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Suggested citation referring to the original publication:
International Journal of Information Management 64 (2022) , Art. 102473 pp. 1 - 16
DOI: https://doi.org/10.1016/j.ijinfomgt.2022.102473
ISSN: 0268-4012

Journal article | Version of record

Secondary publication archived on the Publication Server of the University of Potsdam:
Zweitveröffentlichungen der Universität Potsdam : Wirtschafts- und Sozialwissenschaftliche Reihe 167
ISSN: 1867-5808
URN: https://nbn-resolving.org/urn:nbn:de:kobv:517-opus4-605856
DOI: https://doi.org/10.25932/publishup-60585

International Journal of Information Management 64 (2022) 102473

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

One for all, all for one: Social considerations in user acceptance of contact tracing apps using longitudinal evidence from Germany and Switzerland

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ARTICLE INFO

Keywords:
Digital contact tracing
Privacy calculus
Longitudinal study
Privacy risks
Surveillance
Intention-behavior gap

ABSTRACT

We propose a conceptual model of acceptance of contact tracing apps based on the privacy calculus perspective. Moving beyond the duality of personal benefits and privacy risks, we theorize that users hold social considerations (i.e., social benefits and risks) that underlie their acceptance decisions. To test our propositions, we chose the context of COVID-19 contact tracing apps and conducted a qualitative pre-study and longitudinal quantitative main study with 589 participants from Germany and Switzerland. Our findings confirm the prominence of individual privacy calculus in explaining intention to use and actual behavior. While privacy risks are a significant determinant of intention to use, social risks (operationalized as fear of mass surveillance) have a notably stronger impact. Our mediation analysis suggests that social risks represent the underlying mechanism behind the observed negative link between individual privacy risks and contact tracing apps' acceptance. Furthermore, we find a substantial intention–behavior gap.

1. Introduction

Emerging and re-emerging airborne diseases like SARS, chickenpox, Ebola, tuberculosis, and most recently SARS-CoV-2 (which causes COVID-19) require rapid response and targeted control measures. Pharmaceutical control measures (i.e., vaccines) are often not readily available for new infectious diseases, calling for non-pharmaceutical control methods to be swiftly applied (Müller & Kretzschmar, 2021). Alternative ways of breaking infection chains include social (physical) distancing and mass testing together with subsequent isolation of contagious individuals. Mass screening as an autonomic control measure is pre-conditioned on the availability of cheap, rapid, and reliable diagnostic tools that are rarely feasible in case of a new infection. For example, the most accurate molecular tests for detecting COVID-19 (i.e., PCR) take 4–8 h of laboratory time, allow one technician to process 600 tests daily, and necessitate 24–48 h after a swab before the tested individual can receive their results (Rivm.nl, 2021). The costs depend on the region and exact location of the procedure (e.g., medical center vs. airport) but range in Europe from €40 to €190 (sortiraparis.com, 2021) and in the United States from $40 to $261 charged at San Francisco International Airport (mondassur.com, 2021; skytraxratings.com, 2021).

Contact tracing (CT) is a more targeted method to control contagion. Once an infected individual is diagnosed and isolated, contact persons are identified with whom that index case had potentially infectious interactions (Müller & Kretzschmar, 2021). In the Internet era, implementation of this measure naturally means digital CT (He et al., 2021). A smartphone app first gathers proximity-based data over time. Individuals who have tested positive are asked to report their infection status, enabling the app to notify users who have been exposed to infected individuals. Although in theory it is effective to screen mostly exposed persons (as prevalence within that group will be much higher than in the overall population checked in mass testing) and, if necessary, to isolate them, the actual efficiency of digital CT depends on its large-scale acceptance (Morley et al., 2020; Trang, Trenz, Weiger, Tarafdar, & Cheung, 2020). Centralized and decentralized contact tracing applications (CTAs) are distinguished by how they store user data. In the centralized versions of CTAs pursued by (for example) the United Kingdom, the anonymized individual data gathered by the app is sent to a remote server where matches are made with other contacts in the event of a positive test (Criddle & Kelion, 2021). Decentralized models keep data on a user's phone and are advertised as offering a greater degree of privacy. Studies of primarily hypothetical CTAs show generally high willingness to accept: 40.8% in Germany (statista.com, 2021)

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https://doi.org/10.1016/j.ijinfomgt.2022.102473
Received 3 December 2020; Received in revised form 13 January 2022; Accepted 13 January 2022
Available online 1 February 2022

and 69.4% in the United Kingdom and United States (Comparitech, 2021). However, the actual adoption rate, even for decentralized CTAs, is much lower: In April 2021, the diffusion rate of CTAs was 14.5% in Germany and 20.3% in Switzerland (Comparitech, 2021). This merits an in-depth examination of individuals' choices.

Explaining user acceptance of new technology is often described as one of the most mature research areas in the information systems (IS) literature (e.g., Hu, Chau, Sheng, & Tam, 1999; Venkatesh, Morris, Davis, & Davis, 2003). In this regard, one might assume that understanding acceptance of digital CT is merely a matter of transferring existing definitions, patterns, and measures to a new domain. Several prior works have applied traditional technology acceptance frameworks to CTAs. For instance, Hassandoust et al. (2021) found evidence of a situational privacy calculus for CTA acceptance, and Kaspar (2020), drawing on protection motivation theory, emphasized the role of data security perceptions. What all of these works have in common is their focus on the intrapersonal perceptions of benefits and risks that result in CTA usage.

We argue that the traditional individual perspective of IS acceptance is insufficient for capturing the peculiarities of CTAs. This individual-level view ignores the implications of emerging technologies at more inclusive levels of analysis (i.e., community or social). To advance the understanding of CTA adoption, we pose the following research questions (RQs):

RQ1:. *What is the impact of individual factors on the acceptance of CTAs?*

RQ2:. *What is the impact of social factors on the acceptance of CTAs?*

To answer these questions, on the theoretical front, we build on a privacy calculus framework (Dinev & Hart, 2006) which assumes that IS users weigh their individual benefits against privacy risks before transacting with a provider (e.g., Xu, Teo, Tan, & Agarwal, 2009). We call this an "individual calculus." Indeed, while CTAs deliver the benefits of a convenient notification tool, they simultaneously require the collection of personal information, such as contacts, and the disclosure of sensitive health information (i.e., positive test results) to public authorities, which qualifies them as privacy-invasive IS (Urbaczewski & Lee, 2020). Given the peculiarity of CTAs in their provision of unique affordances for the production and consumption of information, thereby turning users into prosumers (Tilly, Posegga, Fischbach, & Schoder, 2017), we anticipate that CTAs will entail not only individual benefits and risks but also social ones. We build a conceptual model which contends that the expediency of a CTA undergoes consumer assessments at both the individual level (i.e., personal benefits and risks) and the social level (i.e., social benefits and risks). Therefore, on the theory front, we extend privacy calculus with social considerations.

To empirically respond to our RQs, we sought a (1) digital CT that was (2) novel so that we could track its acceptance. We chose COVID-19 CTAs as an apt research site (for a detailed justification, see Section 4.1). We took advantage of the synergistic properties of a mixed-methods approach: 1) a qualitative pre-study to better understand the nature of CTA acceptance and 2) a longitudinal quantitative survey of 589 respondents from Germany and Switzerland. These studies tested the influence of individual and social factors on respondents' intentions to adopt and actual adoption of COVID-19 CTAs at two points in time: before the launch of the apps (T0) and after the launch of the apps (T1).

We report the following results. First, we demonstrate the significance of social factors in addition to individual factors. We also observe that, for COVID-19 CTAs, social benefits are treated as inseparable from—and outperform—individual benefits. This hints at the fact that the selected CTAs lack individual benefits. Individual privacy risks and social risks impede both intention to use and actual use of CTAs. We also find evidence of the reinforcing effect of social risks, which fully mediate the link between individual risks and actual app adoption. Finally, by capturing effects on intention and actual app use, we find a substantial intention–behavior gap in the CTA context based on longitudinal data.

We contribute to the academic literature and practice as follows. Building on prior studies that have tested the privacy calculus model in the context of privacy-invasive IS such as social media (e.g., Krasnova, Spiekermann, Koroleva, & Hildebrand, 2010; Sun, Wang, Shen, & Zhang, 2015), we extend the boundaries of privacy calculus beyond the consideration of individual factors by taking into account the social factors. At the context level, with regard to our research site, we add to the literature on e-health and specifically CTA adoption, which to date has mainly focused on individual-level privacy risks (e.g., Kordzadeh, Warren, & Seifi, 2016; Wang, Duong, & Chen, 2016). Specifically, our contribution lies in illuminating the effects of the social risks (operationalized in this study as fear of mass surveillance) posed by a new digital CT solution in the eyes of users (De, Pandey & Pal, 2020). We illuminate the roles those social deliverables play in attitude formation and actual behavior. Finally, our paper adds to the body of knowledge on intention–behavior gaps in IS acceptance (Wu & Du, 2012, for a meta-review, see Parry et al., 2021). Substantial discrepancies between claimed intention and actual behavior in the context of CTAs suggest the need for more studies that measure actual behavior.

For practitioners, we make providers of CTAs aware of the importance of both individual and social benefits. The CTAs in our sample failed to deliver sufficient individual utility, and social benefits alone ultimately could not counterbalance their overall risks, tipping the scales for many users into delayed decisions or rejection. Both CTA developers and public institutions should keep in mind that the perceived social risks of a new CTA can be expected to impact actual adoption more strongly than individual privacy risks. These actors should therefore invest effort in properly informing users and mitigating these fears.

The remainder of the paper is organized as follows. In Section 2, we present the theoretical background. Based on this background, in Section 3, we derive our hypotheses and propose a conceptual model to explain the rationale behind the effects of individual and social factors on CTA acceptance. Section 4 describes our choice of research site and methodology for the qualitative study and quantitative two-wave survey. Section 5 elaborates on the results. In Section 6, we conclude the paper by discussing the contributions and implications of our investigation, limitations, and future research opportunities.

2. Theoretical background: from individual to social factors

This section lays the theoretical groundwork for our study. First, we present the privacy calculus model. We then set forth arguments as to why the boundaries of the privacy calculus model need to be broadened for the context of CTAs.

2.1. Privacy calculus as a traditional foundation of IS acceptance

Several theoretical lenses have been applied to understand technology choices from an end user perspective—among others, the technology acceptance model, the theory of planned behavior, the unified theory of use and acceptance of technology, and the theory of reasoned action, all of which mainly consider beneficial technologies (for an overview, see Venkatesh et al., 2003). Protection motivation theory (Rogers, 1975) is valuable for predicting the use of protective technologies that mitigate potential threats, such as anti-spyware (e.g., Chenoweth, Minch, & Gattiker, 2009) or health technology (e.g., Fox & Connolly, 2018).

The cost–benefit paradigm, reified as social exchange theory (Homans, 1961) and privacy calculus (Culnan & Armstrong, 1999), represents an alternative overarching principle to predicting IS acceptance and usage. Privacy calculus assumes that Internet users balance their own benefits and privacy risks before transacting with a provider (Krasnova et al., 2010; Xu et al., 2009). It originated in the e-commerce context, where users disclose personal information, such as names and addresses, to a provider in exchange for personalized online services (Dinev & Hart, 2006). In this consumer–provider relationship, benefits and risks are independent of other people's usage decisions. With the growing number of data-driven services, the popularity of privacy calculus in IS research is skyrocketing across domains, moving beyond e-commerce (Dinev & Hart, 2006) to social media (Krasnova et al., 2010), healthcare (e.g., Dinev et al., 2016; Li, Wu, Gao, & Shi, 2016), location-based services (Xu et al., 2009), or tourism services (Morosan, 2019).

2.2. An extended view of the calculus behind CTA acceptance: a socio-technical perspective

Despite its general validity and applicability to various technologies, privacy calculus, as a concept that originated in an era when IS acceptance was an individual decision, overlooks one salient feature of today's audience—namely, the interconnectedness among users. Firmly enshrined in many new technological solutions, interconnectedness grants value-generating opportunities to other peers, apart from a provider (Schmidt, Kirchner, & Razmerita, 2020; Trkman, Popovič, & Trkman, 2021), and is at the core of CTAs.

Thus, a new CT technology to combat airborne diseases leads people to take a socio-technical perspective where, in addition to personal demands, the consequences for the community as a whole are likely to be taken into account. Indeed, IS and communications researchers have recently noticed that not only intrapersonal factors but also interpersonal perceptions play a role in individuals' decision-making. This has predominantly been seen in the context of social networking sites (e.g., Wagner, Krasnova, Abramova, Buxmann, & Benbasat, 2018; Yu, Hu, & Cheng, 2015) and data donation (Skatova & Goulding, 2019). In this vein, research shows that consequences for others, such as negative affect of perceivers, are incorporated into users' formation of their privacy decisions (Wagner et al., 2018) and that social duties drive behavioral intentions (Skatova & Goulding, 2019). Corroborating this, crisis management experts have pointed to a combination of social capital and digital tools as the optimal crisis response (Nakagawa & Shaw, 2004; Thapa, Budhathoki, & Munkvold, 2017). Finally, social psychology scholars have reported that projections about the future of society drive attitudes toward social change (e.g., mitigating climate change, relaxing abortion restrictions, legalizing marijuana use, increasing the power of different religious groups) in the present (Bain, Hornsey, Bongiorno, Kashima, & Crimston, 2013).

In sum, although a calculus analyzing benefits versus risks is expected, the collective features of CTAs (i.e., user interconnectedness, prosumer role, public health at stake) suggest that a potentially more complex train of thought underlies users' decisions to accept or reject this emerging IS. To fill this gap, we extend privacy calculus to incorporate social considerations in modeling users' intentions and actual adoption choices in response to an emerging CTA.

3. Hypotheses

Assuming a trade-off between benefits and risks at the core of our model, we integrate insights from previous works on privacy calculus as well as social considerations to develop arguments to explain CTA acceptance.

In privacy calculus, perceived individual benefits refer to the positive attributes that users achieve with the IS, which commonly drive acceptance (Dinev & Hart, 2006; Krasnova et al., 2010). Since there are a variety of IS that offer a multitude of services, these benefits are highly dependent on context (Smith, Dinev, & Xu, 2011). They are intrapersonal in nature, as they constitute value for users themselves, such as convenience or personalization (Xu et al., 2009). Therefore, we hypothesize:

3.1. Greater perceived individual benefits increase acceptance of CTAs

Privacy risks or sometimes concerns are traditionally conceptualized as a key inhibitor of IS acceptance (Smith et al., 2011). IS use is typically preconditioned on the disclosure of personal information, which carries the risk of unwanted access by third parties, unintended usage by the provider, or lack of awareness and control (Smith et al., 2011). Privacy risks—generally defined as individuals' concerns about losing control over their personal data (Malhotra, Kim, & Agarwal, 2004)—are negatively linked to information disclosure in Internet transactions (Dinev & Hart, 2006), on social networking sites (Krasnova et al., 2010) and using location-based services (Xu et al., 2009). On top of that, privacy risks are consistently shown to be core inhibitor for app acceptance (Dinev et al., 2015; Wu & Wang, 2005; Xu, Teo, & Tan, 2005). Previous studies about CTAs further confirm the negative role of privacy risks in intention to use CTAs (e.g., Trang et al., 2020; Prakash & Das, 2022). Thus, if individuals feel a high degree of losing control over their data requested by CTAs, they are more likely to reject it (Prakash & Das, 2022). Therefore, we assume:

3.2. Greater perceived individual privacy risks decrease acceptance of CTAs

Moving beyond individual factors, we theorize that social considerations also precede CTA acceptance (Trkman et al., 2021). Following Bain et al. (2013), social considerations are defined as envisioning collective futures if new IS are accepted. We are all embedded in complex social structures—ranging from national identity to religious affiliation—that shape much of our behavior (Goldstone & Janssen, 2005). Awareness of interconnection facilitates responsibility not only for one's own decisions but also for the community as a whole. Social psychology research has found that people naturally transfer their own attitudes and beliefs onto others and, in turn, attempt to forecast the social consequences of their actions (Krueger, 1998). In line with this, individuals are likely to consider their concerns and benefits as relevant to the community. This is a significant complement to the "individual calculus," and taking it into account yields a better understanding of IS users' behavioral patterns (Nabity-Grover, Cheung, & Thatcher, 2020; Wagner et al., 2018). Particularly when people are faced with collective troubles, they exhibit a greater sensitivity to the "social good" and "social evils" of their actions (Scotsman, 2020). Investigations in disaster recovery advise that in times of crisis, "[the] safety of a community should be the issue, which is discussed and determined by the community since ultimately the community and/or individuals should be responsible for their own safety" (Nakagawa & Shaw, 2004, p. 5). These insights call into question the premise that people continue to make purely self-focused decisions in the interconnected setting of CTAs. Therefore, we propose that the interplay between social and individual considerations can explain CTA acceptance.

First, by definition, a CTA does not solely create benefits for one individual but also the community in general. To illustrate, imagine that you decide to consume food from an organic farm. This may have benefits for your own health, but your consumption also leads to more sustainable cultivation of fruits and vegetables and consequently additional benefits for the environment, public health, and food suppliers (e.g., farmers). Individuals often assume and act according to the principle "what is good for me is good for others." In an online setting, users typically receive emotional support when they release personal information on a health forum. In addition, posting on such forums promotes discussion, creates knowledge for others, and builds social capital, consequently creating social benefits for all users in the community (Pan et al., 2017). Therefore, it can be argued that, when using CTAs, individual utility can lead to social utility. Specifically, we hypothesize that perceiving individual utility in CTAs is positively linked to the envisioning of ubiquitous benefits for all others:

3.3. *Greater perceived individual benefits increase the perceived social benefits of CTAs*

Vice versa, if an individual expects to incur a high level of risk for her/his own using a CTA, that individual might consider the CTA to be harmful to the whole community. As such, Rowe (2020) argues that, in addition to individual privacy risks, CTAs create surveillance and habituation problems. When CTA characteristics are perceived as a source of trouble, potential users will likely assume a grander scale of these threats upon disseminating these CTAs across the community. Losing control over the own data can be seen as permission to an app provider to accumulate information on a nearly entire population. With the latter at hand, the whole society can be monitored. This threatens democratic compatibility and is often contrasted to Asian countries (Zimmermann et al., 2021). For example, German-speaking individuals point to the high privacy risks of CTAs and vastly understand CTAs as governmental surveillance tools, which facilitates overall technological surveillance (Zimmermann et al., 2021). Therefore, we hypothesize:

3.4. *Greater perceived individual privacy risks increase the perceived social risks of CTAs*

Social benefits are attractive and, in turn, likely to drive individual acceptance. For instance, in the context of social networking sites, social merits such as social capital are an important factor in driving acceptance (Al-Ghaith, 2015). In the context of autonomous cars, the potential to contribute to technological innovations to support a good cause has been identified as a major driver of data disclosure (Cichy, Salge, & Kohli, 2014). Because CTAs rely on open collaboration, their ubiquitous acceptance creates new opportunities for interactions among individual users, thus widening the geographic (city, country, region, continent, worldwide) applicability of a CTA. Thus, increasing social benefits may lead to collective actions such as acceptance of a CTA. Therefore, we hypothesize:

3.5. *Greater perceived social benefits increase acceptance of CTAs*

On the other hand, applying the same logic, collective social risks may hamper the acceptance of a CTA. For instance, if people are aware of the economic and ecological consequences of e-commerce, people might reject such transactions and prefer to make purchases in retail stores. In this vein, they project that the long-term social risks of their potential behavior will harm society as a whole. Apart from economic and ecological issues, CTAs bear the inherent problem of mass surveillance (Amit et al., 2020). Adopting a CTA requires disclosing one's personal information to other CTA users and the CTA provider. The ability to surveil one individual does not generate much value for a CTA provider. However, collecting data from a large mass of CTA users creates the issue of the entire community being traceable. This can lead individuals to develop negative beliefs about using the CTA, which hampers the likelihood of acceptance. Hence, we hypothesize:

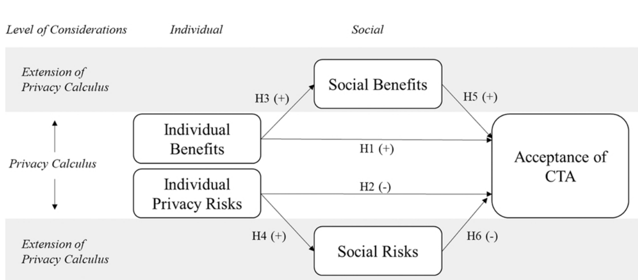

Fig. 1. Proposed research model.

3.6. *Greater perceived social risks decrease acceptance of CTAs*

The above hypotheses culminate in the research model visualized in Fig. 1.

4. Methodology of our empirical studies

To test our hypotheses (Fig. 1), we conducted a multi-methods investigation, which we describe in the following section (divided into three subsections). In the first subsection, we describe our identification of an appropriate research site. As we will discuss, we chose COVID-19 CTAs as a timely CTA for our study's context. In the second subsection, we describe the procedure of our qualitative pre-study, which we undertook to grasp the nature and magnitude of the individual and social thoughts behind the adoption of COVID-19 CTAs as new IS. In sum, our pre-study revealed whether individuals think about social implications when deciding upon CTA use. The subordinate aim of this pre-study was to contextualize the measurement instrument for the subsequent quantitative study, as benefits and risks are very context-sensitive. In the third subsection, we report on the organization of our quantitative longitudinal survey of a sample of German and Swiss respondents. This survey enabled us to capture intentions in the pre-launch phase and actual behavior in the post-launch phase to test (1) our theoretical model and (2) the consistency between participants' intentions and behavior.

4.1. *Research site*

To accomplish our objectives, we empirically validated the CTA acceptance model in the context of emerging COVID-19 CTAs in Germany and Switzerland. CTAs have been developed in many countries across the world as a promising information-based and communication-based approach to combating the COVID-19 pandemic. CTAs measure the physical closeness of smartphones, which acts as a proxy for the proximity of people. The first underlying CTA principle is to continuously record contacts in close proximity to a user. Second, if a CTA user later reports being infected, all of that user's previous contacts receive notifications to make them aware of their exposure and possible infection. Thus, CTAs can be categorized as privacy-invasive IS (Brakemeier, Wagner, & Buxmann, 2017), as CTA users disclose personal information such as location data and COVID-19 test results. After being notified of possible exposure, users can decide on further steps—for example, paying especially close attention to their health over the subsequent few days, getting tested, calling a doctor, or self-isolating.

Moreover, the technology in question should be new and, ideally, previously unknown. COVID-19 CTAs fulfill this last requirement and thus provide a rare opportunity to study early CTA acceptance in the field. When we first investigated attitudes toward COVID-19 CTAs, such apps were still unavailable in app stores. However, detailed descriptions, mockups, and prototypes had circulated in professional media, allowing us to anticipate how CTAs would function before their launch. This unique setting enabled us to design an early qualitative pre-study followed by a quantitative longitudinal survey, with stage 1 including only non-users who were still forming their intentions regarding CTA adoption. We repeated the survey in stage 2, after the CTAs were launched. Taken together, these characteristics of CTAs in Germany and Switzerland make them a proper technological basis for the empirical setting in which we examined our RQs.

4.2. *Qualitative pre-study methodology*

To explore the perceived benefits and risks of CTAs before their launch in Europe, we distributed an online survey (available in English and German) between May 22 and 29, 2020, via different social media channels. Participants responded voluntarily. Following an explanation of the app's functionality with visuals, open-ended questions were presented to the respondents. The question catalog was developed based on Davis (1989) framework and its adaptation to the personal health records context by Ozok, Wu, Garrido, Pronovost, and Gurses (2014). We differentiated between the benefits and risks of the app from both individual and social perspectives using the following phrases: "What are the major positive aspects of the app for individual users?" (individual benefits), "What are the major positive aspects of the app for society?" (social benefits), "What are the major difficulties you anticipate with the app for individual users?" (individual risks), and "What are the major difficulties you anticipate with the app for society?" (social risks). The answers were coded by two researchers. The final categories, examples, and frequencies can be found in Appendix 1.

4.3. Main quantitative study methodology

Next, we used a longitudinal approach to quantitatively examine our research propositions. Unlike the great majority of IS investigations assessing intention, this design allowed us to test willingness to use along with actual behavior. In so doing, we respond to multiple calls to use empirical longitudinal studies as a tool to control for the observed intention–behavior gap (Hassan, Shiu, & Shaw, 2016; Parry et al., 2021).

4.3.1. Data collection

We chose Germany and Switzerland as our empirical setting, as both countries were similarly eager to implement the new CT technology immediately after the Exposure Notification API was deployed on iOS and Android. Moreover, the detailed specifications of the relevant apps (Corona Warn App in Germany and SwissCovid in Switzerland) were available early and described the apps' appearance, functionality, and privacy policies. This enabled us to design the survey in the pre-launch phase as realistically as possible. Finally, functionality and privacy policies exhibit similarities in adopting decentralized CTAs.

The most prominent decentralized CT technology solution was jointly introduced by Apple (2020a) and Google (2020a) in the form of the Exposure Notification API (Riemer, Peter, & Schlagwein, 2020), which was released on May 20, 2020, via automatic firmware updates in iOS 13.5 and Android 6 and above. After this date, the software implementation of decentralized CTAs was relatively easy, as proximity-based tracing using Bluetooth signals was delegated to the smartphone's operating system. Furthermore, in September 2020, Google (2020b) published an infrastructure source code that health authorities could use to quickly implement a national CT server. iOS and Android devices became able to directly connect to such servers via Exposure Notification Express without the need for an additional mobile app (Apple, 2020b).

The first round of data collection (i.e., T0) took place between June 4 and 14, 2020, when the technical documentation for the CTAs was already available, and the technology had been widely discussed in the mass media. However, no CTA had yet been launched in either Germany or Switzerland. The second round of data collection (i.e., T1) took place four weeks after the app launch date (June 16 and 25, 2020, for Germany and Switzerland, respectively), thereby ensuring sufficient time for download and usage. Participants were reached via a market research firm and were fairly compensated (Lowry, D'Arcy, Hammer, & Moody, 2016). The same panel was reinvited at T1 (see Fig. 2).

4.3.2. Longitudinal survey design and procedure

In the pre-launch phase, we started the survey with a short visual explaining the basic working principle of decentralized CT. The explanation was previously pretested with 75 participants and was found to be understandable for non–tech-savvy users. To further control for understandability, we added a multiple-choice comprehension test containing true or false statements (e.g., "In the case of a positive test result, all other users in whose vicinity I was will be notified that: 1) ...they must wear a face mask; 2) ...someone they have met has tested positive"). In total, 22 observations with less than two out of three correct answers were treated as unreliable and were hence excluded. In the main part, we asked participants about their attitudes toward CTAs, controlling for personal characteristics and demographics.

The items (Appendix 2) were adopted from previously validated instruments whenever possible and were modified to fit the research context of the COVID-19 CTA, in line with the exploratory qualitative pre-study. Specifically, since the most common categories in the open-ended questions about individual benefits were "feeling of being timely informed and thus empowered to act" and "feeling of safety," individual benefits were operationalized with the scale developed by Kim, Ferrin, and Rao (2009): "I believe the app is practical" (IB1); "I can save time by using this app" (IB2); and "Using this app will make me feel safe" (IB3). Since the most common categories regarding social benefits in the pre-study were "help containing pandemics," "coming back to normal life," and "lowering the burden on the healthcare system," we operationalized social benefits using a scale adapted from Cohen and Hoffner (2013): "The COVID-19 tracing app: …offers the opportunity to reduce the infection rate (SB1); …benefits society when returning to normal everyday life (SB2); …helps us gain greater control over the virus (SB3)." To measure individual privacy risks, we adopted the scale developed by Malhotra et al. (2004): "In general, it would be risky to disclose my personal information to this COVID-19 tracing app" (PR1); "There would be high potential for loss associated with providing my personal information to this app" (PR2); "There would be too much uncertainty associated with having my personal information gathered by this app" (PR3); "Providing the provider of the app with my personal information would involve many unexpected problems" (PR4); and "I would feel safe giving my personal information to the provider of this app" (PR5; reverse-scored). Responses to the above questions were provided on 7-point Likert scales (1 = *strongly disagree*, 7 = *strongly agree*). To operationalize social risks, which according to our qualitative pre-study mainly involved worries about mass surveillance in the future, we adapted questions from Mikalauskas (2020): "How worried are you that the app used to contain the COVID-19 pandemic could lead to greater government surveillance?" (SR1) and "How worried are you that the monitoring will become irrevocable for our everyday life?" (SR2). Possible answers ranged from 1 = *not at all* to 7 = *very much.*

In the post-launch phase (T1), we began the survey by assessing

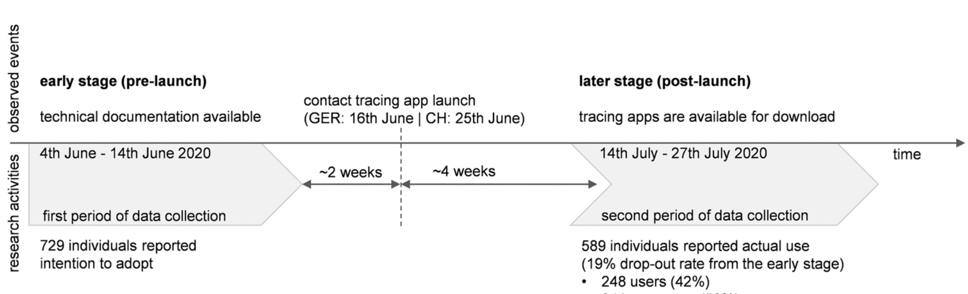

Fig. 2. Overall flow of investigation of contact tracing app acceptance.

respondents' actual current CTA use. Specifically, respondents were required to respond to the statement "I have downloaded the app and activated the risk assessment. I use it" (1 = *yes*, 0 = *no*). Acknowledging the potential bias in self-assessments of behavior, we verified positive answers following Vedadi and Warkentin (2020). Users were presented with three visually similar screenshots of the app, one of which was genuine and two of which were fake. To maximize realism, we made adjustments for the respondent's country (Germany vs. Switzerland) and mobile operating system (Android vs. iOS). This actual usage check was successfully pretested on a group of 22 students, 11 of whom were actual CTA users. In the main study, 10 participants failed the usage check and were disregarded from further analysis. After asking about actual adoption, we repeated the question catalog from T0 with minor adjustments (Appendix 2, column 3) and asked for users' and non-users' current beliefs and perceptions, in line with our research framework.

Our study design incorporated recommended techniques for reducing common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), such as including an "attention trap" item (Meade & Craig, 2012), randomizing items within blocks, measuring dependent variables before independent variables, and including a "blue attitude" construct with the items "I prefer blue to other colors," "I like the color blue," and "I like blue clothes" as a marker variable (Simmering, Fuller, Richardson, Ocal, & Atinc, 2015). Appendix 8 describes the post-hoc testing.

5. Results

5.1. Results of qualitative pre-study

In the qualitative pre-study, 75 respondents shared their opinions. Among those who disclosed their gender ($n = 66$), 53% were female. In terms of age, the sample was dominated by those between 18 and 29 years old ($n = 46$), followed by those between 30 and 49 years old ($n = 13$) and those aged 50 years or older ($n = 5$); 11 respondents did not specify their age. The majority (65.5% of valid responses) had a positive intention to accept the app, 29.3% indicated initial rejection, and 5.2% found it difficult to judge.

Expected primary individual benefits of using the app included "feeling of being timely informed and thus empowered to act" (73.2%) and "feeling of safety" (8.4%). Expected social benefits of using the app included a belief that it would aid in "containing pandemics" (53.5%), "coming back to normal life" (4.2%), and "lowering the burden on the healthcare system" (8.4%). As for anticipated individual risks, respondents considered the privacy aspect of being the most problematic (38%), followed by concerns related to reliability and accuracy of technology (19.7%) and usability (e.g., demands on smartphone battery; 9.9%). Concerning social inhibitors, the difficulty most often named by respondents was "privacy in society," "privacy as a human right" (23.9%), which translates into fear of transition to a surveillance society.

In sum, while our pre-study results confirmed the presence of an individual privacy calculus, they simultaneously informed us about the salience of the social considerations on both sides of the trade-off (Fig. 3). More specifically, although they recognized the advantages of the proposed technology for the health of the general population, respondents also questioned the consequences of mass data transmission, linking it to a common adverse outcome—namely, transition into a surveillance society. Notably, during coding, we noticed that many participants responded to the question about individual benefits with answers such as "contain the infection" and "stop the pandemic" that they later repeated in response to the social benefits question. We did not observe the same pattern for risks: Respondents clearly separated their own data storage issues from human rights concerns.

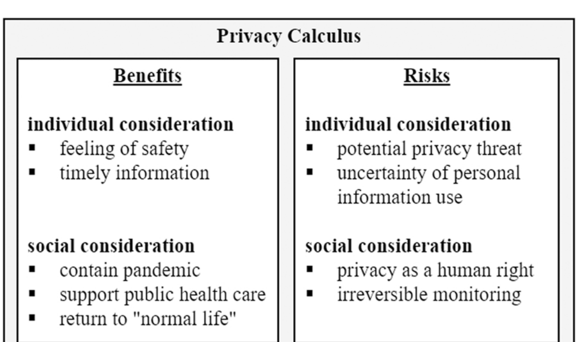

Fig. 3. Qualitative study summary: Privacy calculus extended to include individual and social contact tracing app considerations.

5.2. Results of main quantitative study

For the main longitudinal study, our final net sample contained 589 observations from both countries across both survey times (Germany: $n = 412$, Switzerland: $n = 177$). As the *t*-test did not reveal significant differences between countries for any item, we pooled the subsamples together. In terms of demographics (Table 1), 48% of respondents were female, and 63% were between 20 and 50 years old. The other characteristics of our sample largely corresponded to the demographics of Western Europe (Eurostat, 2018).

To test our hypotheses, we ran regressions on the 589 observations separately for T0 and T1 (Table 2). We modeled all constructs reflectively (Hair, Sarstedt, Ringle, & Gudergan, 2018). First, we assessed the measurement model (MM) using SmartPLS 3.3 (Ringle, Wende, & Becker, 2015). Cronbach's alpha, average variance extracted (AVE), and composite reliability (CR) were all above their recommended respective thresholds of 0.7, 0.5, and 0.7 (Bagozzi & Yi, 2012; Nunnally, 1967; see Appendix 4). When examining discriminant validity (Appendix 5), the pair of constructs "social benefits" and "individual benefits" appeared to be problematic due to high correlation ($HTMT_{SB–IB} = 0.93$) above the recommended threshold of 0.90 (Gold, Malhotra, & Segars, 2001). Recalling that, in the qualitative pre-study (Section 4.2), participants were often unable to distinguish appropriately between individual and social benefits, and given the results of the MM assessment, we decided to treat both as a single construct: "benefits" (Cronbach's $\alpha = 0.94$, $CR = 0.95$, $AVE = 0.77$). Other constructs in the MM evidenced good specificity. We provided descriptive statistics for measurements in Appendix 6.

For the dependent variable "intention to use," we estimated the structural model using bootstrapping with 5000 samples. We used logistic regression to explain the binary dependent variable "actual behavior" (1 = CTA user, 0 = CTA non-user). Mean values were computed as the average of the respective items for all multi-item constructs.

Model T0 used data from T0 and aimed to explain the intention to use CTAs in the pre-launch phase. Model T1 comprised the same constructs as measured in T1 to explain actual behavior in the post-launch period. Time-invariant controls were assessed in T0.

Model T0 explains 76.1% of the variance in intention to use a CTA and 54.0% of the variance in social risks. Effect sizes (f^2) in terms of impact on intention to use a CTA were large for benefits ($f^2(BEN \rightarrow INT) = 0.43$) and small for social risks ($f^2(SR \rightarrow INT) = 0.023$); those for other variables were less than 0.02 and thus neglectable. Effect size (f^2) for the impact of privacy risks on social risks was large (i.e., $f^2(PR \rightarrow SR) = 1.17$). The results for Model T0 indicate that the core components of privacy calculus (i.e., benefits and privacy risks), social risks, and three personality characteristics (age, trust in others, and personal innovativeness) have a significant effect on intention to use CTA during the early phase.

The results for Model T1 indicate that only the calculus-related attributes are reflected in actual behavior. Personality characteristics and environmental controls (e.g., anxiety about COVID-19) were not significantly associated with actual behavior. Adding intention to use

Table 1
Demographics of study participants.

Age group (years)	Composition (percentage)	Gender	Composition (percentage)	Occupation	Composition (percentage)
18–19	9 (1.5%)	Male	305 (51.8%)	Employed	354 (60.1%)
20–29	110 (18.7%)	Female	284 (48.2%)	Civil servant	21 (3.6%)
30–39	121 (20.6%)			Self-employed	33 (5.6%)
40–49	134 (22.8%)			Student	45 (7.6%)
50–59	134 (22.8%)			Not working	86 (14.6%)
60+	81 (13.6%)			Unemployed	17 (2.9%)
				Other	33 (5.6%)

Table 2
Structural model for acceptance intention and logistic regression for actual behavior.

Independent variable	Model T0 Intention to use CTA	Model T1 Actual use of CTA		
	M0	M1	M2	M3
Main calculus variables	β	β	β	β
Constant		**−4.64****	**−4.10****	**−4.61***
Benefits	**0.63*****	**1.11*****	**1.07*****	**1.04*****
Privacy risks	**−0.08***	**−0.48****	−0.25	−0.22
Social risks (i.e., fear of surveillance)	**−0.12*****		**−0.46****	**−0.48****
Privacy risks → Social risks (T0)	**0.74*****			
Time-variant controls				
Anxiety about COVID-19	0.02	0.12	0.15	0.14
Trust in other users	**0.11****	0.10	0.11	0.09
Correctness of technology	−0.01	−0.02	−0.04	−0.13
Time-invariant controls				
Age	**0.06****	−0.001	−0.01	−0.01
Country_Switzerland	−0.02	0.12	0.07	0.08
Gender_Female	0.03	0.13	0.13	0.17
Personal innovativeness	**0.06***	0.12	0.11	0.08
Altruism	−0.01	0.06	0.09	0.06
Perceived severity of pandemic	0.01	−0.12	−0.17	−0.27*
Suffering from lockdown	0.02	−0.04	−0.01	−0.02
General privacy concerns	−0.01	−0.01	0.05	0.14
Intention to use (T0)				**0.37*****
Goodness of fit				
R^2	0.76			
R^2 (Cox & Snell)|R^2 (Nagelkerke)		0.43| 0.58	0.44| 0.59	0.46| 0.62
Correct predictions (%)		82.2	83.70	82.70
−2 log likelihood		469.70	458.40	441.00
Number of respondents	589	589	589	589

Note: †p < *0.1*, *p < *0.05*, **p < *0.01*, ***p < *0.001*.

Table 3
Overview of hypotheses testing using contact tracing apps as a research site.

Hypothesized relationship	Support	Comment
H1: Individual benefits are positively related to CTA acceptance.	Partially supported	As part of a single construct (“benefits”)
H2: Privacy risks are negatively related to CTA acceptance.	Partially supported	Supported for dependent variable “intention to use”
H3: Individual benefits are positively related to the social benefits of a CTA.	Supported	Items for individual benefits and social benefits strongly correlated
H4: Individual risks are positively related to the social risks of a CTA.	Supported	
H5: Social benefits are positively related to acceptance of a CTA.	Partially supported	As part of a single construct (“benefits”)
H6: Social risks are negatively related to acceptance of a CTA.	Supported	

CTA from T0 did not yield significant changes in coefficients or model quality. As a robustness check, we ran the structural models for the binary variable of actual CTA use. The alternative model specification affirmed the initial results (see Appendix 7).

Altogether, our study corroborates three of our hypotheses and provides partial support for the three others. An overview of our hypotheses testing is provided in Table 3.

In the follow-up analysis, we checked whether the effect of individual calculus was mediated by social considerations. Thus, we performed a mediation analysis using the bootstrapping technique with a 95% bias-corrected confidence interval (CI) and 5000 samples based on Hayes (2018) PROCESS model 4. Since the social and individual benefits of the CTAs in our study did not evidence discriminant validity, we performed the test only on the costs side, inserting into our mediation model social risks (i.e., fear of mass surveillance) as a potential mediator, privacy risks as an independent variable, intention to use CTAs (at T0) as well as actual use of CTAs (at T1) as dependent variables, and benefits and intention to use as covariates (Fig. 4).

The results confirmed a statistically significant mediation effect of privacy risks on actual use of CTAs via fear of mass surveillance (indirect effect = −0.2271; $SE = 0.0797$; bias-corrected CI [0.3881; 0.0707]). Specifically, we found that privacy risks significantly increased fear of surveillance ($b = 0.58$, $SE = 0.027$, $p < 0.0001$). The direct effect of surveillance on actual use of CTAs was negative and significant ($b = -0.3903$, $SE = 0.1306$, $p = 0.0028$), indicating that individuals who score higher on fear of surveillance are less likely to use CTAs. When fear of surveillance is added to the model, the path (direct effect) from privacy risks to actual use of CTAs becomes insignificant ($b = -0.169$, $SE = 0.1214$, $p = 0.164$), suggesting full mediation (Zhao, Lynch, & Chen, 2010). The model with intention to use as a dependent variable suggests partial mediation (indirect effect = 0.0912; $SE = 0.0225$; bias-corrected CI [0.1358; −0.0483]). In sum, our results show that privacy risks have a negative indirect effect on actual use of CTAs via fear of surveillance.

Our study design also allowed us to examine the intention–behavior gap. All 589 respondents were non-users at T0. First, we categorized participants into two groups (inclined and disinclined) based on the median value of the intention to use construct (at T0) following Hassan et al. (2016). If the median value of the three items in the construct was greater than 4.60, the respondent was considered inclined to use a CTA (disinclined otherwise). By T1, 248 individuals had become users (i.e., had downloaded a CTA and activated the CT function), 24 had downloaded a CTA but had not activated CT, and 317 had not downloaded a CTA, with the latter two categories comprising the group of non-users ($n = 341$). In line with Sheeran (2002), we examined the relationship between intention to use and the dichotomous measure of actual behavior in a cross-tabulation (Appendix 3). The results indicate a significant association ($\varphi = 0.421$, $p < 0.001$) between intention (inclined vs. disinclined) and action (user vs. non-user), with a large proportion (almost 40%) of inclined participants not transforming their intention into behavior. The correlation between the scale-based average intention measure and behavior yielded a moderate Spearman’s correlation coefficient ($\rho = 0.508$, $p < 0.001$), implying a significant absolute intention–behavior gap.

In the next step, we assessed the differences between users and non-users based on their actual behavior (Table 4). Specifically, we used a *t*-test to check for differences in the means of our study variables at T0

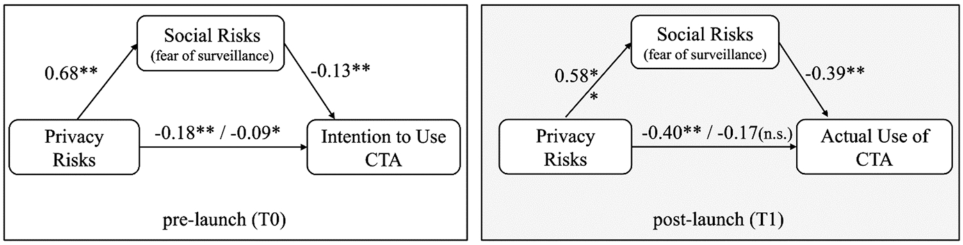

Fig. 4. Mediation analysis results. Note: The first coefficient on a given path represents the direct effect without the mediator in the model, while the second represents the direct effect when the mediator is included in the model. Coefficients were computed using bootstrapping with 5000 samples and 95% bias-corrected confidence intervals (Hayes, 2018). *$p < 0.05$, * *$p < 0.01$.

Table 4
Mean values and *t*-test differences for users versus non-users.

Variable (at T0)	Non-user by T1 (*n* = 341)	User by T1 (*n* = 248)	*t*-test
Individual benefits	**3.63**	**5.04**	−11.88**
Social benefits	**4.40**	**5.78**	−11.50**
Privacy risks	**4.66**	**3.55**	9.15**
Social risks (i.e., fear of surveillance)	**3.71**	**2.58**	10.53**
Anxiety about COVID-19	3.40	3.60	−1.79
Suffering from lockdown	**3.63**	**3.25**	2.69*
Severity of the pandemic	**5.01**	**5.71**	−6.16**
Personal innovativeness	**3.59**	**4.04**	−3.66**
General privacy concerns	**4.50**	**4.00**	4.75**
Altruism	**4.43**	**4.82**	−4.50**
Privacy experience	**2.43**	**2.17**	3.22*
Trust in other app users	**3.88**	**4.93**	−8.87**
Correctness of technology	**4.05**	**5.16**	−9.72**
Intention to use	**3.77**	**5.79**	−13.92**

related to adoption decision at T1. As illustrated in Table 4, users and non-users significantly differed in their assessments at T0. Users perceived more benefits in digital CT and scored higher on personal innovativeness and trust in other app users. They also perceived less privacy risk and expressed less fear that surveillance could become a "new normal" (i.e., social risks). The two groups did not differ in terms of anxiety about COVID-19 ($p = 0.07$), with both scoring below the midpoint. No significant differences could be attributed to demographics (i.e., country, age, gender, or employment status). These results suggest that non-users may be partly influenced by the attributes of new technology and their own individual characteristics in the early pre-launch phase (T0).

6. Discussion

Omnipresent global crises like the ongoing COVID-19 pandemic call for collective ways out (Thapa et al., 2017). As a critical component of the pandemic response together with new tests, therapeutics, and vaccines, digital CT promises to break the chain of transmission of airborne diseases and limit the spread of infections (Fahey & Hino, 2020). Building on the privacy calculus framework and accounting for the peculiarities of an interconnected society, this article presented and tested a conceptual model of CTA adoption using qualitative and longitudinal quantitative investigations of COVID-19 CTA adoption among participants from Germany and Switzerland.

The main goal of this study was to investigate the antecedents of intended and actual CTA acceptance from a privacy calculus perspective. We contend that there is a need to extend the traditional individual trade-off between benefits and privacy risks (Dinev & Hart, 2006) to include social factors. Our empirical findings based on COVID-19 CTA adoption support this proposition.

First, we observe the salience of social benefits and risks in quantitative and qualitative studies (responding to RQ2), which has previously been reported in the context of social networking sites (Wagner et al., 2018; Yu et al., 2015) and other CTAs (Hassandoust, Akhlaghpour, & Johnston, 2021). The core benefits reported in our qualitative study were social in nature, calling into question the sufficiency of the amount of individual benefits for this particular technology (RQ1). We also found statistically significant individual privacy risks ($p = 0.044$) when modeling intention to accept CTAs (RQ1), corroborating earlier findings (e.g., Hassandoust et al., 2021; Sharma et al., 2020; Trang et al., 2020).

Second, the calculus of benefits versus risks explains actual adoption behavior well. While intention to use was also influenced by demographic and personality characteristics (i.e., age, trust in others, and personal innovativeness) that have previously been shown to be significant (e.g., Trang et al., 2020), respondents' actual use did not depend on their characteristics or contextual factors (e.g., anxiety about COVID-19, suffering from lockdown).

Third, in the case of CTAs, social risks mediate the link between individual privacy risks and acceptance. We found partial mediation for intention to use and full mediation for actual use, meaning that it is not privacy risks per se that inhibit CTA acceptance. Rather, it is worries at a higher, social level—which we operationalize as fear of transition to a surveillance society—that prevent CTA acceptance.

Finally, we found evidence of a large intention–behavior gap, consistent with Parry et al.'s (2021) meta-analysis. Nearly 40% of initially inclined participants did not turn their positive intention into actual CTA use behavior.

6.1. Theoretical contributions

We believe that our study offers meaningful insights for research. As a first and superordinate contribution, our study proposes a model to explain acceptance of CTAs. Previous studies investigating CTA adoption have mainly focused on individual factors. We add to the research on CTAs by putting forward social thoughts that potential users might have upon decision-making (i.e., anticipating the omnipresence of a new CTA and the implications this may have). This study shows the interplay between individual and social considerations prior to new CTA acceptance and supports Deffuant, Huet and Amblard's (2005) point that social benefits are more important than individual ones in disseminating an innovation. The study from Trkman et al. (2021) on the CTA in Slovenia further suggests the superiority of social benefits over personal benefits in driving the intention to use proximity tracing smartphone applications.

Second, this study adds to the literature on privacy research, which has traditionally modeled technology acceptance decisions as a result of an intrapersonal trade-off between the benefits and risks to oneself (e.g., Dinev & Hart, 2006; Krasnova et al., 2010; Xu, Dinev, Smith, & Hart, 2011). Building on Nabity-Grover et al.'s (2020) work, information disclosure related to a pandemic response must consider more than personal benefits and personal costs. We extend the intrapersonal and thus self-focused perspective by incorporating the other-focused perspective, including external benefits and external costs (Nabity-Grover et al., 2020). For the context of COVID-19 CTAs, on the external benefits side, protecting others and reducing infection rate were revealed to be the most important factors. On the external costs side, fear of mass surveillance impeded adoption. Thus, we provided evidence that for CTAs, social risks (expressed as fear of mass surveillance) represent the mechanism behind the detrimental effect of privacy risks on app acceptance. With this finding, our study addresses Dinev et al.'s (2015) appeal to test other contextual factors of the privacy calculus. In this vein, our results contribute to the sparse literature on the role of perceived mass surveillance in the information privacy context (Dinev, Hart, & Mullen, 2008; Eneman, Ljungberg, Rolandsson, & Stenmark, 2020) and the recent heated disputes as to whether the close monitoring justified by the current large-scale health crisis will move us toward a "control society" (Leclercq-Vandelanoitte & Aroles, 2020). We show that people indeed consider these downsides in their calculus and are thus aware of the possible transition to a surveillance society upon mass CTA adoption. Recent research has also begun to discuss mass surveillance as a downside of controlling the spread of the virus (Leclercq-Vandelanoitte & Aroles, 2020; Riemer et al., 2020). Although systematic data collection by governments is ubiquitous, there is an ongoing tension between the benefits citizens reap from being traced (e.g., safety) and acceptance of mass surveillance (Eneman et al., 2020). Therefore, our results highlight the importance of surveillance perceptions and thus might be fruitful for future studies in the IS field. Our work thus gives an early answer to Fahey and Hino (2020), who argued that societies worldwide will be in urgent need of assessments of CTAs' success. This success, in terms of long-term usage by citizens, depends not only on the technological design of a local CTA but on citizens' awareness of data collection (e.g., anonymity vs. personal registration) and the motives of policymakers and public institutions (Fahey & Hino, 2020).

Third, in choosing emerging CTAs as a proper setting for the empirical validation of our research hypotheses, we contribute to the recent literature on COVID-19 CTAs and respond to calls for IS research in the age of pandemics (e.g., Ågerfalk, Conboy, & Myers, 2020). Early papers delivered insights into the efficiency of digital CT across countries with different operation modes (mandatory vs. voluntary use; Urbaczewski & Lee, 2020), outlined the heterogeneity of potential adopters (Trang et al., 2020), investigated diffusion strategies (Fahey & Hino, 2020) and elaborated on the reasons for the failure of data-first solutions in the United Kingdom, France, and Australia (Fahey & Hino, 2020; Rowe, 2020; Rowe, Ngwenyama, & Richet, 2020). Further, Riemer et al. (2020) proposed a conceptual framework of IT governance actions needed for mass acceptance of CTAs to occur, suggesting the absence of globally ideal solutions. However, most existing works are either theoretical in nature or use a scenario-based methodology to elicit attitudes toward digital CT, which may substantially deviate from actual user interactions (Hassan et al., 2016). While Rowe et al. (2020), Trang et al. (2020), and Wiertz, Banerjee, Acar, and Ghosh (2020) have shown how CTAs need to be designed and personalized, we provide empirical evidence on their perception and actual acceptance. A great number of publications on CTAs have used the privacy calculus model as a theoretical lens (Bonner, Naous, Legner, & Wagner, 2020; Lin, Carter, & Liu, 2021; Nabity-Grover et al., 2020). For instance, a qualitative study by Sharma et al. (2020) suggested that individuals' intention to adopt CTAs were formed by the privacy calculus together with the cultural standpoint of collectivism, which encompasses the feeling of belongingness to a community. Similarly, Hassandoust et al. (2021) reported that information privacy risks and benefits for society were significant predictors of adoption intention. These insights are in line with our theoretical framework, which we also empirically validated with actual behavior.

Fourth, from a methodological point of view, by assessing both intention and actual behavior and observing a sizable intention–behavior gap, our findings yield interdisciplinary methodological discussions. Particularly, we add to this debate by evidencing a substantial disconnect between intention and actual behavior, similar to that found in Parry et al.'s (2021) meta-review. This pattern is also known as the "privacy paradox"—the observation that, when it comes to real behavior, perceived privacy risks are much less pronounced (if they are significant at all) than studies of behavioral intentions would suggest (Alashoor and Baskerville, 2015). Our results support Wu and Du (2012) claim that studying behavioral intentions does not serve as a profound proxy for actual usage, leveraging the advantages of a two-stage study design. This is especially important when questioning the transferability of intention studies to real-world scenarios.

6.2. Implications for practice

Beyond the aforementioned theoretical contributions, our study has practical implications for providers and public institutions that operate CTAs as well as policymakers. Our results suggest that developers of CTAs intended to break contagion chains should be aware of the importance of both individual and social benefits. We deem especially individual benefits to have been overlooked in the early but important phase of introducing CTAs. At the time that we conducted our survey, public information sources in Germany and Switzerland were focused on the differences between centralized versus decentralized digital CT designs. This is also true for a variety of other countries, such as Canada, a large portion of the United States, and many countries in the EU. We observe that, in our sample, the new COVID-19 CTA failed to deliver sufficient individual utility, and social benefits alone eventually could not counterbalance overall perceived risks. Thus, we recommend that CTA developers and affiliated parties offer explicit individual benefits together with social ones to fuel acceptance. For example, Wiertz et al. (2020) demonstrated in a choice-based conjoint study in the United Kingdom that benefits, such as priority tests upon receiving an exposure notification or priority in booking food delivery while self-isolating, made CTAs more satisfactory and drove acceptance. In the same vein, digital check-ins at locations such as restaurants, theaters, retail stores, and office buildings represent a well-fit opportunity to extend the individual benefits of decentralized CTAs.

Next, awareness of social benefits as a significant acceptance driver should be ensured when a new CTA enters the market. For the particular case of COVID-19 CTAs, the population can be informed as to what extent these CTAs benefit users' social groups and communities in terms of infection rates or percentage of people with reduced severity of disease courses due to timely testing or isolation enabled by a CTA. Further research from scholars in Germany revealed that informative and motivational videos have only a marginal effect, while small monetary incentives strongly increase CTA uptake (Munzert et al., 2021).

Our study informs providers and public institutions (e.g., public health services or governments, in the case of CTAs) that the mechanism behind the observed negative link "privacy risks – CTA acceptance" are perceived social risks expressed in fear of mass surveillance. Thus, it is necessary to ensure not only individual privacy friendliness but also to mitigate perceptions of greater societal threats like the prospect of a fully monitored society. Public institutions or app providers should warrant the current and future absence of ubiquitous surveillance in line with European privacy regulations (Zimmermann et al., 2021).

In addition, a valuable finding for practice is the large proportion of individuals (40%) who intended to use the CTA but later actually refrained from using the CTA (see Appendix 3). Thus, we question the validity of ample public polls about intention to adopt CTA for planning and design purposes. Especially the opinion of inclined non-users is worth scrutiny by contracting authority of the CTA (i.e., the responsible public institution and the software developers) to react swiftly.

6.3. Limitations and future research directions

Our project has certain limitations, which we hope will be considered in future investigations. First, because we chose Germany and Switzerland as an empirical setting, our findings are most relevant for countries with similar app specifications (i.e., that opted for a decentralized model). Both countries conform to the principles of a republic that gives top priority to its citizens' freedom and self-determination. Differences across countries in mentalities (especially with regard to privacy attitudes), healthcare systems, and political systems may reduce our results' transferability (Miltgen & Peyrat-Guillard, 2014). As such, our empirical results should be understood within the Western European political and cultural setting. Similarly, we explored the dynamics of voluntary adoption of CT, which differs from the mandatory use practices in Bahrain, Kuwait, and Norway. Second, we adjusted our measurements for the research context of COVID-19 CTAs based on a qualitative pre-study. Nevertheless, we admit that the item "I can save time by using this app" may be insufficiently specific for measuring how and for what time is saved in the context of using COVID-19 CTAs. Future research should check whether the revealed individual and social considerations are also applicable to CTAs other than COVID-19 CTAs.

Overall, our work paves the way for more research in the field of CTA. While we focused on CTA acceptance in light of privacy calculus, it could be valuable for future research projects to investigate collective outcomes, such as people's prosocial behavior as the result of CTA use.

7. Conclusions

This study sheds light on the crucial and extremely timely IS of digital CT and proposed a model of CTA acceptance, extending the individual privacy calculus to incorporate social considerations. We tested our model empirically in the context of new COVID-19 CTAs using a multi-methods approach that combined a qualitative pre-study and a two-wave quantitative survey of a sample of 589 German and Swiss respondents (Germany: $n = 412$, Switzerland: $n = 177$). We observed that, in interconnected settings such as a global health crisis, people incorporate social factors into their decision formation in addition to considering the benefits and risks to themselves. Social thoughts can, depending on their valence, either drive or hinder acceptance. The latter occurs mainly due to the fear of turning into a surveillance society in the near future. If embedded in CTAs, ethical surveillance needs to be applied and communicated mindfully; otherwise, as exemplified by the adoption of COVID-19 CTAs in Germany and Switzerland in our sample, the voluntary adoption of CTAs risks failing to reach critical mass.

CRediT authorship contribution statement

Olga Abramova: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, revision. **Amina Wagner:** Conceptualization, Writing – original draft, Project administration. **Christian M. Olt:** Conceptualization, Visualization, Software, Resources. **Peter Buxmann:** Supervision, Funding acquisition.

Acknowledgment

The project was funded and supported by the German Federal Ministry of Education and Research and the Hessen State Ministry for Higher Education, Research and Arts within their joint support of the National Research Center for Applied Cybersecurity ATHENE.

Appendix 1. Question catalog in qualitative pre-study with exemplary quotes

Question	Concept	Quotes	Freq.
What are the major positive aspects of the app for individual users?	Feeling of being informed and thus empowered to act	"Fast testing and treatment possible" "To know that you might be in danger"	52
	Feeling of safety	"Feeling of safety"	6
	No personal benefits perceived	"To my mind, I cannot find any useful aspects."	5
	Other	–	4
What are the major positive aspects of the app for society?	To contain pandemics	"Contain infection," "stop pandemic"	38
	To come back to normal life	"Societal reopening and more normality" "Relaxation of measures possible"	3
	Lower burden on healthcare system	"No overload of hospitals"	6
What are the major difficulties you anticipate with the app for individual users?	Privacy	"Privacy and data tracking. I am against such apps that collect this type of information that can be easily misused by anyone."	27
	Reliability, accuracy of technology	"It should be taken care to choose a reasonable radius. People who are too far away to be affected by airborne infection should not be notified unnecessarily"	14
	Usability, battery life	"The app must be designed to be very simple and intuitive so that everyone can use it without any problems."	7
What are the major difficulties you anticipate with the app for society?	Mass adoption[a]	"In order for the contact tracing app to be used successfully, a certain threshold of users must be reached."	27
	Privacy in society, privacy as a human right	"Hacking attack, lose personal information about people"	17

[a] Reflected in outcome variable.

Appendix 2. Measurement for main study

Variable	Definition	Items in pre-adoption phase (T0)	Items in post-adoption phase (T1)
Main calculus variables			
CTA acceptance	Intention to use (T0): Individual's intention to use CTAs (Sun, 2013) Actual use (T1): Individual's actual usage of CTAs	INT1: I would download the COVID-19 tracing app. INT2: I intend to download the app. INT3: It is very likely that I will try the app in the near future.	USE 1: I have downloaded the app and activated the risk assessment. I use it. As an actual usage check, users were required to distinguish a genuine screenshot of the app from similar fakes (Vedadi & Warkentin, 2020).
Individual benefits (Kim et al., 2009)	Positive attributes that users themselves anticipate or perceive to result from adopting a CTA (Kim et al., 2009)	IB1: I believe the app is practical. IB2: I can save time by using this app. IB3: Using this app will make me feel safe.	IB1: I believe the app is practical. IB2: I can save time by using this app. IB3: Using this app will make me feel safe.
Social benefits (adapted fromCohen & Hoffner, 2013)	Perceived positive outcomes of CTA adoption for the community based on social considerations (Cohen & Hoffner, 2013)	The COVID-19 tracing app would… SB1: offer the opportunity to reduce the infection rate. SB2: benefit society when returning to normal everyday life. SB3: help us gain greater control over the virus.	The <local term>… SB1: offers the opportunity to reduce the infection rate. SB2: benefits society when returning to normal everyday life. SB3: helps us gain greater control over the virus.
Individual privacy risks (Malhotra et al., 2004)	Perceived risks of information disclosure to CTAs through losing control over one's personal information (Malhotra et al., 2004)	PR1: In general, it would be risky to disclose my personal information to this COVID-19 tracing app. PR2: There would be high potential for loss associated with providing my personal information to this app. PR3: There would be too much uncertainty associated with having my personal information gathered by this app. PR4: Providing the provider of the app with my personal information would involve many unexpected problems. PR5: I would feel safe giving my personal information to the provider of this app.	PR1: In general, it is risky to disclose my personal information to the <national term>. PR2: There is high potential for loss associated with providing my personal information to this app. PR3: There is too much uncertainty associated with having my personal information gathered by this app. PR4: Providing the provider of the app with my personal information involves many unexpected problems. PR5: I feel safe giving my personal information to the provider of this app.
Social risks (fear of mass surveillance; adapted from Mikalauskas, 2020)	Perceived negative outcomes of CTA adoption for the community based on social considerations	SR1: How worried are you that the app used to contain the COVID-19 pandemic could lead to greater government surveillance? SR2: How worried are you that the monitoring will become irrevocable for our everyday life? (not at all–very much)	SR1: How worried are you that the app used to contain the COVID-19 pandemic could lead to greater government surveillance? SR2: How worried are you that the monitoring will become irrevocable for our everyday life? (not at all–very much)
Time-variant controls			
Anxiety about COVID-19 (Gómez, Hidalgo, & Tomás-Sábado, 2007)	Emotional state of anxiety or having worries because of COVID-19 (Gómez et al., 2007)	ANX1: It makes me nervous to hear/read about COVID-19. ANX2: I think I'm more afraid to get infected with COVID-19 than most people. ANX3: The idea of infecting myself with COVID-19 worries me. ANX4: I am worried that people who are important to me could be infected with COVID-19.	ANX1: It makes me nervous to hear/read about COVID-19. ANX2: I think I'm more afraid to get infected with COVID-19 than most people. ANX3: The idea of infecting myself with COVID-19 worries me. ANX4: I am worried that people who are important to me could be infected with COVID-19.
Trust in other users (Turel, Yuan, & Connelly, 2008)	Perception of trust in other users of CTAs regarding their reliability and honesty in continuously using CTAs and subsequently reporting valid positive test results (Turel et al., 2008)	TRO1: I can count on the other COVID-19 tracing app users. TRO2: I can trust the other app users throughout these pandemic times. The other app users can be trusted. TRO3: When other app users receive a positive test result, I know I can count on these persons for cooperation.	TRO1: I can count on the other <national term> users. TRO2: I can trust the other app users throughout these pandemic times. The other app users can be trusted. TRO3: When other app users receive a positive test result, I know I can count on these persons for cooperation.
Correctness of technology (Gefen & Ridings, 2002)	Perception of trust in the accurate functionality of CTAs, such as reliability of distance measuring, exchange and storage of contact information, and truthfulness of the information provided by CTAs (Gefen & Ridings, 2002)	COR1: I can trust that the technology for contact tracing works dependably. COR2: I trust that the stored contacts are accurate. COR3: I can trust the correctness of the notifications and recommendations of this app. COR4: I can rely on the technology to trace contacts.	COR1: I can trust that the technology for contact tracing works dependably. COR2: I trust that the stored contacts are accurate. COR3: I can trust the correctness of the notifications and recommendations of this app. COR4: I can rely on the technology to trace contacts.
Time-invariant controls			
Personal innovativeness (Sun, 2013)	Individual's willingness to try out any new information technology (Agarwal & Prasad, 1998)	INNOV1: When I hear about a new piece of information technology, I generally think about ways I could use and experiment with it. INNOV2: Among my peers, I am usually the first to try out new information technologies. INNOV3: I like to experiment with new information technologies."	
Altruism (Anderson & Agarwal, 2011)		ALT1: Helping others is one of the most important aspects of life.	

(*continued on next page*)

(*continued*)

Variable	Definition	Items in pre-adoption phase (T0)	Items in post-adoption phase (T1)
	Individual's tendency to be sympathetic and generous toward those in need (Cohen, Wolf, Panter, & Insko, 2011)	ALT2: I enjoy working for the welfare of others. ALT3: My family tends to do what we can to help those less fortunate than ourselves. ALT4: I agree with the old saying, "It is better to give than to receive."	
Perceived severity of COVID-19 pandemic (Witte, 1996)	Expected magnitude of harm caused by COVID-19 (Witte, 1996)	SEV1: I believe that COVID-19 is severe. SEV2: I believe that COVID-19 is serious. SEV3: I believe that COVID-19 is significant.	
Suffering from lockdown (self-developed)		To what extent do you suffer from COVID-19 lockdown measures? (not at all–very much)	
General privacy concerns (Malhotra et al., 2004)	Individual's General worries about possible loss of information privacy (Malhotra et al., 2004)	GPC1: Compared to others, I am more sensitive about the way online companies handle my personal information. GPC2: To me, it is the most important thing to keep my privacy intact from online companies. GPC3: I am concerned about threats to my personal privacy today.	

Appendix 3. Assessing direct intention–behavior relationship

Germany	Users		Non-users		Total
Inclined	139	(61%)	90	(39%)	229
Non-inclined	33	(18%)	150	(82%)	183
Switzerland	Users		Non-users		Total
Inclined	67	(57%)	50	(43%)	117
Non-inclined	9	(15%)	51	(85%)	60
Germany and Switzerland	Users		Non-users		Total
Inclined	206	(60%)	140	(40%)	346
Non-inclined	42	(17%)	201	(83%)	243

Note: If a respondent's median score for the three items of the construct "intention to use" was > 4.60, that respondent was considered inclined (disinclined otherwise).

Appendix 4. Construct reliability and validity

Construct	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Altruism	0.841	0.845	0.893	0.676
Anxiety	0.795	0.859	0.860	0.610
Correctness	0.953	0.954	0.966	0.878
General privacy concerns	0.806	0.934	0.878	0.706
Individual benefits	0.865	0.894	0.917	0.787
Innovativeness	0.893	0.911	0.933	0.823
Intention to use	0.977	0.977	0.985	0.956
Privacy risk	0.937	0.937	0.889	0.800
Severity	0.924	0.925	0.952	0.868
Social benefits	0.932	0.934	0.957	0.881
Surveillance	0.936	0.947	0.969	0.939
Trust in others	0.958	0.959	0.970	0.889

Appendix 5. Discriminant validity assessment using heterotrait–monotrait ratio of correlations (HTMT) and square root of AVE (diagonal elements)

	ALT	ANX	COR	GPC	IB	INN	INT	PR	SEV	SB	SURV	TRO
Altruism (ALT)	**0.822**											
Anxiety (ANX)	0.233	**0.781**										
Correctness (COR)	0.287	0.277	**0.937**									
General privacy concerns (GPC)	0.050	0.124	0.383	**0.840**								
Individual benefits (IB)	0.298	0.325	0.846	0.318	**0.887**							
Innovativeness (INN)	0.095	0.120	0.113	0.053	0.108	**0.907**						
Intention to use (INT)	0.228	0.281	0.750	0.349	0.889	0.131	**0.978**					
Privacy risk (PR)	0.156	0.158	0.755	0.564	0.768	0.056	0.720	**0.894**				
Severity (SEV)	0.263	0.592	0.465	0.073	0.482	0.059	0.462	0.388	**0.932**			
Social benefits (SB)	0.236	0.296	0.814	0.374	**0.932**	0.062	0.843	0.708	0.501	**0.938**		
Surveillance (SURV)	0.122	0.122	0.602	0.528	0.598	0.075	0.625	0.784	0.360	0.576	**0.969**	
Trust in others (TRO)	0.303	0.234	0.782	0.261	0.808	0.136	0.726	0.624	0.401	0.749	0.489	**0.943**

Appendix 6. Descriptive statistics for variables used in regressions

	Construct in T0		Construct in T1	
Main calculus variables	Mean	SD	Mean	SD
Benefits	4.601	1.820	4.323	1.917
Privacy risk	4.193	1.757	3.687	1.866
Social risks (i.e., fear of surveillance)	3.236	1.444	2.786	1.468
Time-variant controls				
Anxiety about COVID-19	3.483	1.889	3.628	1.881
Trust in other users	4.323	1.606	4.112	1.570
Correctness of technology	4.519	1.566	4.408	1.647
Time-invariant controls				
Age	43.611	13.658		
Country_Switzerland	0.301	0.458		
Gender_Female	0.482	0.500		
Altruism	4.596	1.289		
General privacy concerns	4.290	1.552		
Innovativeness	3.779	1.652		
Perceived severity of pandemic	5.305	1.520		
Intention to use (T0)	4.620	2.052		

Appendix 7. Robustness check

As a robustness check, we estimated a structural model in SmartPLS for the binary variable "actual CTA use" as an alternative to a logistic regression model. The same independent variables were used.

Independent variable	Model T1 Actual use of CTA (T1)		
	M1	M2	M3
Main calculus variables	β	β	β
Benefits	**0.54** * **	**0.51** * **	**0.46** * **
Privacy risks	**−0.25** * **	**−0.12** *	−0.10†
Social risks (i.e., fear of surveillance)		**−0.22** * **	**−0.22** * **
Privacy risks →Social risks (T1)		**0.79** * **	**0.79** * **
Time-variant controls			
Anxiety about COVID-19	0.01	0.03	0.02
Trust in other users	−0.01	−0.01	−0.01
Correctness of technology	−0.05	−0.06	−0.08
Time-invariant controls			
Age	0.02	0.004	−0.02
Country_Switzerland	−0.02	−0.02	−0.02
Gender_Female	−0.02	−0.02	−0.02
Personal innovativeness	**0.06** *	0.06†	0.05
Altruism		0.04	0.03
Perceived severity of pandemic	−0.07†	**−0.09** *	**−0.12** *
Suffering from lockdown	−0.001	0.02	0.01
General privacy concerns	0.03	0.05	**0.08** *
Intention to use (T0)			**0.17** * **
Goodness of fit			
R^2	0.43	0.45	0.46
Number of respondents	529	529	529

Note: †p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001
Effect sizes in M1: f^2(BEN→USE) = 0.114, f^2(PR→USE) = 0.048
Effect sizes in M2: f^2(BEN→USE) = 0.104, f^2(SR→USE) = 0.027, f^2(PR→SR) = 1.700. Variance explained: R^2(PR→SR) = 0.63
Effect sizes in M3: f^2(BEN→USE) = 0.084, f^2(SR→USE) = 0.029, f^2(INT→USE) = 0.025, f^2(PR→SR) = 1.700. Variance explained: R^2(PR→SR) = 0.6.

Appendix 8. Common method bias

Beyond procedural remedies to minimize common method variance, the marker variable technique was applied post hoc using the construct "blue attitude." First, we ran baseline structural models. Second, we added the blue attitude construct as a predictor for all endogenous variables (i.e., intention to use/actual use and social risks). The relationships among all primary constructs remained unchanged, signifying that common method bias did not alter the results.

Independent variable	Model T0 Intention to use CTA	Model T1 Actual use of CTA (T1)	Model T0 Intention to use CTA	Model T1 Actual use of CTA (T1)
	Without marker variable		*With marker variable*	
	M0	M3	M0	M3
Main calculus variables	β	β	β	β
Benefits	**0.63** * **	**0.46** * **	**0.63** * **	**0.47** * **
Privacy risks	**−0.08** *	−0.10†	−0.08†	−0.10†
Social risks (i.e., fear of surveillance)	**−0.12** * **	**−0.22** * **	**−0.12** * **	**−0.22** * **
Privacy risks → Social risks	**0.74** * **	**0.79** * **	**0.74** * **	**0.79** * **
Time-variant controls				
Anxiety about COVID-19	0.02	0.02	0.02	0.01
Trust in other users	**0.11** * *	−0.01	**0.11** * *	−0.02
Correctness of technology	−0.01	−0.08	−0.01	−0.08
Time-invariant controls				
Age	**0.06** * *	−0.02	**0.06** * *	−0.02
Country_Switzerland	−0.02	−0.02	−0.03	−0.02
Gender_Female	0.03	−0.02	0.03	−0.02
Personal innovativeness	**0.06** *	0.05	**0.06** *	0.05
Altruism	−0.01	0.03	−0.01	0.03
Perceived severity of pandemic	0.01	**−0.12** *	0.01	**−0.11** *
Suffering from lockdown	0.02	0.01	0.02	0.02
General privacy concerns	−0.01	**0.08** *	−0.01	**0.08** *
Intention to use (T0)		**0.17** * **		**0.16** * **
Marker variable				
Marker → Intention to use			0.02	−0.05
Marker → Social risks			0.04	−0.01
Goodness of fit				
R^2	0.76	0.46	0.76	0.46
Number of respondents	529	529	529	529

Note: †p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001

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