of participants based on a validated privacy index that measures concern and sensitivity [63].

The participants were presented with questions about the contact tracing application and mass surveillance technology. For each type of technology, we presented short excerpts from a daily newspaper that describes the technology, as presented in Appendix A. We then asked the participants to answer several questions about their attitudes towards the particular technology. Questions about the HaMagen App included questions about utility (AU1-2), privacy (AP1-2), and general attitudes (AT1-2). Questions about the involuntary cellular surveillance technology (The Tool) included questions about utility (SU1-2), privacy (SP1-2), and general attitudes (ST1-2). We have randomized the order in which the two technologies were presented to the participants.

Several questions were specific to the contact tracing app. First, we asked whether the participants had installed or uninstalled the app. We asked the participants who had uninstalled the application to respond to three specific potential reasons: 1) "The app does not always recognize my location accurately"; 2) "I have encountered errors in the app"; and 3) "The app wastes my battery". We also asked several specific questions regarding general attitudes toward the contact tracing app (AT1 and AT2). We collected demographic information about gender, age, religion, level of observance, education, and income. In addition, to assess *technical abilities*, we have used a verified scale by Hargittai (2005), which measures people's familiarity with digital technologies [34].

[1] The data that the analysis is based on and the code used in the analysis are available at https://github.com/iWitLab/covid19_contact_tracing

3.2 Surveying Process

A pilot survey of 50 participants was conducted beforehand to assess the quality of the questionnaire and initial effect sizes. The survey was administered through an online panel by a commercial firm that carries out Internet panel surveys. As a result of the pilot study, we made several minor changes to the questionnaire. As almost all participants had heard about the contact tracing technologies, we removed questions about familiarity with the technologies. Furthermore, we have removed some questions that were too general and unintelligible. We used stratified quota sampling to approximate the marginal distributions of vital demographic characteristics in Israel: religion, gender, and age.

The final study sample includes 519 respondents. Our unweighted sample was nearly representative of the Israel population concerning gender, age, religion, observance level, and education. See Table 1 for a full breakdown of our demographic data. The mean age was 38 years (with a standard deviation of 13.80). A total of 53% of the participants were women, 46% were men, and few participants had chosen the “other” category. Religion or ethnic background was as follows: Jews (82%), Arab Muslims (10.5%), Arab Christians (2%), and Druze (4%). These results are in line with representative surveys carried out in Israel [19]. Other demographic variables that were recorded included religious level, education, and income. The study was authorized by the institutional ethics committee.

Table 1. Demographic characteristics of the participants. St Below Ave short for Strongly Below Average.

Gender		**Age**		**Religion**		**Observance**		**Education**		**Income**	
Male	239	18-19	10	Jewish	426	Secular	190	Elementary	3	St Below Ave	141
Female	276	20-29	158	Muslim	55	Traditional	139	Highschool	112	Below Average	165
Other	4	30-39	139	Druze	22	Religious	93	Non	138	Average	138
		40-49	81	Christian	16	Orthodox	57	Bachelor	184	Above Average	61
		50-59	76					Graduate	81	St Above Ave	14
		60-69	52								
		70-80	3								

3.3 Data Analysis

A total of 166 out of our 519 participants had installed the application (32%). This proportion is higher than the ratio of smartphone owners who had installed the application in Israel, which was 25.8% [6]. We explain this higher proportion in the higher technical abilities of the Internet panel that was used in this study. 45 participants had reported uninstalling it (9%), which is similar to the proportion of the general population.

We have carried several data validation processes for the analysis. To examine multicollinearity, the variance inflation factor (VIF) was calculated for all variables. Two factors (Application Utility and Surveillance Utility) were above the threshold [33], so they were standardized using the centering method [40]. After centering, the VIFs of all variables were below the threshold. The proposed constructs had Cronbach’s alpha values above 0.75, which point to good reliability (all Cronbach alpha values are presented in Appendix B). All data analysis tasks were carried out in STATA (ver. 17).

Our data analysis is based on two logistic regression models:

Installed to predict the likelihood of participants installing and consistently using the contact tracing application. The installed model does not include the users who uninstalled the application, as the criteria for contact tracing application success requires long-term use of the app[2]. We computed a categorical variable indicating whether the application was installed:

$$Installed = \begin{cases} 0, & \text{Not installed: if the application was not installed} \\ 1, & \text{Installed: if the application is currently installed} \end{cases} \tag{1}$$

Uninstalled the likelihood of participants who already installed the application to uninstall it until the time in which the survey was conducted (43 days after the contact tracing application was deployed.) We computed a categorical variable indicating whether the application was uninstalled.

$$Uninstalled = \begin{cases} 0, & \text{Installed: if the application is currently installed} \\ 1, & \text{Uninstalled: if the application was removed from the phone} \end{cases} \tag{2}$$

We fitted the logistic regression models on subsets of the whole dataset. We fitted the "install" model to participants who had not installed the app, while we fitted the "uninstall" model to participants who either had installed or uninstalled the app. We opted to use two models instead of a categorical model (such as a multinomial logistic regression) because three questions were presented only for people who had installed the application. We have used a statistical significance threshold of $p < 0.05$.

4 RESULTS

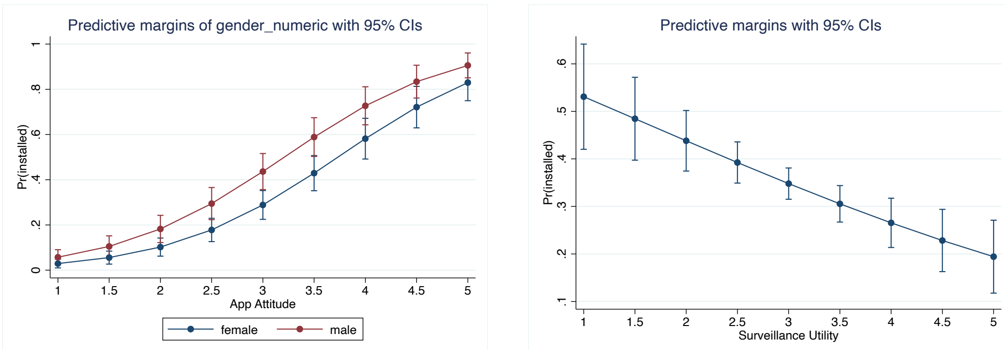
4.1 Application Installation

To analyze the factors contributing to installing the application, We fitted a model for a dataset (n = 474) that contained only the people who installed the app and didn't remove it until the survey was conducted (166 people) or never installed the application (308 people). We fitted a logistic regression model to the installation variable. The model fitted the data with a log-likelihood of -215.39 and a pseudo R^2 of 0.291. The model correctly classifies 78.56% of the data points. Figure 2 provides an overview of the strongest factors associated with installation and the full model is available in Table 4. We control for differences in observed heterogeneity by including gender, age, gender, education, religion, level of religious observance, and income effects.

The likelihood of installing the application is strongly correlated with the perceived attitude regarding the application (OR: 3.923, 95% CI 2.918-5.274), as shown in Figure 2 (a). We found that belief in the surveillance utility was the strongest and most significant negative factor associated with the likelihood of installing the application (OR: 0.547, 95% CI 0.372–0.803). For every positive increase in the belief toward the utility of the mass surveillance system scale, there is a decrease of 45% in the likelihood of installing the application (as seen in Figure 2 (b)). This significant and negative correlation confirms our central hypothesis and points to an interaction between mass surveillance and contact tracing application installation. Privacy concerns about the contact tracing application are also negatively correlated with the likelihood of installation (OR: 0.758, 95% CI 0.605-0.95). We did not find other associations to be significant in a model that included the attitudes towards the application, including concerns about the pandemic, trust in health authorities, and compliance.

We found that some of the demographic factors were related to installation. We found gender to be the most robust significant variable with an effect on installations, with men approximately

[2]To control for possible side effects of our definition, we also computed a secondary model for installation in which the *Installed* group included people who either installed or uninstalled the app, and the *not-installed* group included people who never installed the app. The results were similar to the main model, and are reported in the Results section.



(a) (b)

Fig. 2. Relationship between installation of the application and attitudes (a) and belief in the utility of mass surveillance. Marginal probabilities are shown with 95% CI.

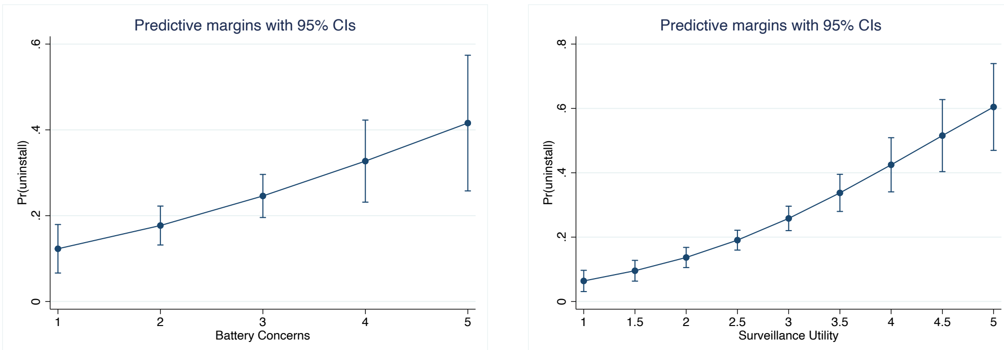
100% more likely to install the application (OR: 2.04, 95% CI 1.215 − 3.429). Younger people are more willing to install the app, but the relationship is generally weak and concentrated on the 18-20 year old demographic. People with graduate degrees are approximately 100% times more likely to install the application (OR: 2.034, 95% CI 0.984 − 4.20), but the large confidence intervals point to a weak effect.

We computed a secondary model (n=519) for installation in which the *Installed* group included people who either installed or uninstalled the app (211 people), and the *not-installed* group included people who never installed the app (308 people). The model fitted the data with a log-likelihood of -282.83 and a pseudo R^2 of 0.187. The independent and control variables were identical to the ones used in the main model (the full model is available in Table 5 in the Appendix). Similarly to the main model, correlated variables included the perceived attitude about the application (OR: 2.721, 95% CI 2.12-3.48), belief in the surveillance utility (OR: 0.666, 95% CI 0.479–0.927), privacy concerns about the contact tracing application (OR: 0.832, 95% CI 0.685-1.009), and male gender (OR: 1.76, 95% CI 0 1.132- 2.742). These results have similar effect sizes and significance to the main installation model, though with somewhat lower goodness of fit.

4.2 Application Uninstallation

In our second research question, we look at the factors related to uninstalling the contact tracing app. We fitted a model for a dataset (n = 209) that contained only the people who either installed (166 people) or uninstalled the application (45 people). This proportion fits the proportion of people who had uninstalled it HaMagen at the time of the study [6]. The appendix presents the full results of the logistic regression, and Figure 3 displays the marginal contribution of selected factors to the probability of uninstallation. The model fitted the data with a log-likelihood of -74.44 and a pseudo R^2 of 0.507. The model correctly classifies 89.32% of the data points.

The most substantial factor associated with uninstalling the contact tracing application is the belief in the utility of the mass surveillance (OR: 8.57, 95% CI 2.837-25.908). While the variance of this effect is relatively wide, on average, a user is approximately two times more likely to uninstall the application with every increase in the belief in the utility of the mass surveillance system (as seen in Figure 3 (b)). The second most powerful reason for uninstalling the application is related to concerns about battery consumption (OR: 2.23, 95% CI 1.28-3.88); users are approximately 120%



(a) (b)

Fig. 3. Relationship between uninstalling the contact tracing application and attitudes (a), attitudes toward mass surveillance (b), and battery concerns (c). Marginal probabilities are shown with 95% CI.

more likely to uninstall the application for every increase in these concerns. Other variables, such as privacy concerns, location inaccuracies, and application errors, were not significant in our model.

Negative associations with uninstallation include positive attitudes toward the application (OR: 0.091, 95% CI 0.036-0.23) and positive beliefs in the app's utility (OR: 0.27, 95% CI 0.11-0.63). Nonacademic users are more likely to uninstall the application (OR: -.27, 95% CI 0.11-0.63). Other factors, such as gender, age, technological level, and religion, were not significant.

4.3 Comparing Attitudes

In this section, we provide some descriptive statistics about the participants' attitudes towards the technologies in question. Figure 4 shows the results of our participants' attitudes towards HaMagen and the Tool. Overall, people expressed negative attitudes regarding the app. Only 28% will tend to recommend their friends and family install it (versus 43% that would not). A somewhat higher proportion have a positive attitude towards making it mandatory for people entering malls or public transportation (35% versus 43%). Only 27% think it will reduce their chances of contracting the coronavirus, and only 32% believe it will reduce the spread of the virus. Privacy concerns are prevalent. 59% feel that it collects sensitive information (versus 19% that disagree), and 43% are worried about privacy (versus 32% that disagree).

How do Israelis view the involuntary mass surveillance operation? The summary of the answers is presented in Figure 4. Our survey shows that most Israelis do not trust the government to delete the data after the crisis is over (53% disagree versus 21% who agree). About 35% of our participants are sympathetic to people leaving their phones at home to avoid being tracked (versus 39% are have an unfavorable view). About 60% agree that cellular tracking can collect sensitive information (versus 17% who disagree). About 42% report privacy concerns because of the cellular tracking technology, versus 32% who disagree.

Overall, we did not find statistically significant differences in the approaches towards privacy between the two architectures (when comparing the factors App Privacy and Surveillance Privacy or when comparing the equivalent questions, AP1 to SP1 and AP2 to SP2). The medians and variances visually look very similar. A Wilcoxon sum test did not find significant differences ($W = 17499.0, p = 0.15$). The differences between the perceived utility are statistically significant, but the effect size is rather small. The median utility is identical, but more participants believe cellular tracing offers better protection against COVID-19 (Wilcoxon sum test, $W = 18579.5, p = 0.018$).

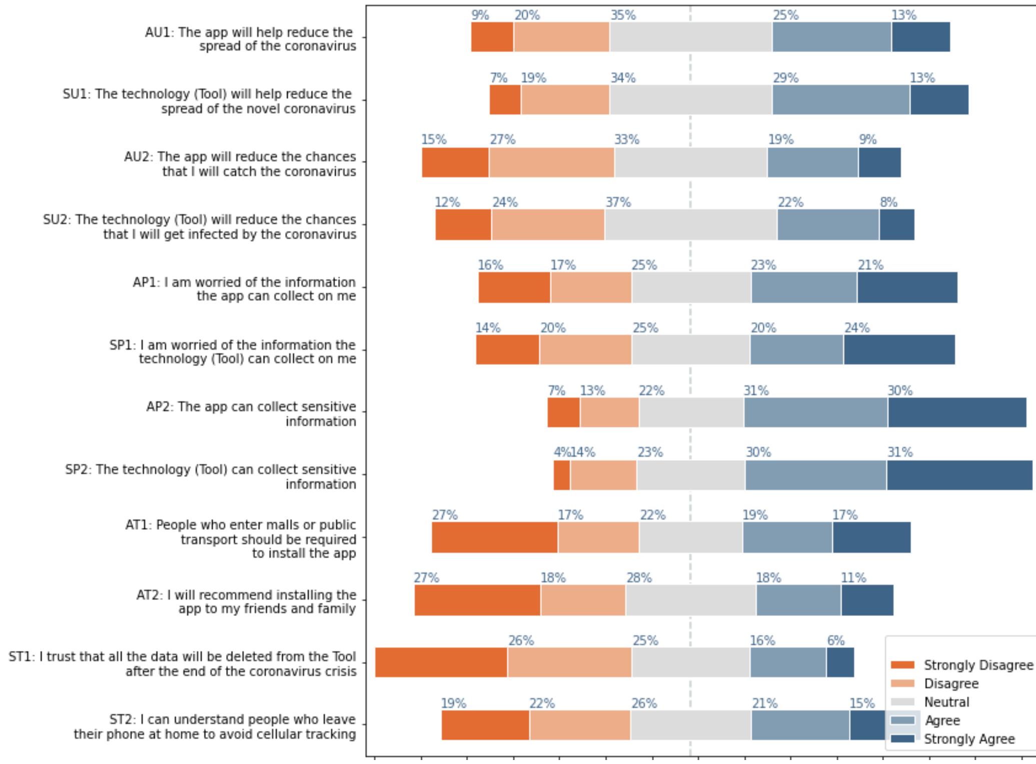


Fig. 4. Overall attitudes regarding the contact tracing application HaMagen (“The App”) and the cellular surveillance technology (“The Tool”) on a 5-point agreement Likert scale.

5 DISCUSSION

The COVID-19 pandemic has provided a rare opportunity to study how people’s preferences matter for the effectiveness of public policies and are affected by the deployment of technological systems. The existing literature analyzed contact tracing apps in isolation, modeling the decisions of people under the assumption that there are no other systems that carry out contact tracing [16, 35]. In contrast, we investigate a setting in which voluntary and involuntary systems are deployed simultaneously and demonstrate a possible spillover effect that arises from the existence of the involuntary system. Our analysis adds to the growing literature that points to behavioral spillover effects in COVID-19 when involuntary measures are deployed, such as social distancing mandates [94], compliance with the recommended precautionary measures [88], or vaccine mandates [76, 85].

5.1 Crowding Out Mechanisms

The relationship between perceptions of surveillance utility and the avoidance of contact tracing apps points to a mechanism that crowds out voluntary participation. Here we ask what are the potential reasons behind crowding out in the context of COVID-19 contact tracing? People’s motivations may differ under participatory and involuntary systems, not only because involuntary methods make participation redundant but also because their existence may affect people’s preferences [13]. It is essential to recognize that conceptualizing this problem requires extending the framework of motivational crowding out theory beyond its original premise. Unlike classic crowding out scenarios, Israeli citizens were not offered a reward to use the mass surveillance system, nor was there a punishment involved in not using it. However, intrinsic motivations such as altruism are associated with installing COVID-19 contact tracing apps [48, 56, 75]. Therefore, we look at mechanisms of crowding out of social preferences that are discussed extensively in the literature [13] and extend them with possible spillover monitoring mechanisms [9] that are relevant to the unique aspects of surveillance.

First, implementing a mass surveillance system reveals the government's beliefs about the ability of citizens and the trust it has in them. Choosing a voluntary application may signal the government's confidence in citizens' responsibility [82]. In contrast, mass surveillance may signal the government's belief that people cannot be trusted to install the application and voluntarily share information in the case of detection of proximity events. Monitoring can lead to a lower level of trustworthiness by agents [39] and to lower productivity when workers retaliate for being distrusted [9]. While these results were obtained in the context of workplace monitoring, it may be the case that similar reciprocity mechanisms can explain reactions to governmental mass surveillance.

Second, monitoring and enforcement may compromise personal autonomy [97]. Unlike a contact tracing application, mass surveillance technology does not leave it to citizens to actively decide whether to notify health authorities about a contact event. Monitoring often backfires, with workers performing worse when they are monitored [9]. Draper and Turow [24] describe how mass surveillance leads to "digital resignation", people's feelings of futility in understanding and committing to action regarding their digital rights.

Third, participatory systems require some setup and incur usage costs. People need to download the application and install it, which may be difficult. Involuntary methods rid citizens of these costs, which may decrease the incentive to participate if they believe in the system's utility. Long-term usage incurs ongoing costs, such as battery drainage, which might hinder people's willingness to run the app, especially if an equivalent solution is available. Our findings point to the strong effect of concerns about the app's battery consumption in uninstalling the app.

Fourth, participatory systems such as the contact tracing application require users to make moral decisions when installing, allowing access to Bluetooth or location services, which will require the user to make a judgment call on privacy. Additionally, it is up to the user to notify the health authorities when a proximity event is detected. The individual needs to make a difficult decision: inform the health authorities and act, which will probably result in quarantine? Or ignore the event? Given the uncertainty of the detection of the event and the fact that the contact tracing application does not provide information about the context of the event apart from the time of day, offloading the moral judgment to the mass surveillance system is understandable.

5.2 Crowding Out and Public Health

What are the implications of crowding out behaviors on public health? Mass surveillance systems drive against the most fundamental principles of consent and control in fair information practices [64]. But understanding crowding out mechanisms may also lead to a closer evaluation of the effectiveness of mass surveillance systems in light of spillover effects. Crowding out effects may be harmful to the overall performance of contact tracing if there is an imbalance in the effectiveness of the two systems. When the involuntary system is less effective than the participatory system, it may hamper the overall objective of the two systems.

In our case study, we have evidence that the mass surveillance system was not efficient in detecting proximity events, and therefore deploying it may have hurt the Israeli contact tracing efforts. The mass surveillance project in Israel revealed the limitations of the system. According to the State Comptroller's October 27 report, 3.5% to 4.7% of those told to quarantine based on the mass surveillance methods contracted the coronavirus, compared with 24% of those told to quarantine by an epidemiological investigation team [41]. The false positively rate of the mass surveillance tool was also high: the system unnecessarily sent into quarantine three to eight times as many people than the manual epidemiological processes. 60% of the appeals against self-quarantine orders due to contact with a verified coronavirus patient were granted [58].

While our study is based on a specific natural experiment, the Israeli parallel deployment of contact tracing technologies, there are several lessons that can be generalize from this particular case study. In almost every country, contact tracing applications were deployed in a specific technological and operational ecosystem, with manual contact tracing procedures or with various forms of centralized contact tracing technologies. Many other countries have multiple contact tracing technologies working in parallel, with private companies and other local governments each requiring different apps [62]. In New Zealand, fragmented deployment of contact tracing processes had created confusion and negatively impacted public health response [18]. Our results point to the need to design towards ecosystems of public health technologies, rather than deploying specific solutions that may have unintended and surprising spillover effects.

5.3 Privacy Perceptions and Trust

Our results support the results of previous studies in other parts of the world about the connection between deeper privacy concerns and lower acceptance of contact tracing apps [5, 16]. Our results also demonstrate that people find it difficult to assess the privacy risks associated with different types of contact tracing technology. The differences between the privacy concerns related to mass surveillance and the privacy-preserving contact tracing apps were too small to be significant. These results support a previous vignette study by Li et al. [56] that shows that people cannot easily distinguish between centralized and privacy-preserving contact tracing apps. It also joins a growing literature that points to the challenges people face when assessing risks related to COVID-19 [1]. This result strengthens the hypothesis that these apps do not communicate well enough with their privacy advantages.

We see that the model for installation has some resemblance to the model for uninstallation but with some considerable differences. Our study analyzed uninstallations of the COVID-19 contact tracing app. Montagni et al. [68] found that most uninstallations were due to negative perceptions of the app's usefulness, forgetting to activate the Bluetooth, and battery draining. Our results support some of these findings, but we see that uninstallations are also dependent on the ecosystem of COVID-19 contact tracing technologies. Our study found that people uninstall the application if their attitudes toward it are negative, if the attitudes toward mass surveillance are positive, if they believe that it will drain their battery, and if they were not found to have COVID. Men uninstall it more than women.

We found some demographic differences in attitudes toward contact tracing apps. Males are generally more inclined to install the apps, as was found in several other studies [29, 48, 52]. This gender difference aligns with past research that showed that women are more privacy-sensitive than men [72]. We also found higher levels of installation for people with graduate degrees, a phenomenon also reported in several other studies [62, 96].

5.4 Designing Systems with Crowding Out in Mind

Understanding the effect of the technological ecosystem on people's behavior is significant for addressing the COVID-19 pandemic and understanding how to design ecosystems of technologies that combine voluntary and involuntary systems. More broadly, our findings are also relevant to situations where automated and participatory methods compete for similar objectives, situations which are becoming more widespread as artificial intelligence systems are increasingly embedded in continuous and long-term processes [91]. Models that aim to analyze the distribution of tasks between humans and AI rely on the assumption that there is a single automated system [23]. However, it is increasingly the case that we need to design an ecosystem of technologies rather than a single system. We can distill the designer's decision of the technological ecosystem into a relatively simple decision: to which extent to deploy the automated system.

Designing ecosystems of technologies that combine both automated and participatory systems requires us to analyze their combined effectiveness and possible spillover effects that originate from the way users make decisions about their involvement. We suggest a simple model that can be useful when discussing design choices, inspired by existing models that are used to analyze crowding out behavior [17], graphically represented in Figure 5. The model reflects a simple scenario in which there are two systems, an automated system, and a participatory system, that are used to pursue a similar objective. For example, in areas such as medical imaging, clinicians might work alongside several parallel AI systems that take part in medical decision-making. These can include manual systems that highlight essential areas while letting the clinician make the inspection [87], through systems that highlight the possible malignancy of suspect areas [15], to fully automated systems [51]. When thinking about whether to deploy the fully automated system along with the participatory system, the designer needs to evaluate the effectiveness of both systems. If there are no negative externalities related to the deployment of the automated system, adding it can increase the chance of identifying a malignant tumor. However, crowding out effects can make the evaluation more complex.

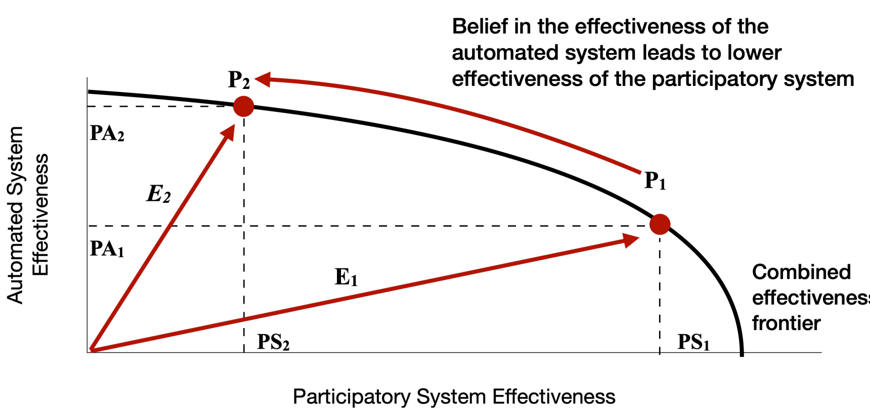


Fig. 5. A combined effectiveness model of the participatory and automated systems, visualizing the effectiveness of the participatory system (points PS_1 and PS_2), the automated system (points AS_1 and AS_2), and the combined effectiveness (lines E_1 and E_2). In this example, the belief of the users of the effectiveness of the automated system causes lower participation in the participatory system (switching from P_1 to P_2), which causes a reduction of the effectiveness of the participatory system ($PS_1 > PS_2$), and as a result, a reduction in the combined effect of the ecosystem ($E_1 > E_2$).

To analyze the ecosystem design decision, we try to evaluate the effectiveness of the whole ecosystem with or without the automated system. We assume each system has its own effectiveness measure that can rely on various properties (points PS_1 and PS_2 and AS_1 and AS_2 in Figure 5). What is essential to the analysis is that the systems have different levels of human involvement: the participatory system's effectiveness is based on the level of human involvement. In contrast, the automated system's effectiveness is unrelated (or weakly related) to the effort users put into interacting with it. To exemplify how we can operationalize our model, let us imagine that our task involves a clinician that inspects medical imagery to find tumors [87]. The designers consider deploying two types of AI systems that can improve the process: a participatory system that highlights suspect areas and let the clinician make a decision [87] and a fully automated system that works independently of the clinician after the examination [51].

As Figure 5 illustrates, let us Imagine that we start when the participatory system is working, but the automated system is working in a partial capacity (point P_1). When the automated system is deployed on a larger scale (point P_2), its effectiveness is higher ($PA_2 > PA_1$), but the effectiveness of the participatory system drops ($PS_2 < PS_1$). The combined effectiveness of the ecosystem is given by the hypotenuse of the triangle, the lines E_1 and E_2. In our example, the introduction of the automated system reduced the overall effectiveness of the ecosystem (as $E_1 < E_2$).

Each analysis of an ecosystem of automated and participatory systems or features depends on each system's effectiveness and the effect of crowding out. If introducing the automated system has no crowding out impact, adding it will always be beneficial. To analyze the ecosystem itself, the designers need to evaluate and analyze the combined effectiveness frontier, which summarizes the combined effect for every value of the effectiveness of the voluntary and involuntary systems.

When deciding whether to introduce the fully automated system, our model can point to several essential elements that we should consider: the participatory system's effectiveness, the automated system's effectiveness, and a possible crowding out mechanism. For example, clinicians might not want to make the legally risky decision about a tumor if they believe that the automated system is performing well. It is important to emphasize that this belief might not be accurate. It is generally hard for people to estimate the accuracy and performance of complicated learning algorithms [51], and it can even be more challenging if adversaries manipulate the explanations and outputs of these algorithms [55]. Estimating and thinking about all these factors may give the product team an idea of the combined effectiveness frontier of their manual and automated systems working together.

Another important lesson in deploying participatory system designs is to reduce *ecosystematic privacy concerns*. We see that installation is strongly associated with lower privacy concerns, and minimizing these concerns by developing privacy-preserving technologies can result in higher installation rates. Active measures to enhance the privacy of contact tracing technology could reduce the friction of installing these apps and increase adoption. However, our findings point to the challenge of communicating privacy-preserving technologies; attitudes regarding the sensitivity of the data and concerns about data collection were similar between the mass surveillance and the contact tracing app, even though the second one is based on consent and anonymized data. Therefore, we argue that thinking about privacy concerns should take an ecosystemic approach, considering different technological facets of similar or related technologies and considering that beliefs about a single system may spill over to beliefs about other systems, even if the actual architecture is very different. Sometimes, there is a need to communicate privacy benefits in a way that strongly distinguishes the technology from its ecosystem.

6 CONCLUSIONS

We provide a model of COVID-19 contact tracing app installation, exploring the effect of mass surveillance on people's decisions to install or uninstall the app. The study investigates this through a representative survey of residents of Israel, drawing on a natural experiment rooted in Israel's parallel deployment of involuntary mass surveillance apparatus and a voluntary mobile app. Our findings suggest that mass surveillance harms installations and positively affects uninstallations, even when controlling for attitudes toward contact tracing privacy, utility, and demographics. We propose a framework for analyzing such situations, understanding how a mandatory system could 'crowd out' a voluntary system.

Deploying a mass surveillance system may substantially impact the voluntary installation of contact tracing apps and may be harmful if involuntary methods are not practical. Given the limited ability of citizens to fully understand digital technologies, enforcing involuntary systems can confuse citizens and discourage them from adopting more complicated technologies. While our analysis is based on an extraordinary historical case, we believe it allows us to define some general observations relevant to many situations in which aspects of voluntary and involuntary surveillance systems operate together.

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A ADDITIONAL MATERIALS

The text was translated from the original Hebrew by the authors.

A.1 Text Related to HaMagen

The "HaMagen" app was developed for the Ministry of Health with the objective of preventing the spread of the novel Coronavirus. According to news articles, it is known that the application works in the background and collects your location history. Throughout the day, it downloads information about the location traces of COVID-positive people and compares these traces with your path. If you were in proximity of a positive person, in the same place and time – you will receive a notification that you should quarantine and will also be referred with a link to the Ministry of Health that would allow you to report a home quarantine. The location data will be stored on the device itself. The Ministry of Health does not have the ability to know where you have been and who did you meet.

Excerpt taken from the news article at TheMarker.com

A.2 Text Related to the GSS Tool

The government announced that it is now using cellular tracking to identify people that were in the in proximity to COVID-19 positive persons in a period of two weeks before the person was identified as positive. According to new articles, for example, a COVID-19 positive person that was standing on a train platform will lead to a creation of a virtual circle of all the people that were two meters or less in a 15-minute time range, according to the criteria of passing COVID from one person to another. The information is then passed from the SHABAK to the Ministry of Health, and it sends text messages to the people and let the know that they might have gotten infected, and they need to self-quarantine.

Excerpt taken from the news article at Haaretz

Fig. 6. An example for a text message received from the Israeli Ministry of Health after being tracked by the GSS Tool. Translated text from Hebrew: "The recipient is informed that, according to an epidemiological investigation, they have been close to a verified Coronavirus patient and must enter home quarantine."

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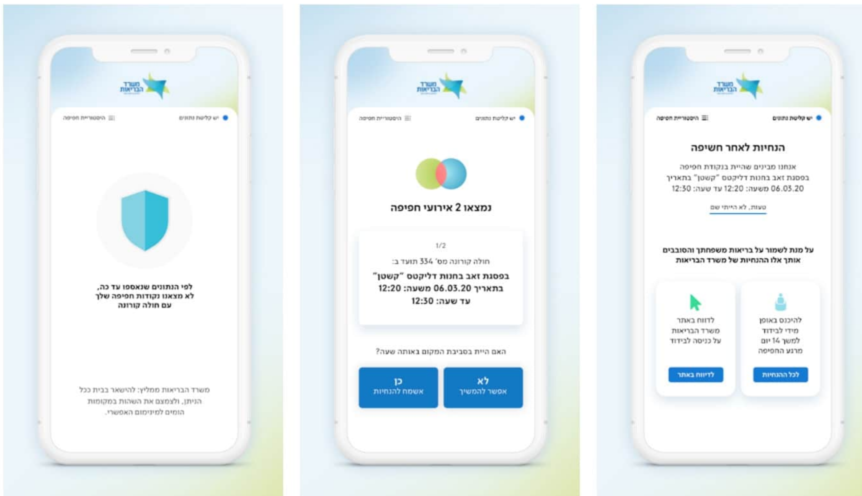

Fig. 7. Screenshots from the HaMagen application. Translated text from Hebrew, from the left panel to the right. Leftmost panel: “According to the updated data, we did not find an overlap location with a COVID patient”; Middle panel: “There were 2 locations of overlap. Patient number 334 was located at Pisgat Zeev (a neighborhood in Jerusalem), in a shop called ‘Kashtan’ at March 6th, 2020 from 12:30 to 12:30. Were you at that place at that time? No - Cancel, Yes - I will be glad for instructions”; Rightmost panel: “Instructions after exposure: We understand that you were in an overlap location in Pisgat Zeev in the Kashtan Shop at March 6th, 2020 from 12:30 to 12:30. (link: Wrong, I wasn’t there). To keep your health and the health of those around you, these are the instructions from the Ministry of Health: Stay in quarantine and report in the Ministry of Health website.

Table 2. A list of all constructs and items questionnaire. Cronbach's alpha is the scale reliability coefficient for internal consistency. The text was translated from Hebrew.

Construct	α	Item	Text	Mean	STD
App Utility	0.84	AU1	The app will help reduce the spread of the coronavirus	3.12	1.13
		AU2	The app will reduce the chances that I will catch the coronavirus	2.82	1.16
App Privacy	0.78	AP1	I am worried of the information the app can collect on me	3.17	1.35
		AP2	The app can collect sensitive information	3.62	1.21
App Attitude	0.71	AT1	I will recommend installing the app to my friends and family	2.75	1.22
		AT2	People who enter malls or public transport should be required to install the HaMagen app	2.82	1.43
Surveillance Utility	0.82	SU1	The technology will help reduce the spread of the novel coronavirus	3.21	1.09
		SU2	The technology will reduce the chances that I will get infected by the coronavirus	2.89	1.10
Surveillance Privacy	0.79	SP1	I am worried of the information the technology can collect on me	3.20	1.35
		SP2	The technology can collect sensitive information	3.70	1.14
Trust Delete		ST1	I trust that all the data will be deleted after the end of the coronavirus crisis	2.46	1.22
Understand Leave		ST2	I can understand people who leave their phone at home to avoid cellular tracking	2.92	1.32
COVID-19 Concerns	0.77	CC1	The novel coronavirus threatens the population of Israel	3.13	1.17
		CC2	The novel coronavirus threatens my health	2.86	1.15
		CC3	I am worried that people I know will get infected by the novel coronavirus	3.61	1.16
		CC4	I am worried to get infected by the novel coronavirus	3.03	1.24
Trust		GA5	I have trust in the professional authorities that lead the handling of the coronavirus	3.25	1.09
Compliance		GA6	I strictly follow the instructions of the health ministry to fight the coronavirus	4.18	0.83
Financial hurt		GA7	The coronavirus crisis is hurting me financially	2.92	1.29

Table 3. A list of all binary items. The text was translated from Hebrew.

Construct	Item	Item Text	No	Yes
Risk factors	RF1	Do you work in a healthcare clinic or a hospital	487	32
	RF2	Are you in a special risk of the coronavirus	409	110
	RF3	Do you have relatives who are in special risk of the virus	84	435
	RF4	Do you know a person that was tested positive for the coronavirus?	373	146
	RF5	Were you ever tested positive for the coronavirus?	509	10
	RF6	Are you or were you in quarantine?	475	44

Table 4. The association between installing the COVID-19 contact tracing app, attitudes, and demographic factors (n = 474). *** p<.001, ** p<.01, * p<.05

Install	Odds.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
App Attitude	3.923	.592	9.05	.000	2.918	5.274	***
Surveillance utility	.547	.107	-3.08	.002	.372	.803	**
App Privacy	.758	.087	-2.40	.016	.605	.950	*
App Utility	1.05	.176	0.29	.772	.756	1.458	
Tech Level	1.178	.139	1.39	.165	.935	1.485	
Gender: Male	2.041	.54	2.69	.007	1.215	3.429	**
Age: 18-20	5.394	4.407	2.06	.039	1.088	26.752	*
Age: 30s	1.159	.384	0.44	.656	.605	2.218	
Age: 40s	1.313	.494	0.72	.469	.628	2.745	
Age: 50s	1.177	.479	0.40	.688	.530	2.613	
Age: 60s	1.149	.517	0.31	.757	.476	2.773	
Education: Graduate	2.022	.748	1.90	.057	.979	4.173	
Education: Highschool	.682	.236	-1.11	.269	.346	1.344	
Education: Non Academic	.677	.218	-1.21	.227	.360	1.274	
Christian	1.751	1.267	0.77	.439	.424	7.228	
Druze	1.237	.837	0.31	.753	.328	4.663	
Jewish	1.93	.809	1.57	.117	.849	4.388	
Constant	.025	.021	-4.27	.000	.005	.135	**

Table 5. The association between uninstalling the COVID-19 contact tracing app, attitudes, and demographic factors (n = 209). *** p<.001, ** p<.01, * p<.05

Uninstall	Odds.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
App Attitude	.091	.043	-5.06	.000	.036	.23	***
Surveillance utility	8.574	4.838	3.81	.000	2.838	25.909	***
App Privacy	1.362	.369	1.14	.253	.802	2.315	
App Utility	.274	.116	-3.05	.002	.119	.63	**
COVID Concern	1.19	.347	0.60	.550	.673	2.106	
Battery Concerns	2.232	.632	2.83	.005	1.281	3.889	**
Wrong Location	.581	.17	-1.86	.063	.328	1.03	*
App Errors	.838	.205	-0.72	.470	.518	1.354	
Tech Level	1.018	.271	0.07	.947	.604	1.715	
Gender: Male	.306	.196	-1.85	.064	.087	1.071	*
Age: 20s	14.8	31.943	1.25	.212	.215	1017.382	
Age: 30s	4.104	8.756	0.66	.508	.063	268.719	
Age: 40s	4.943	10.734	0.74	.462	.070	348.734	
Age: 50s	2.889	6.367	0.48	.630	.038	217.023	
Age: 60s	13.273	29.733	1.15	.248	.164	1071.105	
Education: Graduate	.992	.878	-0.01	.993	.175	5.621	
Education: Highschool	2.97	2.552	1.27	.205	.551	15.998	
Education: Non Academic	7.286	5.441	2.66	.008	1.686	31.485	***
Christian	13.324	28.418	1.21	.225	.204	871.125	
Druze	3.408	5.547	0.75	.451	.140	82.795	
Jewish	4.75	6.481	1.14	.253	.328	68.862	
COVID Positive	.006	.012	-2.52	.012	0.00	.322	*
Income: Above Average	10.645	11.153	2.26	.024	1.366	82.972	*
Income: Average	4.56	3.812	1.81	.070	.886	23.473	
Income: Below Average	.858	.677	-0.19	.846	.183	4.025	
Income: High	8.479	15.344	1.18	.238	.244	294.321	
Constant	.063	.18	-0.96	.335	0.00	17.465	