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One app to trace them all? Examining app specifications for mass acceptance of contact-tracing apps

The current COVID-19 crisis has seen governments worldwide mobilising to develop and implement contact-tracing apps as an integral part of their lockdown exit strategies. The challenge facing policy makers is that tracing can only be effective if the vast majority of the population uses the *one* app developed; its specifications must therefore be carefully considered. We theorise on tracing apps and mass acceptance and conduct a full-factorial experiment to investigate how app installation intention is influenced by different app specifications based on three benefit appeals, two privacy designs, and two convenience designs. By applying quantile regression, we not only estimate the general effect of these app specifications but also uncover how their influence differs among citizens with different propensities for acceptance (i.e. critics, undecided, advocates)—a crucial insight for succeeding with mass acceptance. This study contributes to research in three ways: we theorise how mass acceptance differs from established app acceptance, we provide a fine-grained approach to investigating the app specifications salient for mass acceptance, and we reveal contextualised insights specific to tracing apps with multi-layered benefit structures. Our findings can guide policy makers by providing specification recommendations for facilitating mass acceptance of tracing apps during pandemics or other societal crises.

Keywords: coronavirus; contact-tracing apps; mass acceptance; benefit appeals; privacy; convenience

Introduction

The COVID-19 (coronavirus disease 2019) pandemic has forced governments worldwide to place their countries in lockdown to contain the spread of the virus. However, these lockdowns come with severe economic and social consequences. One promising yet controversial solution to this dilemma is the implementation of contact-tracing apps (hereafter referred to as tracing apps). Such apps exploit mobile technologies to quickly identify and inform users who may have come into contact with an infected person, thus curbing the spread of COVID-19 (Ferretti et al., 2020). Accordingly, governments across the globe are scrambling to introduce tracing apps as a key element of their lockdown exit strategies.

To render such tracing and informing effective for supressing virus transmission, it has been estimated that more than half of a country's population must install and actively use the *one* app that the government rolls out (Hinch et al., 2020). However, most governments plan to introduce their apps on a voluntary basis (Meade, 2020; Merkel, 2020). Therefore, understanding how to achieve mass acceptance is a primary concern for the policy makers responsible for designing and promoting the app. This becomes even more critical given that mere announcements of tracing apps have sparked heated debates regarding their actual benefits (e.g. why healthy citizens should use them), privacy issues (e.g. gathering sensitive data), and usability issues (e.g. battery consumption) (Birnbaum & Spolar, 2020; Miller & Abboud, 2020; Taylor, 2020). Furthermore, surveys on tracing app acceptance have revealed a substantial rift in the population with those in favour and against voicing particularly strong positive and negative opinions on these apps, and a considerable share of the population ambivalent on installing and using them (YouGov, 2020a, 2020b).

In this unique and urgent situation, policy makers must be armed with knowledge to design strategies for encouraging mass tracing app acceptance. While they cannot circumvent app characteristics that come with contact-tracing functionality, they have leeway in choosing between different app specifications that are directly linked to those characteristics of tracing apps that citizens have voiced significant concerns about. Furthermore, keeping the goal of mass acceptance in mind, it is of utmost importance to understand which app specifications matter most for those who may be more difficult to convince. Accordingly, this research is motivated by the following question: *How should tracing apps be specified to achieve mass acceptance?*

We develop a theoretical explanation of the impact of various app specifications (i.e. benefit appeal, privacy design, and convenience design) on app acceptance and challenge the assumption that all segments of the population will respond alike to different app specifications in the context of tracing apps. Building upon an experimental study with 518 participants, we first establish the general influence of the app specifications. We then exploit the participants' heterogeneous propensities for app acceptance and uncover how, beyond the general influence, the effect of app specifications on app acceptance differs across three-categories of citizens—critics, undecided, and advocates.

Our study contributes to both research and policy relating to mobile apps requiring mass acceptance in general and apps for contact-tracing in particular. From a research perspective, our theoretical and empirical approach to understanding the mass acceptance of tracing apps advances our understanding on apps that—if they achieve mass acceptance—contribute to the greater good. From a policy perspective, the findings will be valuable for designing and promoting tracing apps according to population characteristics (e.g. whether they are largely critics, undecided, or advocates), thereby offering a better chance of successful app exploitation.

Research context: The nature of tracing apps and mass acceptance during times of pandemics

While the success of a tracing app depends largely on mass acceptance, we lack a systematic understanding of what makes individuals willing to install and use such an app. To be specific, the unique characteristics inherent to tracing apps require a contextualised understanding of the links between their design specifications and mass acceptance. First, the benefit structure (i.e. the primary motive for using an app) is different from other health apps that focus on improving user health, such as fitness or nutrition apps (Kim & Park, 2012). Similar to the use of vaccines or voluntary blood donation (Bonafide & Vanable, 2015; Sojka & Sojka, 2008), tracing apps have the potential to realise a duality of benefits: not only a benefit for the self (i.e. being informed about high-risk contacts) but also a societal benefit (i.e. contributing to broader tracing coverage and informing others if infected).

Second, tracing apps can only function if they have access to an individual's data (Sharma & Bashir, 2020). Indeed, they trace contacts either by using sensitive, location-based data that requires access to a smartphone's GPS or by employing Bluetooth technology to identify and store less-sensitive data from users in the proximity. The apps can also differ in terms of where the contact data is stored and who has access to it. Contact data is either stored and processed entirely on the mobile phone with a high level of control for the user or it is transferred, stored, and processed using a central server, outside the user's control (Zastrow, 2020).

Third, tracing apps must run continuously to ensure real-time data retrieval thereby potentially causing inconveniences to users (Zastrow, 2020). However, there may be various degrees of inconvenience depending on whether user actions are required to keep the app active, whether frequent updates are required to ensure the most effective functionality, and based on the level of battery drain that results thereof (i.e. due to behavioural tracking) (Kelion, 2020; Taylor, 2020).

Finally, existing research on predicting app demand (e.g. Ghose & Han, 2014) and app usage (e.g. Rutz et al., 2019) points to considerable heterogeneity across apps. While consumer apps or other health apps can be optimised to fit the needs of a particular target group (Zhang et al., 2019), there can only be one set of specifications for tracing apps. That must then succeed in convincing a large majority of the population—potentially even critics—to install and use the app (Morley et al., 2020).

Theoretical foundation

Based on the contextual understanding of tracing apps presented above, we can identify three corresponding app design specifications: benefit appeals, privacy design, and convenience design. Below, we build upon prior literature on prosocial behaviour, privacy, and usability to provide a theoretical explanation for the relationships between these specifications and mass acceptance.

Benefits of tracing apps and appeals for prosocial behaviour

Benefit appeals can be broadly understood as calls to action that offer reasons for adopting individual behaviours (White & Simpson, 2013). For example, they can highlight benefits to the self (self-benefit appeal; e.g. "By using the app, you make an important contribution to your personal health") or to society (societal-benefit appeal; e.g. "By using the app, you make an important contribution to the health of the population")

(White & Simpson, 2013). The former pertains to citizens choosing to install the app based on their own wants and needs, a decision driven by cost–benefit calculations (Blau, 1964). In contrast, the latter relates to putting aside personal needs and prioritising those of others, a decision driven by the motivation to conform to social norms and/or altruism (White & Peloza, 2009; White & Simpson, 2013). We find broad support across a range of technologies (Venkatesh et al. 2003)—including health apps (Briz-Ponce & García-Peñalvo, 2015; Kim & Park, 2012)—examined to determine how benefits that users draw for themselves when using an app affect acceptance. Although studies in other technology contexts have touched upon the collective benefits of usage (e.g. volunteer computing; Nov et al., 2011; Raddick et al., 2009), to the best of our knowledge, no study has examined the effect of societal-benefit appeals on app acceptance. Although policy makers might opt for a combination of both appeals following the mantra of "the more, the better," we lack evidence on whether combining both appeal types yields synergetic or countervailing effects.

To achieve mass acceptance of a tracing app, citizens must be made aware of its benefits. As such apps offer advantages for both individuals and society as a whole, a well-informed citizen's decision to install the app does not solely represent a decision driven by typical consumption motives, but instead it represents a manifestation of self-beneficial and/or prosocial behaviour (White et al., 2019; White & Peloza, 2009). Accordingly, when it comes time for policy makers to promote the app, they must decide which benefit(s) to highlight using benefit appeals.

Sensitive data and privacy concerns

Literature on information privacy informs this study by expanding on how privacy design affects app acceptance via users' privacy concerns (Dinev et al., 2015; Malhotra et al., 2004). Information privacy refers to individuals' control over the conditions under which their personal information is collected and used (Bélanger & Crossler, 2011). An app's privacy design can differ in terms of the amount and type of sensitive information required (e.g. "data minimisation", i.e. only collect what is strictly necessary) and the extent of control over access (e.g., "need-to-know principle and least privileges", i.e. where does the data reside and who has access to it) (Cavoukian, 2009). As a loss of information privacy renders users vulnerable to various types of privacy risks, they evaluate information sensitivity and loss of information control before disclosing information (Malhotra et al., 2004). For example, research on mobile devices and apps has suggested how different types of hardware designs influence privacy concerns and user acceptance (Venkatesh et al., 2017), how users prefer control to steer information access (Sadeh et al., 2009), and how app permission requirements decrease installation intentions (Gu et al., 2017). As privacy concerns are a main inhibitor for app acceptance (Dinev et al., 2015), it stands to reason that an app's privacy design affects acceptance.

For contact tracing to work, the apps need to access and process sensitive data. A citizen's decision to install the app would depend on the app's privacy design in terms of sensitivity (e.g. GPS tracking vs. Bluetooth tracing) and control (e.g. centralised vs. decentralised data processing; restricted vs. extended data usage). It is then up to policy makers to determine the privacy design specification that maximises adoption.

Constant usage and usability requirements

Literature on usability informs this study by highlighting how convenience design affects app acceptance (Hoehle & Venkatesh, 2015). A convenient design reduces the time and effort required to use an app (Chan et al., 2010) and is influenced by interface characteristics (e.g. graphics, information presentation, and input mechanisms) and application design (e.g. responsiveness or data preservation) (Hoehle & Venkatesh, 2015). Poor interface and application designs that require extra time and effort can lead to higher effort expectancies, greater dissatisfaction and unfavourable user attitudes towards the app (Adipat et al., 2011; Hoehle & Venkatesh, 2015).

Since tracing apps must capture real-time data and require constant use, issues of convenience may arise, such as more frequent battery charging, update procedures, and restricted usage of one's mobile phone for other purposes. However, these nuisances can be reduced through a well-devised convenience design that is optimised for low battery consumption, has automated updating procedures, and runs smoothly in the background. As citizens are likely to view a tracing app with a high convenience design as involving less time and effort (Berry et al., 2002), they would also be more likely to install such an app. However, from a policy perspective, achieving high convenience requires additional investments of both time and money, with the former being particularly scarce during the COVID-19 pandemic or other such crises.

Different propensities for app acceptance and user-centred design

Studies on the drivers of mobile app acceptance in general (Ghose & Han, 2014) and health apps in particular (Briz-Ponce & García-Peñalvo, 2015; Kim & Park, 2012) have highlighted the importance of identifying mobile app specifications that best meet the requirements of the target group (Zhang et al., 2019). However, the situation is more complex for the case of tracing apps, which must reach the vast majority of a country's population to work effectively. This means that providers are faced with a heterogeneous mass of citizens who due to differing situational and psychological circumstances vary in their propensity to install the app. This plethora of factors—unobservable to app providers—manifests in individual differences regarding app acceptance, which may in turn influence the effectiveness of benefit appeals, privacy design, and convenience design.

This has important consequences for the unique context of mass acceptance. We expect that the influence of app design specifications on acceptance is not uniform across citizens, instead differing according to one's propensity to use the app in the first place. Contextualised insights on whether and how app specifications should differ as such is the key information policy makers need to reach critical mass.

Drawing on the theoretical background above, we have established benefit appeals for prosocial behaviour, privacy design, and convenience design as key specification options of acceptance. Furthermore, the discussion above suggests that the effects of these specifications are likely to depend on individual differences among citizens, which manifests in different propensities for app acceptance. We formulate two research propositions that describe the impact of tracing app specifications on acceptance at the aggregate (Proposition 1) and at the disaggregate level across groups of citizens with different propensities (Proposition 2). Table 1 summarises these considerations and the two formalised propositions that guide our investigation.

[Insert Table 1 about here]

Research design

Setting of the study and data collection

We selected Germany as the empirical setting, collecting data during the rise of the COVID-19 pandemic but after the government had announced the development of an official tracing app. Thus, the general idea of a voluntary app was known but its exact characteristics remained to be determined – rendering this setting suitable to investigate alternative app specifications.

On 22 March 2020, the German federal and state governments agreed on comprehensive guidelines for the restriction of social contact, which included the closure of schools, restaurants, and personal hygiene services, as well as a ban on gatherings in public places (Bundesregierung, 2020). At the beginning of April, the government reported that it would in principle approve the introduction of a voluntary app for tracking and disrupting infection chains (Merkel, 2020). The subsequent weeks saw a controversial debate about general privacy issues and the usefulness of such an app take spotlight in the public media. We collected data in Germany between 20 and 24 April, recruiting participants (n = 518) for a nominal payment through Clickworker, a large Western European crowdsourcing platform. Using a crowdsourcing platform for recruiting our sample seems particularly appropriate in our study that aims at investigating a great variety of individuals with diverse cognition (Jia et al., 2017). Moreover, it allowed us to carry out our study within the temporally distinct and unique window of time during which the app was announced but not yet released. Our recruiting procedures and screening techniques followed the recommendations for crowdsourcing platforms (Jia et al., 2017). To avoid potential biases (e.g. lack of attentiveness, lack of ability, self-selection, social desirability and non-independence of participants), we applied procedural remedies that included attention checks, comprehension checks, a moderate compensation, explanations highlighting the importance of the study, neutral wording, no exclusion through filtering, a warning that inattentive respondents will not be paid, quality control, ID comparison, and a large sample (Jia et al., 2017, Lowry et al 2016).

Experimental design, pretest and sampling

To test our research model, we conducted a scenario experiment using the three app design features identified in the previous section. We chose a full-factorial 3 (benefit appeal: self vs. societal vs. self and societal) × 2 (privacy design: low vs. high) × 2 (convenience design: low vs. high) between-subjects design. To avoid any past experience effects regarding the app provider, we developed various designs for a fictitious app named COV-19 WATCH. The manipulations of the individual design elements were grounded in observations of the public debate and reflected real-life design and communication options. As a manipulation stimulus, we chose to present the app and its features in a mock app store product page (see Appendix A for the scenario treatments and Appendix B for an example of the mock product page). We conducted a pretest with 100 participants to ensure the effectiveness of the stimulus material.

Across the different treatment groups, we collected 518 questionnaires where participants correctly answered questions regarding the app's general functionality and design aspects, showed no overly inconsistent response behaviour on a repeated question in questionnaire (deviation ≤ 2), and read all text carefully without taking overly long breaks. The average age of participants was 34 years, with 47.5% female. Of these respondents, 9.5% stated that their highest level of education completed was middle school or equivalent, 46.9% had a high school degree or equivalent, and 43.6% held a university degree or equivalent.

Experimental procedure

Participants were randomly exposed to one of the twelve conditions containing different versions of the COV-19 WATCH app. The participants were distributed evenly across the different treatment groups: privacy (low: 257; high: 261), inconvenience (low: 251; high: 267), benefit appeal (self: 179; societal: 161; self/societal: 178).

After exposure to a treatment condition, participants answered questions related to the dependent variable (Installation Intention), control variables (Coronavirus Anxiety, General Privacy Concerns, and IT Self-Efficacy), manipulation checks, comprehension checks, attention checks, realism checks, and demographics. A full list of measurement items including item loadings and Cronbach's alpha can be found in Appendix C, with summary statistics given in Appendix D.

Manipulation checks suggest that all treatments were processed as intended (see Appendix E). The confound checks revealed that participants perceived all app design scenarios to be sufficiently realistic ($M_{perceived\_realism} = 5.29$ across all scenarios) and we found no differences in perceived realism among all scenarios ($F(2, 513) = 1.271$, $p = .281$).

Results

Model specification

We analysed our data in two steps to identify how tracing apps should be specified to encourage acceptance. First, we relied on ordinary least squares (OLS) regression to gain insights on how the mean of installation intention changes with our manipulations. We specified a regression equation that includes the experimental treatment variables and control variables for individual predispositions and demographics:

$$\begin{aligned}\text{Installation\_Intention}_i = {} & \beta_0 + \beta_1 \times \text{Societal\_Benefit\_Appeal}_i + \beta_2 \times \text{Self-Societal\_Benefit\_Appeal}_i \\ & + \beta_3 \times \text{High\_Privacy\_Design}_i + \beta_4 \times \text{High\_Convenience\_Design}_i \\ & + \beta_5 \times \text{General Privacy Concern}_i + \beta_6 \times \text{Coronavirus Anxiety}_i + \beta_7 \times \text{IT-Self-Efficacy}_i \\ & + \beta_8 \times \text{Age}_i + \beta_9 \times \text{Female}_i + \beta_{10} \times \text{Education}_i + e_i. \qquad (1)\end{aligned}$$

In a second step, we expanded the analysis to gain insights into different parts of the distribution of our dependent variable. The descriptive analysis of the frequency distribution of installation intention indicates a multimodal distribution with a spike at the left side, one right of the middle, and another at the right side of our scale. In other words, these different peaks in the data indicate the existence of different groups. This observation aligns well with our expectation of strongly varying individual predispositions regarding the app and reinforces our motivation to conduct quantile regressions to examine whether the app design choices and the benefit appeal have differential effects across the distribution (Boichuk et al., 2019; Kishore et al., 2013).

In contrast to OLS regressions, quantile regressions do not maximise for the mean but for a given quantile (Koenker & Bassett Jr, 1982; Li, 2015). In such a conditional quantile model—for example, the .25 quantile—quantile regressions fit a regression line that passes through data points with 25% of the data points below and

75% above by minimising the sum of absolute residuals. Quantile regression analysis allows us to examine whether the effect of our manipulations varies across different parts of the installation intention distribution. In doing so, we rely on the following quantile regression specification where the quantiles are indexed by θ:

$$\begin{aligned}
\text{Quant}_\theta[\text{Installation_Intention}_i] = {} & \gamma_{0,\theta} + \gamma_{1,\theta} \times \text{Societal_Benefit_Appeal}_i \\
& + \gamma_{2,\theta} \times \text{Self-Societal_Benefit_Appeal}_i + \gamma_{3,\theta} \times \text{High_Privacy_Design}_i \\
& + \gamma_{4,\theta} \times \text{High_Convenience_Design}_i + \gamma_{5,\theta} \times \text{General Privacy Concern}_i \\
& + \gamma_{6,\theta} \times \text{Coronavirus Anxiety}_i + \gamma_{7,\theta} \times \text{IT-Self-Efficacy}_i + \gamma_{8,\theta} \times \text{Age}_i + \gamma_{9,\theta} \times \text{Female}_i \\
& + \gamma_{10,\theta} \times \text{Education}_i + e_{i,\theta} \qquad (2)
\end{aligned}$$

Model estimation

Based on the specification given in Equation 1, we first estimated an OLS regression to examine the effects of benefit appeals, privacy design, and convenience design on the conditional mean of installation intention (see Table 2 column 1 for results). We found that compared to societal-benefit appeal, self-benefit appeal (β_1 = −.594, $p < .01$) and self- and societal-benefit appeal ($\beta_2 = -.420$, $p < .05$) decrease installation intention. Privacy design ($\beta_3 = .335$, $p < .05$) and convenience design ($\beta_4 = .440$, $p < .01$) have a positive and significant effect on installation intention. The effects of the control variables were either in the expected direction or insignificant.

[Insert Table 2 about here]

To uncover the differential effects of benefit appeal, privacy design, and convenience design at different propensities for acceptance, we tested whether Equation 2 has differential effects for the .25, .50, and .75 quantiles. Using a variant of the Wald test (Koenker & Bassett Jr, 1982), we found that the estimations are significantly different across the three quantiles ($F(22, 1532) = 4.580$, $p <.01$)).

The results of the quantile regression are presented in Table 2 (see column 2 - 4). Interestingly, compared to societal-benefit appeal, the negative effects of self-benefit appeal only become significant in the .25 and .50 quantiles. The effect of self-societal-benefit appeal is negative in all three quantiles and significant in the .50 quantile. The difference between self-societal-benefits and self-benefits is significant for the .25 quantile and not significant for the .50 and .75 quantiles ($\Delta(\gamma_{2,.25} - \gamma_{1,.25}) = .569$, $p < .05$; $\Delta(\gamma_{2,.50} - \gamma_{1,.50}) = .311$, *ns*; $\Delta(\gamma_{2,.75} - \gamma_{1,.75}) = .057$, *ns*).

For privacy design, we found a significant positive effect for the first and second quantiles. The effect size decreases with higher-level quantiles. Furthermore, the positive effect of convenience design only becomes significant in the .50 quantile.

Categorisation of citizens for mass acceptance

We developed a categorisation of citizens with different propensities for accepting the tracing app. The radar chart depicted in Figure 1 indicates the effect size of each variable across the three observed quantiles, which we name as: *critics* (.25 quantile), *undecided* (.50 quantile), and *advocates* (.75 quantile). The stronger an effect, the further it is on the outer lines.

[Insert Figure 1 about here]

.25 quantile: The critics. For the critics, societal-benefit appeals are superior to both self-benefit and self-societal-benefit appeals in driving installation intention. Furthermore, a high privacy design appears paramount for the installation decision, as it yields the second strongest effect in the .25 quantile. Convenience design elicits a rather negligible effect size.

.50 quantile: The undecided. For undecided citizens, the effect pattern of societal-benefit appeal is comparable to the one for critics (see yellow marks for societal-benefit appeal): Compared to self-benefit appeals and self-societal-benefit appeals, societal-benefit appeals increase installation intention. Although privacy design has a strong effect on app acceptance, convenience design elicits the strongest effect in this group (see the yellow marks for privacy design and convenience design).

.75 quantile: The advocates. For advocates of tracing apps, the effects of societal-benefit appeal (compared to self-benefit appeal and self-societal-benefit appeal), privacy design, and convenience design are approaching zero (see green marks). Hence, benefit appeal, privacy design, and convenience design play a subordinate role in the installation decision process for such citizens.

Discussion

The aim of this study was to uncover how different specifications of tracing apps contribute to their mass acceptance. In light of the urgency of the situation and our study's practical relevance, we discuss the findings from a policy maker's perspective before reflecting on their theoretical implications.

Practical implications for policy makers

Our study has important implications for policy makers in charge of guaranteeing the mass acceptance of tracing apps. To begin with, we note that there can only be *one* set of specifications of a tracing app for *all* citizens; a precise targeting of different groups is thus infeasible. To arrive at the most promising strategy, policy makers must first determine (i.e. using polls) whether the vast majority of the country's population can be assigned to one of the three groups (i.e. critics, undecided, or advocates) or is split among them. If the former is true, our findings provide precise and actionable guidance. However, in the latter case, policy makers should consider a cautious app specification set that simultaneously speaks to multiple groups. We discuss four strategic options for reaching mass acceptance below in light of the results of our quantile regressions for the different groups.

First, our findings show that the critics respond to societal-benefit appeals and privacy design in their installation decision. If the majority of citizens are critics, it is imperative that policy makers focus on communicating societal-benefit appeals and ensure minimal exposure to privacy risks. Highlighting self-benefits leads at best to neutral (when combined with a societal-benefit appeal) or, in the worst case, to adverse reactions (when deployed alone).

Second, for undecided citizens, employing societal-benefit appeals is even more strongly suggested as appeals highlighting self-benefits are counterproductive, even when they are combined with a societal-benefit appeal. While privacy design continues to play an important role for undecided citizens, convenience in app usage is more relevant for them.

Third, if advocates make up the majority, none of the benefit appeals is superior in achieving mass acceptance. Policy makers may consider deprioritizing privacy and convenience as advocates would not penalise sacrifices to privacy and convenience. However, that should be done cautiously and carefully, as these are important specifications for critics and undecided.

Fourth, when propensities towards app acceptance are dispersed among citizens, success requires an app specification capable of shifting the heterogeneous *mass* towards app acceptance. In this case, policy makers are advised to specify the app for those who need to be convinced. For example, if the groups of advocates and undecided are sufficiently large to have the potential to reach mass acceptance, policy makers should consider high privacy and convenience as powerful levers to convince those who need to be convinced. Additionally, they should speak to citizens' altruistic motives using societal-benefit appeals rather than to self-focused motives using self-benefit appeals. For example, when announcing the deployment of Singapore's tracing app, the government emphasized *"Together we can make our world safer for everyone"* (Baharudin, 2020).

Theoretical implications

Our study contributes to IS research in several ways. First, we theorise on how to achieve mass acceptance of tracing apps, considering the unique context within which they are being applied. We highlight how mass acceptance is distinct from acceptance of apps in general (Ghose & Han, 2014; Venkatesh et al., 2003) and health-related apps in particular (Briz-Ponce & García-Peñalvo, 2015; Kim & Park, 2012): to realise their intended societal benefits, tracing apps require mass acceptance. Therefore, mass acceptance is characterised by the necessity to appeal to a large proportion of the population and little opportunity for gradual uptake. This renders the typical covariates of acceptance such as attitudes, traits, and demographics less pertinent, as they are difficult, if not impossible, to change, leaving app design specifications as the most promising approach to fostering mass acceptance. We suggest that the appropriate set of specifications is likely to increase acceptance. By calling attention to the distinct nature of mass acceptance, our study lays the ground for future research to investigate other citizen- and society-centric technological advancements that require the mobilisation of a large share of society. We believe this is a new theoretical direction in IS research.

Second, our categorisation of citizens (i.e. critics, undecided, advocates) based on propensity to accept the tracing app provides a fine-grained and actionable approach for investigating the app specifications salient for mass acceptance. Our finding that benefit appeals, privacy design, and convenience design have varying impacts across different propensities for acceptance implies that focusing on aggregate effects of antecedents, which has proven valuable for explaining acceptance in other contexts (Ghose & Han, 2014; Venkatesh et al., 2003), can be misleading in this one. As the context of mass acceptance does not allow for flexibility or configuring the app for different target groups (Zhang et al., 2019), identifying the needs of citizens—particularly those sceptical of the app—requires a move beyond aggregate impacts. Thus, we reveal that mass acceptance is a nuanced and complex phenomenon where one size does not fit all. Our quantile regression approach testifies a potential path forward in this research area.

Third, we provide insights specific to disease-related tracing apps and health apps that contribute to the greater good. Tracing apps are characterised by unclear benefit structures, sensitive data requirements, and the fact that their installation brings certain inconveniences. Our design specifications, informed by three theoretical streams—prosocial behaviour, privacy, and usability—point to a context-specific contribution (Avgerou, 2019) that can serve as a starting point for studying and implementing other citizen-driven apps that involve sharing resources and data for a greater benefit. Such apps include those that aid in requesting movement permits during lockdown hours, apps that aggregate and analyse health data based on data donation, or research-oriented apps that rely on volunteer computing.

Fourth, we contribute to the understanding of technology acceptance in the case of multi-layered benefit structures, that is, those offering benefits at both the individual and societal level. The multi-faceted benefits of such technologies coexist with individual-level inconveniences (e.g. having to provide one's location and contact information). We highlight counter-intuitive aspects, particularly benefit appeals, as important new factors joining privacy and convenience in the mass acceptance equation. Prior research has suggested that the helpfulness of self-benefit appeals can backfire in contexts in which individuals can be held accountable for not contributing to the collective effort (White & Peloza, 2009), as is the case with tracing apps. We found that benefits for oneself fail to motivate installation, whether as a standalone appeal (in line with prior research) or in conjunction with a societal-benefit appeal (extending prior research). On the contrary, societal-benefit appeals are effective only when used on their own. This suggests that emphasizing the societally normative objective (i.e. contributing to the collective effort of protecting the population) is a more powerful antecedent of app acceptance than playing up individual benefits (i.e. protecting oneself). In other words, during times of pandemics, benefit appeals are only effective if they can appeal to citizens' altruistic and collective effort–oriented concerns.

Our research has two limitations that suggest opportunities for further research. First, by choosing Germany as a research setting, our insights may be considered particularly relevant for similar societies (e.g. EU, UK or the US). However, this setting was exemplary because it allowed us to collect a dataset within the short time window between the announcement and the specification of a tracing app. Recognizing that national culture affects technology acceptance (Srite & Karahanna, 2006), more empirical evidence is necessary to translate our findings to other countries. We therefore encourage further research that examines the role of cultural characteristics on mass acceptance. Second, we examined the impact of different app specifications for a tracing app on acceptance in a controlled environment to best simulate the unique context: only *one* app can ultimately be released. This constraint required us to capture installation intentions as a proxy for actual installation behaviour. Once tracing apps are readily available, an interesting avenue for future research is to compare different national app specifications and examine actual user interactions.

In conclusion, this study examined the crucial and extremely topical phenomenon of mass acceptance requirements in the context of tracing apps. Its findings provide contextualised theoretical insights to the literature and guide policy makers by providing design implications according to different propensities for app acceptance (i.e. critics, undecided, and advocates).

Appendix A.

Overview of scenario treatments

Table A1. Mock app store product descriptions in the benefit appeal, privacy design, and convenience design conditions

Variable	Level	Manipulations
Benefit Appeal	Self (*n* = 179)	COV-19 WATCH App – Protect yourself If you have been in the vicinity of a person infected with the coronavirus, you will be informed and can quickly arrange for a test. In this way you make an important contribution to your personal health.
	Societal (*n* = 161)	COV-19 WATCH App – Protect the population If you have been infected with the coronavirus, all users who have been in your vicinity will be informed and can quickly arrange for a test. In this way you make an important contribution to the health of the population.
	Self and Societal[a] (*n* = 178)	COV-19 WATCH App – Protect yourself and the population If a person has been infected with the coronavirus, all users who have been in their vicinity (including you) will be informed and can quickly arrange for a test. In this way you make an important contribution to your personal health and the health of the population. COV-19 WATCH App – Protect the population and yourself If a person has been infected with the coronavirus, all users who have been in their vicinity (including you) will be informed and can quickly arrange for a test. In this way you make an important contribution to the health of the population and your personal health.
Privacy Design	Low (*n* = 257)	The app accesses your movement data. Your encounters with other mobile phone users are recorded via GPS tracking and Bluetooth. Together with your identity features, these are forwarded to our cloud servers for evaluation. Anonymous data may be passed on to third parties.
	High (*n* = 261)	The app does not access your movement data. Your encounters with other mobile phone users are recorded via Bluetooth without location data. Your identity features are not recorded by the app. The analysis is carried out exclusively on your device. No data is passed on to external servers or third parties.
Convenience Design	Low (*n* = 267)	To ensure app functionality, you will be prompted daily to perform a manual update. The app must be open throughout this 2- to 3-minute update, during which the app consumes more power and may reduce your battery level.
	High (*n* = 251)	To guarantee app functionality, an automatic update will be performed daily. Updates and the app run comfortably in the background without user intervention. The app is optimised for low power consumption and reduces your battery level only slightly.

Note. All treatments were presented in German.

[a] To counteract an order effect in the self/societal manipulation, i.e. which appeal appeared first, we developed two different manipulations: Self/Societal (n = 89) and Societal/Self (n = 89). As expected, a series of ANOVA estimations comparing these two groups with our research variables suggested that the order does not affect our results (all $p > .10$). We therefore merged these two groups for the following analyses.

Appendix B

Example treatment

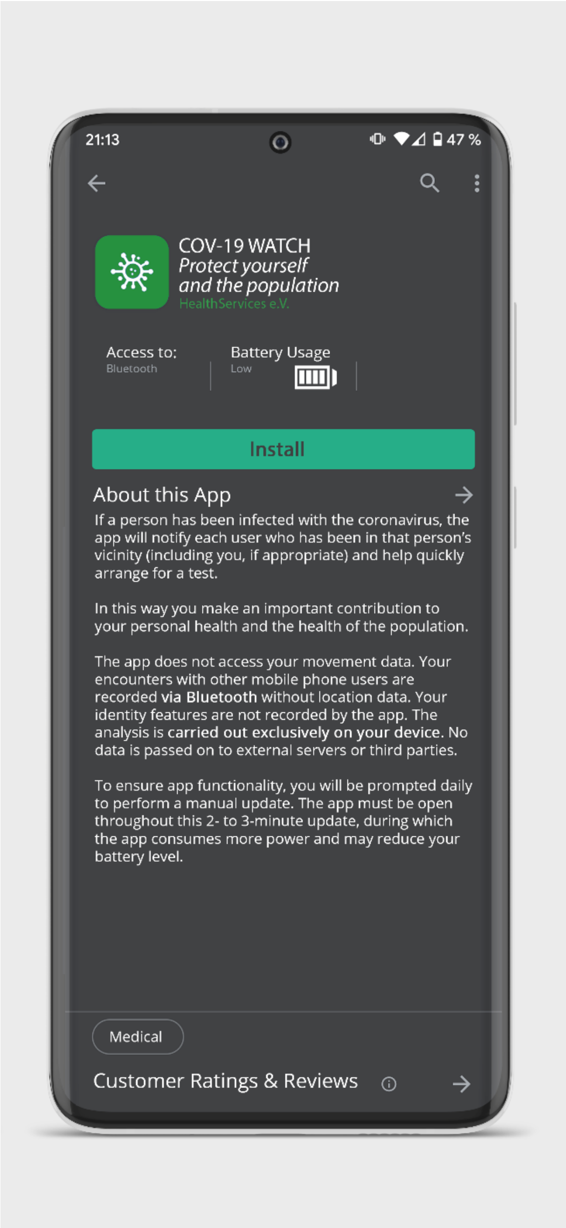

Figure B1. Example treatment: self- and societal benefit appeal, high privacy design; low convenience design

Appendix C

Measurement instruments

Table C1. Item formulations, factor loadings, and construct reliability

Construct	Item	FL	Cron. Alpha	Source
Installation Intention	When the app is available, I intend to install it on my mobile phone.	.956	.982	Adapted from Gu et al. (2017)
	When the app is available, I plan to install it on my mobile phone.	.950		
	When the app is available, I can very well imagine installing it on my mobile phone.	.952		
General Privacy Concern	All things considered, the Internet would cause serious privacy problems.[a]	n.a.	.884	Adapted from Malhotra et al. (2004)
	Compared to others, I am more sensitive about the way online companies handle my personal information.	.784		
	To me, the most important thing is to keep my privacy intact from online companies.	.855		
	I believe other people are too concerned with online privacy issues.	.800		
	Compared with other subjects on my mind, personal privacy is very important.	.876		
	I am concerned about threats to my personal privacy today.	.770		
Coronavirus Anxiety	I spend a lot of time worrying about coronavirus infections.	.821	.850	Adapted from Salkovskis et al. (2002)
	I often worry about getting infected with the COVID-19 virus.	.896		
	When I hear about the coronavirus, I often think that I could have been infected with it.	.822		
	My family/friends would say that I worry too much about a Coronavirus infection.	.754		
IT Self-Efficacy	I feel comfortable learning new technologies.	.896	.785	Adapted from Heinssen Jr et al. (1987)
	I have a good understanding of technology and IT.	.913		

Note. All items were translated to German. FL = factor loading from an exploratory factor analysis with varimax rotation.
[a] dropped due to low factor loading (< .60).

Appendix D

Summary statistics

Table D1. Descriptives and correlations

	Range	Mean (Std. Dev)	1	2	3	4	5	6	7	8	9	10	11	12
1. Installation Intention	0 – 1	4.362 (2.119)	1.000											
2. Privacy Design[a]	0 – 1	0.504 (0.500)	.079	1.000										
3. Convenience Design[b]	0 – 1	0.485 (0.500)	.085	.066	1.000									
4. Societal-Benefit Appeal[c]	0 – 1	0.311 (0.463)	.154	.016	.025	1.000								
5. Self-Benefit Appeal[c]	0 – 1	0.346 (0.476)	−.128	−.018	−.038	−.488	1.000							
6. General Privacy Concern	1 – 7	4.462 (1.327)	−.337	.000	.049	−.097	.104	1.000						
7. Coronavirus Anxiety	1 – 7	2.700 (1.298)	.230	−.001	.017	−.005	−.004	.020	1.000					
8. IT Self-Efficacy	1 – 7	5.734 (1.215)	.122	−.016	−.063	.022	−.030	−.019	−.080	1.000				
9. Gender	0 – 1	n.a.	.048	−.031	.022	−.037	.049	−.067	.070	−.176	1.000			
10. Age	18 – 80	n.a.	.022	−.020	−.026	.018	.004	.168	.100	−.121	.036	1.000		
11. Medium Education[d]	0 – 1	n.a.	.007	−.042	−.014	−.004	.033	.031	.007	−.028	.067	−.096	1.000	
12. Higher Education[d]	0 – 1	n.a.	−.016	.017	−.004	.015	−.001	.046	−.075	.053	−.034	.128	−.827	1.000

Note. [a] Reference level: Low Privacy Design. [b] Reference level: Low Convenience Design. [c] Reference level: Societal-Benefit Appeal. [d] Reference level: middle school or equivalent.

Appendix E

Manipulation checks

The manipulation checks suggest that all treatments were processed as intended. The two-item manipulation check adapted from White and Peloza (2009) ("The description of the app highlights the advantages of the app[for me] [for the population] [for me and for the population];" $\alpha_{\text{societal-benefit}} = .955$, $\alpha_{\text{self-societal-benefit}} = .960$, $\alpha_{\text{self-benefit}} = .901$) yielded significant higher mean for the societal-benefits appeal ($M_{\text{not-societal-benefits\_appeal}} = 4.248$ vs. $M_{\text{societal-benefit}} = 5.133$; $F(1, 516) = 36.299$; $p < .01$), self-societal-benefits appeal ($M_{\text{not-self-societal-benefit}} = 3.927$ vs. $M_{\text{self-societal-benefit}} = 4.677$; $F(1, 516) = 22.738$; $p < .01$), and self-benefit appeal ($M_{\text{not-self-benefit}} = 3.897$ vs. $M_{\text{self-benefit}} = 4.464$; $F(1, 516) = 15.563$; $p < .01$) in the respective groups. Manipulation checks for privacy design treatments used two items adapted from Xu et al. (2009) (e.g. "It would be risky to disclose my personal information to the service provider;" $\alpha = .882$, all items anchored by 1 = strongly disagree and 7 = strongly agree, scale inverted). The mean of perceived privacy design in the high privacy design scenarios was perceived significantly higher than in the low privacy design scenarios ($M_{\text{low\_privacy}} = 3.508$ vs. $M_{\text{high\_privacy}} = 4.348$; $F(1, 516) = 28.561$, $p < .01$). Finally, the two-item manipulation check for convenience design treatments adapted from Childers et al. (2001) (e.g. "Using the app on my mobile phone is impractical for me in everyday life;" $\alpha = .914$, scale inverted) yielded that the mean perceived convenience was higher in the high convenience design scenarios than for the low convenience ones ($M_{\text{low\_convenience}} = 1.994$ vs. $M_{\text{high\_convenience}} = 3.406$; $F(1, 516) = 111.071$; $p < .01$). The confound checks revealed that participants perceived all app design scenarios to be sufficiently realistic ($M_{\text{perceived\_realism}} = 5.29$ across all scenarios) and we found no differences in perceived realism among all scenarios ($F(2, 513) = 1.271$, $p = .281$).

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Table 1. The nature of tracing apps, theoretical perspectives, and resulting decision alternatives

Contextual background	Theoretical background	Decision alternatives for policy makers	Research propositions
Tracing apps yield benefits at the individual and the societal level	Prosocial behaviour	Benefit appeal: focus on self-benefits, societal benefits, or both in appeal presentations Example: “protect yourself” vs. “protect the population” vs. “protect yourself and the population”	
Tracing apps require access to individuals’ data	Privacy concerns	Privacy design: low vs. high Examples: GPS tracking vs. Bluetooth tracing, centralised vs. decentralised processing of data, extended data usage vs. restricted	*Proposition 1*: App specification decisions in terms of benefit appeal, privacy design, and convenience design will influence the acceptance of tracing apps.
Constant usage implies constraints on mobile phone functioning	Usability	Convenience design: low vs. high Example: high vs. low battery depletion, regular manual updates vs. automatic updates	
Tracing apps require mass acceptance	User-centred design	Choosing the app specification that will attract the vast majority of citizens	*Proposition 2*: The influence of app specification decisions in terms of benefit appeal, privacy design, and convenience design will differ across population groups (i.e. critics, undecided, advocates).

Table 2. OLS and quantile regression estimation.

	OLS	Quantile regression		
Variables	*Mean*	.25	.50	.75
Constant	3.24*	1.614	2.764**	4.176**
	(.708)	(1.033)	(.647)	(.871)
Self-Benefit Appeal[a]	−.594**	−.951**	−.717**	−.087
	(.206)	(.291)	(.227)	(.171)
Self-Societal-Benefit Appeal[a]	−.420*	−.382	−.406*	−.031
	(.205)	(.303)	(.178)	(.212)
Privacy Design[b]	.335*	.592*	.507**	.238
	(.166)	(.244)	(.164)	(.174)
Convenience Design[c]	.440**	.116	.699**	.274
	(.167)	(.245)	(.171)	(.175)
Controls				
General Privacy Concern	−.561**	−.703**	−.778**	−.449**
	(.065)	(.114)	(.058)	(.059)
Coronavirus Anxiety	.398**	.538**	.463**	.252**
	(.065)	(.080)	(.059)	(.059)
IT Self-Efficacy	.265**	.313**	.378**	.297**
	(.070)	(.085)	(.075)	(.093)
Female	.125	.132	.259	.125
	(.169)	(.259)	(.171)	(.182)
Age	.014	.015	.017*	.016*
	(.007)	(.012)	(.008)	(.008)
Education (high school or equivalent)[d]	.417	.818*	.680*	.496
	(.301)	(.374)	(.286)	(.325)
Education (university degree or equivalent)[d]	.349	.791*	.586	.366
	(.304)	(.327)	(.316)	(.331)
Adj. R^2 / Pseudo-R^2	.212	.163	. 173	.114

Note. [a] Reference level: Societal-Benefit Appeal. [b] Reference level: Low Privacy Design. [c] Reference level: Low Convenience Design. [d] Reference level: middle school or equivalent.
$*p < .05$. $** p < .01$.

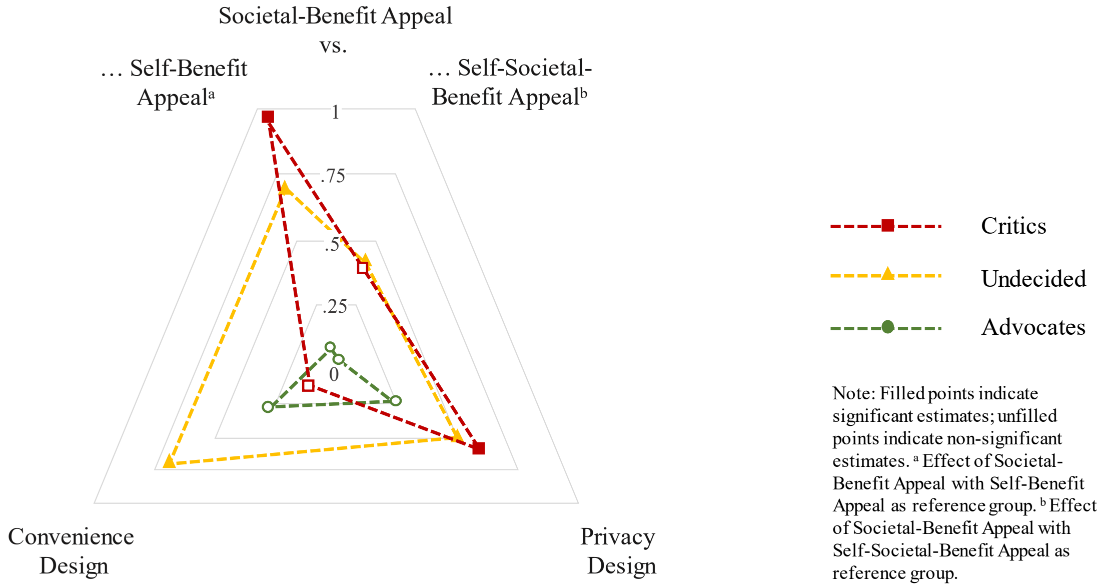

Figure 1. Illustration of the effects of different specification options on tracing app installation intention.