


Sharing is caring: willingness to share personal data through contact tracing apps in China, Germany, and the US

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ABSTRACT

Are citizens more willing to share private data in (health) crises? We study citizens' willingness to share personal data through COVID-19 contact tracing apps (CTAs). Based on a cross-national online survey with 6,464 respondents from China, Germany, and the US, we find considerable variation in how and what data respondents are willing to share through CTAs. Drawing on the privacy calculus theory and the trade-off model of privacy and security, we find that during the COVID-19 pandemic, crisis perceptions seem to have only limited influence on people's willingness to share personal data through CTAs. The findings further show that the data type to be shared determines the suitability of the privacy calculus theory to explain people's willingness to transfer personal data: the theory can explain the willingness to share sensitive data, but cannot explain the willingness to share less sensitive data.

ARTICLE HISTORY

Received 20 August 2021
Accepted 22 July 2022



KEYWORDS

COVID-19; contact tracing apps; data sharing; public opinion; privacy concerns

Introduction

The growing ubiquity of digital technologies in everyday lives forces people to choose which kind of personal information they are willing to share. This willingness is affected by privacy concerns, defined as 'the ability of the individual to control the terms under which personal information is acquired and used' (Westin, 1967, 7). Attitudes towards sharing personal information have become dominant themes in studies of internet use, digital technologies, and state surveillance (Milberg et al., 1995) and spurred a debate about the reach of the state into private lives (Gates, 2006). Several studies have investigated people's trade-offs between the costs and gains of disclosing their personal information - a phenomenon referred to as 'privacy calculus' (Cottrill & Thakuriah, 2015; Wadle et al., 2019). Moreover, previous research suggests fundamental cross-country differences in public opinion on privacy and willingness to share personal data through digital technologies (Bellman et al., 2004; Dinev et al., 2006).

To combat the spread of COVID-19, governments have applied contact tracing apps (CTAs) to supplement human tracing of contacts by infected persons. According to

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MIT's *Covid Tracing Tracker*, 49 countries worldwide have adopted CTAs, but their approaches differ regarding levels of surveillance and transparency (Johnson, 2020). While German and US media discuss privacy protection, data safety, voluntariness, and possible discrimination against people who decide not to use tracing apps (Halpern, 2020; Frank, 2020), the debate in Chinese state-led media seems to be rare (Gan & Culver, 2020).

Despite growing scholarly attention, especially towards public acceptance of CTAs and heated debates about the apps' privacy implications, there is limited research on citizens' privacy concerns and willingness to share data through CTAs. To fill this gap, we analysed an online survey of 6,464 citizens from China ($n = 2,201$), Germany ($n = 2,083$), and the US ($n = 2,180$) conducted in June 2020. Our study has two goals: first, to document the data types that citizens from the three countries are willing to share through CTAs when faced with a global health crisis; and second, to identify the factors that drive (un-)willingness to disclose certain data types. The reasons for choosing these three countries are, first, differing political systems and data privacy laws that have resulted in different kinds of CTAs; and second, different levels of privacy concern between Chinese, American, and German citizens (Krasnova & Veltri, 2010; Wang et al., 2011).

Our analysis draws on the privacy calculus theory (Cottrill & Thakuriah, 2015; Wadle et al., 2019) and the trade-off model of privacy and security (Davis & Silver, 2004; Pavone & Degli Esposti, 2012). We show that during the COVID-19 pandemic, threats to personal health security do not increase the willingness of our respondents in China, Germany, and the US to share personal data through CTAs. We also find that the suitability of the privacy calculus theory to explain willingness to share personal data through CTAs depends on the data type to be transferred. While the approach can explain individuals' willingness to share sensitive data (i.e., actual location and identity), it cannot explain why individuals share less sensitive information such as health and relative location data.

Contact tracing and privacy concerns in China, the US, and Germany

CTAs vary in their design, the types of data they collect, their use case, and the roll-out timing. The main differences lie in the tracing technology (i.e., Global Positioning System (GPS) or Bluetooth); the location where data is stored (i.e., centralised servers or decentralised on smartphones); whether apps are voluntary (like in Germany and the US) or mandatory (like in China); and the date of the roll-out (i.e., China's *Health Code* was released in February 2020, the German app was rolled while our survey was conducted in June 2020 and the US CTAs were rolled out several months after). Table 1 illustrates differences in CTAs across China, Germany and the US.

China's *Health Code* is the most privacy-invading among the four types of apps studied here, collecting a wide range of user data (i.e., citizen ID, phone number, GPS location, shopping and travel histories), storing them on centralised servers and sending some data to local police. By contrast, the voluntary German 'Corona-Warn-App' uses decentralised data storage through Bluetooth signals, which represents the most privacy-preserving option (Kaya, 2020). The US federal government has not deployed a national CTA. Instead, as of April 2022, 33 states are using a diversity of local CTAs,

Table 1. Cross-country comparison of data collected through CTAs.

CTA type	Release date	Type of data collected										
		Personal identity	Residential address	Phone number	Manual activity tracking	Network and online transaction data	Identification data of the phone	Real-time location (exact location)/ Location data	Relative location (not exact location)/ Encounter data	Type of health information (symptoms, etc.)	Transparency of data collection	Usage data
China (Health Code)	11 February 2020	Full name, profile picture, gender, and ID number are required at registration.	Required at registration.	Required at registration.	Required at registration.	Collection of network & transaction data (i.e., shopping history), & user's social networks	No information available.	App collects the location of the phone (GPS or triangulation from cell towers nearby)	Not collected.	General health information required at registration.	Citizens' informed consent for the collection, use, sharing, disclosure, and storage of data not required	No information available.
Germany (Corona-Warn-App)	16 June 2020	Not required.	Not required.	Not required.	Voluntary.	Not required.	Phone's data is identified by an anonymous, secure, random code.*	No collection of location data.	Phones use Bluetooth signal to swap encrypted token with other phones nearby.**	Voluntary symptoms information.	Regularly updated privacy policy on the app's official website.	No collection of usage data without explicit prior consent.
US - Type a (e.g., New York's 'Covid Alert NY')	Different dates. Covid Alert NY: 1 October 2020, others: August 2020 and later.	Voluntary demographic information: country, gender, age-range, race and ethnicity.	Not required.	Not required.	Not required.	Not required.	Phone's data is identified by an anonymous, secure, random code.*	No collection of location data.	Phones use Bluetooth signal to swap encrypted token with other phones nearby.**	Voluntary symptoms information.	Data and privacy policy available on the New York State's official website.	Though anonymized at all times, data related to app adoption and usage are being collected.
US - Type b (e.g., North and South Dakota's 'Care19 Diary')		Not required.	Not required.	Not required.	Voluntary.	Not required.	Phone's data is identified by an anonymous ID number that is assigned to users upon first-time use of the app.	App collects the location of the phone (GPS or triangulation from cell towers nearby).***	No collection of direct user-to-user encounter data. Possible contacts are being traced via overlapping location data.	Not required.	Link to privacy policy available on the official states' websites.	Usage data are collected at a minimum and only after user opt-in.

Notes: *The code is changed regularly in order to make it impossible to identify a phone through the code. Based on Apple and Google's exposure notification system (GAEN). ** The code contains information about the encounter itself, its duration, and the distance between the two people. *** The location data are used to identify the places a person has visited for at least 10 min.

Sources: QQ News, 2021; NASHP, 2022; Hu et al., 2020; Coronawarn, 2021; Johnson, 2020; Liang, 2020; Mozur et al., 2020.

some of which (i.e., ‘Covid Alert NY’) are similar to the German version of the app, while others (i.e., North and South Dakota’s ‘Care 19 Diary’) collect more user information (NASHP, 2022). To allow notifications across state borders and avoid duplication of databases, in August 2020, the US Association of Public Health Laboratories launched a national server that stores COVID-19 exposure notification keys of affected users (APHL, 2021).

Literature Review

The willingness of individuals to share personal information online varies across countries. Studies on social networking sites report that American citizens are more concerned about data privacy than their German counterparts (Krasnova & Veltri, 2010). Similarly, Chinese citizens reportedly care less about privacy and government surveillance (Mozur, 2018). Previous studies have brought forth cultural explanations for these differences, comparing a Chinese instrumental value of privacy to a Western intrinsic value (Lü, 2005). While the latter views privacy as a non-negotiable element of democratic societies, the former views privacy as instrumental to larger social goals such as maintaining social order and facilitating Chinese individuals’ trade-off between privacy and security (Zhang et al., 2019). This argument follows research identifying the importance of contextual factors, such as norms and values, on privacy preferences (Nissenbaum, 2004).

Perceived risks and benefits of sharing data

Privacy concerns greatly influence a person’s willingness to share data when using e-commerce services (Dinev & Hart, 2006), social media (Acquisti & Gross, 2006), and the sharing economy (Lutz et al., 2018). According to the privacy calculus theory, when sharing data through different online channels, users attribute individual value to their data, causing them to weigh the risks and benefits of data sharing (Culnan & Armstrong, 1999; Dinev & Hart, 2006). This calculation leads to a trade-off between the risks users are willing to take by disclosing data and the benefits of the transaction (Cottrill & Thakuriah, 2015; Wadle et al., 2019).

Attributions of risk and benefit are highly subjective and influenced by various contextual factors. First, the values attributed to online interactions lead to different risk-benefit calculations across user groups. For example, a recent study in Germany and the US found that US respondents exhibit more significant privacy concerns and higher willingness to share data through Facebook. Compared to their German counterparts, US respondents attribute more benefit to social networking activities and show more trust towards the service provider (Krasnova & Veltri, 2010). Further, users in Germany appear to more frequently share data for specific benefit scenarios, such as health and security, than for others, such as convenience (Wadle et al., 2019). Second, the people with whom users share data and the perceived reasonability of the data request influence risk-benefit calculations. Users are more willing to share location-based data with friends and family but less so with employers and co-workers, especially if requests for such data were deemed unjustified (Madden, 2014). Third, individuals have different privacy concerns in online spaces, depending on the specific platform they use. Li (2014), for

example, shows how an individual's concern for information privacy with regard to a particular e-commerce platform might differ from this person's concern for information privacy regarding the general e-commerce environment. Fourth, previous experience with privacy infringements may lower the perceived benefit of data sharing (Li & Unger, 2012).

The type of data, which users are expected to disclose also influences risk-benefit calculations. Research reveals that users are less willing to share sensitive information (Rifon et al., 2005) and that greater sensitivity of requested data reduces the perceived benefits of the data transaction. Hesitance to disclose sensitive data is attributed to potential psychological, physical, or material losses such as contact information, personal finances (Mothersbaugh et al., 2012), and real location data. The latter is attributed to both personal security risks (Tsai et al., 2009) and the preservation of offline relationship boundaries (Page et al., 2021). Perceptions of data sensitivity may again vary across countries. For example, German respondents tend to share data that does not allow personal identification (Wadle et al., 2019). In contrast, Americans view social security numbers and health information as the most and purchasing habits as the least sensitive data (Madden, 2014).

Although privacy concerns and the underlying privacy calculus influence peoples' information disclosure behaviour, research shows that these concerns do not necessarily preclude online engagement (Dinev & Hart, 2006). Acquisti and Grossklags (2005) have revealed that consumers often lack sufficient information to decide on privacy-sensitive matters. Even with adequate information, people prefer short-term benefits over long-term privacy. This also applies to cases with few benefits, such as revealing one's income in return for a 1-Euro-discount on a DVD purchase (Beresford et al., 2012). Particularly in social media use, barriers to data sharing are lower (Acquisti & Gross, 2006), and the so-called 'privacy paradox' (i.e., extensive engagement and data sharing despite privacy concerns) is pronounced (Barth et al., 2019; Dienlin & Trepte, 2015).

In this study, we focus on the willingness to share data in the context of the widespread adoption of COVID-19 contact-tracing apps. We argue that in contrast with e-commerce and social media use, unique contextual factors caused by the COVID-19 pandemic drive willingness to share data, including *crisis perceptions* and socio-political beliefs in different national contexts. The utility of CTAs and the immediate benefits and risks resulting from sharing data through them necessitate novel theoretical explanations for why users are willing to share personal information through CTAs. Our analysis contributes to the limited number of studies analysing these theoretical relations with a focus on CTAs and cross-national privacy concerns in authoritarian China and liberal countries.

CTAs and willingness to share data

Research on the willingness to share data through CTAs is limited. Results from a global survey reveal that users are uneasy over government data use and reject app developers sharing user data (Simko et al., 2020). However, public discussions on CTAs in China, Germany, and the US indicate national differences in the willingness to disclose personal information. In China, experts criticised user agreement clauses and privacy policies of the *Health Code*, highlighting that users are not adequately informed about collecting, using, sharing, disclosing, and storing personal information (Hu et al., 2020). Others

have warned that the *Health Code* might lead to data leakage or misuse and have called on the National People’s Congress to supervise data collection through the app (Tang, 2020). Besides that, the health code has received little resistance from the public (Chen et al., 2022).

In Germany and the US, extensive public debate about privacy issues accompanied the development processes of CTAs (Fowler, 2020). A survey conducted in Germany in September 2020 found that one-third of 2000 respondents doubted data security (Frank, 2020). In the US, public adoption of CTAs has been low due to the public’s distrust of technology companies and the government for collecting, use, and store their data (Avira, n.d.). However, support of CTAs increases with more robust privacy protections such as decentralised data storage (Zhang et al., 2020).

Explaining data sharing through CTAs

Previous studies highlight that contextual factors, such as the extent to which individuals perceive the COVID-19 pandemic as a crisis, risk-benefit calculations, and socio-political beliefs influence individuals’ willingness to share data online. Figure 1 illustrates our conceptual framework.¹

- (1) *Crisis perception*: Research on threat perceptions and support for civil liberties shows that individuals are willing to trade civil rights for security when they perceive a sense of threat (Davis & Silver, 2004). Individuals with higher levels of perceived risk from COVID-19 increase their protective behaviour (Wise et al., 2020). Regarding CTAs, an increased risk perception (including financial and health risks) increases an individual’s likelihood of adopting CTAs (Zhang et al., 2020). H1a-d: People who are concerned about their health (a), the health of family (b) or friends (c), or whose financial situation has deteriorated during the pandemic (d) are more willing to share data through CTAs.

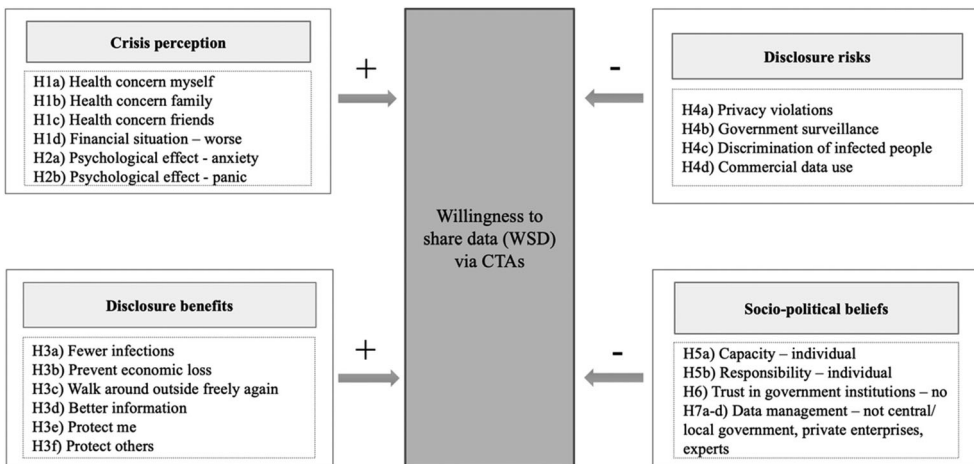


Figure 1. Conceptual framework.

In addition, psychological effects such as anxiety (Liu et al., 2020) and panic (Nicomedes & Avila, 2020) influence individual behaviour during the pandemic:

H2a-b: People who expressed anxiety (a) or panic (b) during the pandemic are more willing to share data through CTAs.

- (2) *Risk-benefit calculations*: Users' trade-off between risks and benefits of data sharing influences their willingness to share data online (Dinev & Hart, 2006). Prior studies on privacy concerns have identified several perceived benefits for users resulting from data disclosure, including monetary rewards (Bucher et al., 2016; Sayre & Horne, 2000), better services (Acquisti & Grossklags, 2005), access to social support and resources (Burke & Develin, 2016) and social hedonic benefits (Lutz et al., 2018). Despite privacy concerns, users' willingness to share data is explained by the tendency of users to prefer present rewards over future risk reductions (Acquisti, 2004). In the case of German and American CTAs, users face a diffuse transaction situation with only one immediate benefit of data sharing, namely receiving *better health information*. Other advantages may only materialise later without a direct link to users' data transaction, including *fewer infections, making it safer to go outside, isolating infected people, protecting oneself and others*, and societal benefits such as *preventing economic loss* (Matt, 2021). In China, the situation is different. The *Health Code* is mandatory for individuals who want to access public spaces. Hence, data sharing leads to immediate benefits (Kostka & Habich-Sobiegalla, 2022). We thus expect the following paths to be more vital in the Chinese sample: H3a-f: People who think that CTAs will result in fewer infections (a), preventing economic loss (b), them being able to walk outside freely again (c), them receiving better health information (d), them (e) or others (f) being protected from COVID-19 are more willing to share data through CTAs.

The risks of data disclosure in online contexts range from online harassment (Page et al., 2018) to financial and reputational harm (Wang et al., 2013). For the specific situation of sharing data through CTAs, based on a review of media discussions in the three countries, we have identified four main risks:

H4a-d: People who think that CTAs will result in privacy violations (a), government surveillance (b), discrimination of infected people (c), commercial data use (d) are less willing to share data through CTAs.

- (3) *Socio-political beliefs*: Cultural values, trust in the state, and confidence in the service provider handling the data also influence a person's willingness to share data. In terms of cultural values, existing studies present mixed results concerning the association between individualist and collectivist societies and privacy concerns. Some studies show that individualist cultures are more concerned about data privacy. In contrast, collectivist ones are more accepting of organisations and specific social groups intruding in the private lives of individuals (Milberg et al., 1995). Other research on privacy concerns concludes the opposite (Bellman et al., 2004). However,

research has identified CTAs as a public good which more individualist-oriented people are less inclined to contribute to (Farronato et al., 2020). We thus derive the following hypotheses: H.5a-b: People who believe that individuals are capable of (a) and responsible (b) for handling the pandemic are less willing to share personal data through CTAs.

Pavone and Degli Esposti (2012) show that citizens who expressed concern about government surveillance also regarded surveillance technology as privacy infringing. In contrast, citizens who trust political institutions tend to believe that surveillance technology increases their security. Altmann et al. (2020) show that the probability of installing CTAs increases with trust in the government. Respondents who have less confidence in their national government are also more likely to express concerns about government surveillance. We hypothesise:

H6: People who do not trust government institutions are less willing to share personal data through CTAs.

Previous work on online data disclosure has shown that willingness to share data is influenced by site-specific privacy concerns, meaning that individuals may be more inclined to share information with certain websites than with others (see Li, 2014). Hence, beliefs in who should manage user data collected through CTAs also matter. While in China and Germany the service provider is the state, in the US it is more mixed, with private enterprises such as Apple, Google and Microsoft, and the non-profit APHL playing a more prominent role in data management (APHL, 2021). We thus derive the following hypothesis:

H7a-d: People who do not want the data they share through CTAs to be managed by the central (a) or the local (b) government, (c) private enterprises or (d) experts are less willing to share personal data through CTAs.

Control variables: socio-demographics and CTA perceptions

Sociodemographic factors may influence individual privacy concerns. However, previous research has shown that the effects of gender and age on both privacy concerns and the willingness to share personal information online are minor (Awad & Krishnan, 2006). According to a cross-national survey on CTAs, older people are more willing to share the data collected through CTAs with the research community (Altmann et al., 2020). Findings regarding income and education have been inconsistent across studies. However, it has been argued that people with a higher income have more to lose in case of identity theft and therefore are less inclined to share their data (Li, 2011), and that individuals with higher education tend to be more sensitive towards data sharing data (Madden, 2014). Our study uses gender, age, income, and education as socio-demographic control variables.

The literature on privacy concerns and information disclosure notes that previous technology experience and understanding affect a person's disposition to privacy (Smith et al., 2011). For example, variations in internet experiences partly explain differences in information privacy concerns (Bellman et al., 2004). Assessments of surveillance technologies are, in turn, influenced by the extent to which users understand how the technology works (Degli Esposti & Santiago-Gomez, 2015). Altmann et al. (2020) further

show that those who use their phones more regularly are more inclined to make data collected through CTAs available to research. We include *CTA understanding* and *acceptance* and *prior use of similar health apps* as additional control variables in our models.

Method

The analysis uses a cross-national online survey conducted through a data survey company between June 5, 2020, and June 19, 2020. River sampling, also referred to as intercept sampling or real-time sampling, was used as a method to draw participants from a base of 1–3 million unique users (Lehdonvirta et al., 2021). As an incentive to participate, respondents received financial and non-monetary compensation.

Our non-probability online survey utilised quota sampling, created from the most recent population statistics (see Table 2). Given this sampling method, our study represents the *internet-connected* population in China, Germany, and the US, which is more affluent, younger, and urban than the rest of the population. Thus, our sample may overrepresent the tech-savvy population. The quotas used for sampling and weighting were based on age (18–65) and gender. For China, respondents were additionally sampled based on region (Central: 37%, Western: 21%, and Eastern: 42%). After collecting the necessary number of respondents for each sub-population, a weighting algorithm corrected discrepancies between the collected sample and the quotas (maximum weight = 1.42; minimum weight = 0.87). Based on the distribution of weights and the size of the sample, we calculated margins of error (MOE, at a confidence level of 95%) for China (2.1%), Germany (2.2%), and the US (2.1%). Table 2 summarises the demographic composition of the samples.

We analysed responses to the survey's closed-ended questions using binary logistic regression. We draw our dependent variables from the multiple-choice survey question *Which of the following information, if any, would you be willing to share on a COVID-19 tracing app?* to which respondents could choose among the following answers: *health information, such as symptoms; relative location (not exact location); real-time location (exact location); phone number or email address; personal identity (name, age, gender, etc.);*

Table 2. Demographic composition of the sample and the total population.

	Three countries		China		Germany		United States	
	Total	Sample	Total	Sample	Total	Sample	Total	Sample
Population	1,821 Mill.	6,464	1,410 Mill.	2,201	83 Mill.	2,083	328 Mill.	2,180
Gender								
Female	50.03%	48.7%	48.9%	46.3%	50.7%	49.1%	50.5%	50.7%
Male	49.97%	51.3%	51.1%	53.7%	49.3%	50.9%	49.5%	49.3%
Age								
Population median in yrs	41	36	38	36	46	41	38	40
Pop. Online	80.7%	100%	64.6%	100%	88.1%	100%	89.4%	100%

Sources: Barro & Lee, 2013 <http://www.barrolee.com>; Pew Global Attitudes Survey. (2017). Spring 2017 Survey Data. <https://www.pewresearch.org/global/dataset/spring-2017-survey-data/>; Statista (2016). Population in China in 2016, by Region (in Million Inhabitants). <https://www.statista.com/statistics/279013/population-in-china-by-region>

Table 3. Summary of independent variables.

Category	Measurement
Crisis perception	
Health concern <i>At the peak of the COVID-19 pandemic, have you worried about any of the following?</i>	1 = catching the virus myself, 2 = family members catching the virus, 3 = friends catching the virus, 4 = I have not been worried about any of these. Three dummies: 1-3.
Financial situation <i>To what extent, if at all, has the status of your monthly household income been impacted from before the COVID-19 virus to now?</i>	1 = improved slightly, 2 = improved somewhat, 3 = stayed the same, 4 = worsened somewhat, 5 = worsened significantly, 99 = don't know/ prefer not to answer; regression dummy variable created: 1 = worsened significantly, 0 = improved slightly, improved somewhat, stayed the same, worsened somewhat, don't know/ prefer not to answer. One dummy that combines 4-5.
Psychological effect <i>Which of the following feelings, if any, have you felt an increase in throughout the COVID-19 pandemic?</i>	1 = panic, 2 = anxiety, 3 = loneliness, 4 = sadness, 5 = tiredness, 6 = boredom, 7 = impatience, 8 = anger, 9 = inspiration, 10 = happiness, 11 = other, 99 = none. Two dummies: 1-2.
Disclosure benefits	
Perceived positive CTA consequences <i>Do you believe that the use of COVID-19 tracing apps would result in any of the following?</i>	1 = fewer COVID-19 infections, 2 = isolating infected people, 3 = making it safer to go out, 4 = better health information, 5 = privacy violations, 6 = discrimination against people who test positive for covid-19, 7 = government surveillance, 8 = use of data for commercial purposes, 9 = other, 10 = none. Two dummies for 1, 4.
Use reasons <i>Which of the following, if any, would motivate you (or has motivated you) to use COVID-19 tracing apps?</i>	1 = to protect myself, 2 = to protect others, 3 = to prevent further economic loss, 4 = to move around outside freely again, 5 = the government enforcing it, 6 = I would never use the app, 7 = other, 8 = none. Four dummies for 1-4.
Disclosure risks	
Perceived negative CTA consequences <i>Do you believe that the use of COVID-19 tracing apps would result in any of the following?</i>	1 = fewer COVID-19 infections, 2 = isolating infected people, 3 = making it safer to go out, 4 = better health information, 5 = privacy violations, 6 = discrimination against people who test positive for COVID-19, 7 = government surveillance, 8 = use of data for commercial purposes, 9 = other, 10 = none. Four dummies: 5-8.
Socio-political beliefs	
Capacity <i>In general, who do you think has the most capability in managing the COVID-19 pandemic?</i>	1 = central government, 2 = local government, 3 = private companies, 4 = non – government organizations, 5 = international organizations, 6 = individual citizens, 7 = scientific expert community, 8 = other, 9 = none. Four dummies: 1, 2, 3, 6.
Responsibility <i>In general, who do you think holds the most responsibility in managing the COVID-19 pandemic?</i>	1 = central government, 2 = local government, 3 = private companies, 4 = non-government organizations, 5 = international organizations, 6 = individual citizens, 7 = scientific expert community, 8 = other, 9 = none. Four dummies: 1, 2, 3, 6.
Trust in government institutions <i>How much do you trust the governmental institutions of your country?</i>	1 = a lot, 2 = somewhat, 3 = neither trust nor distrust, 4 = not much, 5 = not at all, 6 = Prefer not to answer. Two dummies: 4 & 5.
Data management <i>Who should have the rights to access and manage the data collected?</i>	1 = local government, 2 = central government, 3 = private companies, 4 = non-government organizations, 5 = international organizations, 6 = medical staff, 7 = scientific expert community, 8 = individual citizens, 9 = other, 10 = none. Four dummies: 1, 2, 3, 7
Control Variables	
Age	In years (open box)
Gender	0 = male, 1 = female
Income	Germany, US: 1 = below 250, 2 = 250-500, 3 = 500-1,000 ... 12 = more than 15,000, 99 = prefer not to say (in local currency); China: 1 = below 700, 2 = 700–1,400, 3 = 1,400–2,100 ...

(Continued)

Table 3. Continued.

Category	Measurement
	12 = more than 28,000, 99 = prefer not to say (in CNY); regrouped: 1 = low (1-3), 2 = medium (4-6), 3 = high (7-12), 99 = prefer not to say (99)
Education	1 = no formal education, 2 = high school diploma or equivalent, 3 = vocational training, 4 = Bachelor's degree, 5 = Master's or Doctorate degree
CTA understanding	1 = fully understand, 2 = somewhat understand, 3 = not understand at all One dummy for each category.
CTA acceptance	1 = strongly agree, 2 = somewhat agree, 3 = neither agree nor disagree, 4 = somewhat disagree, 5 = strongly disagree One dummy for each category.
Similar app use	1 = several times per week, 2 = several times per month, 3 = yes, but not often, 4 = only once, 5 = never used before. Dummy 1 = Regular use (categories 1-2). Dummy 2 = Irregular use (categories 3-4). Dummy 3 = No use (category 5)

other; none of the above. Therefore, the dependent variables are the willingness of individuals to share health information, relative location, real-time location and identity.² We also included *any data type* as a dependent variable, for which we recoded *none of the above* (0 = none; 1 = any). Table 3 summarises our independent and control variables and measurements. The area under our models' receiver-operating curve (AUC) ranges between 0.69 and 0.93, indicating that our models perform well. We ran a linear regression to calculate variance inflation factors (VIF) with a mean VIF of 1.06 and 2.15, allowing us to rule out multicollinearity in our models (see Appendix Tables A2 and A3).

Results

We find that the willingness to share data through CTAs and the data types that respondents are willing to share vary across countries. Figure 2 shows that users are most willing to share health information in all three countries. Apart from these similarities, willingness to share data varies across countries, especially between China on the one and Germany and the US on the other side.

Willingness to share through CTAs

In the following, we first present the results of our three binary logistic regression models for willingness to share *any data* through CTAs before delivering results for the *different data types*. Figure A2 in the Appendix shows that overall willingness to share data is significantly lower in Germany and the US than in China. Figure 3 further reveals the effects of our predictors on willingness to share in each country. First, crisis perceptions (i.e., health and financial concerns or psychological effects) do not correlate with willingness to share data through CTAs. Only in China does reported anxiety positively and significantly associate with individuals' willingness to share. Second, while risks of data sharing show no statistically significant correlation, benefits almost exclusively show positive and significant ones, some of which are the strongest in the respective models. For example,

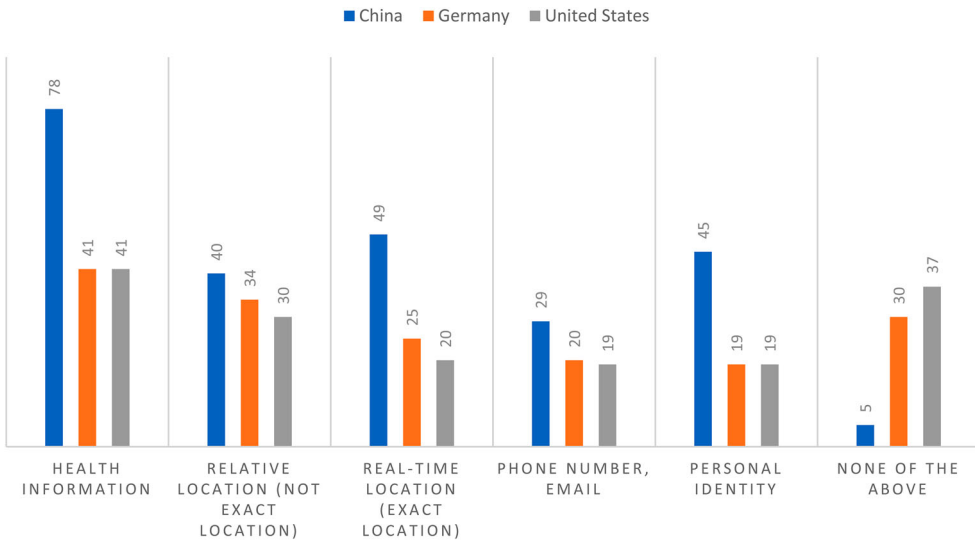


Figure 2. Willingness to share different types of data through CTAs by country.

Note: Sample size = 6464; weighted sample, numbers = percent.

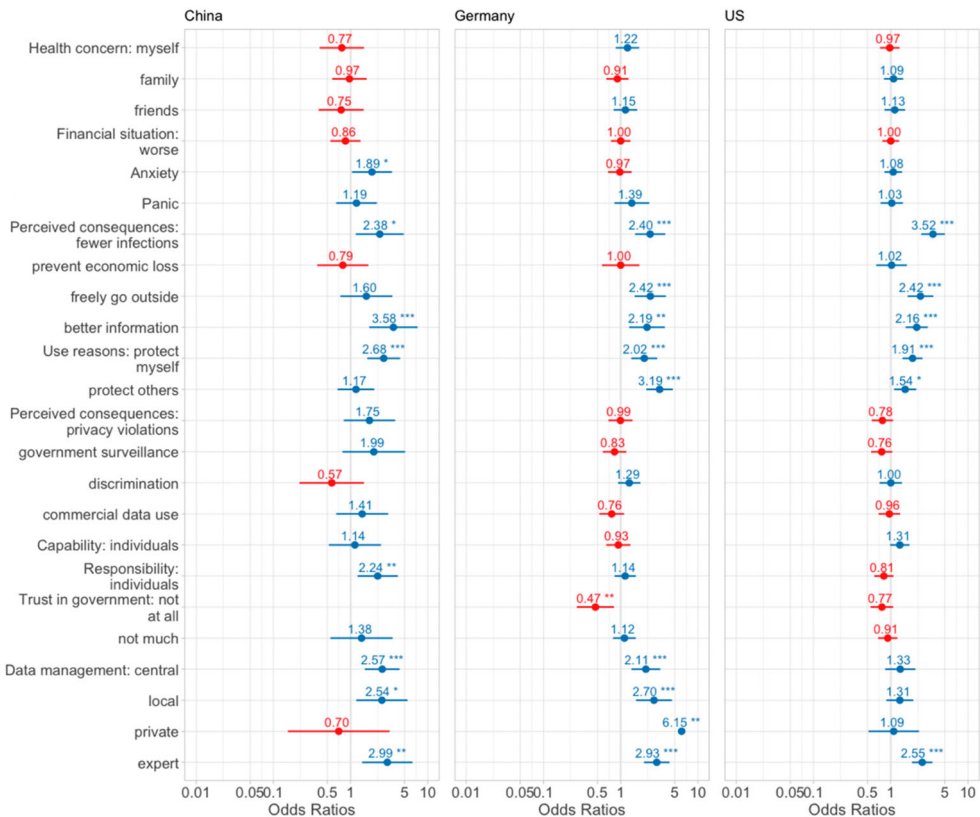


Figure 3. Odds ratios of effects on willingness to share any type of data through CTAs.

Note: For brevity and clarity reasons, control variables are not shown in the graph, but have been included in the model. * $p < .05$; ** $p < .01$; *** $p < .001$.

the potential consequence of reducing infections through CTAs positively correlates with disclosure willingness in all three models with a powerful effect in the US. In the Chinese sample, the strongest predictor in the entire model is receiving better information through the app. In the German sample, the perception of protecting others through the app is the second strongest predictor of willingness to share through CTAs.

Socio-political beliefs and other contextual factors show several significant correlations only in the German and Chinese models. Distrust of governmental institutions only influences data sharing in the German model. In contrast, the Chinese model does not deliver results for this predictor due to a meagre answer rate for this category ($n = 11$). Preference falsification induced by China's authoritarian regime discouraging respondents from reporting mistrust in the government may have caused this low answer rate. In the US model, the only significant predictor in this category is the belief that the scientific expert community should manage the data collected through CTAs. Data management preferences are mostly positively and significantly correlated in the models for China and Germany. The association between data management by private enterprises in Germany and willingness to share data is exceptionally high which may be due to Germany's history of surveillance by both the Nazi regime and the Stasi.

Table 4 summarises the main findings for the individual hypotheses and citizens' willingness to share any data type through CTAs. To understand if and how data sharing willingness differs across data types, the following sections present individual model results for sharing health information, relative and real location data, and one's identity. We focus only on the main differences to overall disclosure willingness presented in this section to avoid repetition.

Table 4. Overview of hypotheses for willingness to share any type of data through CTAs.

Hypothesis number	China	Germany	US
H1a own health	X	X	X
H1b family health	X	X	X
H1c friends' health	X	X	X
H1d financial situation	X	X	X
H2a anxiety	✓	X	X
H2b panic	X	X	X
H3a fewer infections	✓	✓	✓
H3b prevent economic loss	X	X	X
H3c freely walk outside	X	✓	✓
H3d health information	✓	✓	✓
H3e protect me	✓	✓	✓
H3f protect others	X	✓	✓
H4a privacy violations	X	X	X
H4b government surveillance	X	X	X
H4c discrimination	X	X	X
H4d commercial data use	X	X	X
H5a capability individuals	X	X	X
H5b responsibility individuals	X	X	X
H6 trust in government institutions	X	✓	X
H7a data management central government	✓	✓	X
H7b data management local government	✓	✓	X
H7c data management private enterprises	X	✓	X
H7d data management experts	✓	✓	✓

Note: 'X' refers to failure to reject the null hypothesis, '✓' refers to a rejected null hypothesis.

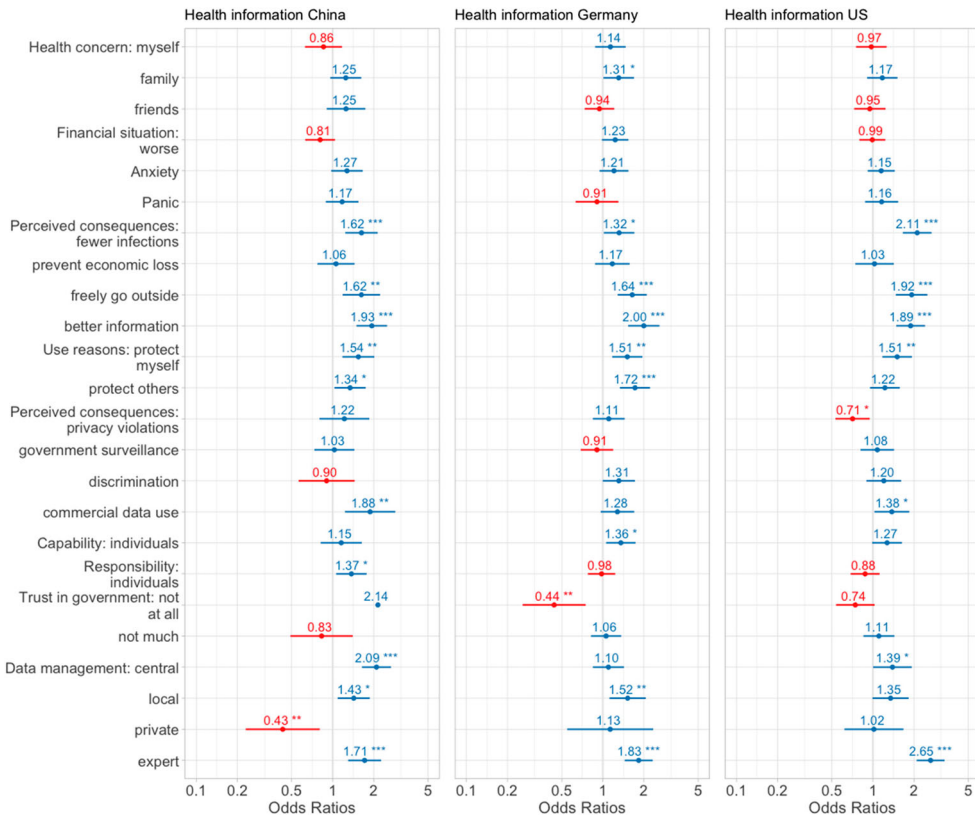


Figure 4. Odds ratios of effects on willingness to share health information.

Note: For brevity and clarity reasons, control variables are not shown in the graph, but have been included in the model. $p < .05$; ** $p < .01$; *** $p < .001$.

Health information

When setting health information as the dependent variable, we again find no correlation with crisis perceptions – except in the German model where concern for a family member’s health during the pandemic positively and significantly correlates with individuals’ willingness to share health data.

Regarding risks and benefits, results are similar to above models with two exceptions: first, perceived privacy violations reduce the willingness to share health information in the US model. Second, in the US and China, the perception that data collected through CTAs will be used for commercial purposes positively and significantly influences willingness to share health information. Moderating effects of other variables not measured here may have caused these positive correlations. For example, the higher willingness to share health information among those who think CTA data will be used for commercial purposes might be explained by better knowledge of how technology companies use data.

Regarding socio-political beliefs and other contextual factors, in contrast to the previous models, responsibility and capability attributed to individuals to fight the COVID-19 pandemic are positively associated with willingness to share health

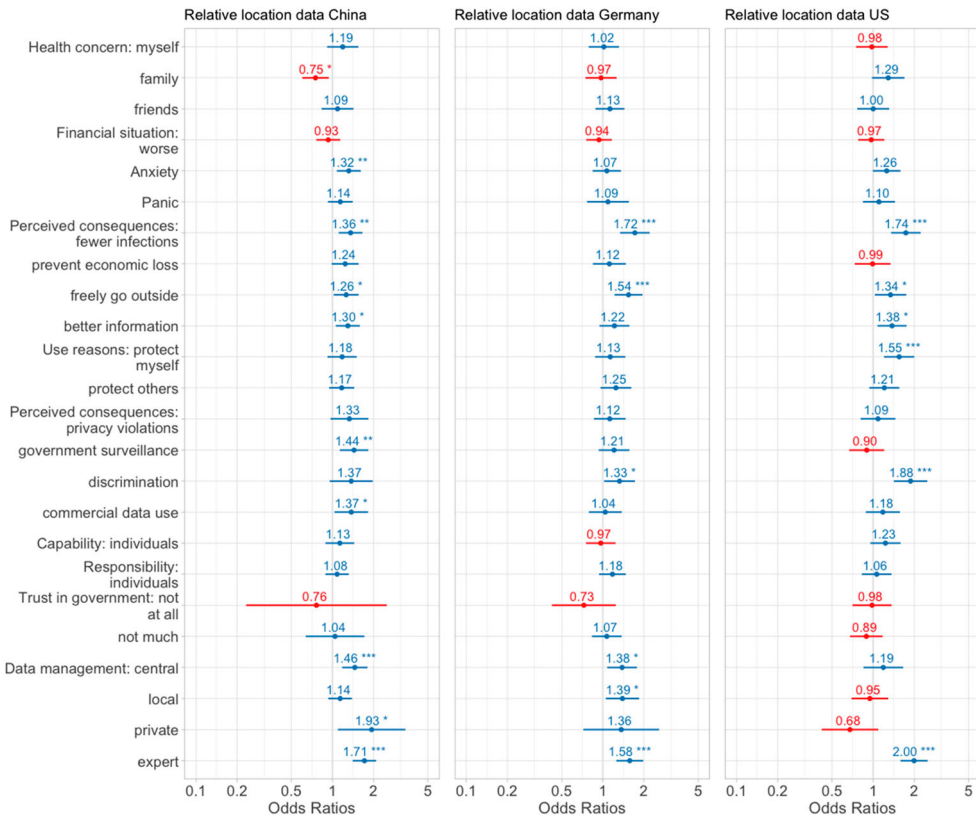


Figure 5. Odds ratios of effects on willingness to share relative location data.

Note: For brevity and clarity reasons, control variables are not shown in the graph, but have been included in the model. * $p < .05$; ** $p < .01$; *** $p < .001$.

information in China and Germany, respectively. The Appendix (Table A4) includes an overview of hypotheses for different data types.

Relative versus real location data

Crisis perceptions associate with willingness to share relative or real location in the three samples. In China and the US, concern for family members’ health negatively correlates with willingness to share relative and real location data, respectively. Reported anxiety positively and significantly affects willingness to share relative location in China. Panic (in the German model) and concern about friends’ health (in the China model) increases the willingness to share one’s real location.

Regarding risks and benefits, results are even less clear-cut than in prior models. Those in China who think that CTA use results in government surveillance and commercial data use are more likely to share their relative location than those who do not share these perceptions. Similarly, those in Germany and the US who think that CTAs result in discrimination of infected people are 1.33 and 1.88 times, respectively, more likely to share their relative location than others. This willingness to share one’s relative location despite concerns about surveillance and discrimination indicates an awareness of the

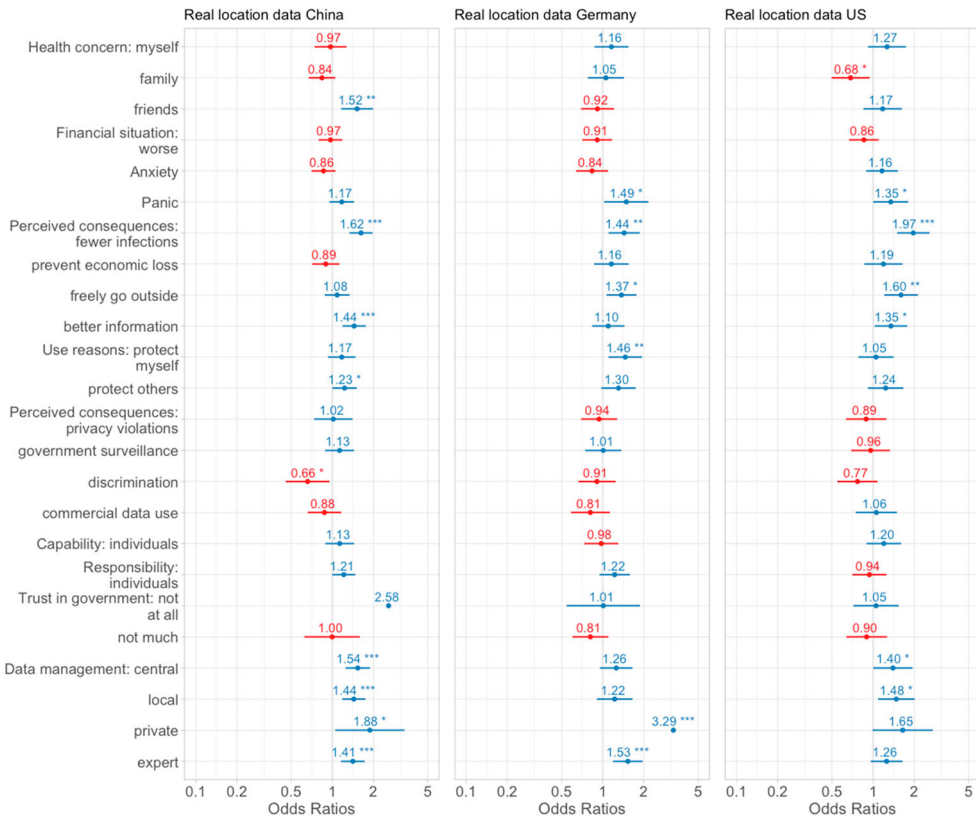


Figure 6. Odds ratios of effects on willingness to share real location data.

Note: For brevity and clarity reasons, control variables are not shown in the graph, but have been included in the model. $p < .05$; ** $p < .01$; *** $p < .001$.

privacy-preserving nature of relative location data in the three samples. Moreover, regarding real location data, the perception that CTA use may lead to discrimination of the infected in the China model is negatively correlated with sharing one’s real location, indicating an awareness of the privacy-intrusive nature of GPS data collection.

Regarding socio-political beliefs and other contextual factors, only data management preferences correlate with willingness to share location data. Two things stand out: first, those who want private enterprises in China to manage their data are more willing to share their relative location through CTAs. This contrasts above results for health data, where this correlation is negative, indicating differences in how the Chinese population treats these two data types. Second, in the German sample, those who think private enterprises should manage CTA data are more than three times more likely to share real location data than those who did not choose this data management option. The low number of respondents that had selected this option – four, three, and five percent in the China, Germany, and US sample, respectively – may have caused this result (see Table A1). Moreover, those who chose this option may hold more positive views towards private technology companies with whom they are used to sharing their real location through applications such as Google Maps.

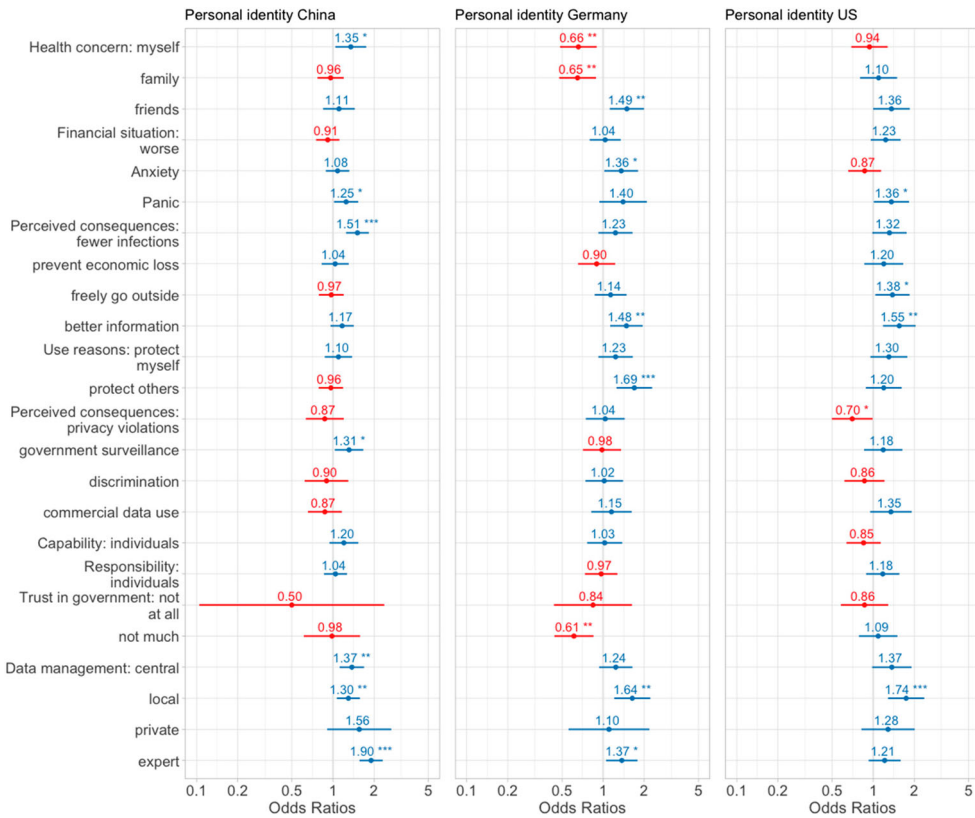


Figure 7. Odds ratios of effects on willingness to share personal identity.

Note: For brevity and clarity reasons, control variables are not shown in the graph, but have been included in the model. * $p < .05$; ** $p < .01$; *** $p < .001$.

Personal identity

Crisis perceptions more clearly correlate with willingness to share one’s identity. Concern about one’s health in China, concern about friends’ health in Germany, reported panic in China and the US, and anxiety in Germany are all positively and significantly correlated with willingness to share one’s identity. The findings for Germany are surprising as correlations between concern for one’s own and family members’ health are negative. Possibly, people in Germany are uncomfortable revealing their identity when catching COVID-19.

Like in the above models, most data sharing benefits positively correlate with the willingness to share one’s identity. Associated risks do not show clear negative associations, except for fears of privacy violations in the US model which are negatively correlated. Surprisingly, in China, government surveillance is positively and significantly correlated with willingness to share one’s identity. The fact that the Chinese *Health Code* is technically mandatory and requires users to register with their IDs may have caused this correlation.

Regarding contextual factors, individual responsibility and capability, and trust in governmental institutions seem to not influence willingness to share personal data (with the exception of Germany) and findings for data management preferences are mostly consistent with those of prior models.

Conclusion

Contract tracing apps (CTAs) have attracted global attention. Apart from questions about the usefulness of CTAs to fight the pandemic, user privacy and personal data collection have been major concerns voiced by critics of CTAs. Prior research on data disclosure has shown that users hesitate to share data online especially when the requested data is considered sensitive (Rifon et al., 2005). More specifically, data sensitivity influences the privacy calculus that users make by reducing the perceived benefits of data sharing whilst increasing its perceived risks (Mothersbaugh et al., 2012). A range of contextual factors such as socio-political beliefs and norms also influence users' risk-benefit calculations during data disclosure (Nissenbaum 2004). Studies on e-commerce have further shown that immediate gratification strongly affects benefit perceptions, motivating customers to share their data (Acquisti 2004). The pandemic presents a unique context for data sharing that shapes individual crisis perceptions and the utility of CTAs. In contrast to e-commerce and social networking sites, CTAs in most contexts provide societal benefits rather than individual gratification (Matt, 2021).

Our study of the drivers of willingness to disclose data through CTAs in three national contexts provides several theoretical and practical implications. First, the general willingness to share data through CTAs is significantly higher in China than in the US and Germany. This echoes prior findings on low privacy concerns (Mozur, 2018) and the high acceptance of CTAs in China (Kostka & Habich-Sobieggalla, 2022).

Regarding the different predictors influencing sharing willingness, we find that, first, crisis perceptions seem to not influence, neither negatively nor – as we had hypothesized – positively (Davis & Silver, 2004; Pavone & Degli Esposti, 2012). This finding contrasts prior research on the positive effects of fear appeals by governments on citizens' willingness to share personal data (Tannenbaum et al., 2015). Nevertheless, we find that crisis perceptions impact the willingness to disclose different data types across the three samples. For example, the negative impact of health concern on the willingness to share one's identity in the German sample might indicate the fear of stigmatization if someone has contracted COVID-19. Future studies should thus investigate the impact of crisis perceptions, and differentiate between feelings of crisis that increase or decrease data disclosure.

Second, we find that the factors influencing peoples' willingness to share personal data through CTAs depend on the data type. Previous literature has shown that privacy concerns reduce the willingness to disclose sensitive information such as users' identity and real location with no effect on less sensitive data such as relative location (Mothersbaugh et al., 2012). We can only partly confirm these results and only for the US sample where privacy concerns lower users' willingness to share their identity. Relatedly, we find that the suitability of the privacy calculus theory to explain people's willingness to share also depends on the data type (Cottrill & Thakuriah, 2015; Wadle et al., 2019): the theory can explain sensitive data (i.e., real location and identity), but it is unable to explain the willingness to share less sensitive data such as health information and relative location data. Given the increasing prevalence of sharing anonymous data, this finding reveals the need for a new theory to explain people's willingness to share different data types. Our findings suggest that the same person can in some situations be oblivious or willingly share their data while in other situations be very concerned about privacy issues.

Moreover, whereas perceived benefits of data sharing are more clearly and positively associated with willingness to share, risks show no similarly clear indication. Instead, if at all, risks only negatively affect the disclosure of sensitive data while positively affecting the sharing of less sensitive data. Hence, policymakers wanting to encourage their citizens to share data through CTAs should highlight the benefits of CTAs more so than attempting to reduce risk perceptions.

Fourth, our findings reveal that contextual factors such as socio-political beliefs have varying effects on willingness to share data. Capability and responsibility attributed to individuals handling the crisis and trust in governmental institutions seem to have negligible effects. For example, in the Chinese case, individual responsibility positively correlates with willingness to share any data type through CTAs. Contrasting prior research (Farronato et al., 2020), this indicates that, at least in China, CTAs are not considered a public good. The integration of the *Health Code* into WeChat may explain this. The latter is a multi-purpose app that users attribute to their daily and private lives, which may normalise the use of the *Health Code*.

Fifth, our study reveals that despite differences in national contexts and the types of CTAs studied here, some results are strikingly similar across the three samples, including the direction of the effects of perceived benefits and data management preferences on willingness to share different data types. Hence, national or cultural differences found important elsewhere (e.g., Wang et al., 2011) may not substantially affect the pandemic's global impact or the convergence of privacy concerns across national contexts. The strong association of data management preferences, especially for scientific experts, means that policymakers should make the actors involved in data management transparent and strengthen the role of scientific experts in data management.

Our research has some limitations that provide direction for further investigation. First, our online survey is representative of the Internet-connected population. Further research on privacy concerns in times of health and other crises should include those parts of the population that are less technologically affine. Second, our survey was about the use, perception, and desired management of CTAs rather than primarily about privacy-related behaviour. Future research should investigate the impact of users' previous data disclosure on their adoption of privacy-preserving strategies during the pandemic. Third, only the Chinese *Health Code* had been rolled out at the time of the survey, while the German CTA was released during the survey period and the US CTAs were released later. These differences might have influenced the survey outcome. Fourth, our survey used river sampling, a nonprobability sampling technique that may lead to some populations being overrepresented in our sample (such as tech-savvy citizens). Finally, in China's authoritarian context, questions about trust in governmental institutions and perceived government surveillance might be deemed sensitive and therefore influenced by preference falsification. Future research could use list experiments when analysing politically sensitive questions (Robinson & Tanenbergh, 2019).

Notes

1. A previous version of this paper included further hypotheses on the influence of people's CTA perception on willingness to share data through CTAs. These hypotheses have been

excluded during the first round of revision in response to a reviewer's concern about the high number of hypotheses tested in the earlier version.

2. To focus our article on the most important data types, we do not analyze *phone number and email address* in detail, but provide regression results in the Appendix in Figure A1. While in the case of the Chinese *Health Code*, the sharing of users' personal identity, phone number and real-time location is mandatory, in the German and US cases it is not.

Acknowledgements

We acknowledge funding from the Volkswagen Foundation Planning Grant on 'State-business relations in the Field of Artificial Intelligence and its Implications for Society' (grant 95172). We are also very grateful for excellent research assistance by Danqi Guo and Anna Heidemann. All remaining errors are our own.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by Volkswagen Foundation: [Grant Number 95172].

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Appendix

Table A1. Hosmer-Lemeshow and AUC tests

Hosmer-Lemeshow and AUC tests					
	Model name	X-squared	df	p-value	AUC
China	Health information	13.837	8	0.086	0.804
	Relative location	26.726	8	0.001	0.716
	Real location	2.648	8	0.954	0.720
	Personal identity	7.036	8	0.533	0.705
	Phone no./ email	5.497	8	0.703	0.697
	None	7.1406	8	0.522	0.903
Germany	Health information	11.467	8	0.176	0.815
	Relative location	10.14	8	0.255	0.770
	Real location	6.617	8	0.578	0.825
	Personal identity	3.690	8	0.884	0.793
	Phone no./ email	4.047	8	0.853	0.769
	None	15.555	8	0.049	0.929
US	Health information	22.009	8	0.005	0.828
	Relative location	10.122	8	0.257	0.802
	Real location	11.04	8	0.199	0.809
	Personal identity	16.928	8	0.031	0.798
	Phone no./ email	5.776	8	0.672	0.769
	None	13.774	8	0.088	0.891

Table A2. Variance inflation factors (VIFs)

Variable name	VIFs		
	China	Germany	US
age	1.088062	1.170909	1.095378
gender	1.064115	1.055976	1.065824
income	1.137762	1.056325	1.055961

(Continued)

Table A2. Continued.

Variable name	VIFs		
	China	Germany	US
education	1.208909	1.112151	1.158757
healthConcern_me	2.148902	1.568971	1.667716
healthConcern_family	1.340397	1.290352	1.368872
healthConcern_friends	2.106080	1.499759	1.664983
finance	1.081724	1.074032	1.066793
panic	1.141004	1.129479	1.182932
anxiety	1.198297	1.303618	1.265119
understanding	1.566703	1.123402	1.185504
similarApp	1.209012	1.175318	1.250097
CTA_experience	1.379277	1.122378	1.172083
acceptance	1.288786	2.100664	1.748733
perceivedConsequences_fewerInfections	1.130961	1.543222	1.363320
perceivedConsequences_betterInfo	1.206696	1.232797	1.335416
perceivedConsequences_privacyViolations	1.274290	1.502195	1.632771
perceivedConsequences_govSurveillance	1.098133	1.489266	1.564161
perceivedConsequences_discrimination	1.214267	1.285045	1.406552
perceivedConsequences_commercialDataUse	1.227847	1.494107	1.435471
useReasons_protectMyself	1.295425	1.677685	1.650574
useReasons_protectOthers	1.321097	1.702126	1.570294
useReasons_preventEconLoss	1.111332	1.164109	1.240609
useReasons_moveOutside	1.127674	1.274635	1.298664
capability_individuals	1.120409	1.157516	1.256024
responsibility_individ	1.131418	1.172738	1.278367
dataManag_local	1.111716	1.188054	1.248559
dataManag_central	1.175308	1.277840	1.245941
dataManag_private	1.081500	1.062798	1.094688
dataManag_expert	1.135225	1.147731	1.170517
trust	1.169.762	1.434366	1.233182

Table A3. Hypotheses results for different types of data

Hypothesis	Country	Health information	Relative location	Real location	Personal identity
H1a own health	China	X	X	X	✓
	Germany	X	X	X	X
	US	X	X	X	X
H1b family health	China	X	X	X	X
	Germany	✓	X	X	X
	US	X	X	X	X
H1c friends' health	China	X	X	✓	X
	Germany	X	X	X	✓
	US	X	X	X	X
H1d financial situation	China	X	X	X	X
	Germany	X	X	X	X
	US	X	X	X	X
H2a anxiety	China	X	✓	X	X
	Germany	X	X	X	✓
	US	X	X	X	X
H2b panic	China	X	X	X	✓
	Germany	X	X	✓	X
	US	X	X	X	X
H3a fewer infections	China	✓	✓	✓	✓
	Germany	✓	✓	✓	X
	US	✓	✓	✓	X
H3b prevent economic loss	China	X	X	X	X
	Germany	X	X	X	X
	US	X	X	X	X
H3c freely walk outside	China	✓	✓	X	X
	Germany	✓	✓	✓	X
	US	✓	✓	✓	✓

(Continued)

Table A3. Continued.

Hypothesis	Country	Health information	Relative location	Real location	Personal identity
H3d health information	China	✓	✓	✓	X
	Germany	✓	X	X	✓
	US	✓	✓	X	✓
H3e protect me	China	✓	X	X	X
	Germany	✓	X	✓	X
	US	✓	✓	X	X
H3f protect others	China	✓	X	X	X
	Germany	✓	X	X	✓
	US	✓	X	X	X
H4a privacy violations	China	X	X	X	X
	Germany	X	X	X	X
	US	X	X	X	X
H4b government surveillance	China	X	X	X	X
	Germany	X	X	X	X
	US	X	X	X	X
H4c discrimination	China	X	X	✓	X
	Germany	✓	X	X	X
	US	X	X	X	X
H4d commercial data use	China	✓	X	X	X
	Germany	X	X	X	X
	US	✓	X	X	X
H5a capability individuals	China	X	X	X	X
	Germany	✓	X	X	X
	US	X	X	X	X
H5b responsibility individuals	China	✓	X	X	X
	Germany	X	X	X	X
	US	X	X	X	X
H6 trust in government institutions	China	X	X	X	X
	Germany	✓	X	X	Somewhat ✓
	US	X	X	X	✓
H7a data management central government	China	✓	✓	✓	X
	Germany	X	✓	X	X
	US	X	X	X	X
H7b data management local government	China	✓	X	✓	✓
	Germany	✓	✓	X	✓
	US	X	X	✓	✓
H7c data management private enterprises	China	X	✓	✓	X
	Germany	X	X	✓	X
	US	X	X	X	X
H7d data management experts	China	✓	✓	✓	✓
	Germany	✓	✓	✓	✓
	US	✓	✓	X	X

Note: 'X' refers to failure to reject the null hypothesis, '✓' refers to a rejected null hypothesis.

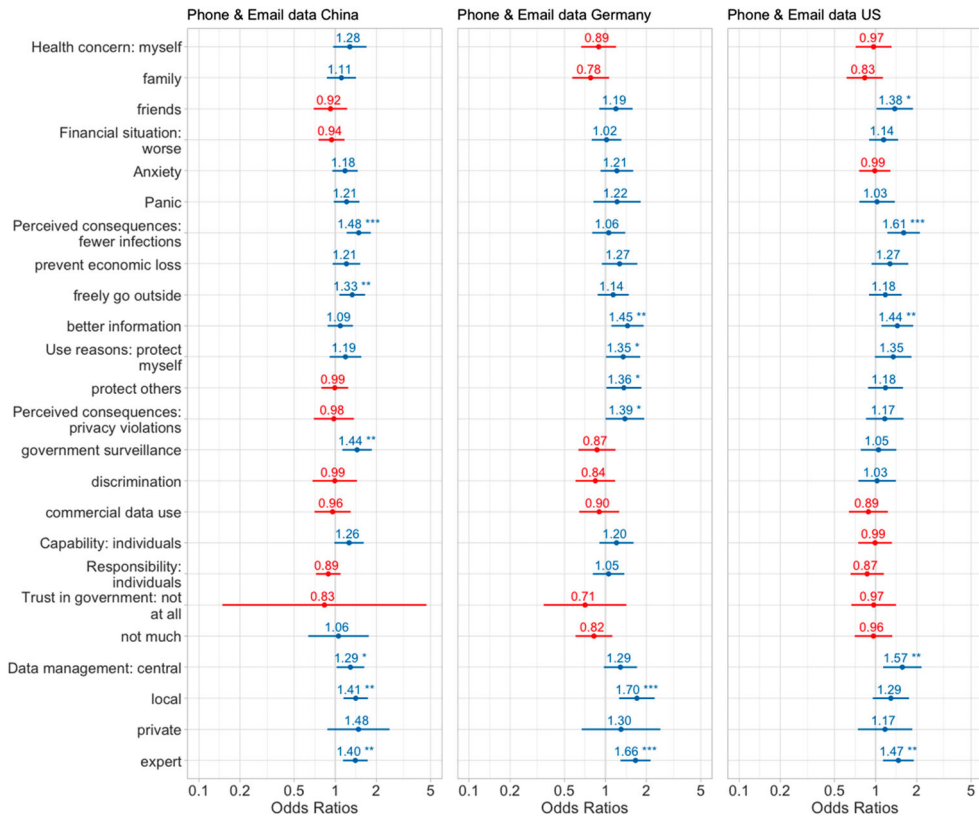


Figure A1. Odds ratios of effects on willingness to share phone number and email address.

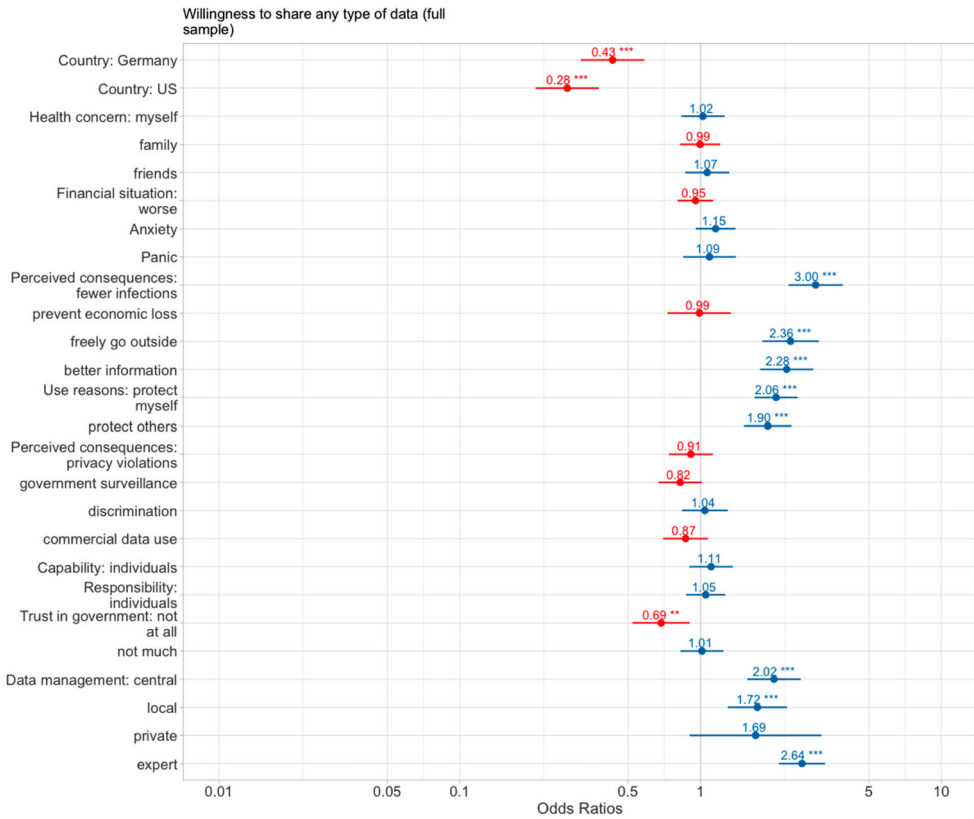


Figure A2. Full sample – Odds ratios of effects on willingness to share any data.