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Ready or Not for Contact Tracing? Investigating the Adoption Intention of COVID-19 Contact-Tracing Technology Using an Extended Unified Theory of Acceptance and Use of Technology Model

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Abstract

To diminish the risk of spreading COVID-19 as society exits the lockdowns, several apps have been developed for contact tracing. These apps register which users have been in proximity of each other. If a user is diagnosed with COVID-19, app users who have been recently in proximity to this person are notified. The effectiveness of these apps highly depends on public support. Therefore, this study investigated the factors that influence app use intention, based on an extended unified theory of acceptance and use of technology model. A survey was administered in Belgium (Flanders) to 1,500 participants aged 18 to 64 years old. Structural equation modeling was used to test the relationships among the model's constructs. Our results indicated that 48.70 percent of the respondents wanted to use the app. The model explained 39 percent of the variance in app use intention. The most important predictor was performance expectancy, followed by facilitating conditions and social influence. Effort expectancy was not related to intention. Moreover, individuals' innovativeness was positively related with app use intention, whereas app-related privacy concerns negatively influenced intention. Based on the results, suggestions are made for policy makers and developers.

Keywords: COVID-19, coronavirus, contact tracing, proximity tracing, UTAUT, privacy

Introduction

COVID-19 has rapidly spread across the globe[1] and led to confinement and other measures to flatten the curve of infections. However, epidemiologists predict possible rebounds of the epidemic once lockdown measures are loosened.[2] Part of some countries' deconfinement policies are the use of apps that focus on contact tracing. Citizens are encouraged to download and run an app that keeps track of their proximity with other app users. More concretely, when two app users come near each other, their smartphones estimate the distance between them (e.g., through Bluetooth signal strength). Based on the spatial nearness between the smartphones and the time for which the users are nearby each other, the smartphones exchange tokens. Each app logs the encounters with other app users by keeping a list of tokens. When an app user identifies as being infected by COVID-19, the user is asked to share the list of locally saved tokens with a central server. The server receives a list of all tokens of phones of individuals with whom the infected user has crossed paths. Consequently, the potentially affected phone users are notified, and recommendations are given (e.g., to self-quarantine or consult a physician).[3] In this way, measures are targeted only to individuals who have been exposed to the virus.

Traditionally, contact tracing occurs through call center operators, who interview individuals who have been diagnosed and the people who have crossed paths with them. This form of contact tracing can consume significant amounts of time and human resources.[4] Moreover, it could be difficult for interviewees to recall strangers they met who would fit the conditions for close-range proximity.[5] Furthermore, traditional contact tracing would not be fast enough to keep up with the pace of COVID-19's spread.[6] As a result, contact tracing through smartphones is increasingly being investigated and implemented. However, concerns have been voiced about the ethical and legal aspects of digital contact tracing, calling for clear conditions on the processing and use

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of data to respect citizens' privacy rights.[7] Moreover, the effectiveness of a COVID-19 app largely depends on public support.[3] In general, the adoption of new technologies is confronted with high failure rates.[8]

Therefore, investigating the factors that would stimulate or slow down a contact-tracing app's uptake is crucial for integrating it successfully into deconfinement strategies. This study used a unified theory of acceptance and use of technology (UTAUT) perspective to investigate the factors that would influence citizens' willingness to use an app that traces nearness with COVID-19–diagnosed individuals and notifies app users of this contact.

Unified theory of acceptance and use of technology

The UTAUT model has become a frequently used technology-acceptance model for assessing the adoption and use of new technologies. It includes four constructs that are expected to influence the intent to use a specific technology.

Performance expectancy is the extent of the benefits that users expect from using a technology. In short, we predict that respondents who have positive expectations concerning the app's performance in detecting positive cases and in contributing to the prevention of the virus's spread will be more inclined to install the app.

Effort expectancy is the degree of ease expected for using the COVID-19 app.[9] When respondents expect it to be easier for them to use the app, they will be more inclined to do so.

Facilitating conditions are individuals' own resources and the support they can count on. We expect that as individuals are more convinced, they can rely on resources to facilitate the app's use, they will be more inclined to adopt the app.

Social influence refers to individuals' beliefs that important others think they should be using the technology. Social influence has been found to be important in the early stages of individuals' experience with a new technology, whereas its role erodes over time and eventually becomes insignificant once usage of the technology is sustained, as one's own experience gives a more instrumental basis for an individual's continued use of a technology.[9] Therefore, as we investigate a new technology, we expect that if individuals believe significant others will support their use of the app or advise them to use the app, they will intend to do so. This leads to the following hypotheses based on the UTAUT model:

H1: Performance expectancy is positively related to app-uptake intention.

H2: Effort expectancy is positively associated with intention to use the app.

H3: Facilitating conditions positively relate to behavioral intention to use the app.

H4: Social influence is positively associated with app use intention.

More recently, UTAUT2 has extended the original framework with new constructs (i.e., hedonic motivation, price value, and habit).[10] However, this study relied on the original UTAUT because the constructs added to the original model by UTAUT2 are less applicable in the context of the adoption of a COVID-19 app. The authors of UTAUT have called for further identification of additional factors for comprehending the intention of using consumer technology.[10] Therefore, the following constructs that are relevant to the particular context of the COVID-19 epidemic were added.

Innovators are valuable resources for organizations that are launching a new technology or product.[11] Their innovativeness reflects their desire to seek and try out new and different ideas, products, and services.[12] We expect that in the case of a COVID-19 app, individuals' orientation toward rapidly adopting new technologies[13] will positively influence their intention to use the app. As they are eager to use new digital applications, they could be the first to use the app and, consequently, can also influence their social network. Therefore, we hypothesize:

H5: Individuals' innovativeness is positively associated with app use intention.

Some studies have found that privacy concerns about health informatics negatively affect patients' health-related technology use.[14] In the context of launching a COVID-19 app, we expect that privacy concerns would negatively influence app-uptake intention, especially because privacy organizations have raised concerns about data-protection issues related to the implementation of contact-tracing apps.[15,16] We, therefore, formulate the following hypothesis:

H6: The higher the individuals' app-related privacy concerns, the lower their intention to use the app.

Previous research has found that individuals' perceived risk of a threat influences specific protective behaviors.[17,18] Thus, we hypothesize that the more worried individuals are about the consequences of the COVID-19 crisis, the more they will be inclined to adopt the app. This leads to the final hypothesis:

H7: The higher the individuals' COVID-19–related stress, the higher their intention to use the app.

Methods

An online survey was administered in Belgium to 1,500 respondents aged 18 to 64 years old. The survey took place from April 17 to 19, 2020. A professional research agency recruited the respondents. A sample of 1,500 respondents was taken with the following eligibility criteria: (1) being a resident of Belgium, (2) being aged between 18 and 64 years, and (3) speaking Dutch. A stratified sampling procedure was followed to achieve a heterogeneous sample. Based on Belgian federal statistics, we *a priori* stratified the data regarding gender, age, employment status, and educational degree, so that the proportions of the sample's strata would reflect the proportions of the Flemish population. The respondents were first informed about the study's purposes and asked for their informed consent before being asked to fill in the questionnaire. When 1,500 respondents were reached, in accordance with the strata, the research agency closed the survey. Table 1 provides the descriptive statistics of the sample, including age, gender, highest education, and having a health condition.

The study was approved by Ghent University's ethics committee.

Measures

The study's measures operationalizing the model's constructs are summarized in Table 2. The items were

Table 1. Characteristics of the Study Sample

	Study sample (n = 1,500)
Gender, *n* (%)	
Male	756 (50.4)
Female	744 (49.6)
Age in years, *M* (*SD*)	41.58 (13.94)
Educational level, *n* (%)	
No diploma or primary or lower secondary education diploma	338 (22.5)
Secondary education diploma	611 (40.7)
Higher education diploma	551 (36.7)
Having a health condition (yes), *n* (%)	485 (32.3)

SD, standard deviation.

included in the survey in Dutch but have been translated for this article. All of the items were measured using a 5-point Likert scale with the anchors 1 = *not agree* and 5 = *agree*. The scales for the UTAUT constructs were derived from operationalizations developed by Venkatesh et al.[9,10] and adapted to this study's focus.

The innovativeness component from the National Technology Readiness Index was integrated in the survey to assess individuals' tendency to be a pioneer in using new technology.[13] To measure respondents' app-related privacy concerns, we tailored items from the privacy concern scale[19] to fit the present study's focus. Finally, the respondents' stress related to the COVID-19 crisis was measured with three self-constructed items assessing respondents' concerns about the COVID-19 situation and its consequences.

The covariates were age, gender, education level, and having a health condition. Education was measured with three levels (lower level of secondary education, higher level of secondary education, and higher education [university or college]). The respondents were asked whether they suffered from one or several of a list of health conditions that can be a risk factor when infected with COVID-19 (heart or lung conditions, renal disease, diabetes, cancer, weakened immune system, or high blood pressure).

After informing the respondents about the study's objectives and asking for their informed consent, the respondents were confronted with a short paragraph explaining the key features of a COVID-19 app: (1) the use of Bluetooth or GPS signals to detect the proximity between users, (2) the anonymous disclosure of users' COVID-19–positive status to others who have crossed their path, and (3) access to supplementary information and advice on dealing with COVID-19. This information was based on available information on apps that have already been developed and used in other countries because a COVID-19 app was not available at that time in the country where this study was performed. This introduction and the whole questionnaire were piloted by three respondents to check the clarity of the questions and explanations.

Data analysis

Structural equation modeling was applied to the collected data using Mplus 8.4 with maximum likelihood estimation to examine the relationships among the UTAUT constructs.[20] The analyses were performed using the following approach. First, the measurement model was tested to determine the appropriateness of the model for hypothesis testing. To detect the potential presence of multicollinearity among the predictor variables, the variance inflation factor (VIF) has been taken into account. VIF values >5 are considered as indicator for multicollinearity.[21] The analyses revealed that all VIF values were <2. Thereafter, we estimated a structural model with COVID-19 app use intention as the outcome.

The model fits of the measurement and path models were evaluated according to several fit indices. Given that χ^2 is almost always significant and not an adequate test of the model fit,[22] we also report the χ^2/df ratio as well. A χ^2/df ratio of 2:1 to 5:1 is required, and it indicates an acceptable fit, although values <3 are considered favorable.[22] In addition, we examined the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR).[22] The CFI and TLI range from 0 to 1.00, with a cutoff of 0.95 or higher indicating that the model provides a good fit and 0.90 indicating that the model provides an adequate fit.[23,24] RMSEA values <0.05 indicate a good model fit, and values between 0.06 and 0.08 indicate an adequate fit.[25] The SRMR is a standardized summary of the average covariance residuals.[22] A relatively good model fit is indicated when the SRMR is <0.08.[24] Given the large sample size, *p*-values <0.01 are considered significant.

Results

The descriptive statistics of the variables (mean, standard deviation, and factor loadings), together with the Cronbach's alpha values of the constructs, are presented in Table 2.

In total, 48.70 percent of respondents would like to use the app (20.40 percent disagreed, 10.40 percent somewhat disagreed, 20.50 percent neither disagreed nor agreed, 27.90 percent somewhat agreed, and 20.80 percent agreed).

The measurement model provided an acceptable fit for the data, $\chi^2(224) = 813.03$, $p < 0.001$, $\chi^2/df = 3.63$, CFI = 0.974, TLI = 0.963, RMSEA = 0.042, 95 percent confidence interval (CI) [0.039–0.045], SRMR = 0.042. All factor loadings were significant and >0.477. Subsequently, we tested the structural model. The results of the fit statistics indicate an acceptable model fit, $\chi^2(312) = 1099.412$, $p < 0.001$, $\chi^2/df = 3.52$, CFI = 0.963, TLI = 0.956, RMSEA = 0.041, 95 percent CI [0.038–0.044], and SRMR = 0.048. The results of the structural model (standardized β's) are presented in Figure 1. Our analyses revealed that performance expectancy, effort expectancy, social influence, and facilitating conditions, together with the covariates, explained 39.0 percent of the variance in intention. The most important predictor of intention was performance expectancy ($\beta = 0.40$, $p < 0.001$), followed by facilitating conditions ($\beta = 0.15$, $p < 0.001$) and social influence ($\beta = 0.14$, $p < 0.001$). These results confirm H1, H3, and H4. Effort expectancy was, however, not significantly related to intention ($\beta = -0.09$, $p = 0.04$), which falsifies H2. With regard to the covariates, we found that innovativeness ($\beta = 0.15$, $p < 0.001$) and app-related privacy concerns ($\beta = -0.16$, $p < 0.001$) were significantly related to intention. The results confirmed H5 and H6. Contrary to H7, COVID-19–related stress ($\beta = 0.05$, $p = 0.034$) was not

Table 2. Descriptions of the Study Variables

	M	SD	*Cronbach's α*	*Factor loadings of the items*
Behavioral intention			0.98	
I would be willing to use the COVID-19 app	3.18	1.41		0.974
I plan to use the COVID-19 app	3.08	1.40		0.968
I want to use the COVID-19 app in the future	3.18	1.41		0.983
Performance expectancy			0.94	
Using the COVID-19 app will improve my knowledge about the hazard of being infected by COVID-19	3.37	1.18		0.620
I would find the COVID-19 app useful for assessing my risk of being infected by COVID-19	3.40	1.19		0.918
By using the COVID-19 app, one can limit the spread of COVID-19	3.41	1.20		0.870
Effort expectancy			0.88	
Learning how to use the COVID-19 app will be easy for me	3.69	1.17		0.954
Using this COVID-19 app would not be complicated for me	3.65	1.19		0.904
I will rapidly become skillful in using the COVID-19 app	3.69	1.12		0.667
Social influence			0.88	
People who are important in my life will think that I should use the COVID-19 app	3.24	1.19		0.936
People who influence me will advise me to use the COVID-19 app	3.17	1.16		0.962
People whose advice I value will recommend that I use the COVID-19 app	3.19	1.15		0.660
Facilitating conditions			0.89	
I have the knowledge needed to use the COVID-19 app	3.62	1.23		0.821
I have the necessary resources to use the COVID-19 app	3.78	1.21		0.888
The COVID-19 app will be compatible with other technologies I use on my smartphone	3.57	1.23		0.850
Innovativeness			0.76	
Other people come to me for advice on new technologies	2.76	1.31		0.896
In general, I am among the first in my circle of friends to acquire a new technology when it appears	2.40	1.23		0.818
I can usually figure out how to use new high-tech products and services without help from others	3.39	1.29		0.503
App-related privacy concerns			0.89	
Using the COVID-19 app would make me concerned about my personal privacy	3.42	1.20		0.631
Using the COVID-19 app would make me feel uncomfortable concerning the protection of my privacy	3.33	1.21		0.972
I would be concerned about my privacy if I were to use the COVID-19 app	3.34	1.21		0.966
COVID-19–related stress			0.71	
Even when I am busy with other things, I am concerned about the current COVID-19 situation	3.52	1.18		0.749
The current COVID-19 situation is very stressful for me	3.67	1.11		0.790
I am concerned about the consequences of the COVID-19 crisis	4.23	0.89		0.477

significantly related to intention. The covariates were not significantly related with app-use intention.

Discussion

Although some countries have implemented a COVID-19 app for tracing users and informing them about possible risky contacts, some doubts concerning individuals' uptake have been voiced. Based on U.K. data, Hinch et al. have simulated the COVID-19 epidemic and estimated that when 56 percent of the population would use a contact-tracing app, the epidemic would be suppressed. Even if app uptake were lower, it would still slow down the spread of COVID-19.[26] Also other studies simulating the spread of the virus and testing epidemic control when a digital contact tracing is implemented found a reduction of the epidemic. Still, the contribution of a contact-tracing app toward epidemic control results is dependent on app uptake, the combination with testing and compliance with preventive measures such as physical distancing and self-isolation.[6,27,28] As app adoption can play an important role, this study used an extended UTAUT model to investigate predictors of COVID-19 app use intention.

The most important predictor of COVID-19 app-uptake intention is performance expectancy. The more respondents are convinced about the app's efficacy to augment their knowledge of potential exposure to the virus and to limit its spread, the higher the individuals' intention is to adopt the app. Therefore, when governments choose to develop and launch such an app, its different (individual and social)

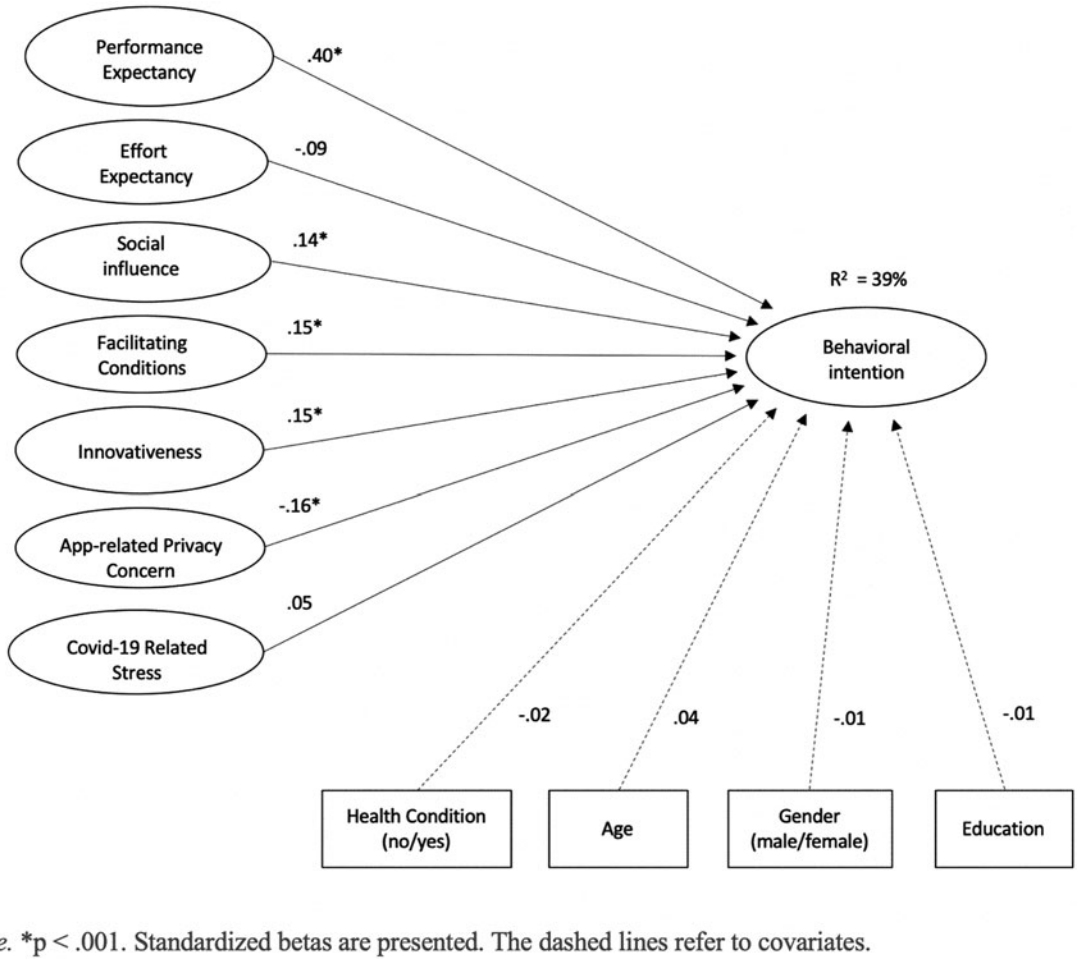

FIG. 1. Structural model.

benefits should be made clear. To augment the performance expectations of such an app, other health care services could be envisioned alongside its basic functions. The app's value proposition could be strengthened by including more information on symptoms and how and where a user can be tested. Moreover, as different apps are developed and as traveling resumes, communication between apps or the implementation of a COVID-19 app that operates in different countries will be necessary to further contain the pandemic.[4]

Facilitating conditions were found to positively influence app-uptake intention. The presence of several conditions that support technology use, such as information and assistance, can influence individuals' uptake of the app.[29] Therefore, facilitating conditions should be implemented when launching a COVID-19 app, such as a help function, a tutorial, or testimonials of other individuals who use the technology.[30]

Previous research has already found that social influence is a strong predictor of fitness and health app use.[31] As our study showed that social influence positively impacted COVID-19 app-uptake intention, it has to be integrated in promoting the app. For instance, indicating who from one's friend list has downloaded the app or communicated their use of the app could augment individuals' perceived social influence to install it. Moreover, communication about the app could stress the personal and social benefits of using it (e.g., protecting one's family and friends) and make recruitment of new users easy through peer-to-peer promotion and support from virologists, other medical experts, and popular influencers.[32]

Effort expectancy was not significantly related with app use intention. This contrasts with other empirical studies concerning mobile app adoption.[33] In general, users' easy handling of a technology is an important determinant of use intention in the context of devices to monitor health data.[34] In the context of a contact-tracing app, required manipulations are limited. Contact tracing only needs to be activated and users are informed which actions they have to take when they crossed paths with COVID-19 infected users. As no testable app was developed for this study and the app's general functioning was described in this study, it could have been difficult for respondents to assess the efforts needed to use the app. Nevertheless, when users are warned about a possible risky contact, it is important that they be rapidly assisted and informed about which measures they must take. Notifications should be easy to understand and include clear recommendations to reduce users' misjudgments when receiving this stressful message.[4] To be able to cope with this news, contact with a general practitioner or a specialized contact-tracing collaborator could be advised and facilitated.

Innovativeness was positively related to individuals' use intention. In general, innovators are an important resource for organizations that are launching a new technology. They serve as opinion leaders in their social network[35] by exerting influence orally and by example.[36] Hence, opinion leaders (e.g., online influencers in the domain of technology and health) can be invited to use and explain the app when it is launched to make the options concrete.

In addition, individuals' stress caused by the COVID-19 crisis was not significantly related with app-use intention. In general, people could be sensitized (e.g., using emotional appeals)[37] as to how the app could inform them about possible exposure to the virus and how they can quickly take the necessary measures to protect themselves and their relatives.

App-related privacy concerns were negatively correlated with app-uptake intention. Thus, it is important to inform potential users about the data needed by the contact-tracing app for it to be effective. To fulfill its basic functions, the only information needed is about an infected person's physical proximity during the period when transmission could occur.[5] Stressing this data-minimizing approach may influence individuals' uptake.[3] However, if personalized services are offered through the app (e.g., telemedicine), this could conflict with users' privacy concerns. Therefore, when launching a contact-tracing app, it is important to have a clear view of how the collected data will be used and the personalized services and information to be offered. Users need to be informed about these options in the app's privacy policy and offered the possibility to opt-in. Because most apps briefly confront new users with a privacy policy for them to accept, developers of COVID-19 apps could integrate information about how they securely process data and which data are needed to use the app's COVID-19 personal warning feature. While informing potential app users that the privacy policy is essential, research has found that when joining a social network site, 7 out of 10 participants skip the privacy policies.[38] To minimize the (time) cost of reading and assessing the privacy terms, a visual presentation could integrate how the app processes personal data.[39]

Some limitations to this study should be acknowledged. This study was conducted in a country where a COVID-19–tracing app had not been launched at the time of the research. Future research could present several app options or combinations of options by conducting a factorial survey to investigate which combinations of options lead to more or less use intention. Moreover, when an app is launched, international comparative research could investigate the factors that influence app use and how they are related to the country's epidemiological situation regarding COVID-19. Future (experimental) research could also investigate how the framing of the message users receive when they crossed paths with a COVID-19–positive user leads to specific adaptive coping behaviors.

Notwithstanding the possible contributions of an app, specific populations can be missed if they have no access to smartphones or do not want to run the app due to convictions. For instance, in the country where this study was conducted, 90 percent of the population has a smartphone. However, for individuals >65 years, this lowers to 73 percent.[40] Existing health inequalities could, therefore, be exacerbated. Moreover, not all individuals who contracted COVID-19 develop symptoms and are subsequently tested, triggering a warning to app users who have been in proximity with them. In other words, asymptomatic patients could further transmit the virus. Consequently, contact-tracing apps need to be integrated within a global plan that includes rapid and effective testing and further promotes personal protective measures.

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