Public Perceptions of COVID-19 Digital Contact Tracing Technologies During the Pandemic in Germany

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Abstract

Digital contact-tracing technologies are being used for epidemiological purposes at scale for the first time in response to the COVID-19 pandemic. This poses challenges for governments aiming at high and efficient uptake and for people weighing the advantages (e.g., public health) against the potential risks (e.g., loss of data privacy) of these unprecedented measures. Our cross-sectional survey with repeated measures across four samples in Germany ($N = 4,357$) focused on public perceptions of digital contact-tracing technologies and related attitudes toward privacy. We found that public acceptance of potential privacy-encroaching measures decreased over time. Levels of acceptability were high for all three hypothetical tracking apps representing a range of privacy encroachments. Intentions to download the actual tracking app (the Corona-Warn-App) that became available during our study were also high. However, this did not directly translate into actual uptake. Our results point to the crucial roles of trust in government and in the app's security, as well as of concerns about the app's effectiveness. A conflict between prosocial intentions and personal benefit on the one hand, and lack of trust in data security and the app's effectiveness on the other, are at the heart of people's decisions about whether to use digital contact-tracing technologies.

Keywords: COVID-19 | digital contact tracing | privacy | public attitudes | Corona-Warn-App

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Public health interventions and vaccinations, economic aid, and behavioral regulations have all been enlisted to curb the damage of the COVID-19 pandemic (Habersaat et al., 2020; World Health Organization, 2020). Before vaccines were introduced, behavioral measures—restricting public gatherings and other lockdown policies, tracing contacts of infected persons, and implementing a combination of physical distancing rules and hygiene measures (e.g., Germany's "AHA+L"—distance, hygiene, mask + ventilation—rules; Robert Koch Institute, 2020)—were the most promising way to contain the pandemic. Technological solutions have also helped stem the spread of COVID-19 (Grantz et al., 2020; Oliver et al., 2020). Indeed, with the exception of the Ebola outbreak in West Africa in 2014–2016 (Danquah et al., 2019), the COVID-19 pandemic is the first large-scale use of digital contact tracing for epidemiological purposes (Kahn & Johns Hopkins Project on Ethics and Governance of Digital Contact Tracing Technologies, 2020). The current study focuses on the behavioral factors that contribute to the adoption of tracking apps during the course of the COVID-19 pandemic.

Smartphone tracking apps use GPS, telecommunication, and Bluetooth data to create a list of contacts with whom a user may have been colocated (Oliver et al., 2020). This contact information is stored locally on the phone or on a centralised server. If a person later tests positive for COVID-19 and shares their infection status with an app, all users in their contact list can be notified instantly, allowing them to self-isolate and get tested, thus ideally helping to slow the virus' spread (Ferretti et al., 2020).

So far, about 50 countries have introduced COVID-19 contact-tracing apps; most use Bluetooth tracking technologies (O'Neill et al., 2020). The Corona-Warn-App, introduced in Germany in June 2020, is an open-source Bluetooth-based decentralized smartphone app (https://www.coronawarn.app/en) that aims to ease the burden of the pandemic on local public health authorities by complementing their offline contact tracing efforts. The app employs a privacy-preserving model, collecting anonymized contact data that are stored locally on the user's smartphone. Like Spain's Radar COVID app or the United Kingdom's NHS COVID-19 app, the Corona-Warn-App's Bluetooth-mediated contact-tracing functionality and architecture is based on Google and Apple's Exposure Notification system.

Given that COVID-19 is likely to become endemic in many parts of the world, it is crucial to evaluate and understand the factors that can make digital contact tracing an effective long-term epidemiological measure (Colizza et al., 2021). The potential of tracking technologies to battle the pandemic depends on a combination of related but distinct factors (see Figure 1 for a graphical representation), including (see also Colizza et al., 2021; Rodríguez et al., 2021): (1) *functionality*: the app's architecture (e.g., which protocol or exposure notification system it uses), and the privacy and risk models it relies upon; (2) *integration*: how the app is integrated into a larger environment, including public health system capacity and how test results are shared with an app (e.g., via QR codes); (3) *communication*: includes media coverage and how the app and its risks and benefits are communicated to the public; (4) *usage*: consists of a number of behavioral factors, including the technology's adoption (number of downloads), people's continuous and correct use of the app (e.g., keeping it installed and keeping Bluetooth on), and compliance (e.g., people's willingness and ability to share their test results in the app); (5) *detection*: includes key effectiveness metrics such as the number of positive test results shared with an app as a proportion of all clinically diagnosed infections in the population, the app's overall detection rate (i.e., the proportion of an infected person's contacts who are notified by the app about their risk exposure—including contacts unknown to the infected individual), and detection accuracy (i.e., the proportion of detected infections in the app that are free from both false positives and false negatives; see Redmiles, 2020); and (6) *response*: complying with risk warnings in the app following risk exposure notification and taking appropriate

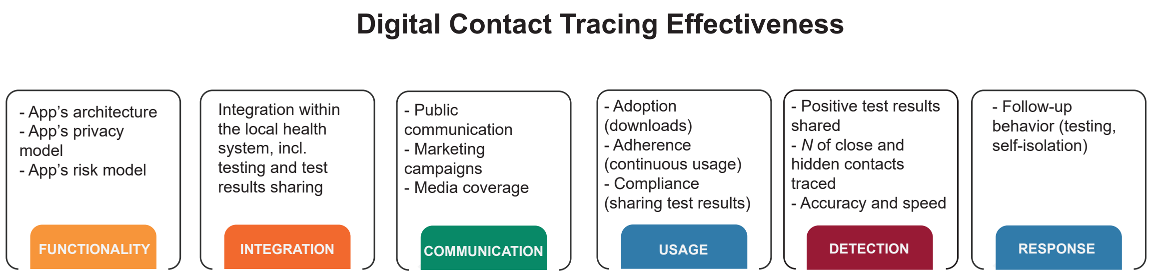

Figure 1: Factors contributing to the effectiveness of digital contact tracing technologies. Expanded based on the analysis by Rodríguez et al. (2021).

measures (e.g., taking a test, self-isolating or self-quarantining).

So far, the uptake of digital contact-tracing apps among the populations of most countries has not reached the target of 60% (Figure 2), which is derived from early simulation models suggesting that an uptake by 60% of the population would effectively mitigate the spread of the virus (Hinch et al., 2020; Whitelaw et al., 2020). More recent simulation studies suggest that even levels of adoption above 20% can have a mitigating impact (Aleta et al., 2020; Bianconi et al., 2021). Indeed, recent evidence suggests that this is the case in the United Kingdom (Wymant et al., 2021).

Many factors may play a role in people's decision to download and use digital tracing apps. A recent study in Germany revealed higher adoption rates of the Corona-Warn-App among respondents with a higher risk of severe illness, respondents who follow behavioral guidelines (e.g., wearing a mask), and respondents who trust the national government, the healthcare system, and science in general (Munzert et al., 2021). A study from France also found that higher trust in government is associated with higher acceptability and increased use of contact-tracing apps (Guillon & Kergall, 2020); similar findings have been observed in the United Kingdom as well (Lewandowsky et al., 2021).

A U.S. study on the willingness to adopt warning apps has shown, using hypothetical scenarios, that people consider both the risks and the benefits of such technologies (Redmiles, 2020). Benefits include knowing about one's risk exposure, feeling altruistic,

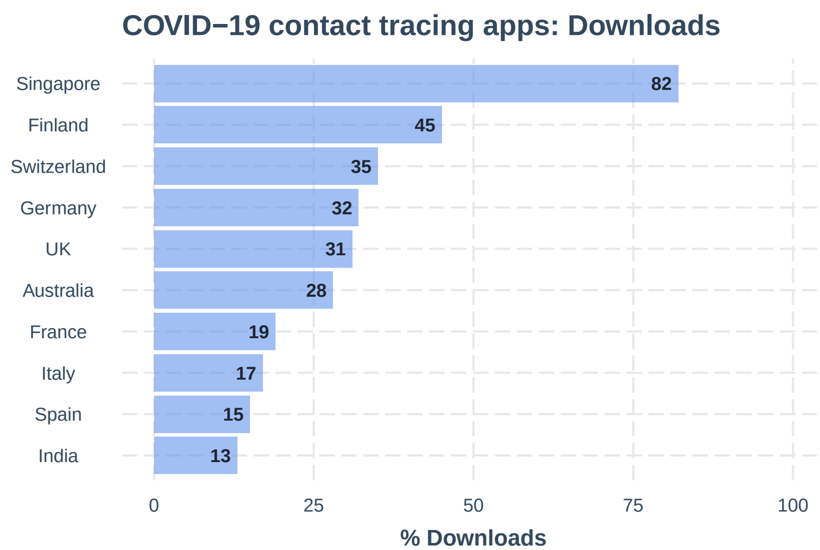

Figure 2: Adoption of selected COVID-19 contact-tracing apps as the percentage of the population that downloaded the app. See Table A1 for detailed information. Latest update: April 7, 2021.

and protecting others, while potential downsides include privacy costs and costs for mobile data. Another study in the United States found that people value both accuracy and privacy in a tracking app (Kaptchuk et al., 2020). In a similar vein, an international study highlighted the importance of privacy concerns, at the same time showing that 37% of participants would not download an app even if it protected people's privacy perfectly (Simko et al., 2020). Further studies in Australia (Garrett, White, et al., 2021), the United Kingdom (Lewandowsky et al., 2021), and among young adults in Taiwan (Garrett, Wang, et al., 2021) showed high acceptance of potential tracking technologies, especially in the presence of privacy-preserving conditions. Other studies and opinion pieces also highlight the crucial role that privacy plays in public adoption of tracking technologies during the pandemic (Cho et al., 2020; Hart et al., 2020).

The present survey focuses on Germany as part of an international consortium of representative surveys that includes Australia (Garrett, White, et al., 2021), the United Kingdom (Lewandowsky et al., 2021), Taiwan (Garrett, Wang, et al., 2021), and others. Our study investigated two main research questions (preregistered at https://osf.io/6mkag): (1) What factors influence the public acceptance of governmental use of location tracking data in an emergency? This includes the question of how people perceive location tracking technologies, including their data privacy and effectiveness. (2) How did people's attitudes change during the pandemic? This longitudinal aspect allowed us to compare hypothetical scenarios in the early waves (before the app was introduced) and later examine attitudes toward Germany's Corona-Warn-App (introduced before we ran the later waves; Figure 3). Our third preregistered research question concerned a crosscultural perspective and is not included in the present article but will be addressed in a forthcoming international project report.

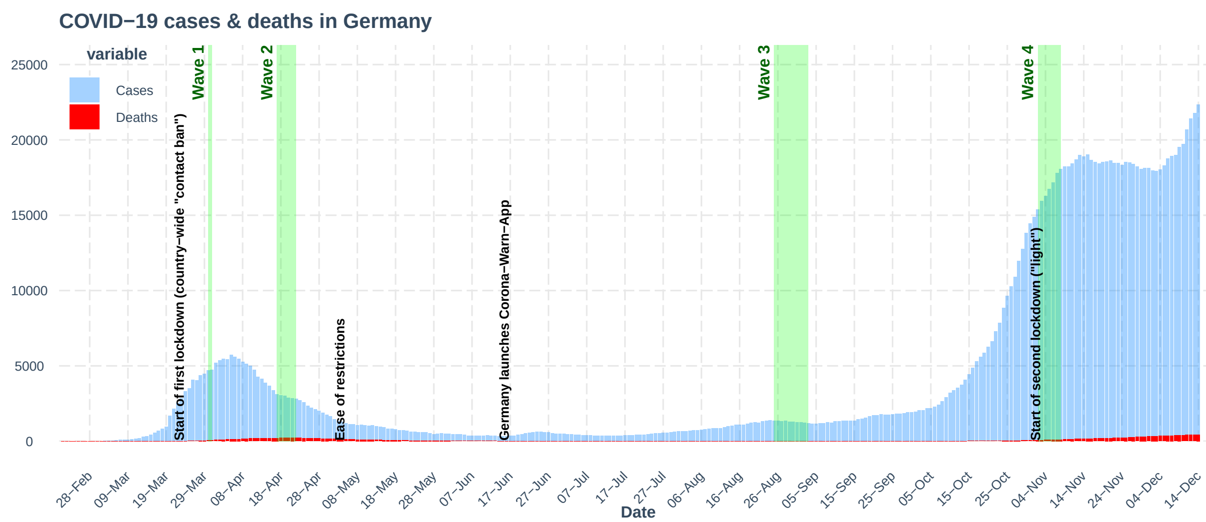

Figure 3: Rolling 7-day averages of daily reported COVID-19 cases (blue) and deaths (red) in Germany between February and November 2020. Collection dates of the current study are highlighted in green; introductions of key policy decisions and the Corona-Warn-App are displayed in black text.

Our study was conducted throughout the first 8 months of the pandemic in Germany (March to November 2020). It included four waves, which all examined how acceptable respondents found a range of privacy-encroaching measures. The study focused particularly on how opinions changed throughout the pandemic. The first two waves of the survey presented respondents with one of three hypothetical scenarios representing different degrees of privacy invasion. Each scenario described a tracking app and accompanying policies (e.g., the government is required to delete all data collected by the app after 6 months). The last two waves probed people's attitudes toward the actual

Corona-Warn-App. We also collected a variety of attitude measures, such as people's worldviews, trust in government, and their risk perception related to COVID-19, in order to identify potential predictors of policy acceptance (for details see the Methods section). Advantages of our approach include the ability to compare attitudes toward three hypothetical scenarios (in the earlier waves) with actual adoption rates of an existing app (in the later waves). Our cross-sectional study with large representative online samples and various behavioral measures allowed us to disentangle the factors that influence digital contact-tracing adoption, and to examine how these factors change over time.

The insights from our surveys focus on the following questions, which we describe in detail in the Results section: (1) How do people's risk perceptions of COVID-19 change over the course of the pandemic? (2) How do people's attitudes towards various privacy-encroaching measures change over the course of the pandemic? (3) How acceptable do people find various types of tracking technologies? Do people respond to the extent of encroachment involved? And how does it compare to the download rates of the Corona-Warn-App? (4) How do people rate various measures of effectiveness and risk of these technologies? (5) What are the most important reasons for people to download or not download the app once it is available? (6) What factors are most predictive of app adoption and intention to download?

We conclude by incorporating these insights into a behavioral framework for digital contact tracing and offering policy recommendations aiming to encourage the public to adopt contact-tracing apps.

Results

COVID-19 Risk Perception

We begin our results with an overview of changes in people's risk perceptions of the COVID-19 pandemic (Figure 4).

Figure 4: Perceived risk of COVID-19 across four samples.

The majority of participants indicated that they thought the virus posed a moderate to severe threat to the German population as a whole: The number of participants stating that the virus' severity for the population was somewhat, very, or extremely high ranged from 84% to 97% across the four waves. Changes in the categories of high and extremely high severity closely follow the pandemic's development in Germany, with severity ratings increasing along with increasing infections rates. The proportion of people who believed that the virus poses only some threat to their health remained stable (between 27% and 31%), while the proportion of people who thought the threat was very or extremely high tended to fluctuate towards higher numbers with time (March: 35%, April: 30%, September: 46%, November: 41%). Overall, on the aggregate level, people were more concerned about the health of others than about their own health (Figure 4). Across all four waves, on the individual level (within respondents) the majority of participants were equally concerned about the risk of infection to themselves and to others (Appendix Figure A2). However, over time, more people showed increased concern for themselves, which is reflected in the rising proportions of people concerned equally for themselves and others (March and April: 49%, September and November: 59%) and decreasing proportion of people reporting more concern for others (March and April: 43–44%, September and November: 33%). The proportions of respondents who indicated more concern for themselves than for others remained stable (7–8%) across all four waves.

Acceptability of Privacy-Encroaching Measures

The question stem we used to examine people's attitudes towards privacy-encroaching measures such as temporarily suspending data protection or granting the government access to people's medical records (for all six items, see Appendix Table B6) was: "How acceptable is it for the government to take the following measures to limit the spread of the virus during the COVID-19 pandemic?"

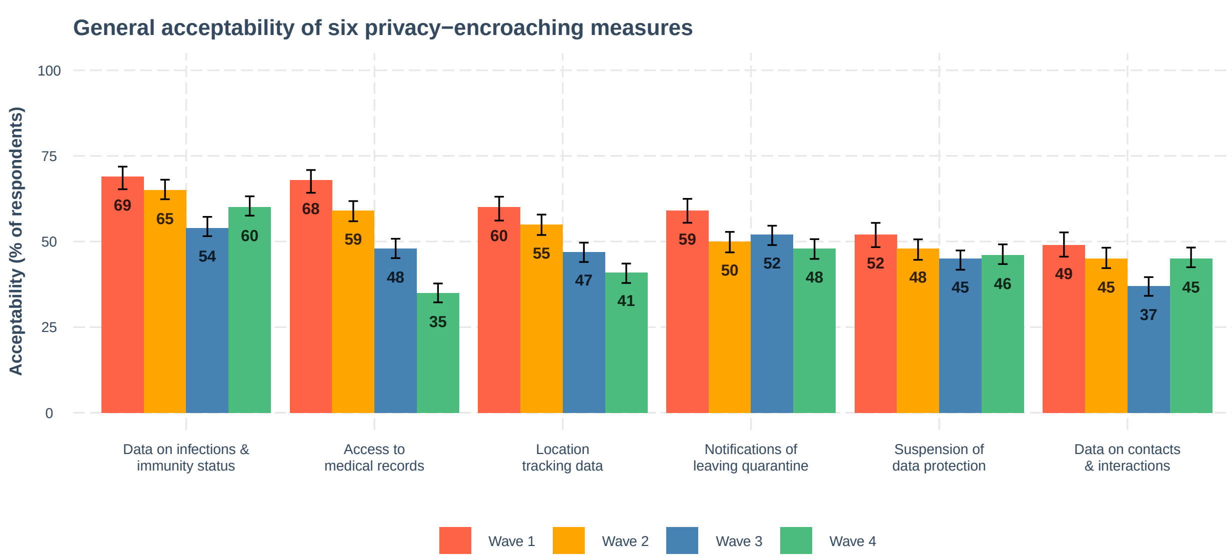

Figure 5: Acceptability of privacy-encroaching measures in Germany across the four waves of the study. Acceptability scores represent the total percentage of participants who chose the response options "very acceptable" or "somewhat acceptable" to the question "How acceptable is it to take the following measures to limit the spread of the virus during the COVID-19 pandemic?" Black numbers display percentages. Error bars are 95% confidence intervals computed with the R function *prop.test*. Wave 1: $N = 788$, Wave 2: $N = 1{,}102$, Wave 3: $N = 1{,}230$, Wave 4: $N = 1{,}182$. See Appendix Table B6 for the wording of the measures.

Figure 5 shows that acceptability of privacy-encroaching measures was fairly high, but tended to decrease over the course of the pandemic. Even though respondents' risk perception tracked the pandemic's development in Germany—that is, perceived risk was higher in April and November, when infections were rising (Figure 4)—respondents' attitudes toward privacy-encroaching measures followed a different pattern. After the initial shock of the pandemic, all measures tended to decrease in overall acceptability from thereon in.

Within the overall trend of decreasing acceptability over time, there were two distinct patterns of attitudinal change: a steep gradual decrease in acceptability and a pattern that more closely mirrored the development of the pandemic. Measures such as allowing access to medical records or location-tracking data fall into the first pattern. Granting the government access to citizens' medical records was deemed very or somewhat acceptable by 68% of participants in Wave 1; this number dropped in each wave, reaching just 35% in Wave 4 despite the rise of infection numbers and new lockdown measures at that time (Figure 5). Acceptability of collecting people's location-tracking data followed the same pattern (Figure 5). Measures such as collecting data on people's infections and immunity status or their contacts and interactions seemed to be more responsive to the pandemic's development and associated risk perceptions (see also Appendix Figure A1). For example, 49% of respondents found collecting data on people's contacts and interactions to be somewhat or very acceptable at the end of March, during the first phase of the pandemic in Germany. This decreased over the next two waves, then rose to 45% in November, mirroring the increase in infections in Germany at that time.

Acceptability of Tracking Technologies

We found relatively high levels of acceptance for the three hypothetical tracking technologies presented in the scenarios in Waves 1 and 2 (mild, severe, and Bluetooth; Waves 3 and 4 examined attitudes toward the actual Corona-Warn-App and did not introduce hypothetical technologies). Acceptability of all three was above 50% in both waves. There were no large differences between acceptability in the three hypothetical scenarios (Figure 6).

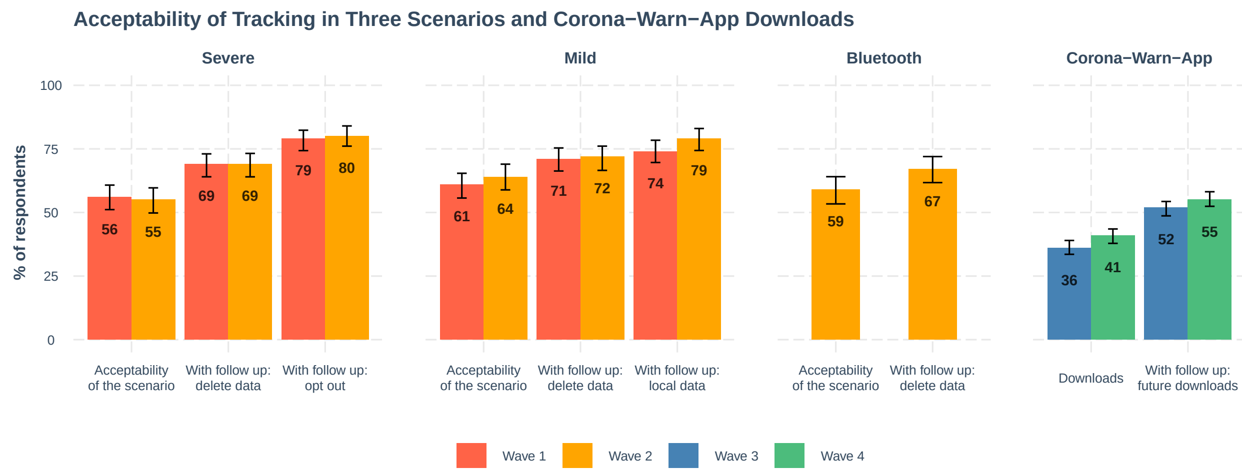

Figure 6: Acceptability of hypothetical tracking technologies and Corona-Warn-App downloads. Within the hypothetical scenarios, the first column displays baseline acceptability ratings after participants responded to items querying tracking effectiveness. Remaining columns display acceptability under varying conditions: the introduction of an option to delete all data and stop tracking after 6 months, tracking with an "opt out" option, and tracking where data is stored locally on the user's phone. Corona-Warn-App usage is displayed in terms of current downloads and intentions to download. Black numbers display percentages. Error bars are 95% confidence intervals computed by R function *prop.test*. Total responses: Wave 1 (severe): $N = 425$; Wave 2 (severe): $N = 407$; Wave 1 (mild): $N = 404$; Wave 2 (mild): $N = 362$; Wave 2 (Bluetooth): $N = 340$; Wave 3 (Corona-Warn-App): $N = 1{,}231$; Wave 4 (Corona-Warn-App): $N = 1{,}188$. For questions see Appendix Table B3; for descriptions of scenarios see Appendix Table B1.

Surprisingly, although the "severe" scenario was deemed least acceptable (55% and 56% compared to 61% and 64% for mild and 59% for Bluetooth), its acceptance level was not particularly low. The differences between scenarios virtually disappeared when respondents considered follow-up options (e.g., deleting all data after 6 months or opting out of data collection). The reported downloads of the Corona-Warn-App in our samples was smaller (36% and 41% for Waves 3 and 4, respectively) than the acceptability of hypothetical scenarios. This low number of reported downloads is consistent with the actual download rates for the Corona-Warn-App in Germany (currently estimated at about 30% of the population; see Figure 2). The somewhat higher rates of downloads reported in our sample compared to the actual national download rate might be explained by our demographics, which skewed towards online users who were aged 18 years or older. Moreover, when respondents in Waves 3 and 4 of the study were asked whether the Corona-Warn-App should be mandatory, only 30% said yes (Appendix Table A3). This could indicate that people were less likely to find tracking technologies acceptable over time (consistent with the trend in Figure 5); it could also indicate that participants approached hypothetical scenarios and the actual app differently (e.g., in terms of weighing privacy against other considerations).

Perceptions of Risk and Effectiveness of Tracking Technologies

Figure 7 displays participants' perceived risk and effectiveness of the tracking technologies and policies in the presented scenarios. It shows that participants were aware that the severe scenario posed a greater risk to data privacy and data sensitivity, control over user data, and ability to decline participation. They also judged the potential effectiveness of the severe scenario, in general, to be on the same level as in the other two scenarios (mild and Bluetooth). It is therefore puzzling that the acceptability of the severe scenario was almost on par with the other two, even though participants thought the risk to privacy protection and the level of intrusion in citizens' lives was much higher. Figure 7 also shows that even though participants thought the Corona-Warn-App presented only a low risk of harm, they were pessimistic about that app's effectiveness, including its ability to reduce the spread of the virus and to help people return to their normal activities. This pessimism toward the Corona-Warn-App was stronger than the pessimism directed toward the hypothetical scenarios presented in earlier waves of the study. Moreover, participants showed only moderate levels of trust in the Corona-Warn-App's security. Trust in the Corona-Warn-App's security was closest to that found in the mild scenario, but higher than that in the severe and Bluetooth scenarios. Given that the technology in the Bluetooth scenario was attributed to Apple and Google, while the Corona-Warn-App was attributed to the German government, the lower level of trust in the Bluetooth scenario may be due to a lack of trust in international corporations and their standards of data protection. In our follow-up questions and analyses, we explored potential drivers behind people's decisions to download or not download the Corona-Warn-App.

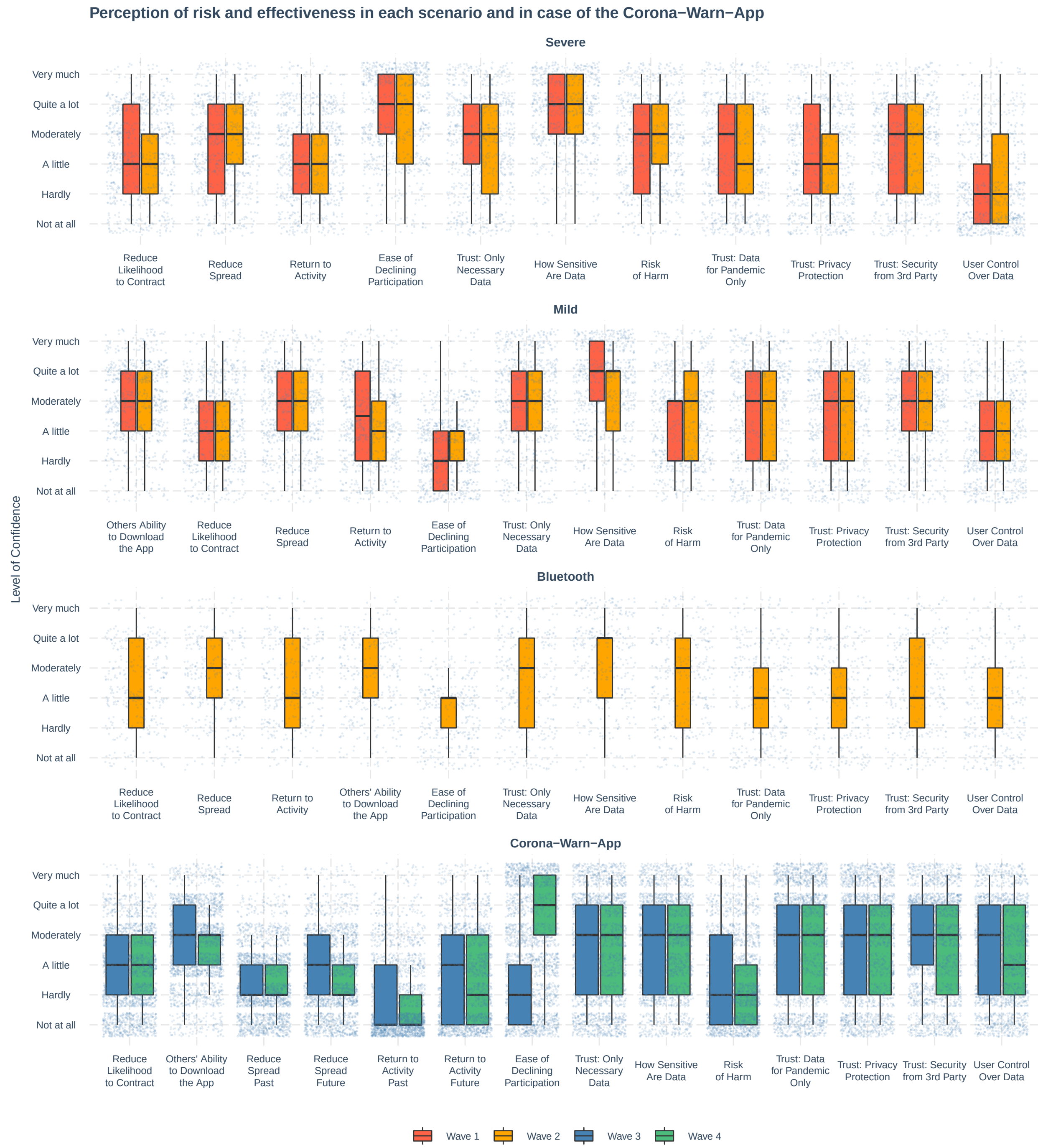

Figure 7: Perception of risk and effectiveness of the tracking policy in each scenario. Boxes show the interquartile range (IQR; responses between the 25th and 75th percentiles); the black horizontal line inside the boxes indicates the median value. Lower and upper whiskers extend from the respective end of the box to the largest value no further than 1.5*IQR. Individual responses are jittered horizontally and vertically. For items see Appendix Tables B7 and B8; for descriptions of scenarios see Appendix Table B1.

Corona-Warn-App: Reasons for Download

The relatively low uptake of the Corona-Warn-App could be due to a variety of factors. To explore the factors that might lead people to decide against downloading the app, we asked people to choose among several possible reasons to download or not download the Corona-Warn-App (multiple selections allowed; Figure 8).

The results indicate that people's main reason for downloading the app was their desire to protect their health and the health of others. The two leading reasons for people not downloading the app were privacy concerns and the belief that the app is not effective. Concerns about third-party access and lack of trust in the government also played a role. The distribution of reasons not to download the app is more uniform than that for reasons to download it.

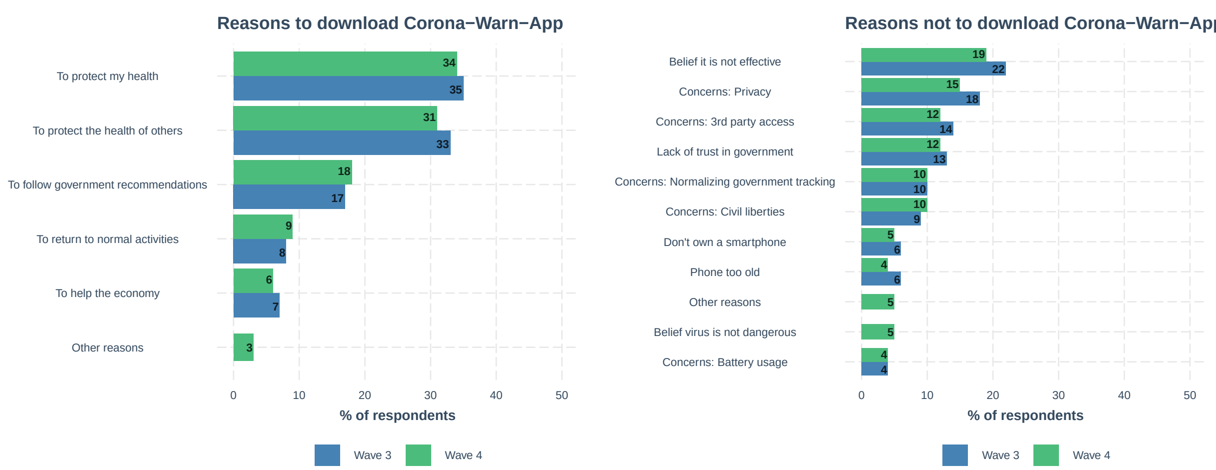

Figure 8: Self-reported reasons to download or not download the Corona-Warn-App. Panels show results from preselected multiple-choice items in Waves 3 and 4. By design, "Reasons" and "Reasons not" have more response options in Wave 4 than in Wave 3.

To analyze people's open responses about their reasons to download or not the app, we extracted unigrams (i.e., individual words) from the responses and counted their overall frequencies as well as their co-occurrences within responses. Figure 9 shows the resulting co-occurrence networks for reasons to download the app from 477 individual responses (panel a) and reasons to not download the app from 530 individual responses (panel b).

Clusters of frequent words indicate the main arguments.

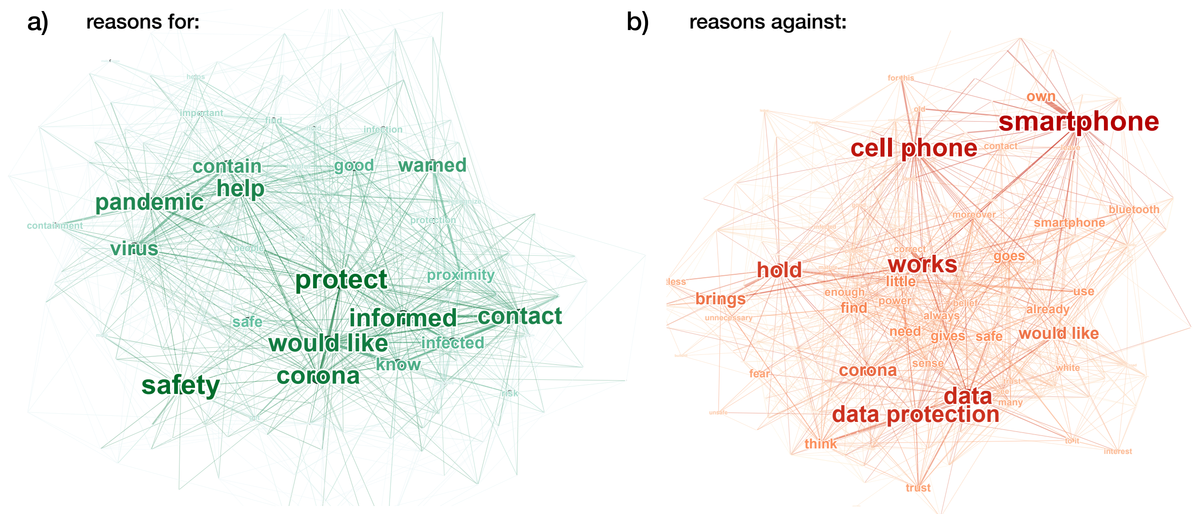

Figure 9: Self-reported reasons to download or not download the Corona-Warn-App in an open-response question (Wave 4 only; reasons for: $N = 477$; reasons against: $N = 530$). Co-occurrence networks of unigrams from positive (panel a) and negative (panel b) reasons for downloading the app. Connections appear whenever two words were used by the same participant. Node and font sizes and color code are proportional to the absolute frequency of the corresponding word; their position follows a spring layout. Color indicates community affiliation. Only unigrams that appeared at least three times in the responses are shown. Translation on a unigram basis via DeepL.com; visualization via Gephi (Bastian et al., 2009).

Reasons to download the app include protecting others and oneself (around the term "protect"), being informed about infections in the social surrounding (around the terms "informed" and "contact"), and helping to mitigate the pandemic ("pandemic," "virus," and "help"). Reasons against downloading the app include technical issues with their smartphone ("smartphone"), data privacy ("data protection" and "trust"), problems with the functionality ("functionality"), and doubts around how useful and necessary the app is ("hold", "brings" and "pointless"). Another reason was rarely leaving the house ("leave" and "home"). Overall, the reasons for not downloading the app are slightly more diverse than the reasons to download it; this was also the case for the multiple-choice question (Figure 8). The main difference between the multiple-choice and the open-ended responses is the more prominent role of problems with smartphones (reasons against) and of being informed (reasons for) in the open responses.

Corona-Warn-App: Predictors of Download

To further examine why people chose to download the Corona-Warn-App, we used various independent variables measured in the survey as predictors for the dependent variable of downloading the Corona-Warn-App, then fit a logistic regression model (Figure 10). Once again, trust in the app's security and perceived effectiveness emerged as leading positive predictors of whether the app was downloaded. These two variables represent combined measures from variables presented in Figure 7. The variable "trust in the app's security" included items asking respondents how much they trust the government to ensure individuals' privacy and to only use the Corona-Warn-App data to deal with the pandemic, as well as how secure they think the data collected by the app actually is. It thus simultaneously represents trust in government and trust in the app's data security. The variable "perceived effectiveness" included items asking for people's assessment of whether the app will help reduce the virus' spread, reduce their likelihood of coming into contact with the virus, and help return them to their normal activities. This variable therefore represents people's assessment of the app's potential to impact the course of the pandemic and help them personally.

As trust in the app's security and perceived effectiveness emerged as strong predictors for downloading the Corona-Warn-App, we used the same modeling approach to assess predictors for both of them separately. Appendix Figures A7 and A8 show the results of the linear regression models where trust in the app's security and perceptions of its effectiveness were the dependent variables. Acceptance of privacy limits during the pandemic (a combined measure for items discussed in the Results section "Acceptability of Privacy-Encroaching Measures" and Figure 5) and trust in science and government guidelines emerged as moderate positive predictors of both variables. Furthermore, believing in conspiracy narratives and perceiving the Corona-Warn-App as harmful was associated with lower trust in the app's security, but not with the perception of its effectiveness.

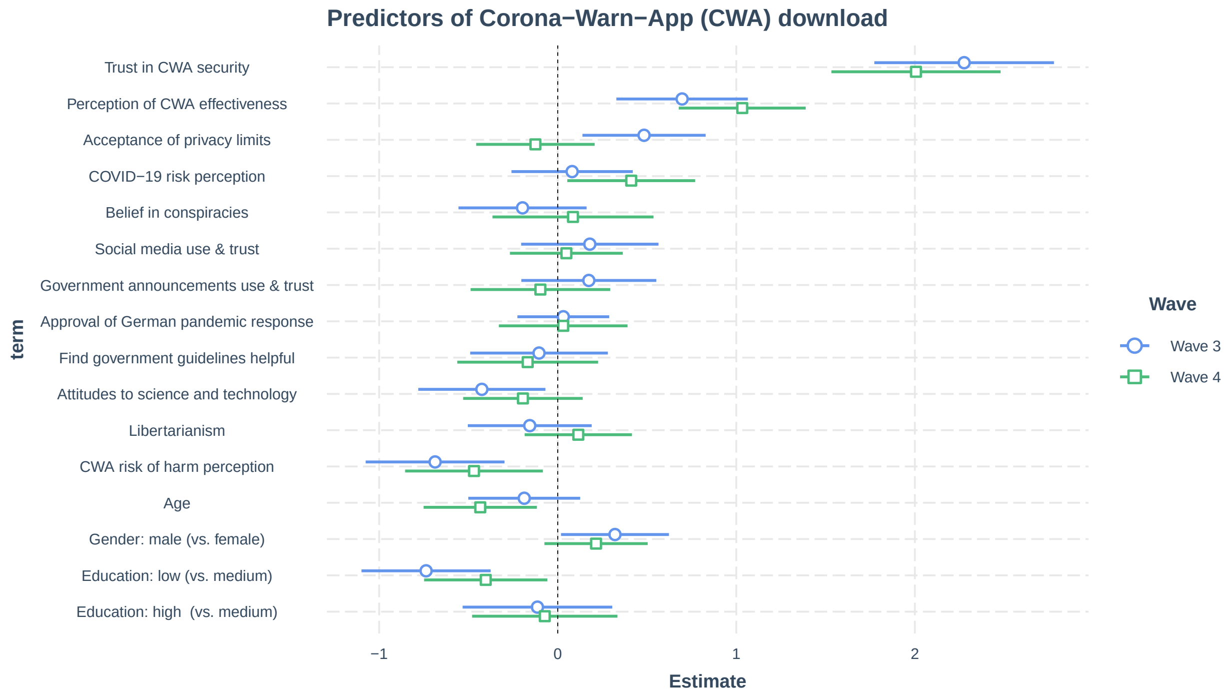

Figure 10: Logistic regression models for Corona-Warn-App download for Waves 3 and 4. Horizontal bars span 95% confidence intervals. Dependent variable: app downloads (yes/no). Coefficients: measures from the survey (e.g., a combined measure for trust in app security or a combined score for conspiracy beliefs; Appendix Table B9). Education was dummy coded with the reference level medium education, yielding two coefficients: low (vs. medium) and high (vs. medium) education. Following Gelman (2008), we standardized all continuous variables by two standard deviations (SD) and mean centered the binary gender variable. This way a 2-SD change in a continuous predictor variable is approximately equivalent to changing the category in a roughly balanced binary predictor variable (e.g., gender). In a logistic regression model a slope reflects the relative change in log odds (while keeping all other predictors at their average values). Appendix Table A4 shows a summary of the regression results for these two models. Appendix Figures A5 and A6 display Pearson correlations for all the variables in the regression model.

Demographic factors such as higher education and identifying as male—but not age—also emerged as positive predictors of having downloaded the Corona-Warn-App. As Appendix Figure A3 shows, proportions of respondents who reported having downloaded the app were higher at high and medium education levels: For instance, 45% of participants with a university degree downloaded the app, while only 29% (Wave 3) and 35% (Wave 4) of participants with a lower level of education category had done so. Slightly more male respondents (Wave 3: 40%, Wave 4: 44%) than female respondents (Wave 3: 32%, Wave 4: 37%) reported having downloaded the Corona-Warn-App.

We used a logistic regression model to analyze intention to download the

Corona-Warn-App among respondents who reported that they had not already done so. Perceived effectiveness of the app emerged as the most important predictor of downloading it (Figure 11).

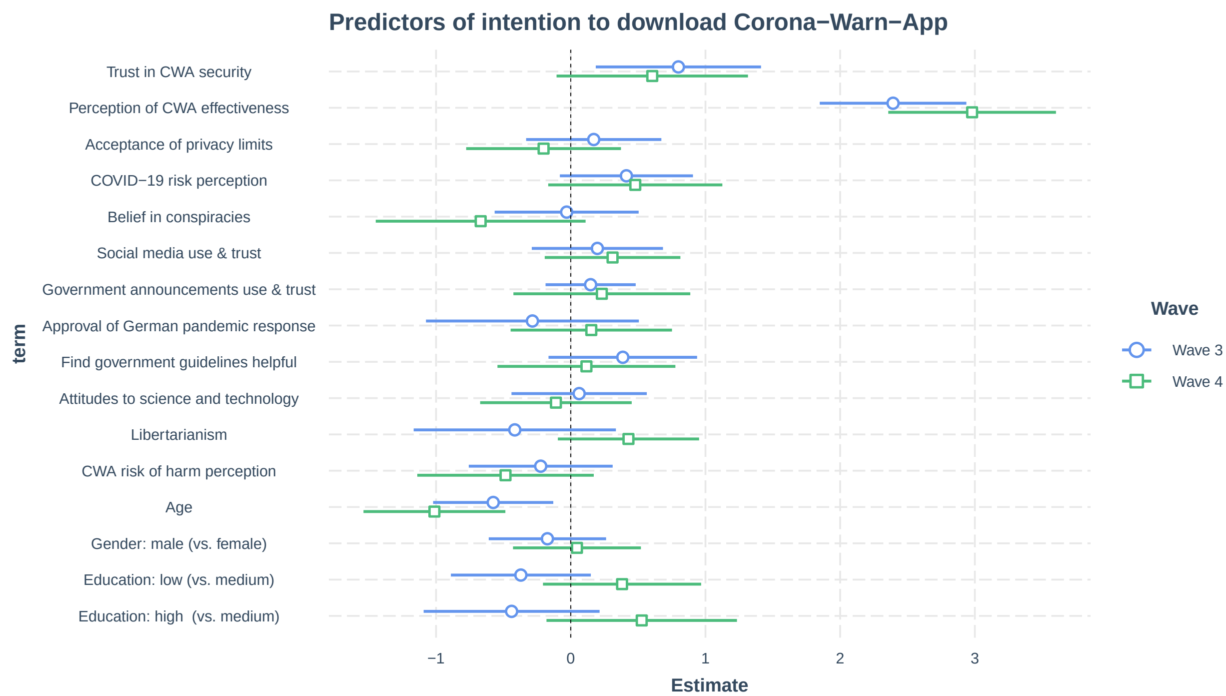

Figure 11: Logistic regression models for intention to download the Corona-Warn-App (Waves 3 and 4). Horizontal bars span 95% confidence intervals. Dependent variable: intention to download the app in the future (yes/no). Coefficients: measures from the survey (e.g., a combined measure for trust in the app security or a combined score for conspiracy beliefs; Appendix Table B9). Education was dummy coded with the reference level medium education, yielding two coefficients: low (vs. medium) and high (vs. medium) education. Following Gelman (2008), we standardized all continuous variables by two standard deviations (SD) and mean centered the binary gender variable. This way a 2-SD change in a continuous predictor variable is approximately equivalent to changing the category in a roughly balanced binary predictor variable (e.g., gender). In a logistic regression model a slope reflects the relative change in log odds (while keeping all other predictors at their average values). Appendix Table A5 shows a summary of the regression results for both models.

Discussion and Conclusion

As a response to the COVID-19 pandemic, digital contact-tracing technologies are being used for epidemiological purposes at scale for the first time. This development poses a number of challenges for both the governments aiming at high and efficient uptake and for people weighing the advantages (e.g., public and individual health) against the potential risks (e.g., loss of data privacy) these unprecedented measures may entail. Digital contact tracing is poised to become a long-term epidemiological tool; it is therefore crucial to understand which factors contribute to its effectiveness and public uptake. In our survey in Germany, we focused on the behavioral aspect of digital contact tracing.

We found that public acceptance of potential privacy-encroaching measures decreased over time. Acceptability ratings for all three hypothetical scenarios in waves 1 and 2 were high, as were intentions to download the real-world app, the Corona-Warn-App in waves 3 and 4. Surprisingly, the details of the scenarios mattered little to public acceptance: The severe scenario relied on harsh, nearly oppressive measures while the mild and Bluetooth scenarios were compatible with privacy protection standards. This phenomenon is not specific to Germany. High and similar acceptance rates for all three scenarios were also observed in similar surveys in Australia (Garrett, White, et al., 2021), the United Kingdom (Lewandowsky et al., 2021), and Taiwan (Garrett, Wang, et al., 2021).

While the details of the tracking technologies in the presented scenarios mattered little, privacy measures such as the option to delete all data after 6 months or the ability to opt out of data collection further increased acceptance. People seem to weigh the benefits against the risks of disclosing sensitive data when making their decisions (see also Dienlin and Metzger, 2016).

Taken together, these findings indicate that even though people might accept certain limitations to their privacy in a crisis, they are also mindful of privacy-respecting measures and weigh the benefits of such measures against the potential risks. Long-term tracking solutions thus cannot rely on privacy-encroaching measures. Instead they must provide sustainable privacy-preserving opportunities that are more likely to be accepted in the long term.

We also observed that high acceptability of digital contact tracing does not directly translate into public uptake. Trust in an app's security—in this case, the Corona-Warn-App—plays a crucial role in its actual uptake. This finding is in line with other studies exploring uptake of and attitudes toward digital contact-tracing technologies:

Studies in the United Kingdom (Lewandowsky et al., 2021), Germany (Munzert et al., 2021), and France (Guillon & Kergall, 2020) all show that trust in government is correlated with the acceptability and use of digital contact-tracing apps. Our study also indicates the crucial role of an app's perceived effectiveness (i.e., its ability to help stop the spread of the virus and facilitate a return to normal life), in particular for nonusers' intentions to download the app. At the same time, pro-free market attitudes, as a proxy for conservative political views, play only very limited role (see Libertarianism in Figure 10 and Figure 11), suggesting that these policies have not become entirely polarized in Germany. If so, a similar lack of political polarization was observed in another survey of people's attitudes to online personalization (Kozyreva et al., in press).

A Behavioral Framework for Digital Contact Tracing

Our analyses highlight several factors that might influence people's attitudes towards digital contact-tracing technologies, including privacy concerns, trust in the app's security and belief about its effectiveness. We therefore suggest mapping out these factors into a behavior change framework (Michie et al., 2011) such as the one shown in Figure 12.

This framework consists of three components whose interaction determines behavior: capability (an individual's psychological and physical capacity to engage in a behavior), opportunity (environmental affordances and external factors that enable or prompt a behavior), and motivation (mental processes that direct a behavior, e.g., habits, emotions, decisions; Michie et al., 2011).

Capability encompasses technical capacity (i.e., having a smartphone) and the skills required to download and use the app, as well as the digital skills and risk literacy necessary to understand risk warnings in the app and to communicate test results to the app. In our samples, the majority of participants had a smartphone (Table 1), and only about 5% of responses in Figure 8 indicated not having a smartphone as a reason for not downloading the app. Nevertheless, technical problems related to smartphones (e.g., not having one or the app not working properly) played a prominent role in the open-response questions in Figure 9. Almost all respondents who reported having downloaded the app also reported that the app was still installed on their phone (Wave 3: 92%, Wave 4: 93%) and that they kept Bluetooth switched on either always or when leaving the house (Wave 3: 95%, Wave 4: 93%; Appendix Table A3).

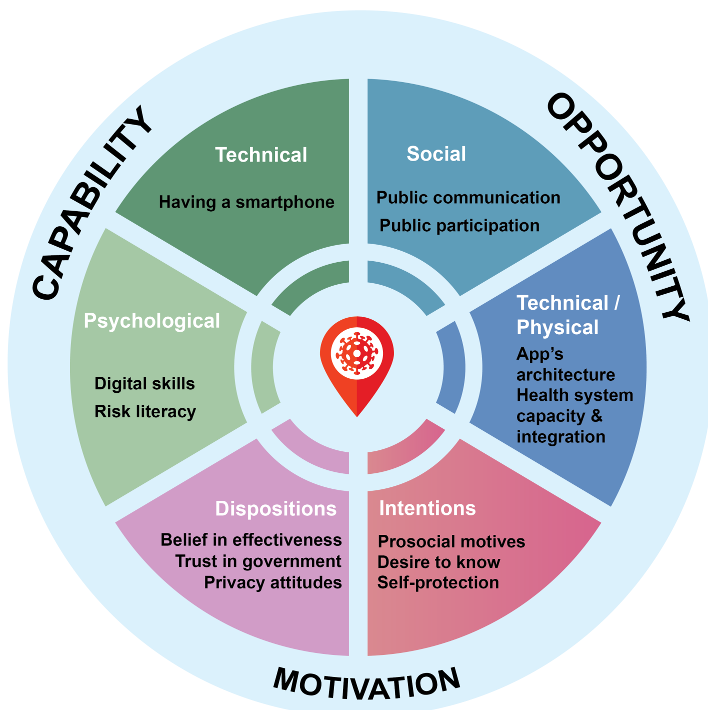

Figure 12: Behavioral framework for digital contact tracing. Adapted from the behavior change wheel (Michie et al., 2011)

Opportunity encompasses all the social and physical factors external to the individual themselves. Social factors include successful communication of the app's advantages and how to use it, as well as risk communication that explains the risk warnings and associated individual actions. Physical factors include the app's architecture (e.g., where data are stored, the system's security) and the broader system in which the app is embedded, such as the health care system and how it facilitates successful app usage. Connecting opportunity in this behavioral framework to the factors that contribute to effectiveness presented in Figure 1, it is clear that a digital contact-tracing app must be integrated into the national health care system in order to ensure ease of use (e.g., communicating a positive test result anonymously and without friction).

Decentralized privacy-respecting applications like the Corona-Warn-App represent a laudable attempt to create an opportunity to contain the virus spread that rests on the data minimization and protection principles outlined in Article 5 of the European Union's General Data Protection Regulation (European Parliament, 2016). Yet clear communication of the app's privacy model and its risk model is also necessary. Many of our respondents in Waves 3 and 4 did not understand how the Corona-Warn-App works. For instance, only 35% (Wave 3) and 25% (Wave 4) of respondents who had not downloaded the Corona-Warn-App knew that it uses Bluetooth technology—compared to 76% (Wave 3) and 65% (Wave 4) of respondents who had downloaded the app (Appendix Figure A4). The same difference in knowledge was observed for Australia's COVIDSafe app (Garrett, White, et al., 2021). Poorly informed decision making or a knowledge gap appears to be affecting uptake.

Motivation here encompasses two key factors that are supported by our analyses of predictors of and reasons for downloading the Corona-Warn-App. One factor is people's direct motives, such as their intentions to protect themselves and others, to stay informed, and to curb the spread of the virus (Figures 8 and 9). The other is people's underlying dispositions, such as privacy attitudes, trust in government and technology, and beliefs in the app's effectiveness (Figures 7 and 10). Balance between these two factors is important. For instance, even people driven by prosocial motivations may decide against using a technology they do not trust with their data. When people's direct motives conflict with underlying dispositions, the resulting trade-offs they make may be crucial to their decision to not adopt digital contact tracing.

Taking into account the interdependency of all these factors in a behavior system is essential not only to understanding people's behavior regarding digital contact tracing, but also to designing successful behavioral interventions and communication strategies.

Our study suggests several insights that should be used to shape behaviorally informed policy. First, do not compromise on privacy. As our analyses show, even though privacy-encroaching measures might initially be accepted in times of crisis, they are unlikely to be accepted long-term. Moreover, trust in the app's security was the leading predictor in Corona-Warn-App uptake in our study and data privacy concerns were among the most-cited reasons to not download the app in both multiple-choice and open-response questions. Second, educate people who have not yet downloaded the app about its technology, privacy model, and risk model. Third, make the app and uploading test results as simple as possible. Finally, address the issue of trust, for example by effectively communicating how the app preserves privacy, underlining that neither the government nor any other institutions have access to people's data.

Our findings suggest that arguments for digital contact-tracing technologies may be particularly effective when the messaging focuses on prosocial motives, such as contributing to stopping the spread of the virus and protecting other people's health, and personal benefits, such as protecting one's own health and being informed about one's own potential exposure. Messaging should also address people's concerns about the app's effectiveness and about security of their data. We base these conjectures on the reasons respondents gave for downloading or not downloading the app (Waves 3 and 4). The effectiveness of framing messages along these lines should be empirically tested.

If digital contact-tracing technologies are to become a long-term solution for managing viral infectious diseases such as COVID-19, they must be effective, understandable, and acceptable to most people.

Methods

Participants and Procedure

Four representative online samples of German participants (total retained participants $N = 4,357$) were recruited through the online platform Lucid using quota sampling to account for current population distributions with regard to age (> 18 years), gender, and residence (see Table 1 for information about the study, smartphone use, and basic demographics, and Figure 3 for data collection times in relation to the pandemic's development in Germany). Appendix Table A2 provides additional information on education and residence distribution for the four waves. The Institutional Review Board of the Max Planck Institute for Human Development approved the surveys (approval L2020-4).

Table 1
Study and Demographic Information

	Wave 1	Wave 2	Wave 3	Wave 4
Recruitment				
Date of data collection	30–31.03.20	17–22.04.20	25.08–03.09.20	02–08.11.20
Sample size (recruited)	1,224	1,665	1,633	1,518
Sample size (retained)	829	1,109	1,231	1,188
Scenarios				
	Severe, Mild	Severe, Mild, Bluetooth	Corona-Warn-App	Corona-Warn-App
Smartphone use (%)				
No	—	3.6	7.4	6.7
Yes	—	96.4	92.6	93.3
Gender (%)				
Female	50.4	50.2	49.6	50.6
Male	49.2	49.3	50.1	49.3
Other	0.4	0.5	0.2	0.1
Age				
Median	48.0	48.0	51.0	50.0
SD	17.0	16.0	17.0	18.0

Study Design

The project started during the peak of the first phase of the pandemic in March 2020, when mobile tracking applications were still at the development stage and public authorities around the world were considering which technology to use (e.g., centralized vs. decentralized). After Germany introduced the Corona-Warn-App in June 2020, we switched from hypothetical scenarios to the actual app. In total, we completed four waves (for dates of the study waves and sample information see Table 1 and Figure 3). There were notable differences between the content of these four waves of our study, as we adapted them to the developments in digital contact-tracing technology (see Figure 13 for a schematic representation of the study design across the four waves).

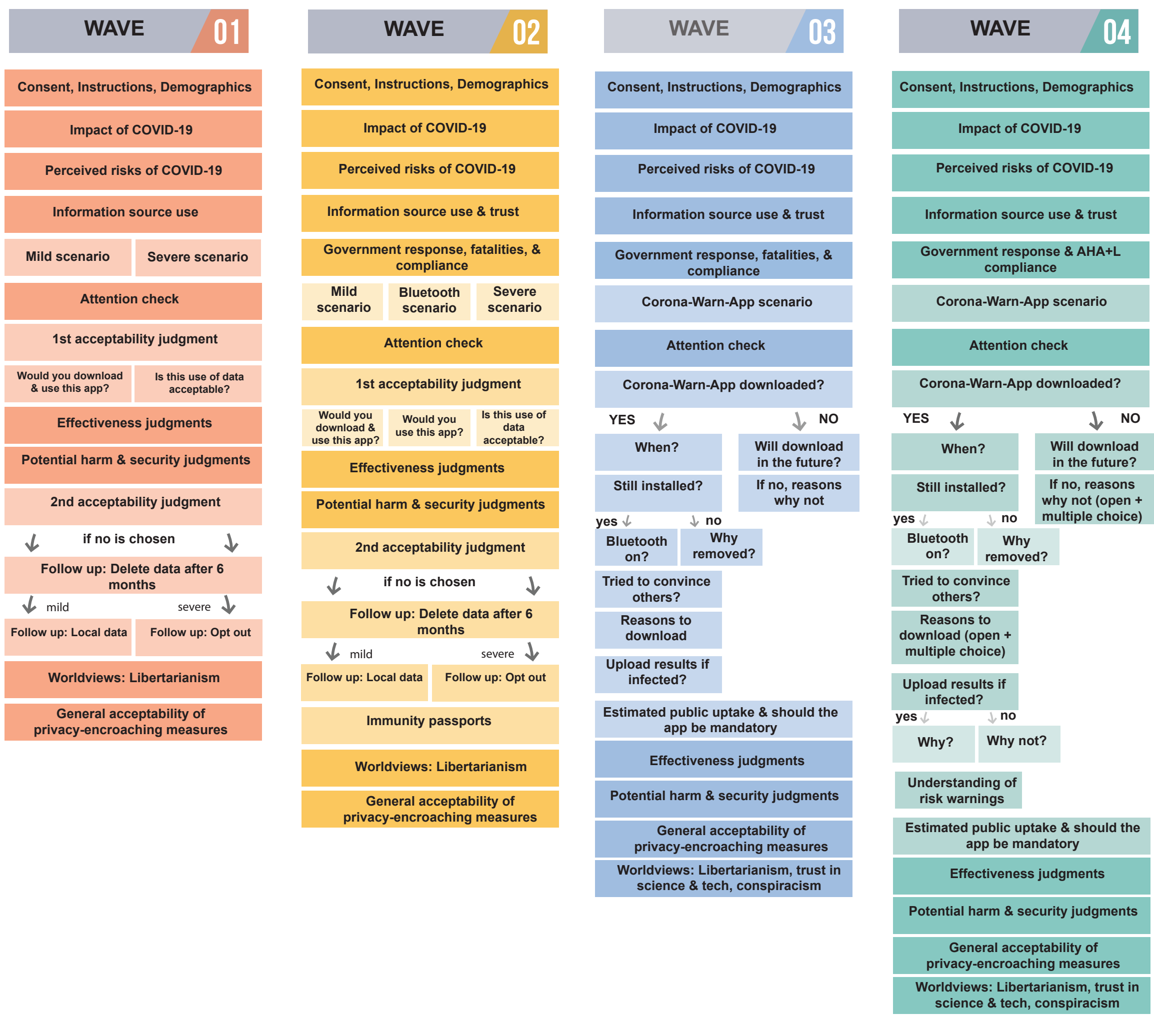

Figure 13: Design for Waves 1–4 of the survey. Each box represents a block with one or more questions pertaining to that topic or construct. Blocks in deeper shades denote common elements between all four waves. For scenario descriptions see Appendix Table B1. Full questionnaires (in German) are available at https://osf.io/xvzph.

All surveys shared a basic structure. Participants first completed an inventory of perceived risks from COVID-19, then saw one tracking policy scenario. This was followed by an inventory of people's attitudes towards the tracking technologies involved in the scenario they had seen. This inventory was the same across all scenarios, with one exception: Participants in Waves 3 and 4 were asked about the Corona-Warn-App's past and future expected impact, whereas participants in Waves 1 and 2 were only asked about an app's potential impact. Participants also answered a comprehension question; those who failed to correctly identify the scenario they had seen from three alternatives were excluded from the analysis. The surveys concluded with a query of people's political worldviews.

The details of these basic building blocks—perceived risk, scenario, attitudes toward scenario, comprehension question, and political worldview—differed between waves. Starting in Wave 2, we included questions about participants' assessment of the government's response, estimation of fatalities, and personal compliance with social distancing rules. Starting in Wave 3, we added worldview items such as attitudes towards science and technology and belief in conspiracy narratives. The scenarios also differed between waves. In Waves 1 and 2, participants were randomly assigned to one of two (Wave 1) or three (Wave 2) hypothetical scenarios, whereas in Waves 3 and 4 they saw a description of the Corona-Warn-App.

Scenarios: The first two waves presented hypothetical scenarios about potential tracking technologies. In the mild scenario, the public could voluntarily download an app. In the severe scenario, all mobile users would automatically be included in data collection via telecommunication tracking with no possibility to opt out, and the government could issue quarantine orders and use the tracking data to locate and fine people who violated them. Wave 2 also included a third hypothetical scenario, the Bluetooth scenario, in which people's phones would exchange messages anonymously whenever they were in proximity. Use of the app, which was modeled after the then-announced decentralized exposure notification systems by Apple and Google, was voluntary. The last two waves surveyed attitudes towards the actual Corona-Warn-App, which was launched in Germany on 16 June 2020. See Appendix Table B1 for descriptions of all scenarios.

Acceptability and uptake: In Waves 1 and 2, participants answered a series of questions probing their acceptance of the scenario they had viewed, as well as their willingness to adopt the app described in the scenario. Binary acceptability judgements ("Would you download and use the app?" for the mild and Bluetooth scenarios, and "Is this use of the tracking data acceptable?" for the severe scenario) were introduced twice: immediately after participants read the scenario and again after they had answered questions (standardized across waves) about the effectiveness and risks of the app presented in the scenario. Participants who answered "No" after the second set of acceptability questions were then asked follow-up questions highlighting additional privacy measures by asking whether their decision would change if the government (or Google and Apple in the Bluetooth scenario) were obliged to delete all data and to stop tracking after 6 months. In the mild and severe scenarios, an additional clause was introduced allowing for people to opt out of data collection (see Appendix Table B3 for all questions). In Waves 3 and 4, after participants read the Corona-Warn-App scenario, they were asked whether they had downloaded the app or planned to download it in the future; they also answered questions about their app usage as well as reasons to download/not download the app and to upload/not upload their test results in the app (multiple selections allowed). In Wave 4 we asked participants to describe their reasons in their own words using an open-response question before presenting them with the same question in a multiple-choice format with set options.

Perceptions of risk and effectiveness of tracking technologies: After answering questions about downloads and acceptability, participants answered two further blocks of questions: one probing their perception of the app's effectiveness and another probing their perception of potential risks associated with using the app (see Appendix Tables B7 and B8 for the full list of questions).

Privacy attitudes: We asked respondents to indicate how acceptable they found the government taking measures that could limit the spread of the virus during the COVID-19 pandemic but also compromise people's privacy. Such hypothetical measures included giving the government access to people's medical records, tracking people's location using mobile phone data, or temporarily relaxing data protection regulations (for a full list, see Appendix Table B6).

Worldviews: At the end of the survey, we collected information about participants' worldviews, including attitudes toward the free market (based on Heath and Gifford, 2006; Lewandowsky et al., 2013), which were scored such that higher averaged responses reflected more conservative/libertarian worldviews. In Waves 3 and 4, we also surveyed respondents' trust in science and endorsement of conspiracy beliefs. To measure conspiracy beliefs in Wave 3, we adapted a general conspiracy scale from Imhoff and Bruder (2014), selecting the five items with the highest item-total correlations and adding one additional item specifically tailored to the COVID-19 pandemic ("Selfish interests have conspired to convince the public that COVID-19 is a major threat," designed based on the conspiracy beliefs inventory from van der Linden et al., 2021). In Wave 4, we created our own items based on COVID-19-related conspiracy narratives that were growing in popularity at the time. To counteract this exposure to conspiracy narratives, we included a debriefing flyer based on the European Commission (2020) at the end of the survey. For all worldview items, see Appendix Table B5.

Data Analysis and Reporting

To examine predictors of Corona-Warn-App downloads, we used logistic regression that predicted downloads for Waves 3 and 4 of the survey. To analyze the open-response question on why people did or did not download the app, we counted the frequencies with which terms occurred across different respondent's responses and the frequency with which the terms co-occurred within the same respondent's response. Based on these frequencies we built co-occurrence networks of unigrams (individual words) using a simple feature extraction method from the Python package scikit-learn (version 0.24.1) for collecting unigram frequencies (Pedregosa et al., 2011); we used the graph-tool library (version 2.37) to build the networks of unigrams according to their co-occurrences within a response (Peixoto, 2014). In this article, we report selected results relevant for understanding public attitudes towards privacy and tracking technologies during the pandemic. Descriptive results for all four waves of the survey with all collected information are available online here: https://ai_society.mpib.dev/tracking-app.

Data availability

Anonymized data and code are available at Open Science Framework (OSF) (https://osf.io/xvzph).

Supporting information

Appendix A at the end of this manuscript includes additional figures and tables to support our reporting. Appendix B includes tables with items used in our figures and covariates for our models. The study questionnaires in German are available on https://osf.io/xvzph .

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Authors' contributions

SL, PG, SH, PLS, AK, TP, and RH adapted and designed the study; AK and PLS managed and conducted research; AK and PLS analyzed data with support from SH, SL, and PG; AK, PLS, SL, PG, SH, TP and RH wrote the manuscript. Correspondence concerning this article should be addressed to Anastasia Kozyreva, Center for Adaptive Rationality, Max Planck Institute for Human Development, Berlin. Email: kozyreva@mpib-berlin.mpg.de

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Appendix A

Supplementary Information: Figures and Tables for the study data analysis

Table A1

COVID-19 Contact-Tracing Apps and Downloads by Selected Countries

Country	Name	Developer/Deployer	Technology	Release date	Downloads (N)	Downloads (%)	Numbers updated on
Germany	Corona-Warn-App	Deutsche Telekom, SAP / Robert Koch Institute	Bluetooth, Google/Apple	16.06.2020	26,700,000	32%	01.04.2021
United Kingdom	NHS COVID-19 App	NHS	Bluetooth, Google/Apple	24.09.2020	20,900,000	31%	23.12.2020**
Switzerland	SwissCovid	Swiss National Covid-19 Science Task Force	Bluetooth, Google/Apple	23.07.2020	3,059,000	35%	06.04.2021
Finland	Koronavilkku	Finnish Institute of Health and Welfare	Bluetooth, Google/Apple	31.08.2020	2,500,000	45%	05.11.2020**
France	TousAntiCovid	Inria	Bluetooth	22.10.2020	13,000,000	19%	01.03.2021**
Italy	Immuni	Bending Spoons	Bluetooth, Google/Apple	01.06.2020	10.400.709	17%	01.04.2021
Spain	RadarCOVID	Ministry of Economic Affairs and Digital Transformation	Bluetooth, Google/Apple	August 2020	7,200,000	15%	28.03.2021
Singapore	TraceTogether	GovTech Agency	Bluetooth, BlueTrace	20.03.2020	4,700,000	82%	07.04.2021*
Australia	COVIDSafe	Australian government	Bluetooth	26.04.2020	7,000,000	28%	07.04.2020*
India	Aarogya Setu	Indian national government	Bluetooth, Location	02.04.2020	173,700,000	13%	07.04.2020

*the app's website provides only approximate numbers of downloads and no information about when the numbers were updated. ** the app's website provides no information about downloads, the reported numbers are taken from the press coverage or statista.com.

Table A2
Demographic Information

	Wave 1	Wave 2	Wave 3	Wave 4
Sample size				
N	829	1,109	1,231	1,188
Smartphone use (%)				
No	—	3.6	7.4	6.7
Yes	—	96.4	92.6	93.3
Gender (%)				
Female	50.4	50.2	49.6	50.6
Male	49.2	49.3	50.1	49.3
Other	0.4	0.5	0.2	0.1
Age				
Median	48.0	48.0	51.0	50.0
SD	17.0	16.0	17.0	18.0
Education (%)				
University	25.8	23.2	21.5	21.7
Abitur (high school)	26.8	27.8	23.5	26.1
Realschule (secondary school)	33.3	35.3	36.6	36.1
Hauptschule (secondary school)	13.5	13.1	17.6	15.5
None	0.6	0.7	0.7	0.6
Residence (%)				
Bremen, Hamburg, Niedersachsen, Schleswig-Holstein	16.2	16.3	16.5	16.6
Nordrhein-Westfalen	22.7	22.2	21.3	23.1
Hessen, Rheinland-Pfalz, Saarland	13.9	15.6	14.5	13.3
Baden-Württemberg	11.2	9.8	12.0	10.4
Bayern	14.8	14.6	14.6	14.8
Berlin, Brandenburg, Mecklenburg-Vorpommern, Sachsen-Anhalt	13.8	14.2	13.4	13.8
Sachsen, Thüringen	7.5	7.3	7.7	8.0

Table A3
Corona-Warn-App Usage

	Wave 3	Wave 4
Have you downloaded the Corona-Warn-App?		
Yes	36.2	40.7
No	63.8	59.3
Is the Corona-Warn-App still installed on your phone?		
Yes	91.6	93.2
No	8.4	6.8
Do you generally have Bluetooth switched on so the Corona-Warn-App can operate effectively?		
Yes	76.9	74.4
No	3.3	4.9
Only when I leave the house	18.0	18.4
I don't know	1.8	2.2
Have you made any attempts to convince your friends and/or family to download the Corona-Warn-App?		
Yes	73.1	67.3
No	26.9	32.7
Will you download the Corona-Warn-App in the future?		
Yes	23.9	24.7
No	76.1	75.3
Do you think that the government should make the Corona-Warn-App mandatory?		
Yes	28.8	30.1
No	71.2	69.9

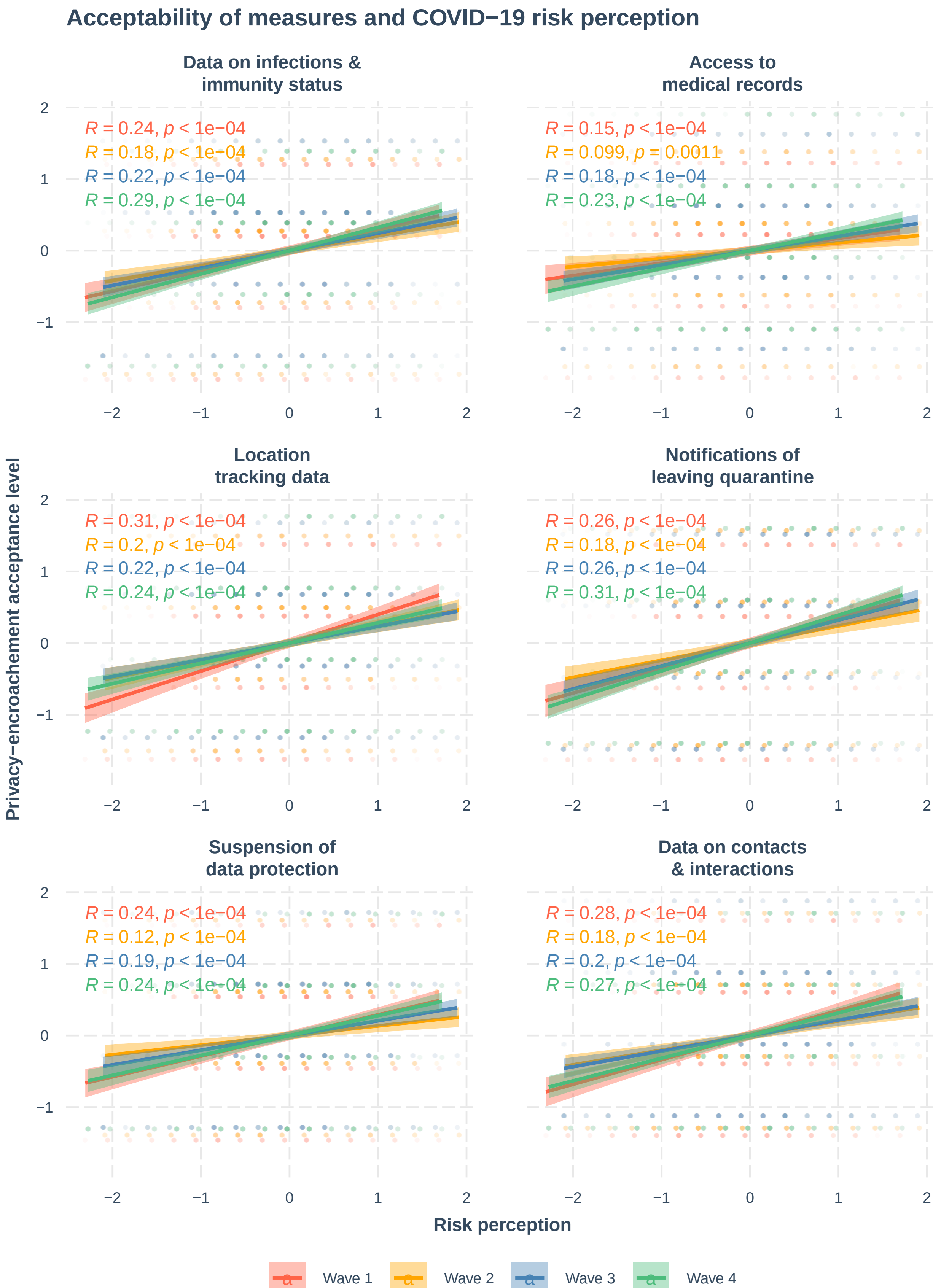

Figure A1: Correlations between acceptability of various privacy-encroaching measures and COVID-19 risk perceptions within respondents across all four waves of the survey. Variable for risk perception is a combined score for four measures from Figure 4. All variables are center-scaled. Individual responses are jittered. Lines represent simple linear regression slopes and their 95% confidence band.

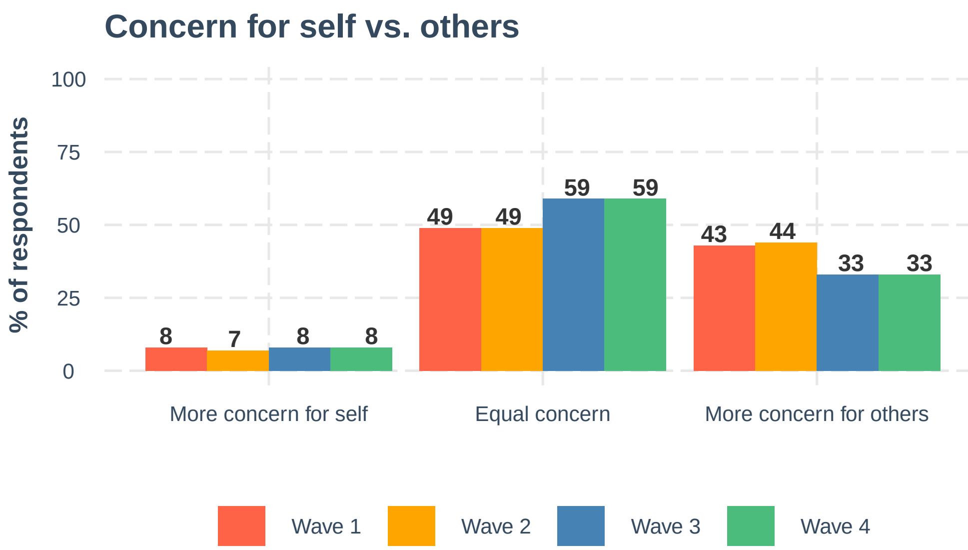

Figure A2: Concern for self and others: COVID-19 risk perceptions within respondents. Responses are grouped into three categories: (1) respondents who rated concern for themselves higher than concern for others, (2) respondents who gave the same rating to both, and (3) respondents who rated concern for others higher than concern for themselves. Questions: (1) Concern self: How concerned are you that you might become infected with COVID-19? (2) Concern others: How concerned are you that somebody you know might become infected with COVID-19?"

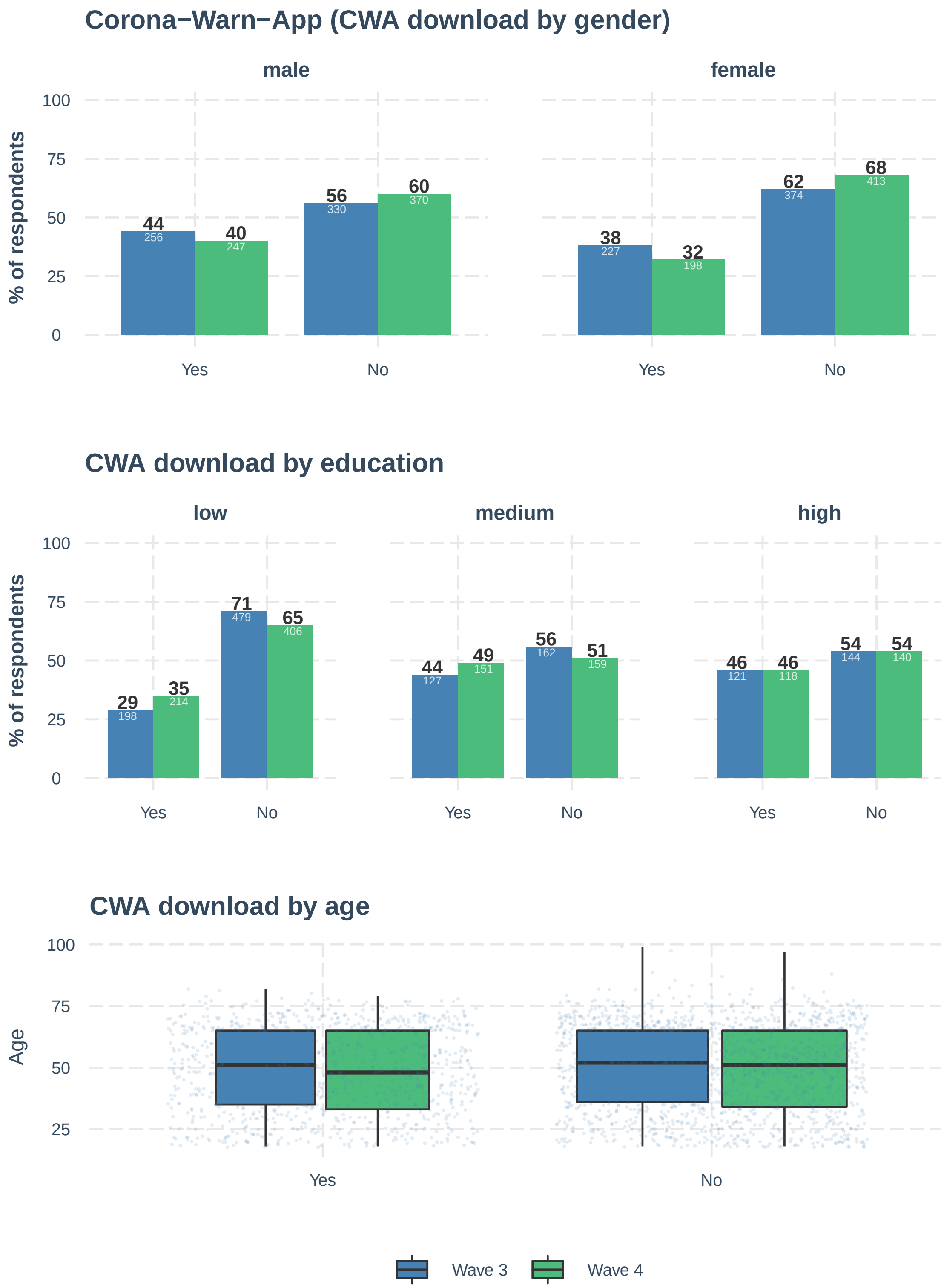

Figure A3: Reported Corona-Warn-App downloads by demographics. In education, "low" comprises "*Realschule*," "*Hauptschule*," and "None;" "medium" refers to "*Abitur*;" and "high" refers to "University". Barplots: Black numbers correspond to percentages; white numbers correspond to number of respondents. Boxplots: Boxes show the interquartile range (IQR) of the age distribution (values between the 25th and 75th percentiles); black lines inside boxes correspond to the median value. Lower and upper whiskers extend to the largest value no further than 1.5*IQR. Individual responses are jittered both horizontally and vertically.

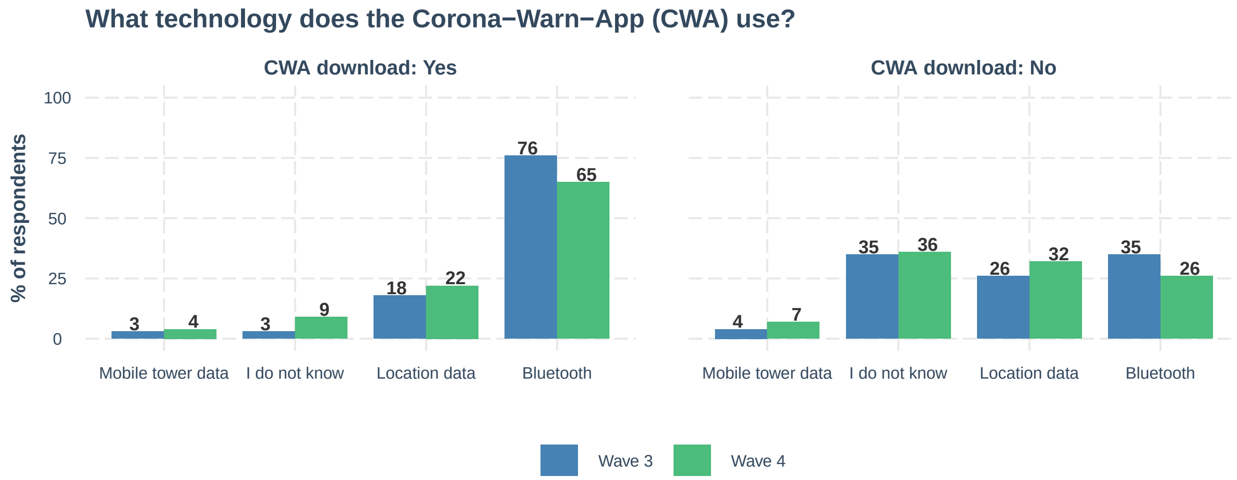

Figure A4: Understanding of Corona-Warn-App technology. Public perceptions of the tracking technology used by the Corona-Warn-App, grouped by whether participants reported having downloaded it. Participants who had downloaded the app were much more likely to give the correct answer, Bluetooth.

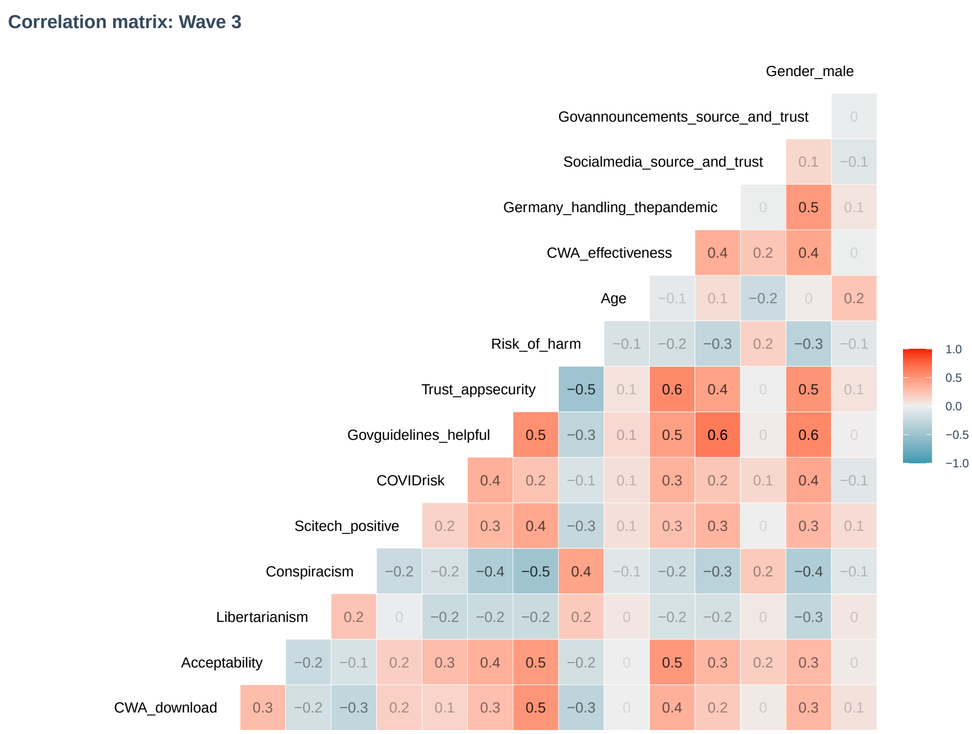

Figure A5: Pearson correlation matrix for variables in Figure 10, Wave 3. Positive correlations are displayed in red, negative correlations in blue, and small correlations in gray. Color intensity is proportional to the correlation coefficients.

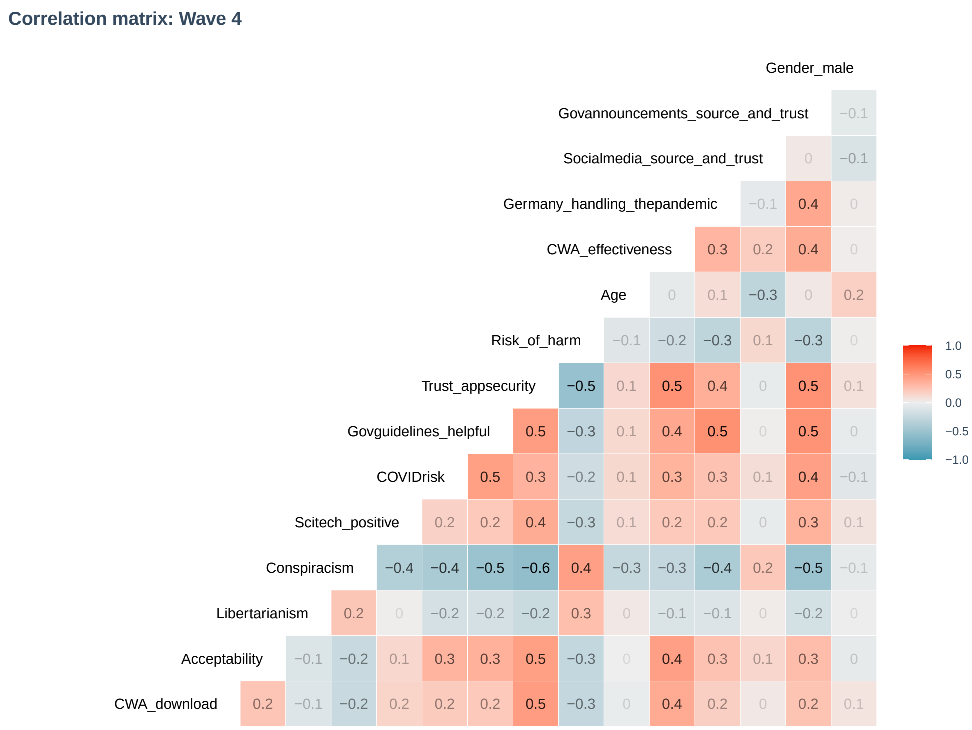

Figure A6: Pearson correlation matrix for variables in Figure 10, Wave 4. Positive correlations are displayed in red, negative correlations in blue, and small correlations in gray. Color intensity is proportional to the correlation coefficients.

Table A4

Regression Results for Figure 10: Predictors of Corona-Warn-App (CWA) Downloads

	Dependent variable:	
	CWA downloads	
	Wave 3	Wave 4
	(1)	(2)
Trust in CWA security	2.240	2.006
	(1.730,2.751)	(1.532,2.480)
Perception of CWA effectiveness	0.682	1.033
	(0.303,1.061)	(0.678,1.389)
Acceptance of privacy limits	0.434	−0.125
	(0.079,0.789)	(-0.457,0.207)
Approval of German pandemic response	−0.302	0.031
	(-0.725,0.122)	(-0.330,0.391)
Find government guidelines helpful	−0.048	−0.168
	(-0.498,0.402)	(-0.563,0.226)
Social media use and trust	0.170	0.048
	(-0.165,0.504)	(-0.268,0.364)
Government announcements use and trust	0.327	−0.097
	(-0.090,0.743)	(-0.488,0.294)
Belief in conspiracies	−0.188	0.085
	(-0.562,0.186)	(-0.366,0.536)
Libertarianism	−0.249	0.115
	(-0.577,0.080)	(-0.185,0.416)
COVID-19 risk perception	−0.005	0.412
	(-0.357,0.348)	(0.054,0.770)
Attitudes to science and technology	−0.366	−0.195
	(-0.731,-0.001)	(-0.530,0.140)
Gender: male (vs. female)	0.337	0.215
	(0.031,0.642)	(-0.075,0.504)
Age	−0.168	−0.434
	(-0.489,0.154)	(-0.751,-0.117)
CWA risk of harm perception	−0.696	−0.469
	(-1.097,-0.295)	(-0.855,-0.083)
Education: low (vs. medium)	−0.704	−0.403
	(-1.068,-0.341)	(-0.748,-0.058)
Education: high (vs. medium)	−0.130	−0.073
	(-0.554,0.294)	(-0.480,0.335)
Constant	−0.573	−0.399
	(-0.871,-0.274)	(-0.683,-0.116)
Observations	1,183	1,140

Table A5

Regression Results for Figure 11: Predictors of the Corona-Warn-App (CWA) intention to download

	Dependent variable:	
	CWA intention to download	
	Wave 3	Wave 4
	(1)	(2)
Trust in CWA security	0.725	0.640
	(0.560,0.891)	(0.489,0.791)
Perception of CWA effectiveness	0.295	0.462
	(0.131,0.460)	(0.303,0.621)
Acceptance of privacy limits	0.257	−0.070
	(0.047,0.467)	(-0.256,0.116)
Approval of German pandemic response	−0.163	0.017
	(-0.391,0.066)	(-0.181,0.215)
Find government guidelines helpful	−0.021	−0.073
	(-0.217,0.175)	(-0.244,0.098)
Social media use and trust	0.083	0.023
	(-0.081,0.247)	(-0.124,0.169)
Government announcements use and trust	0.137	−0.042
	(-0.038,0.312)	(-0.210,0.126)
Beliefs in conspiracies	−0.063	0.044
	(-0.188,0.062)	(-0.190,0.279)
Libertarianism	−0.133	0.062
	(-0.309,0.043)	(-0.100,0.225)
COVID-19 risk perception	−0.003	0.229
	(-0.200,0.195)	(0.030,0.427)
Attitudes to science and tech	−0.149	−0.079
	(-0.297,-0.0004)	(-0.216,0.057)
Gender: male (vs. female)	0.337	0.215
	(0.031,0.642)	(-0.075,0.504)
Age	−0.005	−0.012
	(-0.014,0.005)	(-0.022,-0.003)
CWA risk of harm perception	−0.242	−0.162
	(-0.382,-0.103)	(-0.296,-0.029)
Education: low (vs. medium)	−0.704	−0.403
	(-1.068,-0.341)	(-0.748,-0.058)
Education: high (vs. medium)	−0.130	−0.073
	(-0.554,0.294)	(-0.480,0.335)
Constant	−2.457	−3.302
	(-3.916,-0.997)	(-4.883,-1.721)
Observations	1,183	1,140

Figure A7: Linear regression model for trust in the Corona-Warn-App security for Waves 3 and 4. Horizontal bars span 95% confidence intervals. Dependent variable: Trust in the CWA security. Coefficients: various measures from the survey (e.g., a combined measure for trust in app security or a combined score for conspiracy beliefs; Appendix Table B9). Education was dummy coded with the reference level medium education, yielding two coefficients: low (vs. medium) and high (vs. medium) education. Following Gelman (2008), we standardized all continuous variables and the dependent variable by two standard deviations (SD) and mean centered binary variables. This way a 2-SD change in a continuous predictor variable is approximately equivalent to changing the category in a roughly balanced binary predictor variable (e.g., gender). Furthermore, because we also standardized the dependent variable by 2 SD, a slope of, say, +0.1 can be interpreted as follows: If the predictor is increased by, for instance, 1 SD of its distribution, the dependent variable increases by 0.1 SD of its distribution (while keeping all other predictors at their average values). Appendix Table A6 shows a summary of the regression results for these two models.

Table A6

Regression Results for Appendix Figure A7: Trust in Corona-Warn-App Security for Waves 3 and 4

	Dependent variable:	
	Trust in Corona-Warn-App security	
	Wave 3	Wave 4
	(1)	(2)
Acceptance of privacy limits	0.276	0.239
	(0.233,0.319)	(0.195,0.283)
Approval of German pandemic response	−0.005	0.006
	(-0.057,0.047)	(-0.042,0.053)
Find government guidelines helpful	0.168	0.078
	(0.111,0.225)	(0.024,0.132)
Social media use and trust	0.012	0.028
	(-0.030,0.054)	(-0.015,0.072)
Government announcements use and trust	0.150	0.193
	(0.098,0.202)	(0.142,0.245)
Belief in conspiracies	−0.197	−0.189
	(-0.244,-0.150)	(-0.246,-0.132)
Libertarianism	0.012	−0.041
	(-0.030,0.054)	(-0.083,0.001)
COVID-19 risk perception	−0.029	−0.019
	(-0.073,0.014)	(-0.067,0.030)
Attitudes to science and technology	0.152	0.117
	(0.110,0.195)	(0.074,0.161)
Corona-Warn-App risk of harm perception	−0.236	−0.261
	(-0.281,-0.192)	(-0.307,-0.215)
Gender: male (vs. female)	0.013	0.077
	(-0.027,0.053)	(0.037,0.117)
Age	−0.010	0.025
	(-0.052,0.032)	(-0.019,0.068)
Education: low (vs. medium)	−0.014	−0.040
	(-0.063,0.034)	(-0.089,0.009)
Education: high (vs. medium)	0.001	0.046
	(-0.057,0.059)	(-0.012,0.104)
Constant	0.008	0.011
	(-0.032,0.048)	(-0.029,0.051)
Observations	1,183	1,140
Explained variance: Adjusted R^2	0.556	0.551

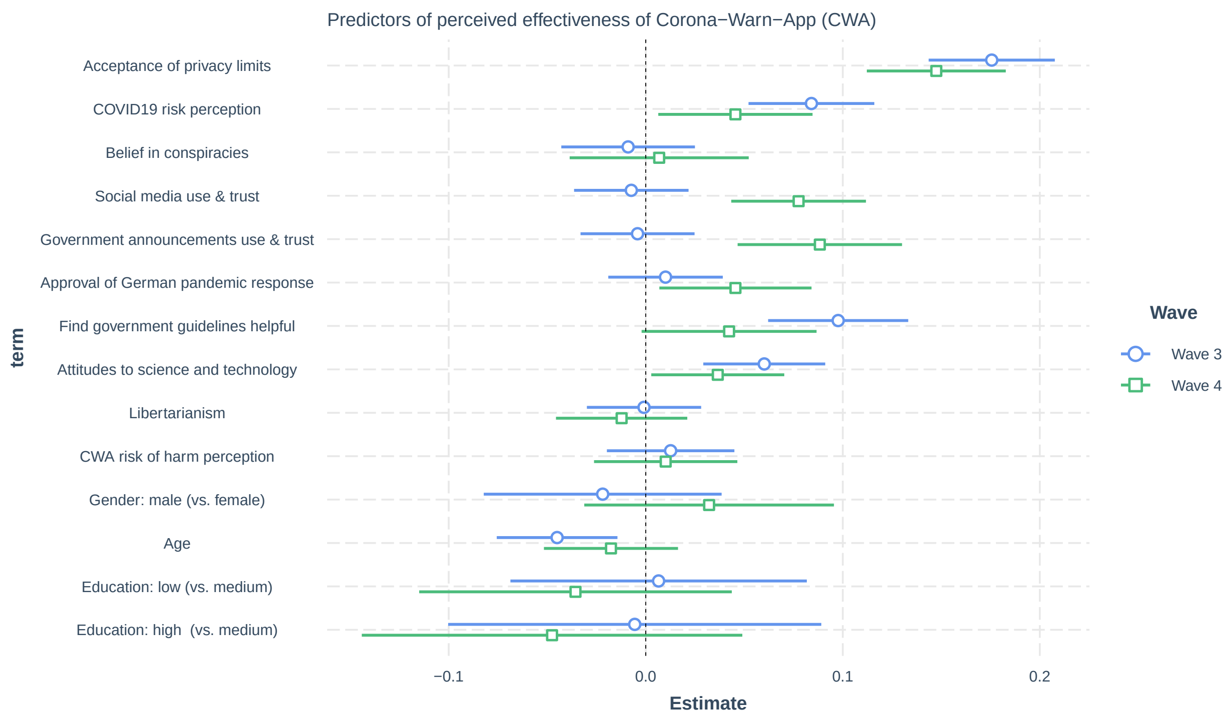

Figure A8: Linear regression model for perceived effectiveness of the Corona-Warn-App for Waves 3 and 4. Horizontal bars span 95% confidence intervals. Dependent variable: Perceived effectiveness of the Corona-Warn-App. Coefficients: various measures from the survey (e.g., a combined measure for trust in the app security or a combined score for conspiracy beliefs; Appendix Table B9). Education was dummy coded with the reference level medium education, yielding two coefficients: low (vs. medium) and high (vs. medium) education. Following Gelman (2008), we standardized all continuous variables and the dependent variable by two standard deviations (SD) and mean centered binary variables. This way a 2-SD change in a continuous predictor variable is approximately equivalent to changing the category in a roughly balanced binary predictor variable (e.g., gender). Furthermore, because we also standardized the dependent variable by 2 SD, a slope of, say, +0.1 can be interpreted as follows: If the predictor is increased by, for instance, 1 SD of its distribution, the dependent variable increases by 0.1 SD of its distribution (while keeping all other predictors at their average values). Appendix Table A6 shows summary of the regression results for these models.

Table A7

Regression Results for Appendix Figure A8

	Dependent variable:	
	Perceived effectiveness of the Corona-Warn-App	
	Wave 3	Wave 4
	(1)	(2)
Acceptance of privacy limits	0.351	0.295
	(0.287,0.415)	(0.225,0.365)
Approval of German pandemic response	0.020	0.091
	(-0.038,0.078)	(0.014,0.168)
Find governement guidelenes helpful	0.195	0.085
	(0.124,0.266)	(-0.004,0.173)
Social media use and trust	−0.015	0.155
	(-0.073,0.043)	(0.087,0.223)
Governement announcements use and trust	−0.008	0.177
	(-0.066,0.049)	(0.093,0.260)
Belief in conspiracies	−0.018	0.014
	(-0.086,0.050)	(-0.077,0.104)
Libertarianism	−0.002	−0.024
	(-0.060,0.056)	(-0.091,0.042)
Covid-19 risk perception	0.168	0.091
	(0.104,0.232)	(0.013,0.169)
Attitudes to science and tech	0.120	0.073
	(0.059,0.182)	(0.006,0.140)
CWA risk of harm perception	0.025	0.020
	(-0.039,0.090)	(-0.052,0.093)
Gender: male (vs. female)	−0.022	0.032
	(-0.082,0.038)	(-0.031,0.095)
Age	−0.090	−0.035
	(-0.151,-0.029)	(-0.103,0.033)
Education: low (vs. medium)	0.007	−0.036
	(-0.069,0.082)	(-0.115,0.044)
Education: high (vs. medium)	−0.006	−0.048
	(-0.100,0.089)	(-0.144,0.049)
Constant	−0.003	0.030
	(-0.068,0.062)	(-0.037,0.097)
Observations	1,183	1,140
Explained variance: Adjusted R^2	0.386	0.335

Appendix B

Supplementary Information: Items and Covariates

Table B1
Scenarios Used in the Study

Scenario	Description	Wave
Severe	The COVID-19 pandemic has rapidly become a worldwide threat. Many experts agree that slowing the spread of the virus is essential to minimise the impact on the health care system and the economy, and to save many lives. The government might consider using mobile phone data to identify and contact those who may have come into contact with people with COVID-19. All people using a mobile phone would be included in the project, with no possibility of opting out. Data would be stored in an encrypted format on a secure server accessible only to the government, which may use the data to locate people who violate lockdown orders and fine or arrest them where necessary. Data would also be used to help shape the public health response and to contact people who might have been exposed to COVID-19. Individual quarantine orders could be made on the basis of this data.	1, 2
Mild	The COVID-19 pandemic has rapidly become a worldwide threat. Many experts agree that slowing the spread of the virus is essential to minimise the impact on the health care system and the economy, and to save many lives. The government could consider using mobile phone data to identify and contact those who may have come into contact with people with COVID-19. Only people who download a government app and agree to be tracked and contacted would be included in the project. The more people who download and use this app, the more effectively the government would be able to contain the spread of COVID-19. Data would be stored in an encrypted format on a secure server accessible only to the government. Data would only be used to contact those who might have been exposed to COVID-19.	1,2
Bluetooth	The COVID-19 pandemic has rapidly become a worldwide threat. Many experts agree that slowing the spread of the virus is essential to minimise the impact on the health care system and the economy, and to save many lives. Apple and Google have proposed adding a contact-tracing capability to existing smartphones to inform people who have been exposed to others with COVID-19. This would help reduce community spread of COVID-19 by enabling people to voluntarily self-isolate. When two people are near each other, their phones would connect via Bluetooth. If a person is later identified as being infected, the people to whom they have been in close proximity are then notified without the government knowing who they are. The use of this contact tracing capability would be completely voluntary. People who are notified would not know the identity of the person who had tested positive.	2
Corona-Warn-App	The Corona-Warn-App app is designed to help detect and break infection chains at an early stage. Currently, local health authorities are trying to trace infection chains. With the app, this process can be automated and thus unfold much faster and more accurately. Users can be warned immediately if they have been in the vicinity of an infected person. The app was developed by Deutsche Telekom and SAP and published by the Robert Koch Institute. It records which smartphones have come in proximity to each other. To do this, smartphones with the app exchange randomly generated encryption keys via Bluetooth. The distance is estimated on the basis of the signal strength. If a user tests positive for COVID-19, they can share their test result in the app in order to inform users who have been in their vicinity. Infected users are explicitly asked whether they want to share their result for contact tracing. As an alternative to digital transmission, validation is available via a call center. Every 24 hours, the app checks whether the user has had contact with a person who has registered an infection on the app. The app does not evaluate any geodata and does not transmit any location information. The developers also assure that no personal data is sent or stored. The anonymized contact data is not stored centrally, but locally on the user's smartphone. The comparison of whether an infected person has been encountered is carried out locally on the smartphone. No data leaves the phone for matching, according to the developers. Only the anonymized list is stored centrally and regularly retrieved by the smartphones to identify possible infectious encounters.	3,4

Table B2

Items Querying Risks From COVID-19 on a 5-Point Likert Scale (1 = Not at All, 5 = Extremely)

Question	Label
How severe do you think the novel coronavirus (COVID-19) will be for the general population?	General harm
How harmful would it be for your health if you were to become infected COVID-19?	Personal harm
How concerned are you that you might become infected with COVID-19?	Concern self
How concerned are you that somebody you know might become infected with COVID-19?	Concern others

Table B3

Items Querying Acceptability of Tracking in Three Scenarios and Corona-Warn-App Downloads

Scenario	Question	Label
Severe	Is the use of cell phone data for location tracking acceptable in this scenario?	Acceptability of the scenario
Severe	Would your decision change if the government was required to delete the data and stop tracking after 6 months?	With follow up: delete data
Severe	Would your final decision change if there was an option to opt out of data collection?	With follow up: opt out
Mild	If, as depicted in this scenario, the government developed a tracking app to help reduce the spread of COVID-19, would you download and use it?	Acceptability of the scenario
Mild	Would your decision change if the government was required to delete the data and cease tracking after 6 months?	With follow up: delete data
Mild	Would your final decision change if data was only stored on your smartphone (not on government servers) and you had the ability to provide this data if you tested positive for COVID-19?	With follow up: local data
Bluetooth	If, as depicted in this scenario, Apple and Google added a COVID-19 contact tracing capability into smartphones, would you use it?	Acceptability of the scenario
Bluetooth	Would your decision change if Apple and Google promised to delete all data and remove the contact tracing system after 6 months?	With follow up: delete data
Corona-Warn-App	Have you downloaded the Corona-Warn-App?	CWA downloads
Corona-Warn-App	Will you download the Corona-Warn-App in the future?	With follow up: future downloads

Table B4

Items Querying Reasons Not to Download the Corona-Warn-App (Participants Could Choose Any Number of Available Options).

Question	Label
I am concerned about privacy.	Privacy concerns
I don't trust the government.	Lack of gov trust
I am worried about battery usage on my phone.	Concerns: Battery usage
I don't think it will be effective.	Believe it is not effective
I am worried about normalizing government tracking.	Concerns: Normalising gov tracking
I am concerned about civil liberties.	Concerns: Civil liberties
I don't own a smartphone.	Don't own a smartphone
My phone is too old to run the app.	Phone too old
I am concerned about others gaining access to my data.	Concerns: 3rd party access

Table B5
Items Querying Worldviews

Scale	Question
Free market attitudes (Libertarianism)	1. An economic system based on free markets unrestrained by government interference automatically works best to meet human needs. 2(reverse). The free market system may be efficient for resource allocation but it is limited in its capacity to promote social justice. 3. The government should interfere with the lives of citizens as little as possible.
Attitudes to science and technology	1. Science and technology are making our lives healthier, easier, and more comfortable. 2. Because of science and technology, there will be more opportunities for the next generation.
Belief in conspiracies (Wave 3)	1. There are secret organizations that have great influence on political decisions. 2. Most people do not see how much of our lives are determined by plots hatched in secret. 3. There are certain political circles with secret agendas that are very influential. 4 (control). I think that the various conspiracy theories circulating in the media are absolute nonsense. 5. Secret organizations can manipulate people psychologically so that they do not notice how their life is being controlled by others. 6. Selfish interests have conspired to convince the public that COVID-19 is a major threat.
Beliefs in conspiracies (wave 4)	1. COVID-19 does not really exist. It is a myth created by some influential people or institutions. 2. COVID-19 was created in a laboratory and deliberately released to achieve geopolitical or economic goals. 3. There is a link between 5G and the spread of COVID-19.; 4. The severity of COVID-19 is overstated. The actual risk is not higher than that of a seasonal influenza. 5. The government exaggerates the seriousness of the pandemic in order to divert attention from other problems within Germany. 6 (control). Wearing masks (mouth and nose protection) protects oneself and others from contracting a COVID-19 infection. 7. COVID-19 was created by pharmaceutical companies to benefit from the need for a vaccine.

Table B6

Items Querying General Acceptability of Privacy-Encroaching Measures During the Pandemic on a 4-Point Likert Scale (1 = Very Acceptable; 4 = Not Acceptable at All). Question: How Acceptable Is it For the Government to Take the Following Measures to Limit the Spread of the Virus During the COVID-19 Pandemic?

Question	Label
Provide access to the medical records of individuals.	Access to medical records
Track people's locations using their smartphone data.	Location tracking data
Enable temporary relaxation of data protection regulations.	Suspension of data protection
Collect data about personal contacts and interactions.	Data on contacts & interactions
Enforce people to use an app that notifies when those in quarantine leave the house.	Notifications of leaving quarantine
Collect data on the infection and immunity status of citizens.	Data on infections & immunity status

Table B7

Items Querying Effectiveness of Hypothetical Tracking Apps in Different Scenarios (Waves 1 and 2) and of the Corona-Warn-App (Waves 3 and 4)

Question	Label
Waves 1 and 2	
How confident are you that the government app would reduce your likelihood of contracting COVID-19?	Reduce Likelihood to Contract
How confident are you that the government app would help you resume your normal activities more rapidly?	Return Activity
How confident are you that the government app would reduce the spread of COVID-19?	Reduce Spread
How confident are you that other citizens like yourself would be able to download and effectively use the app?	Others' Ability to Download the App
Waves 3 and 4	
Has the Corona-Warn-App already helped you to resume your normal activities?	Reduce Likelihood to Contract
How confident are you that the Corona-Warn-App will help you to maintain your normal activities in the future course of the pandemic?	Return to Activity Past
To what extent do you think the Corona-Warn-App has already reduced the spread of COVID-19?	Return to Activity Future
How confident are you that the Corona-Warn-App will reduce the spread of COVID-19?	Reduce Spread Past
How likely do you think it is that the Corona-Warn-App will reduce your risk of coming in contact with COVID-19?	Reduce Spread Future
How sure are you that other citizens like yourself are able to download and effectively use the Corona-Warn-App?	Others Ability to Download the App

Table B8

Items Querying Security of Tracking Apps in Different Scenarios (Waves 1 and 2) and of the Corona-Warn-App (Waves 3 and 4)

Question	Label
Waves 1 and 2	
How easy is it for people to decline participation in the proposed project?	Ease to Decline Participation
To what extent is the government collecting only necessary data?	Trust: Only Necessary Data
How sensitive is the data being collected in the proposed project?	How Sensitive Are Data
How serious is the risk of harm that could arise from the proposed project?	Risk of Harm
How much do you trust the government to use the tracking data only to deal with the COVID-19 pandemic?	Trust: Data for Pandemic Only
How much do you trust the government to be able to ensure the privacy of each individual?	Trust: Privacy Protection
How secure is the data that would be collected for the proposed project?	Trust:Security From 3rd P.
To what extent do people have ongoing control of their data?	User Control Over Data
Waves 3 and 4	
How easy is it for people to decline participation in Corona-Warn-App contact tracing?	Ease to Decline Participation
To what extent is the Corona-Warn-App collecting only the data necessary to achieve its purposes?	Trust: Only Necessary Data
How sensitive is the data being collected by the Corona-Warn-App?	How Sensitive Are Data
How serious is the risk of harm that could arise from the Corona-Warn-App?	Risk of Harm
How much do you trust the government to use the Corona-Warn-App data only to deal with the COVID-19 pandemic?	Trust: Data for Pandemic Only
How much do you trust that the Corona-Warn-App can ensure the privacy of each individual that uses it?	Trust: Privacy Protection
How secure is the data collected by the Corona-Warn-App?	Trust:Security from 3rd P.
To what extent do people have ongoing control of their data when using the Corona-Warn-App?	User Control Over Data

Table B9
Variables and Items for Regression models

Variable	Items	Scale
CWA download	Have you downloaded the Corona-Warn-App?	Yes (1), No (0)
Trust in CWA security	1. How much do you trust the government to use the Corona-Warn-App data only to deal with the COVID-19 pandemic? 2. How much do you trust that the Corona-Warn-App can ensure the privacy of each individual who uses it? 3. How secure is the data collected by the Corona-Warn-App?	6-point Likert scale: 1 = not at all, 6 = very
Perception of CWA effectiveness	1. How confident are you that the Corona-Warn-App will help you to maintain your normal activities in the future course of the pandemic? 2. How confident are you that the Corona-Warn-App will reduce the spread of COVID-19? 3. How likely do you think it is that the Corona-Warn-App will reduce your risk of coming into contact with COVID-19?	6-point Likert scale: 1 = not at all, 6 = very
CWA risk of harm perception	How serious is the risk of harm that could arise from the Corona-Warn-App?	6-point Likert scale: 1 = not at all, 6 = very
Acceptance of privacy limits	How acceptable is it for the government to take the following measures to limit the spread of the virus during the COVID-19 pandemic? Combined measure for 6 items: See Appendix Table B6	4-point Likert scale: 1 = not acceptable at all, 4 = very acceptable
Social media use & trust	1. How often do you rely on the following media (social media) to keep you informed about the developments surrounding the COVID-19 pandemic? 2. How do you rate the following sources (social media)? 3. Do you think that the information on the COVID-19 pandemic is correct and trustworthy?	5-point Likert scale: 1 = never/not at all, 5 = always/completely
Government announcements use & trust	1.How often do you rely on the following media (government announcements) to keep you informed about developments surrounding the COVID-19 pandemic? 2. How do you rate the following sources(government announcements)? Do you think that the information on the COVID-19 pandemic is correct and trustworthy?	5-point Likert scale: 1 = never/not at all, 5 = always/completely
COVID-19 risk perception	Combined measure for 4 items: See Appendix Table B2	5-point Likert scale: 1 = not at all, 5 = extremely
Approval of German pandemic response	How well overall do you think the governments in the following countries have handled the COVID-19 pandemic? - Germany	5-point Likert scale: 1 = not at all, 5 = extremely
Find government guidelines helpful	How helpful are the government guidelines in deciding how to act in relation to the COVID-19 pandemic?	5-point Likert scale: 1 = not at all, 5 = extremely
Attitudes to science and technology	Combined measure for 2 items: See Appendix Table B5	7-point Likert scale: 1 = strongly disagree, 7 = strongly agree
Free market attitudes (libertarianism)	Combined measure for 3 items: See Appendix Table B5	7-point Likert scale: 1 = strongly disagree, 7 = strongly agree
Belief in conspiracies (Wave 3)	Combined measure for 6 items: See Appendix Table B5.	7-point Likert scale: 1 = strongly disagree, 5 = strongly agree
Belief in conspiracies (Wave 4)	Combined measure for 7 items: See Appendix Table B5	5-point Likert scale: 1 = undoubtedly false, 7 = undoubtedly true
Gender (male)	What gender do you identify with?	Male (1), Female (0)
Education	Please indicate your highest level of education.	"Low" = None, *Hauptschule*, *Realschule*; "Medium" = *Abitur*, "High" = University
Age	How old are you?	Free numeric text entry