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Exploring User Acceptance Determinants of COVID-19-Tracing Apps to Manage the Pandemic

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ABSTRACT

Tracing infectious individuals and clusters is a major tactic for mitigating the pandemic. This paper explores the factors impacting the intentions and actual use of COVID-19 contact tracing apps based on a technology acceptance model. A partial least squares structural equation model has been applied to understand determinants for the usage of tracing apps based on a large sample (N = 2,398) from more than 30 countries (mainly from Germany and USA). Further, the paper presents a classification of COVID-19 apps and users. Through that, the study provides insights for technologists and designers of tracing apps as well as policy makers and practitioners to work toward enhancing user acceptance. Moreover, the results are abstracted to general social participation with apps in order to manage future strategies. The theoretical contribution of this work includes the results of the acceptance model and a classification of COVID-19 tracing and tracking apps.

KEYWORDS

Corona, COVID-19, Digital Contact Tracing, SARS-CoV-2, TAM, Technology Acceptance

INTRODUCTION

Achieving positive and sustainable global digital transformations is not a trivial endeavor (Basu et al., 2021; Stibe, 2020). However, at a time of the ongoing pandemic, both our scientific and technological strengths must be leveraged to develop the most efficient ways of mitigating the implications of COVID-19 with digital solutions.

Unlike any other application development, digital contact tracing has the potential to form a significant building block for this transformative time to cope with the pandemic (Walrave et al., 2020; Zeng et al., 2020). In response to the risk of another wave, new standards and processes have

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been developed that enable the tracing of known and unknown contacts. Traditionally, local health authorities have previously orchestrated contact tracing (identifying, contacting, and assessing risk with potentially law-enforced quarantine). Several countries are currently attempting to develop a single national digital tracing app. Mathematical models have indicated the potential of overcoming SARS-Cov2 if approximately 60% of citizens in a country use such applications (Hinch et al., 2020).

Thus, our first research question is: *How can tracing and tracking apps be classified?*

Both academia and industry are researching technical solutions for automized contact tracing, push-notifications for potentially infected people, and the integration of local health authorities and laboratories (e.g., SAP, 2020; see the next section for details). The majority of democratic countries encourage privacy-by-design as a guiding principle, for instance, by following the ten touchstones for the evaluation of contact tracing apps guideline by the Chaos Computer Club (2020). These touchstones follow a decentralized architecture. However, centralized approaches are in a conceptual stage—like the past initiative Pan-European Privacy-Preserving Proximity Tracing (PePP-PT, 2020)—but with different protocols released, most notably in Singapore and France. Currently, there is no clear differentiation and definition in the literature between the terms *COVID-19 tracing* and *tracking app,* and their implemented functionalities or data interfaces. Thus, to understand the differences between these approaches and to leverage the potential for interaction within each of them, we must first develop a structural framework for coronavirus tracking and tracing apps and possible design and architectural decisions.

We investigate the second research question: *Which factors can improve the use intention and usage of* COVID-19 *tracing apps and in general social-participial apps?*

Understanding social and political reasons for using COVID-19 tracing apps, it is the role of the IS discipline to offer scientific insights and practical recommendations about information technology (in this research with tracing apps) and its role in coping with the crisis (Madhavan et al., 2021; Thomas et al., 2020).

A further research gap we are addressing is the detailed level of acceptance criteria, that are based in the above-mentioned cases on vignette studies only. Although substantial results—e.g., about the tracing app installation intention for different user groups—have been previously generated (Trang et al., 2020), the qualitative value of this study shall enrich the presented concepts through concrete insights on publicly available COVID-19 tracing apps. Our research aims to construct a solid understanding of factors determining the use intention and actual use of such apps. Subsequently, these results can be abstracted to the general social participation of apps in order to manage future strategies. In response to this, we designed a partial least squares structural equation model (PLS-SEM) to support scientists, political decision makers, and industrial interest groups in amplifying the mass acceptance, usage, and coverage of COVID-19 tracing apps as an instrument to lower infection rates. For model testing and validation, we conducted a survey ($N = 2{,}398$) and gathered user insights from 35 Western European countries, with a special focus on Germany. As Kondylakis et al. (2020) criticize in their work, recent research projects in this field involve mostly younger people (students), although the epidemiological impact of older people seems to be more significant. We were able to include this point into our data collection procedure by recruiting a wide range of age categories.

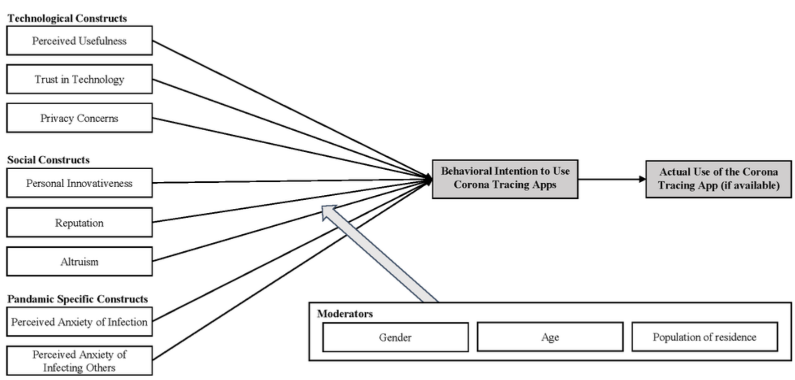
The remainder of this paper is organized as follows. We first provide background information on digital pandemic instruments and related papers. From this information, we derive our research hypotheses and build our research model (section 3). Next, our measurement model and the data gathering approach itself are presented (section 4), followed by the survey results and the computed PLS-SEM model in section 5. The discussion of these results (section 6) expands on this and provides implications for theory and practice as well as limitations of our study. The paper ends with conclusions in section 7.

CLASSIFICATION OF COVID-19 APPS

Common knowledge and understanding of COVID-19 apps remains an emerging topic in both the research and public sector. In light of this, we have presented a technical overview of general approaches in Figure 1. Hereby we focused on applications in the concrete context of COVID-19 tracing. The figure provides a meta-perspective of COVID-19 apps (Madhavan et al., 2021), contributing to the body of knowledge in the research of participatory e-Health applications.

A broader perspective of COVID-19-related apps, also including apps for health workers, can be found in Davalbhakta et al. (2020), where the Apple App Store and the Google Play Store have been reviewed for the US, India and the United Kingdom. Collado-Borrell et al. (2020) and also Almalki & Giannicchi (2021) conducted a similar study on a global perspective. For Saudi Arabia, Hassounah et al. (2020) analyzed 19 official governmental apps, the case of Netherlands has been undertaken a review by Jonker et al. (2020). Both papers find country-specific indicators for the uptake of the local apps. Tebeje & Klein (2021) and Singh et al. (2020) provide a broad international view on e-Health applications on a personal level, which occurred during the pandemic. A systemic literature review was also published by Kondylakis et al. (2020), which primarily focuses on the clinical benefits of contact tracing. That variety of papers underline the potential bandwidth of participatory surveillance applications, as also systematically reviewed by Wirth et al. (2020). To provide a better understanding of the meta-perspective of such apps, the following structural scheme explains the output and user interactions we derived from the named literature.

Figure 1. Structural diagram of COVID-19 apps



In general, four different design layers or architectural decisions of COVID-19 apps can be differentiated. The first layer, called the *storage layer*, covers the general communication and storage architecture. This might be centralized, decentralized, or a hybrid. In a centralized architecture, each phone is registered on a central server, where data of the following layers is captured as well. This approach may expose users to high privacy risks, as it was the case with the Pan-European Privacy-Preserving Proximity Tracing (PePP-PT, 2020). This was one reason why this initiative was terminated before being implemented. In a decentralized approach, neither a registration (e.g., by the user) nor other personal data is located on central servers. To avoid that, smartphones permanently share encrypted information via Bluetooth Low Energy and receive various encrypted information from other smartphones. In contrast to PePP-PT, DP-3T[1] was another pan-European initiative to implement a decentralized COVID-19 framework. This initiative has been rendered obsolete through the joint initiative by Apple and Google (2020). Finally, a hybrid approach combines both worlds in order to source the cryptographic workload out to a central server or to enable governmental access to data (e.g., infectious users), simultaneously ensuring user anonymity.

The second layer centers around the data input that symbolizes which sources of data are used to build the service. This list might be incomplete, as recent research indicates that some governments also include open-source intelligence (OSINT) to link phone numbers, smartphone applications, and social networks (Krüger et al., 2020). In China, drone operations with retrofitted temperature sensors occurred during the pandemic peak. Hussein, Apu et al. (2020) see these operations as indications of actions towards a digital health surveillance system.

In the approach layer, we clustered four different use cases of COVID-19 applications, which represent the general scope of such an application. Based on the Google–Apple Framework, privacy-enhancing contact tracing can be realized with Bluetooth Low Energy. As this approach measures only the distance between two smartphones—without geographical information—it is also commonly known as proximity tracing. Other combinations of input data, such as Wi-Fi signals and GPS coordinates, allow different scenarios. They were initially used to build the first apps at the beginning of the pandemic, rather than focusing on storing users' location data (Whitelaw et al., 2020).

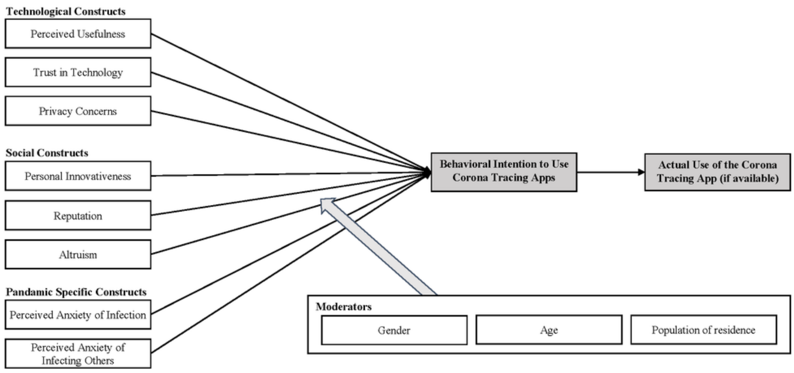
These scenarios build the data output or user interaction picture in our scheme (Whitelaw et al., 2020). While most countries performed a COVID-19 risk assessment, the above-described data exchange with COVID-19 laboratories and a derived warning for positive cases is another scenario. Another feature could be a manual tracking of COVID-19 symptoms by the user itself. In less privacy-friendly countries, quarantine-monitoring (geofencing) by government organizations emerged, as did as a warning system when approaching a COVID-19-infected person (Ahmad et al., 2020). The German tracing app (Corona-Warn-App) approach is an implementation of the exposure framework by Google and Apple, however it represents a public money and public code approach, that is publicly documented on GitHub.

Compared to other papers, this study involves existing COVID-19 tracing applications and we combine the sample and the model itself with qualitative insights, like the meta-model in Figure 1. To the best of our knowledge, previous research on COVID-19 has firstly focused on a general acceptance criteria (e.g., Altmann et al., 2020; Morley et al., 2020). Secondly, the research has been directed at only prototyped applications (e.g., Becker et al., 2020; Kaptchuk et al., 2020), and primarily limited to a single country or region (e.g., Dehmel et al., 2020; Zhang et al., 2020). The paper of Zimmermann et al. (2021) focused on German-speaking countries, but neglected the technological de-facto standard of Apple and Google (2020).

RESEARCH MODEL AND HYPOTHESES

Figure 2 describes our research model with eight independent and two dependent variables. Table A1 (Appendix A) presents an overview of the constructs. With regard to the original constructs, we carefully adapted all items to the context of the coronavirus pandemic and partly added new items.

Figure 2. Research Model



The construct *behavioral intention to use*, developed by Davis (1989), examines the willingness of people to use a technology. There are several reasons that can hamper the actual usage of a technology, or even prevent it completely. In the case of the COVID-19 tracing apps, a person may intend to use them, but may have their own individual reasons for not doing so. We requested these main reasons with the help of a list and the free text fields. For instance, owning an old smartphone on which the application does not work, may be a primary reason for a person's lack of app use. Nevertheless, the following hypothesis can be made:

H1: The higher the intention to use the COVID-19 tracing app, the more likely the actual use of the COVID-19 tracing app.

We derived the construct *perceived usefulness* from Davis (1989) and refined it for utilization within the coronavirus app context. This construct describes the perceived benefit of an app for users. In our context, this means whether users feel relief in handling everyday life through the COVID-19 tracing app, perceive greater control of the pandemic situation, and whether the application meets the user's expectations. Numerous studies show that the perceived usefulness of a technology or application has a significant influence on its usage in real life (Straub & Burton-Jones, 2007; Yousafzai et al., 2007a, 2007b). From these considerations we have derived the following:

H2: The greater the perceived usefulness, the stronger the behavioral intention to use.

Moreover, *trust* is an important factor influencing the adoption and usage of technologies. Trust is regarded here as the belief in technology's ability to meet expectations (McKnight et al., 2011). Trust is one of the key factors for adopting digital technologies (Chandra et al., 2010; Lee et al., 2011; Pearson, 2013). In particular, when it comes to health data, trust in providers is of significant importance (Adelmeyer et al., 2019; Ermakova et al., 2014). People may fear that their health data could be exposed and that they risk being prejudiced. A similar argument can be made for COVID-19 tracking apps. These applications collect sensitive and personal data such as location information and medical conditions. Users must be confident in the amount of data collected (only what is stated), the data collection will be anonymous, and no private data will be leaked. Users of COVID-19 tracing apps must trust the government—at least to some degree, the app developers and other included entities (such as laboratories and health departments). From these considerations we conclude the following hypothesis:

H3: The greater the trust in technology, the stronger the behavioral intention to use.

Privacy concerns present a major challenge regarding the acceptance and usage of COVID-19 tracing apps. Even in interactions and use of services such as e-commerce (Malhotra et al., 2004) where less sensitive data (compared to health data) is recorded, stored, and processed, privacy concerns have emerged as a major challenge for adoption. Most countries, such as the USA and European states, have laws regulating the access and use of data in general and in particular for health data (e.g., GDPR). Nevertheless, the central online storage of health data is viewed critically by users, as it provides a central point of attack for a large amount of data (Abbas & Khan, 2015). Regarding the COVID-19 applications, we assume that users may have privacy concerns regarding data protection, such as the possibility of third parties accessing their data (Krasnova et al., 2009). Privacy concerns are particularly important in regards to the usage of health data (Adelmeyer et al., 2019; Ermakova et al., 2014). Therefore, we investigate the following hypothesis:

H4: The greater the privacy concerns, the lower the behavioral intention to use.

Personal innovativeness describes an individual's openness to experience new technologies and adopt these (Agarwal & Prasad, 1998). In the context of mobile internet usage, personal innovativeness has been proven to be a significant influence (Lu et al., 2005). We propose the inclusion of this construct, as the usage of an app in the fight against a pandemic situation is new and innovative (Christou et al., 2020), at least in countries without any previous digital tracing or tracking solution. Moreover, we argue that innovators and early adopters often serve as multiplicators for technology usage. Because they might convince other people to use COVID-19 tracing apps, innovators might be a crucial group of people for the success of COVID-19 tracing apps. Therefore, we investigate whether personal innovativeness is a decisive factor for the intention to use. This leads us to the following hypothesis:

H5: The higher the personal innovativeness, the stronger the behavioral intention to use.

Reputation is closed to the subjective norm and can be summarized as the social pressure from society to follow a certain behavior (Liobikienė et al., 2016). Thus, this construct describes the influence (e.g., expectations) of the environment on one's own behavior. This influence may follow several reasons, such as environmental, organizational, and social factors. This is linked to the perceived reputation earned by a person who follows this behavior (Church et al., 2019). We argue that within a social group, the individual members have a certain reputation and that this reputation is of importance within the group. Furthermore, we assume that the containment or tracing of COVID-19 is generally perceived as a positive goal. Since the media coverage of COVID-19 tracing applications is mostly positive in many countries (e.g., Germany), and the widespread use is mostly demanded by various stakeholders (e.g., companies and politicians), a person's reputation can be increased through application use. Based on this argumentation, we derive the following hypothesis:

H6: The greater the need for reputation, the stronger the behavioral intention to use.

Smith (1981, p. 23) defines *altruism* as:

an aspect of human motivation that is present to the degree that the individual derives intrinsic satisfaction or psychic rewards from attempting to optimize the intrinsic satisfaction of one or more other persons without the conscious expectation of participating in an exchange relationship whereby those "others" would be obligated to make similar/related satisfaction optimization efforts in return.

Thus, it is the support without expecting any return. An altruistic person enjoys helping others (Church et al., 2019). One major goal of the COVID-19 tracing app is to improve the analysis of COVID-19 infection chains and to interrupt the infection process as fast as possible. Thus, we investigate the influence of altruism on the probability of using the COVID-19 tracing app because this app was developed to thwart the pandemic by reducing widespread infections and helping the majority of the population by eliminating chains of infection. The idea of preventing the spread of the virus and hence reducing the risk of infection for all people constitutes a key factor for installing such applications. These considerations lead to the following hypothesis:

H7: The stronger the altruism, the stronger the behavioral intention to use.

During the present pandemic, people must navigate through emotional constructs, such as *perceived anxiety of infection* and *perceived anxiety of infecting others*. Some people might be afraid of personal infection, infecting their nearest family members, or a consequential quarantine. In addition, some individuals prefer to self-quarantine immediately to avoid spreading the virus, while others prefer to be warned only by a concrete infection or in case of contact with an infected person. This contrast in preferences can be reduced to a fear of being isolated and the resulting effects during a quarantine period (Robson, 2020). According to Becker et al. (2020), respondents who were infected or whose personal environment was infected with COVID-19 have a significantly increased willingness to use the app. The reason for the willingness to use the app could also be explained through people's fear of infection, and the infection of their peers. The result is an attempt to try to protect themselves or their peers in advance with a contract tracing app. Subsequently, we investigate whether people are motivated to use the app to protect others, themselves, or both. To examine these factors, we propose the following hypotheses:

H8: The higher the perceived anxiety of infection, the higher the intention to use.
H9: The higher the perceived anxiety of infecting others, the higher the intention to use.

RESEARCH METHOD

Measurement

The basis of our research forms the technology acceptance model (Davis, 1989) with careful adaptations of single items (see Appendix A). To reflect the health orientation of our research objective, we followed Pfeiffer et al. (2016). In our survey, all items were asked on seven-point Likert-type with multiple-item scales (Göb et al., 2007; Likert, 1932; Weiber & Mühlhaus, 2014). We conducted two pre-tests to improve our questionnaire. In view of the first pretest, we checked the translation of the items and constructs as well as the technical implementation. This led to linguistic optimizations of the items as well as minor corrections of display errors. In addition, open free-text questions were added to allow participants to give their opinions on specific topics. The second pretest resulted in minor linguistic improvements.

After conducting our survey, we used a reflected measurement model, because the items correlate, and the latent variables affect the dependent variable (Wong, 2013). According to Venkatesh et al.

(2003) and Venkatesh et al. (2016), we integrated two demographic variables as moderators (gender and age). In addition, we tested *population of residence* as moderating variable, meaning the number of inhabitants at the current permanent place of living. Further, we inquired about the aspects *country*, *already tested,* and *person close to him/her infected by COVID-19* in order to examine whether these factors affect the answers of the respondents.

After testing the constructs' reliability and validity, we used the PLS-SEM to interpret the survey results (Hair et al., 2014). Because of its visually driven model design process and the complex statistical modification options, PLS-SEM became a well-known method in the field of information systems (e.g., Xu et al., 2012) and human-centered design (e.g., Orji et al., 2017, and Van Schaik et al., 2012). Therefore, we examined the relationship of the dependent variables. This was achieved with the analysis tool WarpPLS (Kock, 2019).

Besides the constructs in our acceptance model, we asked the respondents about other reasons for the usage or non-usage of the COVID-19 tracing app. As an automated measurement of the actual use was not possible for the different kinds of international COVID-19 apps, the study relies on the given answer of the proband. Thus, we added further questions about the channel where the app was noticed, personal affection of COVID-19, infection of a person close to the respondent and whether the use of the app is due to coercion.

Data Collection

To gather as many participants as possible, we translated the survey with the help of native speakers into six languages (German, English, French, Spanish, Korean, and Brazilian Portuguese). We created social media templates for interested participants, the press, and our own accounts, which helped us to reach out to various local radio stations, newspapers, and magazines, asking the public for help and participation in our survey. Overall, we ended the data collection in mid-July 2020. In total, we were able to reach more than 3,500 people, of which 2,682 completed the questionnaire.

Prior to interpreting the data, we conducted two data-cleansing steps. The final number was 2,398 respondents. First, we deleted all uncompleted answers (929). Second, we calculated the average time participants needed to fulfill our survey and defined a minimal processing time (4 minutes). All answers below this time were filtered out as well (284).

The remaining data set reflects the demographic criteria, presented in Table 1. In our results, country-specific interpretations are provided for three countries (Germany, USA, France) with the most participants.

DATA ANALYSIS AND RESULTS

Measurement Model

To ensure the validity and reliability of the measurement model, we conducted several tests. *Reliability* describes the extent to which repeated measurements yield the same results (Weiber & Mühlhaus, 2014). In other words, it is a measure for determining the measurement error (Burns & Burns, 2008). Contrastingly, *Validity* is the extent to which a measuring instrument determines what it is supposed to measure (Burns & Burns, 2008; Weiber & Mühlhaus, 2014). Ringle et al. (2012) examined the frequency of the techniques used for these measurements, and we have used their results as a reference point for our analysis. As a first step, we investigated the internal consistency reliability. For criteria, we used Cronbach's alpha (CA), corrected inter-scale correlation (CISC), and composite reliability (CR; Weiber & Mühlhaus, 2014). The internal consistency reliability evaluates the indicators of a construct as a set of equivalent tests, each of which measures the same construct. If these measurements are congruent with each other, internal consistency can be assumed (Weiber & Mühlhaus, 2014). Cronbach's alpha is considered the standard measure in this regard (Ringle et al., 2012). Basically, the higher CA is, the higher the internal consistency reliability is, whereby a maximum value of 1

Table 1. Demographics of the Survey Respondents

Demographic Criteria		Total	Percentage
Age	18–24	207	8.63
	25–34	730	30.44
	35–44	677	28.23
	45–54	473	19.72
	55–64	240	10.01
	65–74	61	2.54
	Older than 74	10	0.42
Gender	Female	914	38.12
	Male	1462	60.97
	Other	22	0.92
Country	Germany	1992	83.07
	United States of America	283	11.80
	France	38	1.58
	Other countries	85	3.54

can be achieved. According to Weiber and Mühlhaus (2014), CA should have a value of at least 0.7, as is the case for all values (see Table 2). It should be noted, however, that even very high values are considered critical, as they may indicate items that are quite homogeneous in terms of content or language (Ringle et al., 2012; Weiber & Mühlhaus, 2014). Apart from the CA, Table 2 also contains the CISC value and the CR. The corrected item-scale correlation indicates the degree to which an item contributes to or represents the construct. It is corrected, because the correlation between the item and the construct without the observed item is considered (Weiber & Mühlhaus, 2014). In the literature, a value of 0.5 is mentioned as the threshold (Shimp & Sharma, 1987; Zaichkowsky, 1985). This threshold is always exceeded (cf. Table 2). The composite reliability, which was the next criterion to be examined, refers to the reliability at the construct level (Weiber & Mühlhaus, 2014). According to Bagozzi and Yi (1988), acceptable values are usually defined from 0.6 upwards. In our

Table 2. Construct reliability and validity

Latent Variable	CR	AVE	CA	CISC
Behavioral intention to use COVID-19 tracing apps (BEIN)	**0.966**	**0.906**	**0.948**	**0.936–0.97**
Perceived usefulness (PEUS)	**0.890**	**0.506**	**0.857**	**0.61–0.827**
Trust in technology (TRUS)	**0.906**	**0.828**	**0.793**	**0.91**
Privacy concerns (CONC)	**0.975**	**0.929**	**0.961**	**0.954–0.97**
Reputation (REPU)	**0.855**	**0.671**	**0.738**	**0.594–0.919**
Altruism (ALTR)	**0.915**	**0.845**	**0.815**	**0.919**
Personal innovativeness (PIIT)	**0.932**	**0.819**	**0.890**	**0.896–0.913**
Perceived anxiety of infection (INME)	**0.857**	**0.666**	**0.749**	**0.87–0.844**
Perceived anxiety of infecting others (INOT)	**0.859**	**0.671**	**0.755**	**0.806–0.838**

case, the values range from 0.86 to 0.98; hence this criterion can be considered fulfilled (see Table 2). Finally, the average extracted variance (AVE) was analyzed to determine what percentage of the dispersion of the latent construct is explained on average by the items (Weiber & Mühlhaus, 2014). These should reach a value higher than 0.5 (Bagozzi & Yi, 1988; Fornell & Larcker, 1981), which is the case in our analysis.

Furthermore, the discriminant validity was tested successfully so that the measurements of these individual constructs differ significantly from each other (Weiber & Mühlhaus, 2014). A common and strict criterion applied was achieved by Fornell and Larcker (1981). The Fornell–Larcker criterion states that discriminant validity exists if the squared correlation between two factors is smaller than the AVE of the corresponding factors (Fornell & Larcker, 1981). The diagonal (see Table 3) comprises the squared AVE of the factors. In each case, these are higher than the correlations in the respective row and column. Consequently, discriminant validity can be concluded.

Table 3. Discriminant Validity Testing, According to Fornell and Larcker (1981)

	PEUS	TRUS	CONC	NORM	ALTR	PIIT	INME	INOT	BEIN
PEUS	0.51								
TRUS	0.14	0.83							
CONC	0.06	0.00	0.93						
NORM	0.39	0.10	0.00	0.67					
ALTR	0.02	0.02	0.01	0.02	0.84				
PIIT	0.11	0.07	0.02	0.11	0.03	0.82			
INME	0.29	0.05	0.05	0.15	0.02	0.08	0.67		
INOT	0.18	0.02	0.15	0.07	0.09	0.03	0.38	0.67	
BEIN	0.33	0.08	0.17	0.12	0.03	0.08	0.17	0.19	0.91

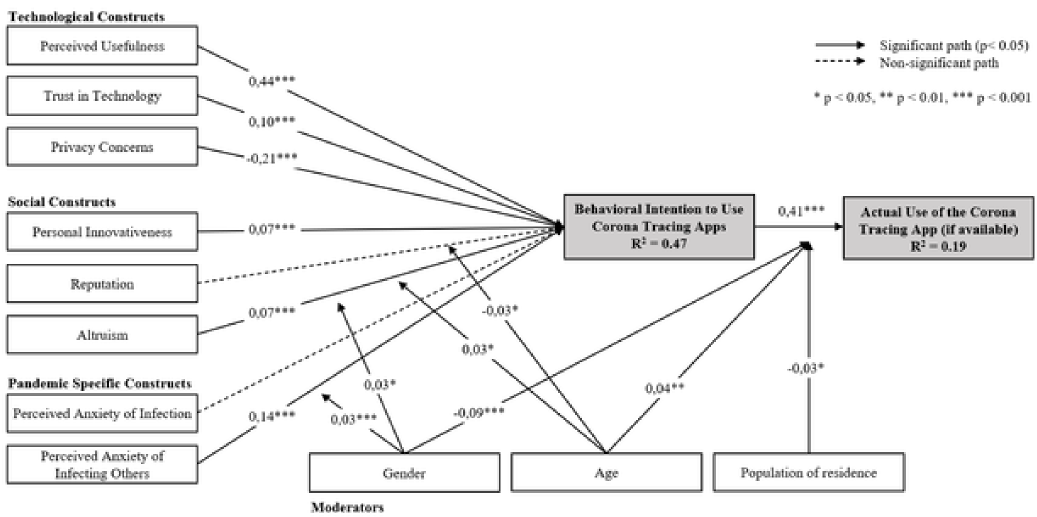
Structural Model

Table 4 shows path coefficients and p-values. We can use these values to interpret whether the variables are significant and to which extent. The results confirm Hypothesis 1 (BEIN ® USAP), which means that for participants who want to use the app, there is actually a positive impact on their use of the app. In terms of the constructs INME and REPU, there is no statistically significant association between them and behavioral intention to use. Thus, we argue that the usage behavior varies when people are afraid to infect themselves (INME ® BEIN). In return, there is a significant positive connection that comes from the fear of infecting others (INOT ® BEIN). This indicates that people with interest in protecting others are more likely to use the app. Regarding the reputation, respondents are not significantly influenced and motivated by status gain or potential acknowledgment of their peers as a result of using the tracing app (REPU ® BEIN). In contrast, there are significant positive effects from self-recognized benefits of using the app (PEUS ® BEIN). Trust (TRUS ® BEIN) and concerns about data protection (CONC ® BEIN) have a significant negative effect on the behavioral intention to use. Thus, when concerns are greater, the respondents are less motivated to share data with tracing apps. Furthermore, the structural coefficients of two significant variables—altruism and personal innovativeness—are low, indicating their minor influence. Consequently, there is little noticeable motivation for people to use the app the more altruistic (ALTR ® BEIN) or personally innovative they are (PIIT ® BEIN). In conclusion, these variables have little influence and are therefore not decisive for the use of COVID-19 apps.

In total, seven of the nine hypotheses can be confirmed. In addition, four effects of the latent variables on the intention to use are of strong significance, having a path coefficient equal or greater than +/-0.1 (perceived usefulness, trust in technology, concerns about privacy, and anxiety to infect others). The coefficient of determination (R2) presents the effect of the exogenous variables on the endogenous variable, and behavioral intention to use COVID-19 tracing apps. In this model, R2 of the endogenous variable BEIN is 0.47 (just below 0.5), indicating a moderate predictive accuracy according to Hair et al. (2014).

In addition, Figure 3 provides information about seven significant moderating effects (e.g., age, gender, and population of residence). Among these, four slightly stronger ones. For strong moderators, we measured a positive effect on the relation between two variables. This increases the path coefficient for positive moderating measures and vice versa. In this model, for participants intending to use the COVID-19 tracing app, older people, women, and habitants of smaller residences use the app most frequently. Furthermore, more men use the app because they are afraid to infect others or are altruistic. Additionally, altruism is more important for older people, compared to younger people, and social status plays a weaker role in the use of COVID-19 tracing apps. In total, all results, significant moderating effects, and significant path coefficients are summarized in Figure 3.

Figure 3. Result in the Structural Model



Further Insights

Besides the presented structural model itself, our survey revealed additional insights. Out of our sample, 94.12% of participants are aware of the official COVID-19 application in their region. The main source of information (multiple answers were possible) was the news, followed by social media. A total of 8% of the participants chose “others” as an information source, e.g. enriched with further manual entries such as government advertisement (see Table 4). More than 100 people recorded podcasts as an *other* source (in particular the *Drosten Podcast*, *Logbuch Netzpolitik*, *UKW*, *Wochendämmerung*, and *NDR Info Podcast* have been mentioned). Concerning this, 97.25% of podcast listeners are also active COVID-19 tracing app users.

Table 4. Information sources about corona apps

Channel	Total	Percentage
News	**1769**	**73.77**
Social media	**1261**	**52.59**
Friends	**467**	**19.47**
Family	**385**	**16.06**
Job	**344**	**14.35**
Other	**209**	**8.72**

Table 5. Reasons for Usage and Non-Usage of Tracing Apps

Reasons for App Usage	Total	Percentage
Contribute to overcoming the crisis	1754	73.14
More clarity about my own health	1147	47.83
People in my environment (e.g., friends, family, and colleagues) use this app	452	18.85
Political support	435	18.14
Social acknowledgment	252	10.51
Other	114	4.75
Reasons for App Non-Usage	Total	Percentage
Data protection concerns/possibility of data misuse	119	4.96
Mistrust in the quality of analyses	94	3.92
Other	90	3.75
Annoyed by coronavirus issue	89	3.71
No support of my smartphone	85	3.54
Sensitivity of data	85	3.54
Mistrust in technologies	56	2.34
Time or organizational effort of app installation	22	0.92

In total, 1,945 respondents report using the app (81.11%), while 312 gave a negative response (13.01%), and 141 did not share an answer (5.88%). A total of 89 participants (3.71%), primarily from the USA (80.90%), replied that they were somehow forced to use the app. Additionally, we asked for the reasons for using or not using the country-specific app. The results are presented in Table 5. The most mentioned answer for usage was the contribution to overcoming the crises, and for non-usage, it was privacy concerns.

Table B1 (Appendix B) presents summarizing descriptive statistics, where we picture the PLS-SEM constructs, moderators, and additional variables collected from the data with the associated response range, median and standard deviation.

Table 6. Quotes and key topics of free-text answers

Topic	Q#	Quote
Decentral	Q1	"I am a software developer and close to the Chaos Computer Club. I am therefore aware of the precautions taken so that no data can leak. Switching to a decentralized model helped me a lot to trust the system and recommend it to others."
	Q2	"A decentralized open-source approach to the COVID-19 tracing app has a huge influence on the level of acceptance for me."
	Q3	"I am very data privacy-concerned but trust the chosen model of decentral usage and storage of data."
Opensource	Q4	"It is great that a decentralized open source approach has been chosen in Germany."
	Q5	"I'm very privacy concerned but thought the Germany app was (surprisingly) very good planned, communicated and trustworthy because of the open-source approach. Only the Google Play services, and the Apple services are proprietary, but there isn't much to do there in real life. By using the app, I wanted to show that if technical and privacy points are considered. I'm happy to help by using the app."
	Q6	"I'd like to point out the extremely professional and transparent development based on the open source idea. This should be a template for every governmental development."
Requirements	Q7	"Statistics within the app would be interesting, for example the number of contacts."
	Q8	"It would be desirable if the app was compatible with older operating systems."
	Q9	"As a German in Austria, I can only install the German COVID-19 App, because the App Store only allows me to do this because my smartphone is only registered for the German App Store. Therefore, I cannot use the perhaps more useful app from Austria from the Red Cross. A transnational exchange between the apps is planned, but not yet implemented here."
Context	Q10	"We torture ourselves every day in the clinic with mouthguards but the patients in their room do not need to wear mouthguards (only outside in the corridor)—means: I am endangered every day and can do not do anything—no app helps!"
	Q11	"[I] work as a nurse in a covid station and am always exposed to the risk of infection, despite protective clothing. Have a lot of old people there who don't have smartphones."
	Q12	"We had to close our refugee aid office because of Covid-19. The app would have been REALLY helpful if older phones had not been excluded. I am really angry about that."
Supporter	Q13	"I have a high risk for a severe course of Covid-19 and I hope that many people feel that we should protect each other."
	Q14	"I hope that many will use the app and follow the recommendations. This could make life a little bit more "normal" and you can contain possible herds faster."
	Q15	"The COVID-19 app is a small part of a big possible solution."
Ease of use	Q16	"I would like to continue using the app, but unfortunately it no longer works. It annoys me so much that I will uninstall it!"
	Q17	"I often get an error that the contact notification does not work properly, and I should configure it."
	Q18	"Error messages of the app should be removed as soon as possible, because they make many people insecure/annoyed. In addition, it should be made visible that the app is working. Communication about infected messages/notifications is absolutely necessary. It would also be helpful to receive additional information during daily use ("create incentive," almost gamification): "Your app encountered 120 keys of other users yesterday, 2 of them at a risky distance" or similar. I'm worried that the initial euphoria about the app will quickly evaporate, because people don't see any benefit in it, but are rather annoyed by error messages."

As suggested by Kelley et al. (2003), we can generate further insights into the research topic and the audience due to an open question in this survey. With a total word count of 12,440 words overall respondents, and an average answer length of 24 words per survey participant (bandwidth from 1 to 293 words for all submitted answers), the audience made intensive use of this possibility. Thus, we were able to build six thematic groups of open feedback: decentralization, open-source, app requirements, context-specific information, hope, and ease of use. Table 6 presents the most dominant topics and selected quotes (Q).

DISCUSSION: SCIENTIFIC AND PRACTICAL IMPLICATIONS

The results of our study allow an observing perspective for understanding the reasons for acceptance and rejection of the use of COVID-19 tracing apps. It is highly relevant that this understanding is abstracted to the general social participation of apps and can be used for the future. In the following, the transferability of our results will be marked as learnings. To provide an example regarding the need for more social-participial apps, we refer to the healthcare sector, which increasingly relies on prescriptive and predictive analytics to deliver its healthcare in the future (Oesterreich et al., 2020). This is based on the social participation of users. With this study and the derived findings, we contribute to IS research from different aspects. We summarized our major findings in six propositions, which provide insights for scientists and practitioners such as for policy makers, app developers, and communication strategists in the context of digital disease control.

Proposition 1: Classification of Tracing and Tracking Apps

First, the scientific perspective of IS can encourage the improvement and implementation of digital instruments against the COVID-19 disease (Dehmel et al., 2020; Urbaczewski & Lee, 2020), which range from low-invasiveness symptom tracking on a person's smartphone to surveillance technology with modified drones (Hussein, Apu, et al., 2020; Urbaczewski & Lee, 2020). Thus, the structural diagram of COVID-19 apps, their input and output layers, and potential approaches are the first artifacts in this research presented (see Figure 1). We suggest further research to continue a taxonomy, when larger data sources are available.

Proposition 2: Understanding User Acceptance

The presented technology acceptance model constitutes one of the main artifacts of this research. We identified three significant and crucial factors that cause the intention or non-intention to use the country-specific COVID-19 tracing app. Firstly, trust in technology (TRUS), secondly, concerns about the privacy of the specific tracing app solution (CONC), and thirdly, the anxiety of infecting other people (INOT). These three aspects explain about 50% (R^2) of the intention to use the COVID-19 tracing app and might be valuable for future communication strategies (learning 3): this is required on the one hand to address privacy concerns in a given social context and, on the other hand, to convince with emotional stories about protecting the people nearby. In contrast to the USA (REPU: 6 of 7 Likert points), with regard to the reputation and subjective norm, French and German respondents gave lower values (4 of 7 Likert points in both countries). Other participants added personal information about the context in which they are using the app and which concrete obstacles they are experiencing (Q10–Q12; see Table 6). A valuable solution to most of these obstacles might be increased and improved communication (e.g., government advertisement and support) The importance of tracing app use, needs to be effectively communicated and presented in several contexts (e.g., for clinic workers; learning 4). However, it is important to restrict this information by relevancy when informing society. In contrast to these statements, the research highlighted that many users also like the overall approach of their local apps and shared positive, hopeful, or thankful comments.

As mass acceptance within a society matters (Hinch et al., 2020; Trang et al., 2020), the shown model includes new constructs as well as adapted constructs from the respective literature. The chosen constructs were able to explain the usage or non-usage of COVID-19 tracing apps from different perspectives (behavioral, technical, social, and pandemic-specific). The independent variables explain the behavioral intention to a medium degree 0.47% (R^2), while the actual usage can be explained to 19%. Thus, other variables beyond that study exist and might be elaborated in upcoming research. In total, our acceptance model with other acceptance models (e.g. Hassandoust et al., 2020) can serve as a foundation for the IS community developing a deeper understanding for innovative apps.

Proposition 3: Communication Strategies and the Importance of Podcasts

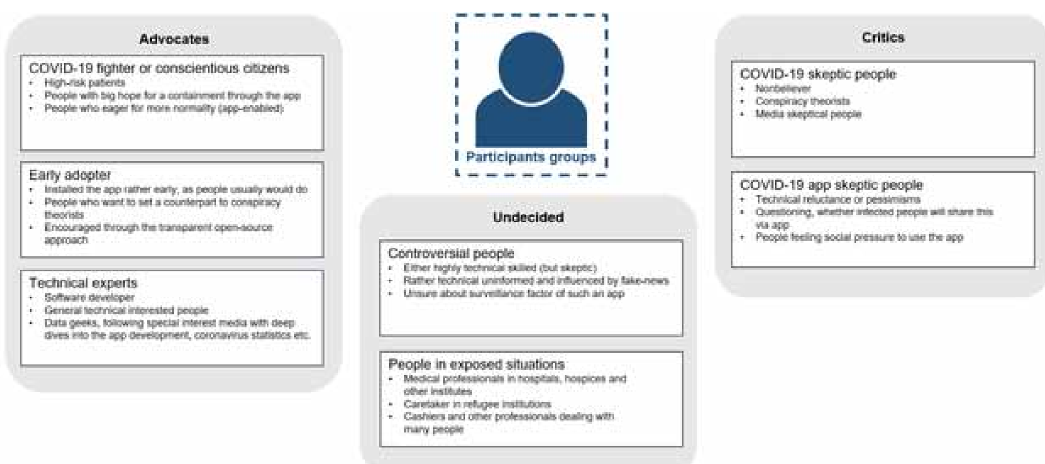
We identified the high importance of communication campaigns. These include the specific context of users, instead of just broadcasting the app availability. For instance, we received several responses from people working in the health sector who were willing to use the app but were unsure if and how this would be possible when dealing with infected people on a day-to-day basis under strict protection. Besides, the presented technology acceptance model revealed that respondents with higher perceived usefulness, fewer privacy concerns, and higher anxiety to infect others are more likely to use the app. Thus, these aspects are recommendable communicational ingredients.

We are contributing to the new field of infodemiology through the qualitative interpretation of the survey feedback, that revealed important information sources for the participants in our sample and can help to mitigate the infodemic (Bao et al., 2020), caused by incomplete or misleading information. One prominent finding we uncovered is the importance of both personal and public media podcasts. Furthermore, improved scientific communication can be incorporated within the academic job scope, subsequently making research results explainable and accessible to a broader audience, especially in the regards to the proliferation of fake news.

Proposition 4: User Classification

Establishing trust and overcoming concerns is an issue of great importance, as confirmed by the significant correlation in our model. In that respect, it is necessary to confront and involve a variety of population groups—from strong proponents to opponents and COVID-19 deniers. According to our derived six thematic issues within the free text answers, we identified seven groups that describe a participant's perspective on COVID-19 apps (one person might be part of different groups at the same time). Trang et al. (2020) examined three groups in their investigation about acceptance and app

Figure 4. Enhanced Core Clusters of COVID-19 App User Classification by Trang et al. (2020) with Further In-Depth Details

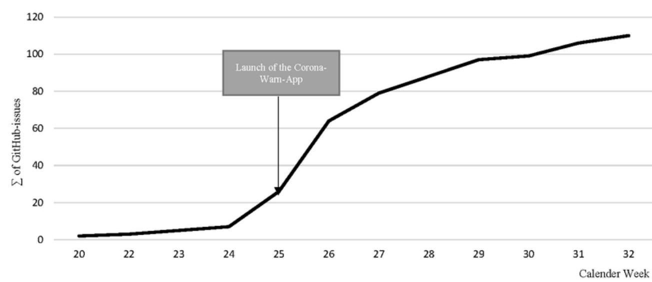


specification: critics, advocates, and the undecided. As a result of the answers to the open questions in our survey, we derived the following seven groups enriching the classification by Trang et al. (2020) with further in-depth insights (Figure 4). The groups are as follows: (1) Early adopters (advocates), (2) COVID-19 fighters or conscientious citizens (advocates), (3) technical experts with high interest in the details of the app development, features, and limitations (advocates), (4) people in exposed situations, e.g., medical staff (undecided), (5) ambivalent people, being neither for nor against an app but looking for valid arguments on both sides (undecided), (6) COVID-19 skeptic people (critics), and (7) COVID-19 app skeptic people (critics). Further insights into the characteristics of the different user groups are presented in Figure 4. As a learning for future social-participial apps, it can be concluded that all potential user groups should be well considered and analyzed beforehand. We see that as a major step to increase the likelihood of a higher uptake rate (learning 5).

Proposition 5: Improve Acceptance Through an Open-Source Approach

Open-source creates unanimous security as it allows anyone (such as privacy advocates as well as NGOs and security professionals) to view the code (Cho et al., 2020). In this way, data security concerns can be lowered because the application transmission data is transparent (Bock et al., 2020). However, Dehmel et al. (2020) noted that besides the initial publication of the code, a management concept is required in reaction to feedback and experiences in the field (learning 1). SAP, the developer of the COVID-19 tracing app in Germany, considers this the right approach to increase feelings of transparency and trust. This is shown with the GitHub repository, which made it not only possible to review the entire interaction concept up-front, but simultaneously to provide feedback and direct

Figure 5. Cumulated GitHub Issues for the Corona-Warn-App[2]



communication with the development team (Mueller, 2020). This was intensively used even prior to the official app launch (Figure 5). Further, the open source was a discussion topic that had a positive impact on trust, as already seen in Q1 and Q4–6 (cf. Table 6)—especially as this pushed the "public money, public code" paradigm of governmental software projects (Federal Chief Information Officers, 2016). In contrast, Sandvik (2020) criticizes the fact that trust and voluntariness are hard to achieve for closed-source apps. Thus, open-source approaches for app development are met with a high level of interest and openness on the part of the community, which also shows greater trust in an app (learning 2).

Our results indicate the counterproductivity in not making a COVID-19 tracing apps public (or at least parts). This includes the backend and APIs of the operating system. Open-source also facilitates the global effort against COVID-19. With regards to the legal, technical, and cultural distinctiveness, tracing apps cannot just be replicated for each country. Thus, open-source enhances the reproducibility of important elements in the development process, like technical specifications, interaction concepts, and the overall user journey.

Proposition 6: Interoperability Across Borders

Joined semi-private initiatives like PePP-PT and DP-3T have not succeeded. This lack of success should prompt policy makers to ensure (1) complete accessibility to a local app, (regardless of language barriers or settings) and home app-stores as well as (2) bidirectional data transfer across borders. Following a visit to a holiday residence, people need to know—back in their home country—if they have endangered themselves and should therefore conduct a COVID-19 test. Those people who have tested positive in the visited region (locals, staff, and other visitors) also require this information about potential infection risk.

LIMITATIONS

Our paper faces some limitations. Primarily, the effect of zero rating has not been included in this research, as internet service providers (ISPs) decided not to count traffic caused by the COVID-19 app while the research was already ongoing. When each app user might interact with megabytes of data (e.g., because of dozens reported infectious IDs), traffic consumption, and the subsequent costs could impact the willingness to use such a service. Future research could test this variable as well. The coefficient of determination (R2) in the technology acceptance model shows a medium value of 0.47 for the dependent variable intention to use and a small value of 0.19 for the actual usage behavior. The investigated independent variables explain the actual usage of the German COVID-19 tracing app to only 20% and the variables with higher coefficients do not have as great an impact as might initially be thought.

Secondly, we focused on social media and press to gain participants. As COVID-19 and its digital and physical countermeasures divided society into supporters and opponents, our research faced intense discussions in the media. We did not check for any bias with regard to COVID-19 believers and non-believers (and even conspiracy theories) in our survey.

Thirdly, although our data is based on feedback from 35 countries, we needed to merge groups of countries to build a solid statistical base for our model. Generating specific results for all of the countries included would have required equal panel acquisitions across the globe. Nevertheless, we were able find meaningful results for the regions with substantial progress in the development and outreach of COVID-19 tracing apps.

CONCLUSION

In this study, we explored existing COVID-19 applications and factors influencing the use intention and actual use of COVID-19 tracing as social participation apps. We developed a classification overview of tracing and tracking approaches (see Figure 1) and evaluated a technology acceptance model with a worldwide survey involving 2,398 respondents (see Figure 3). Analyzing the feedback, this research expands on the results of Trang et al. (2020) and identifies and describes seven different user groups (see Figure 4). We derived practical recommendations for policy and app makers and several implications for research in the context of technology, in total six implications (see discussion section). These implications depend on mass acceptance and broad participation within a population.

We were able to identify significant determinants for the usage of tracing apps in the areas of user behavior, user trust in technology, and social attitudes towards the pandemic itself. The independent variables explain the intention to use to a moderate extent (R^2=0.47) and the actual usage to a low extent (R^2=0.19). Nevertheless, the study generates a solid qualitative insights for the understanding of COVID-19 tracing apps. General findings for social-participial might help app and policy makers in the future to increase the uptake rate of such apps by considering user groups in their communication strategies, an open-source approach, and participation in app development. Especially the critics and undecided people should be considered when creating an effective communication strategy to encourage the use of COVID-19 apps.

Future research may extrapolate on our findings. We plan on undertaking a longitudinal study to measure the enhancement of the COVID-19 tracing apps over time. A taxonomy of digital technologies against the disease might strengthen the theoretical foundation. An understanding of the effect of tracing apps on the containment of COVID-19 will be required in the future. From a broader perspective, the positive impact of open-source approaches, a socio-technical point of view and a target-group specific communication strategy are recommendable for social-participatory apps in the field of e-Health.

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APPENDIX A: PLS-SEM CONSTRUCTS

Table A1. Constructs, items, and sources used in the study.

Behavioral intention	**I would consider to share data with the official COVID-19 tracing app. I would be willing to share data with the official COVID-19 tracing app. I would like to share data with the official COVID-19 tracing app.**	**According to Stibe (2014)**
Perceived usefulness	**I think I have a better possibility to visit business or social events using the COVID-19 tracing app (workshops, restaurants, clubs, sport etc.). My private life would be difficult to perform without the COVID-19 tracing app. My job would be difficult to perform without the COVID-19 tracing app. Using the COVID-19 tracing app makes it easier to cope with the pandemic situation. Using the COVID-19 tracing app me greater control over my health. The COVID-19 tracing app addresses my expectations. Overall, I find the COVID-19 tracing app useful. I feel more safe using the COVID-19 tracing app.**	**Adapted from Davis (1989) (The first item was added)**
Trust in technology	**I usually trust a technology until it gives me a reason not to trust it. I generally give a technology the benefit of the doubt when I first use it.**	**McKnight et al. (2011)**
Privacy concerns (probably regarding trust in technology)	**How much are you concerned that the information submitted to the COVID-19 tracing app: ... can be used in a way you did not foresee? ... can become available to someone you don't want? ... can become available to someone without your knowledge?**	**According to Krasnova et al. (2009)**
Reputation	**My family or friends think it's a good thing using the COVID-19 tracing app. I earn respect from others by actively participating in the COVID-19 tracing app. I feel that active participation improves my status.**	**First: Liobikienė et al. (2016) Last two: Church et al. (2019)**
Personal innovativeness	**If I heard about a new information in the domain of technology, I would look for ways to experiment with it. Among my family and friends, I am usually the first to try out new information technologies. I like to experiment with new information technology.**	**According to Agarwal and Prasad (1998)**
Altruism	**I enjoy helping others. It feels good to help someone else.**	**According to Church et al. (2019)**
Perceived anxiety of infection	**I am afraid of getting infected with COVID-19. I want to know my personal risk of being infected (without the need of a classical COVID-19 test). I want to know a potential infection as soon as possible.**	**Self-developed**
Perceived anxiety of infecting others	**I am afraid of infecting others with COVID-19. I want to inform automatically others in case that I am infected. I do not want to be responsible infecting others.**	**Self-developed**

Table A2. Combined loadings and cross-loadings.

	PEUS	TRUS	CONC	NORM	ALTR	PIIT	INME	INOT	BEIN
PEUS1	0,636	0,352	0,023	0,448	0,084	0,158	0,241	0,138	0,353
PEUS2	0,621	0,271	0,202	0,53	-0,015	0,2	0,215	0,028	0,199
PEUS3	0,61	0,288	0,219	0,521	-0,04	0,19	0,201	0,003	0,187
PEUS4	0,75	0,239	-0,367	0,361	0,176	0,211	0,46	0,483	0,525
PEUS5	0,797	0,303	-0,142	0,486	0,099	0,202	0,437	0,312	0,417
PEUS6	0,659	0,137	-0,439	0,341	0,17	0,306	0,409	0,446	0,47
PEUS7	0,75	0,2	-0,514	0,387	0,202	0,303	0,516	0,564	0,596
PEUS8	0,827	0,317	-0,226	0,518	0,15	0,276	0,488	0,366	0,469
TRUS1	0,347	0,91	-0,029	0,287	0,126	0,218	0,186	0,124	0,269
TRUS2	0,324	0,91	-0,013	0,3	0,142	0,264	0,202	0,137	0,254
CONC1	-0,24	-0,027	0,954	-0,058	-0,09	-0,136	-0,233	-0,379	-0,414
CONC2	-0,227	-0,022	0,97	-0,063	-0,106	-0,153	-0,218	-0,362	-0,394
CONC3	-0,232	-0,017	0,966	-0,06	-0,104	-0,15	-0,215	-0,362	-0,399
NORM3	0,544	0,248	-0,343	0,594	0,186	0,289	0,41	0,422	0,471
NORR4	0,511	0,274	0,022	0,919	0,086	0,271	0,309	0,165	0,253
NORR5	0,518	0,276	0,064	0,901	0,08	0,285	0,291	0,121	0,219
ALTR2	0,145	0,141	-0,08	0,105	0,919	0,159	0,13	0,254	0,146
ALTR3	0,136	0,13	-0,111	0,135	0,919	0,161	0,149	0,286	0,157
PIIT1	0,336	0,316	-0,154	0,347	0,181	0,896	0,281	0,185	0,299
PIIT2	0,277	0,186	-0,109	0,285	0,121	0,907	0,254	0,132	0,222
PIIT4	0,273	0,219	-0,149	0,285	0,171	0,913	0,254	0,164	0,24
INME1	0,373	0,133	-0,016	0,307	0,027	0,167	0,78	0,416	0,231
INME2	0,474	0,221	-0,148	0,365	0,143	0,272	0,844	0,443	0,336
INME3	0,461	0,164	-0,393	0,288	0,197	0,267	0,823	0,654	0,448
INOT1	0,361	0,099	-0,218	0,253	0,185	0,162	0,558	0,813	0,318
INOT2	0,47	0,173	-0,441	0,276	0,238	0,193	0,549	0,838	0,481
INOT3	0,221	0,077	-0,275	0,094	0,3	0,078	0,413	0,806	0,265
BEIN1	0,544	0,256	-0,406	0,34	0,165	0,277	0,412	0,442	0,949
BEIN2	0,555	0,268	-0,415	0,328	0,163	0,255	0,405	0,435	0,97
BEIN3	0,549	0,298	-0,37	0,34	0,142	0,268	0,373	0,363	0,936

APPENDIX B: DESCRIPTIVE STATISTICS

Table B1. Descriptive statistics.

Question (Groups)	Values	Yes		No
Knowledge of the official tracing app	0; 1	2,257		141
Usage of the official corona tracing app	0; 1	1,945		312
COVID-19 infected person among friends and family	0; 1	1,075		1,588
	Values	Median	Average	Standard Deviation
Behavioral intention [BEIN]	1–7	6.00	5.27	1.91
Perceived usefulness [PEUS]	1–7	5.00	4.14	2.10
Trust in technology [TRUST]	1–7	5.00	4.44	1.66
Privacy [CONC]	1–5	2.00	2.14	1.32
Reputation [REPU]	1–7	4.00	3.94	1.85
Personal innovativeness [PIIT]	1–7	5.00	4.83	1.63
Altruism [ALTR]	1–7	6.00	6.06	0.92
Perceived anxiety of infection [INME]	1–7	5.00	5.17	1.61
Perceived anxiety of infecting others [INOT]	1–7	6.00	5.97	1.36
Age (category)	1–7	3.00	3.01	1.24
Gender (0 = female, 0.5 = other, 1 = male)	0; 0.5; 1	1.00	0.61	0.48
Country (1 = Germany, 2 = France, 3 = Other Europe, 4 = Other World, 5 = USA)	1–5	1.00	1.57	1.33
Residential area (1 = Village, 2 = Small town, 3 = Medium city, 4 = Large city, 5 = Metropol)	1–5	4.00	3.33	1.26

ENDNOTES

1 Cf. https://github.com/DP-3T/documents, retrieved August 21, 2020.

2 There are different issue areas for the German Corona-Warn-App, e.g., for all operating systems. Thus, we analyzed the general "wish list," cf. https://github.com/corona-warn-app/cwa-wishlist/issues, retrieved August 21, 2020.

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