



Predictors of contact tracing app adoption: Integrating the UTAUT, HBM and contextual factors

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ABSTRACT

Contact tracing apps (CTAs) have been introduced as a means to identify and isolate possible cases infected with COVID-19. Since the adoption rate determines the effectiveness of CTAs, it is important to examine what factors contribute to a higher CTA uptake. This study aimed to use an integrative approach to explain early CTA adoption, whereby three perspectives are distinguished: technology-related (derived from the Unified Theory of Acceptance and Use of Technology [UTAUT]), health-related (derived from the Health Belief Model [HBM]), and context-related. A survey was administered among a representative sample of the Dutch population ($N = 1865$). A hierarchical logistic regression analysis was performed in which the models were compared. Results showed that an integrative model including all three perspectives (i.e., UTAUT, HBM, and context-related variables) resulted in better model fit than any of the other models. All UTAUT variables were associated with CTA adoption in the expected directions. Regarding the HBM, self-efficacy, perceived barriers and perceived benefits were associated with CTA adoption in the expected directions. Several context-related variables, such as fear, were associated with CTA adoption. Our findings demonstrate that extending the UTAUT with preventive health-behavioral factors and contextual factors contribute to better understanding of CTA adoption.

1. Introduction

Due to the rapid spread of COVID-19, contact tracing apps (CTAs) have been introduced in several countries worldwide as a means to identify and isolate possible cases infected with COVID-19, aiming to reduce the spread of the virus. Widespread adoption is important for the effectiveness of CTAs. Though it has been shown that CTAs contribute to the reduction of spread at low adoption rates (e.g., 20% [1]), simulations show that the effects increase at higher rates of adoption [2,3]. In the Netherlands, the contact tracing app “CoronaMelder” was introduced in October 2020. The Dutch CTA was designed to complement the regular contact tracing by reaching close contacts faster after a positive test result, and by providing advice after being tested positive [4]. Similar to the majority of CTAs [5], the CoronaMelder uses Bluetooth to recognize other smartphones that have the app installed, and stores unidentifiable codes of the other users in the app. When a CoronaMelder

user is tested positive for COVID-19, this user is able to anonymously notify other app users who have been in close contact with that person for a certain amount of time.

Research has shown that during periods of lockdown, the Dutch CTA had a noticeable but small impact, whereby the added value of the CoronaMelder was expected to be larger with reopening of society when more social contact is possible again [4]. When this study was conducted in October 2020, 27.2% of the sample used the Dutch CTA. This percentage increased to around 32% until March 2021. In October 2021, the percentage of users was decreased to 25.6% [6–8]. The 5% increase of users in half a year time indicates the high percentage of early adopters among the app users.

Considering that higher adoption rates are desirable to reach the full potential of CTAs [9], it is important to examine which factors contribute to a higher app adoption. This study provides a holistic approach in identifying the variables that explain CTA adoption, by

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integrating three perspectives: a technology-related (i.e., factors related to new technology adoption), health-related (i.e., factors related to health behavior change), and context-related (i.e., factors related to the specific COVID-19 situation) perspective.

The technology-related perspective will be represented by the unified theory of acceptance and use of technology (UTAUT; [10], which is a widely used theoretical model for predicting adoption of new technologies (e.g., e-learning, e-commerce, e-banking [11]). Performance expectancy (i.e., the expected effectiveness of the technology), effort expectancy (i.e., the expected ease of the technology use), facilitating conditions (i.e., infrastructure, knowledge and resources that are necessary for technology use), and social influence (i.e., social norms regarding the use) are argued to be predictors of new technology adoption [10].

CTAs differ from other technologies that were previously examined with UTAUT, in a way that most of these technologies are used actively and consciously, and on a frequent (e.g., daily/weekly) basis. CTAs are designed to be used passively: after installation of the CTA, there is no need to open or use the app, unless the user is infected with COVID-19 or receives a notification that the user has been near another CTA user that tested positively. Until now, UTAUT has predominantly been investigated on apps that demand higher activity levels, such as online banking [12] and social networking sites for learning [13]. The abrupt and widespread need for CTAs has provided an opportunity to study the UTAUT in a different context, namely for a technology that is introduced nationwide and that is designed to be used passively.

While several scholars have adopted (parts of) the UTAUT to explain the intention to use CTAs [14–16], or usage frequency [15], no studies yet have examined whether the UTAUT can be used to explain self-reported CTA adoption. It is well-known that for many behaviors, including technology adoption [10], the intentions to perform a certain behavior do not always lead to actual behavior. The intention-behavior gap regarding CTAs was already observed in a study carried out in Australia, in which intentions to use a hypothetical CTA (before the actual CTA was launched) were compared to the number of downloads of the actual CTA [17]. While the hypothetical CTA had an acceptance rate of approximately 60%, a total of 44% had downloaded the CTA. It is therefore important to focus on the main variables associated with CTA adoption, as a high adoption rate is the ultimate goal to suppress the pandemic. Hence, the first aim of this study is to focus on the UTAUT variables to explain actual CTA adoption.

During earlier pandemics (e.g., SARS, swine influenza), psychological processes as specified in ample health behavior change models have been identified, that are related to behaviors aimed to prevent the spread of infectious disease (i.e., keeping distance, washing hands [18]). This indicates that health-related factors could be of importance when it comes to CTA adoption, as the communicated utility of CTAs is to prevent the spread of COVID-19 as well. The health belief model [19] is a theoretical model that explains how personal risk assessment of getting a disease, as well as barriers and benefits of performing the health-promoting behavior, can predict the extent to which that health-promoting behavior is performed. More specifically, perceived susceptibility (i.e., the extent to which one feels vulnerable to get a certain disease) and perceived severity (i.e., the personal assessment of the seriousness of the disease) are factors that could influence the performance of preventive behavior related to that disease. Furthermore, the model takes into account self-efficacy (i.e., the extent to which one has the feeling that one has the abilities to perform the recommended behavior), perceived benefits, and perceived barriers of performing the recommended behavior.

The HBM is mostly used to predict preventive behavior to protect oneself (e.g., condom use: [20]; quit smoking [21]) while in case of a CTA, one prevents *others* from becoming infected. Using the HBM to explain CTA adoption extends theoretical knowledge about this model, namely by assessing the predictive value for a behavior that helps to protect others. Furthermore, this paper will contribute to previous work

by assessing the actual CTA adoption instead of intention, as the intention-behavior gap is a commonly occurring phenomenon within the domain of health behavior change [22]. Previous studies have used the HBM to explain CTA adoption intention [23], and significant relationships with adoption intention were found in this study (i.e., perceived benefits, self-efficacy, perceived barriers), but it is still unknown whether these processes also translate intentions into behavior. Furthermore, this study will contribute to the field by extending the UTAUT with HBM to explain CTA adoption, as no previous studies have done so. One study that used a similar approach, integrated the theory of planned behavior (TPB) with UTAUT to explain adoption intention and adoption frequency, leading to a higher explained variance for the integrated model (67%) than for the UTAUT (56%) or TPB (63%) separately [15]. This integrative approach has not been adopted yet for actual behavior, leading to the second aim of this study: the UTAUT will be extended with the HBM to assess the relative contribution of the HBM variables to explain CTA adoption.

The COVID-19 pandemic is characterized by several contextual factors which are important to take into account when explaining CTA adoption. Expanding theoretical frameworks with context-related variables is likely to better explain real-world phenomena, as demonstrated in various research fields. For example, scholars used the UTAUT to explain remote mobile payment, whereby adding contextual factors (i.e., innovativeness, risk and trust) led to a 37% increase in explained variance [24]. In a similar vein, scholars extended the HBM with peer norms and social sexualization to explain condom use, whereby 28% of the variance was explained in the extended model, versus 13%–22% in ‘traditional’ HBM studies predicting condom use [25].

As CTA adoption is applicable to the whole society, there are many extrinsic factors that could influence personal beliefs and attitudes towards CTAs, which eventually lead to (the inhibition of) CTA adoption. To illustrate, discussions that arose with regard to privacy issues [26], conspiracy theories that gained public support [27] and the emphasis on the societal responsibility to protect vulnerable others [28], are specifically applicable to the COVID-19 pandemic, and could be indicative for CTA adoption. No previous studies have aimed to incorporate these factors into well-founded theoretical models, and therefore the third aim of this study is to explore the contribution of context-related factors in order to explain CTA adoption.

The overall aim of this study is to identify variables that explain CTA adoption, using an integrative approach. Generally, it is expected that the integration of the three perspectives (i.e., technology-related, health-related and context-related), will lead to a better-explaining model than each of the models separately. This leads to the following research questions: RQ1 To what extent do UTAUT variables explain CTA adoption?; RQ2 Does extending the model described in RQ1 with constructs from the HBM result in a better-explaining model for CTA adoption?; and RQ3 Does extending the model described in RQ2 with context-related variables result in a better-explaining model for CTA adoption? In addition to these general higher-level questions, this study will also zoom in on each factor to gain more insight into the specific processes that play a role in CTA adoption in the current COVID-19 pandemic.

2. Theoretical framework

2.1. UTAUT factors explaining CTA adoption

2.1.1. Performance expectancy

In the domain of CTAs, performance expectancy refers to the degree to which an individual believes that using a CTA will contribute to the prevention of infections [14]. Several studies have investigated determinants of CTA adoption intention with the UTAUT framework, whereby a higher performance expectancy was shown to lead to a higher adoption intention [14,15]. High levels of performance expectancy of CTAs are mainly a results of users expecting CTAs to contribute to

reducing the spread of COVID-19 [29]. On the other hand, performance expectancy will be reduced when users have doubts about the usefulness of the app [30]. It is thus expected that a higher performance expectancy will lead to a higher CTA adoption (H1).

2.1.2. Effort expectancy

In several research domains, the role of effort expectancy in technology adoption has been demonstrated (e.g., online banking: [12]; mobile payment: [31]; mobile health: [32]; mobile apps: [33]; social networking apps [13]). For CTAs, the effort implies installing the application, as no further action is required in order for the app to work.

In the CTA domain, there is some support for the relationship between effort expectancy and CTA adoption (i.e., users experience a higher perceived ease of use than non-users [15]), but not for adoption intention [14,15]. A study investigating the variables that explained adoption of warning apps used for natural disasters, which are also considered passive apps, stated that effort expectancy is of less importance for warning apps as the only action that needs to be taken is downloading the app [34]. In line with this argument, it is likely that effort expectancy is one of the weaker UTAUT predictors in the CTA domain. However, in different contexts the effort expectancy is associated with technology adoption, which leads to the hypothesis that the less effort expectancy someone perceives, the more likely one is to adopt a CTA (H2).

2.1.3. Facilitating conditions

The lack of appropriate resources, such as a compatible phone or knowledge about app installation [35,36], is often found to be associated with technology adoption in various fields (for a review, see Ref. [11]), such as mobile banking [37], e-government [38], and health care [39]. In the context of CTAs, Walrave et al. [14] found that having the knowledge and resources to use a CTA positively influenced the intention to use a CTA. It is hypothesized that more facilitating conditions are associated with a higher likelihood of people adopting the CTA (H3).

2.1.4. Social influence

Social norms, which are the perceived extent to which one's own social network uses the technology (i.e., descriptive norms), or the extent to which important others approve or disapprove of the use (i.e., injunctive norms) is another UTAUT predictor. CTA adoption is different from most other preventive behaviors related to COVID-19, as most behaviors are observable by others (i.e., keeping distance, wearing mouth masks). CTA adoption however, is not something easily visible, and therefore social influences might play a weaker role than with predicting other preventive health behaviors. On the other hand, scholars have argued that a CTA can be seen as an act of social responsibility, indicating that social norms are an important factor for CTA adoption intention [15].

Empirically, the effect of social norms on adoption intention has been demonstrated by several studies. Research showed that the more social influence someone experiences (both descriptive and injunctive normative influence), the higher one's CTA adoption intention [40]. Another study only examined the injunctive norm, and found a positive relationship between the injunctive norm and CTA adoption intentions [14]. A third study showed that both the injunctive and descriptive norms were related to CTA adoption, with descriptive norms being more strongly related [41]. It is therefore expected that higher levels of social influence lead to higher levels of CTA adoption (H4).

2.2. HBM factors explaining CTA adoption

2.2.1. Perceived susceptibility and perceived severity

Perceived susceptibility (i.e., one's perceived likelihood of getting a disease) and perceived severity (i.e., one's assessment of the severity of the disease) are two HBM constructs that are indicative of the perceived

threat of a disease [19]. In many of the studies in which the HBM is adopted to explain preventive behavior of infectious diseases during pandemics, both perceived susceptibility and perceived severity were significantly associated with the preventive outcome behavior (e.g., face mask use: [42]; adherence to recommended behavior from the government: [43]; having a vaccine or antiviral medication [44]).

The HBM has been applied to a much lesser extent to adoption of CTAs. Using CTAs is a fundamentally different health-related behavior than prior behaviors studied using HBM, as CTAs are primarily used to protect others from getting the disease instead of oneself. Thus, even though people could have a high threat appraisal regarding COVID-19, when knowing that using a CTA does not directly affect your own health, this could suppress the potential effect of threat appraisals on CTA adoption. On the other hand, people perceive higher risks with novel threats and when one has a feeling that the risk cannot be controlled [45]. This is relatable to the COVID-19 situation, and thus indicative of a higher likelihood to perform the preventive behavior of adopting CTAs.

Results from previous studies are equivocal regarding the relationship between perceived susceptibility and perceived severity of getting infected with COVID-19 on the one hand, and CTA adoption intention on the other hand. One study found significant effects of both trait appraisals: those with a low perceived susceptibility (i.e., perception of chance of being infected) and low perceived severity (i.e., perception of chance of becoming ill when infected), were more likely to reject the app [46]. It was also found that those with stronger perceived severity had higher CTA adoption intentions [47]. Other studies have shown that particularly those with existing health complaints [35], those expecting high individual health consequences [48], and those who know someone who has been infected with COVID-19 [49], have higher adoption intentions. These findings indicate that those who are (or feel) more susceptible to COVID-19, are also more likely to adopt a CTA.

Contrastingly, a number of studies failed to demonstrate any support for the effect of perceived susceptibility [15,23] or perceived severity [23] on CTA adoption intention. Nevertheless, following the HBM, it is hypothesized that those who perceive higher perceived susceptibility (H5) and perceived severity (H6) are more likely to adopt CTAs.

2.2.2. Perceived benefits and barriers

People could have several reasons for (not) performing a certain health behavior, due to the benefits and barriers they perceive. The perceived benefits and barriers are shown to be consistently associated with performing health behavior, as concluded from a meta-analysis [50]. In relation to CTAs, perceived benefits and barriers have been mostly investigated in an explorative manner, asking respondents which barriers and benefits they perceive of using a CTA. Often-mentioned benefits are protecting friends and family, social responsibility, and ending the pandemic, while the main barriers are fear for more governmental control, risk of one's phone being hacked when the app is installed, and feelings of stress caused by the app [51].

Only one study, to our knowledge, has examined how expected benefits and barriers of using a CTA influence adoption intention [23]. As expected and in line with the HBM, it was found that perceived benefits were positively related, and perceived barriers were negatively related to CTA adoption intentions. Perceived benefits were found to be the most important variable in explaining adoption intention of all included variables in their model (i.e., perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, self-efficacy). We therefore also hypothesize that the more benefits of using a CTA people perceive, the more likely they are to adopt a CTA (H7), while the more barriers of using a CTA people perceive, the less likely they are to adopt a CTA (H8).

2.2.3. Self-efficacy

Self-efficacy is the extent to which one has the feeling that one can successfully execute the recommended health behavior [52]. According to HBM, people must have a feeling of competence to overcome the

perceived barriers to change behavior [53], and this turns out to be a significant determinant in many health-related studies (for a meta-analysis, see Ref. [54]). Self-efficacy has been linked to technology adoption in the form of ‘computer self-efficacy’, which is defined as the beliefs of individuals to be able to competently use computers [55]. This definition could also be translated to apps, as previous studies found that higher self-efficacy leads to higher intentions to adopt mHealth-apps [56], and mobile shopping apps [57].

Regarding CTAs, scholars found that self-efficacy was strongly associated with CTA adoption intention [23]. An effect was also found of self-efficacy on CTA adoption intentions in a TPB framework, but this effect disappeared when the TPB was extended with UTAUT [15]. While self-efficacy is not adopted in UTAUT as a separate construct, it could be argued that it is captured in the facilitating conditions, since it is a necessary resource in order to perform the behavior. It is thus expected that those with a higher self-efficacy are more likely to adopt a CTA (H9).

2.3. Context-related factors explaining CTA adoption

This study included a variety of potential context-related variables, which are clustered and outlined below. Many of these variables are retrieved from exploratory data analyses performed by previous studies, in which respondents had to indicate which barriers and benefits they perceive for adopting a CTA. Since relationships between these context-related factors and CTA adoption have not been tested in most cases, this study will adopt a research question to give more insight in the role these factors play: which context-related factors explain CTA adoption (RQ4)?

2.3.1. Privacy perceptions of CTAs

Issues about privacy and data safety have been an important topic of debate during the development of CTAs in the COVID-19 pandemic. Concerns about location tracking and personal data storage led to fears of going towards a surveillance state, where health information is misused for purposes other than suppressing the virus [58].

The fear of privacy issues [30], data misuse, and normalizing government tracking [17] are important reasons not to install a CTA, and are associated with CTA adoption intention [59]. An experimental study showed that the use of a high privacy design (vs. low privacy design) led to higher adoption intentions, both among CTA critics and those who were undecided whether to use a CTA or not [60]. Contrastingly, Fox et al. [40] did not find a significant relationship between privacy concerns and adoption intentions, but found that the more privacy concerns someone has, the less someone is willing to comply to advices given by the CTA [40]. Tomczyk et al. [15] only found a relationship between privacy concerns and the number of times the app was used, and not between adoption intention. Tran et al. [61] showed that people who have a high privacy risk perception are less likely to adopt the app, even if they also perceive high personal health risks.

2.3.2. Conspiracy beliefs

Since the start of the COVID-19 pandemic, various theories have been circulating that provide alternative explanations for the ‘uncontrollable’ event of the spread of the virus. As people have a psychological need for explaining events, conspiracy theories provide patterns that are able to give some explanation to the current situation, even though these patterns are not verified [62]. Several studies have found effects of believing in conspiracy theories on COVID-19 related preventive behaviors. More specifically, studies have for example found that people believing in conspiracy theories performed less preventive behaviors, such as increased hygiene behavior and keeping physical distance [62, 63]. Kowalski et al. [64] also found a negative effect of believing in conspiracy theories on adherence to safety and self-isolation measures as recommended by the World Health Organization. No studies to date have yet looked into the relationship between conspiracy beliefs and CTA adoption, but considering the studies investigating preventive

health behaviors in the COVID-19 context, it is likely that conspiracy beliefs negatively affect CTA adoption.

2.3.3. Fear beliefs

Fear beliefs regarding the CTA are beliefs about whether the app itself is scary to use or whether someone is afraid to receive any notifications. From exploratory studies, in which respondents had to indicate their reasons for not using CTAs, feelings of fear and stress were mentioned as a barrier [29]. Contrastingly, a study among a Swiss sample found that feelings of stress and fear are one of the least mentioned reasons for not using a CTA [36]. A cross-country study showed that feelings of stress and fear caused by CTAs are seen as a barrier for installing the app in the studied countries (i.e., U.S., Germany, France, U.K., and Italy [51]). These exploratory results have not yet been confirmed by statistical testing.

2.3.4. Societal beliefs

In most countries in which CTAs are available, the use of CTAs is part of the governmental policy to combat the COVID-19 pandemic. This is different from most other health app development, since these apps are merely developed by commercial parties. Government involvement reflects the importance of the societal context in which CTA adoption takes place. With societal beliefs we refer to the beliefs related to the broader societal context in which CTAs are used and the consequences of CTAs thereon. In a general context, the feeling of responsibility for others has previously been found to increase the likelihood of compliance to behavioral guidelines for COVID-19 [28]. The importance of collective responsibility is also reflected in both explorative and empirical studies regarding CTA adoption [51,65].

More societal facets could influence CTA adoption, such as governmental trust. Previous research has shown that those with a higher governmental trust have higher adoption intentions [29,41,51]. In a different domain, a study identified trust in insurance companies as a main predictor of intentions to use location-based emergency applications [66]. Lastly, helping the economy, which can be facilitated through widespread CTA adoption, might be a reason for people to actually install a CTA. However, a descriptive study found that the economy’s recovery was the least important reason to adopt a CTA [17].

2.3.5. Perceptions about others

While health apps are generally adopted to gain benefits for oneself (i.e., diet apps, workout apps), installing a CTA will mainly be beneficial for others’ health. From descriptive analyses, it has been shown that the concern for others’ health was an important [17], or even the most important [51] reason to adopt a CTA. In another study however, only 4.1% would adopt a CTA to protect vulnerable others/populations [30]. Until now, there is no empirical evidence of whether higher susceptibility of others in the personal environment, or higher perceived severity for others could affect CTA adoption.

3. Methods

3.1. Data collection

In this paper we make use of the data of the LISS (Longitudinal Internet studies for the Social Sciences) panel administered by CentERdata. The LISS panel is a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register. Households that could not otherwise participate are provided with a computer [67] and Internet connection¹. The data reported in this study are from the first wave of a large-scale six-wave longitudinal survey study. Data collection of the first wave took place between the 19th of

¹ See www.lissdata.nl for more information.

October and the November 1, 2020, one and a half week after the launch of the Dutch CTA. The survey completion time was 8 min and participants were.

Reimbursed for their participation. A total of 2093 respondents were invited to take part in this study. The response rate of the study was 90.8% ($N = 1910$). Only complete data were used in the analysis of this study ($n = 1896$). Furthermore, those who had used the contact tracing app in the past but did not use it at the time of filling out the survey, were removed from the sample ($n = 31$), since this study only aimed to investigate determinants of CTA adoption vs. non-adoption. The final sample consisted of 1865 respondents. Table 1 shows an overview of sample characteristics.

3.2. Measures

All items were measured on a 7-point Likert scale (i.e., 1 totally disagree – disagree – somewhat disagree – neutral – somewhat agree – agree – totally agree 7), unless indicated otherwise. In Fig. 1, the final included scales per model are visualized. In Supplement A, more details on the development of the measurements can be found, and in Supplement B, the questionnaire items relevant to this study are added.

3.2.1. CTA adoption

To measure whether respondents have, or have not adopted the contact tracing app, respondents were asked which situation was applicable to them, with the answer options ‘I have never used the CoronaMelder’ (71.2%), ‘I use the CoronaMelder at this moment’ (27.2%), and ‘I have used the CoronaMelder in the past, but not anymore’ (1.6%). As highlighted previously, respondents in the latter answer category were excluded from the analyses. The final sample consisted of 72% non-users, and 28% users.

3.2.2. UTAUT measures

The items to measure UTAUT constructs were adopted from Venkatesh et al. [10] and adjusted to fit this study.

3.2.2.1. Performance expectancy. Performance expectancy was measured with two items: ‘By using the CoronaMelder app, I contribute to fighting the disease’, and ‘The CoronaMelder app is useful to ensure that the virus will spread to a lesser extent’. Higher scores on the scale represented a higher performance expectancy. The reliability of the two items was excellent ($M = 4.58$, $SD = 1.64$, $\alpha = 0.92$).

Table 1
Sample demographics ($N = 1865$).

		Frequency	Proportion
Age			
	17–34	431	23.1%
	35–54	480	25.7%
	55–64	438	23.5%
	65–96	516	27.7%
Gender			
	Male	834	55.0%
	Female	1031	45.0%
Education level			
	Low	484	25.9%
	Medium	649	34.8%
	High	732	39.3%
Net income (euro/month)			
	No income	177	9.5%
	1–1000	290	15.5%
	1001–2000	619	33.2%
	2001–3000	501	26.9%
	3001–4000	124	6.6%
	More than 4000	41	2.2%
	Don't know/don't want to answer	113	6.1%

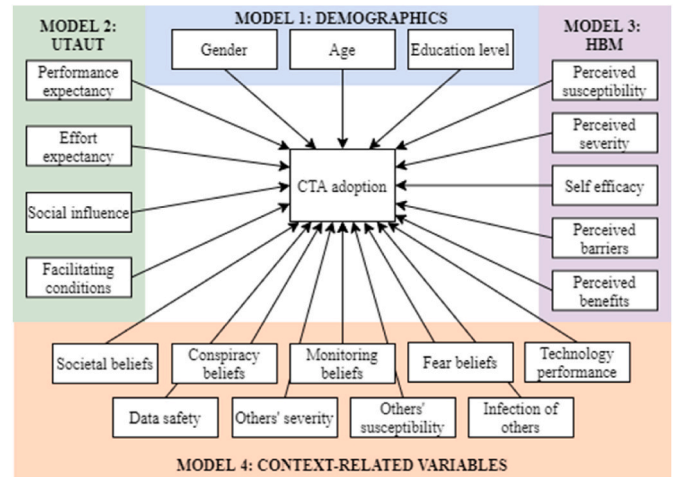


Fig. 1. Conceptual model.

3.2.2.2. Effort expectancy. Effort expectancy was measured with two items, whereby the question formulation was adjusted to the respondent’s user status: ‘It will take/it took me a lot of time and energy to use the CoronaMelder’, and ‘It will be easy/it is easy to use the CoronaMelder’. The first item was recoded so that a higher score on the scale represented less expected effort to use the contact tracing app ($M = 5.00$, $SD = 1.35$). The reliability of this scale was acceptable ($\alpha = 0.65$).

3.2.2.3. Social influence. Two items were used to measure social influence: ‘Many people in my environment use the CoronaMelder app’, and ‘People around me think that I should use the CoronaMelder app’ ($M = 3.31$, $SD = 1.36$). The scale was reliable, $\alpha = 0.78$.

3.2.2.4. Facilitating conditions. The facilitating conditions were measured with two items, namely ‘I have a smartphone with internet access’, and ‘I have enough (technical) skills to use the CoronaMelder’. Respondents were asked to what extent they had access to those resources ($M = 5.55$, $SD = 1.60$). The two items formed a reliable scale ($\alpha = 0.78$).

3.2.3. HBM measures

The items to measure HBM constructs were adopted from Rosenstock [19] and adjusted to fit this study.

3.2.3.1. Perceived susceptibility. Perceived susceptibility was measured with two items: ‘In the next two months, I am at risk of being infected with the coronavirus’ and ‘Chances are high that I get infected with the coronavirus in the next two months’ ($M = 4.32$, $SD = 1.22$). A reliable scale was formed with the two items ($\alpha = 0.79$).

3.2.3.2. Perceived severity. To measure perceived severity, two items were included in the questionnaire: ‘I think it is severe to be infected with the coronavirus’ and ‘A coronavirus infection has huge physical, psychological or economic consequences for me’ ($M = 4.82$, $SD = 1.38$). The two items were averaged and formed a reliable scale ($\alpha = 0.73$).

3.2.3.3. Self-efficacy. Self-efficacy was measured with a single item which was differently formulated for each user status. Respondents had to answer the question ‘I am able to use the CTA’ or ‘I expect to be able to use the CTA’ ($M = 5.46$, $SD = 1.73$).

3.2.3.4. Perceived barriers and perceived benefits. Within HBM, there is not a ‘one size fits all’ operationalization for measuring the perceived barriers and benefits, as these are varying per health behavior [68]. Furthermore, it is difficult to grasp the perceived barriers and benefits in

only a few items, as there are many reasons for performing or not performing a behavior. In this study, it was aimed to formulate the question as general as possible to get a notion of the overall assessment of CTAs. Respondents had to answer the statement “It has personal disadvantages for me to use the CTA” ($M = 3.24$, $SD = 1.73$) and “It has personal advantages for me to use the CTA” ($M = 3.80$, $SD = 1.79$).

3.2.4. Context-related measures

The survey included 14 items measuring context-related beliefs, based on previous studies that suggested a relationship between these variables and CTA adoption (e.g. Refs. [19–21,23,43]). A factor analysis with Varimax rotation was performed to examine the dimensionality of the context-related beliefs that were assessed in the survey. For data preparation, items which were measured on a five-point scale (1 = definitely not true, 2 = maybe not true, 3 = maybe true, 4 = definitely true, 5 = I don’t know), were rescaled so that the ‘I don’t know’ category represented the middle value.

The scree-plot indicated that four distinct components could be formed with the context-related beliefs. Factor 1 was composed of four societal beliefs with factor loadings ranging from 0.56 to 0.80. Factor 2 contained two beliefs about conspiracy theories, with factor loadings of 0.59 and 0.79. The third factor comprised two items with monitoring beliefs, with factor loadings of 0.63 and 0.75. The last factor contained two items about fears, with factor loadings of 0.72 and 0.64. The four items that did not load strongly on any factor (i.e., technology performance, perceived susceptibility for others, perceived severity for others, data safety) were included as single items in the logistic regression. Factor loadings per component can be found in Supplement A.

3.2.4.1. Societal beliefs. The factor measuring societal beliefs was obtained from the factor analysis and contained several items considering civic duty (e.g., ‘Using the CoronaMelder will make you a good citizen’), economy (i.e., ‘Using the CoronaMelder will help the Dutch economy’), protecting risk groups (i.e., ‘The CoronaMelder helps to protect vulnerable people’), and trust in government (i.e., ‘I trust the way in which the Dutch government is trying to control the coronavirus’). These items were taken together to form one scale ($M = 4.00$, $SD = 1.32$), which was reliable ($\alpha = 0.83$).

3.2.4.2. Conspiracy beliefs. Conspiracy beliefs were measured with two items on a 5-point scale. Respondents had to indicate the extent to which the statements ‘The coronavirus is a biological weapon that is created in a lab’ and ‘The coronavirus outbreak is related to the construction of the 5G-network’ were true or false. The reliability of the scale was acceptable ($M = 1.72$, $SD = 0.96$, $\alpha = 0.66$).

3.2.4.3. Monitoring beliefs. The items about monitoring beliefs measured to what extent one believes that the CoronaMelder tracks your location, and to what extent one believes that the CoronaMelder stores personal information, on a 5-point scale. The final scale had an acceptable reliability ($M = 3.45$, $SD = 1.22$, $\alpha = 0.67$).

3.2.4.4. Fear beliefs. Two items were used to measure fear-related beliefs. One item measured fear towards the CTA (i.e., “I think the CoronaMelder app is scary”) and one item measured fear towards notifications of the CTA (i.e., “I would be scared if I receive a notification of the CoronaMelder app”). The reliability of the scale was acceptable ($M = 3.17$, $SD = 1.46$, $\alpha = 0.63$).

3.2.4.5. Technology performance. Technology performance measured to what extent people were aware of the technology used in the CTA, with the statement ‘The technology (Bluetooth) that is being used in the CoronaMelder app indicates who has been close to someone infected with the coronavirus’. Respondents had to rate whether the statement was true or false on a 5-point scale, with the categories ‘definitely not

true, maybe not true, maybe true, definitely true, don’t know’ ($M = 4.26$, $SD = 1.05$).

3.2.4.6. Data safety. Respondents were asked to report to what extent the statement ‘The information I provide in the CoronaMelder app is treated confidentially’ was true or false to them on a 5-point scale, including the answer category ‘I don’t know’ ($M = 2.46$, $SD = 1.19$).

3.2.4.7. Others’ susceptibility. One item measured the perception of the susceptibility of others, by asking respondents to what extent they agree with the statement ‘If I get infected with the coronavirus, it is very likely that I will infect others’ ($M = 4.44$, $SD = 1.41$).

3.2.4.8. Others’ severity. The severity of infecting others with the coronavirus was measured with the single item ‘I think it is severe when I infect others with the coronavirus’ ($M = 6.02$, $SD = 1.15$).

3.2.4.9. Infection of others. Respondents were asked whether people in their personal networks had been infected with the coronavirus. They could answer the question with yes or no, for several specified relationships (e.g., my partner, one or more family members, one or more friends etc.). The variable was dummy coded, whereby ‘no’ represents those who did not have any acquaintances that were infected, they did not know or they did not want to answer the question, and ‘yes’ represents one or more acquaintances being infected with the coronavirus. Almost half the sample knew someone that was infected (45%). It should be noted that this variable was not added to the factor analysis due to the nominal measurement level.

3.2.5. Control variables: gender, age and education level

Gender was added as a binary variable, with the category ‘male’ as the reference category. Age was dummy coded, resulting in three dummy variables: 35–54 ($n = 480$), 55–64 ($n = 438$) and 65+ ($n = 516$). The age group 17–34 ($n = 431$) served as the reference category. Two dummy variables for education level were created, namely medium (intermediate vocational education, higher general).

Secondary education and pre-university education, $n = 649$ and high (higher vocational education and academic education, $n = 732$). The low education level (primary school and lower general secondary education, $n = 484$) was included as the reference category.

3.3. Statistical analysis

3.3.1. Analysis plan

We performed four logistic regression analyses in RStudio version February 1, 5033. Model 1 served as a baseline model with demographic predictors only. In model 2, the UTAUT variables were added to model 1. In model 3, the HBM variables were added to model 2. Finally, in model 4, the COVID-19 context-related variables were added to model 3, leading to the full, integrative model. To answer the research questions, the four models were evaluated using the Likelihood Ratio Test, the Hosmer and Lemeshow Test and the Pseudo R^2 . Research questions were answered with the integrative model and hypotheses were tested with separate models representing the UTAUT, HBM and context. Standardized coefficients were reported for the analyses.

3.3.2. Assumption-testing

For each model, scatter plots were inspected to see whether the predictors were linearly related to the log odds, showing no issues of non-linearity. Furthermore, the models were tested for multicollinearity, using the Variance Inflation Factor (VIF). There was no sign of multicollinearity as none of the predictors had a VIF higher than 10 (VIF values varied between 1.02 and 2.32). Lastly, the data were checked for influential observations, using the Cook’s distance values. Cases were considered influential when the Cook’s distance value was

greater than the mean times three. The number of influential cases varied per model, ranging between 183 and 191. All the analyses were run without these influential observations, leading to slight differences in the results. These differences are reported with the tables.

4. Results

4.1. Overarching research questions

In Table 2, fit statistics for each model comparison are visualized. First, the Hosmer and Lemeshow Test was used to test whether the observed proportions are similar to the predicted proportions, whereby H_0 is that the observed and expected proportions are the same, in other words, the model fits. The four specified models all had a non-significant p -value, and therefore H_0 could not be rejected. This indicated that there was not enough evidence that the models have a poor fit. Similar conclusions were drawn from the Pseudo R^2 , which is the proportion of log likelihood the fitted model and the log likelihood for the null-model (intercept only). The model fit of all the models was good, given that a Pseudo R^2 of 0.2–0.4 is already considered high [69].

The Likelihood Ratio Test was used to statistically compare the model fit of the four models. This test is used to provide evidence against the parsimonious (reduced) model in favor of the more elaborate model. From the Likelihood Ratio Test it was concluded that the integration of HBM with UTAUT provided a significant improvement of the model compared to UTAUT only. Additionally, the model integrating UTAUT, HBM and context-related variables again improved model fit compared to the model with UTAUT and HBM variables only. In sum, answering the research questions, the UTAUT variables predicted CTA adoption to a good extent already (RQ1), but extending the model with HBM variables (RQ2) and, subsequently, context-related variables (RQ3), led to an improvement of model fit. In Table 3, the log odds, p -values and odds ratios for the models can be found.

4.2. Hypothesis testing

The UTAUT, HBM and context-related models were adopted separately for hypothesis testing, while controlling for demographics (see Table 4). For the sake of conciseness, only the odds ratio (OR) is reported in text. With regard to the control variables, age appeared to be a significant predictor of CTA adoption in UTAUT. The age groups 35–54 ($OR = 1.52$), 55–64 ($OR = 2.41$) and 65+ ($OR = 2.21$) reported higher adoption rates than the reference age group 17–34. Gender and education level were not significant predictors of CTA adoption in UTAUT. In the HBM, only the age group 55–64 had higher adoption rates than the reference age group 17–34 ($OR = 1.55$). Furthermore, those with a high education level were more likely to adopt the CTA in comparison to

those with a low education level ($OR = 1.52$). For the context-related model, no demographics were significant predictors of CTA adoption (Table 4).

4.2.1. UTAUT variables

All UTAUT variables were significant and positive predictors of CTA adoption, with social influence being the strongest predictor. This indicated that those who were more susceptible to important others' actions and opinions in favor of the CTA, were more likely to adopt the CTA ($OR = 2.04$). Performance expectancy was also a significant predictor, indicating that the more people believe that using the CTA contributes to reducing COVID-19 infections, the more likely they are to adopt the CTA ($OR = 1.92$). Furthermore, if people expect the efforts required to use the CTA to be smaller, they are significantly more likely to adopt the CTA ($OR = 1.60$). Lastly, facilitating conditions were significantly predicting CTA adoption, indicating that those having the equipment and knowledge to install and use the CTA are more likely to actually do so ($OR = 1.57$). Thus, higher levels of social influence, performance expectancy, effort expectancy and facilitating conditions were associated with adopting the CTA, which is in line with H1 to H4.

4.2.2. HBM variables

Of the HBM variables, self-efficacy was the stronger predictor ($OR = 1.84$), meaning that those who believe to be capable to use the CTA, are more likely to actually use it. Perceived benefits were also a strong positive predictor ($OR = 1.76$), which indicates that those who expected more benefits were more likely to adopt a CTA. Perceived barriers had, as expected, the opposite effect ($OR = 0.68$), as those with stronger perceived barriers were less likely to adopt a CTA. Therefore, H7 to H9 were supported. H5 and H6 were not supported, as perceived susceptibility and perceived severity did not significantly predict CTA adoption.

4.2.3. Context-related variables

Considering the context-related variables, several significant predictors were retrieved from the analysis. Those with stronger monitoring beliefs (e.g., that the app registers personal information; $OR = 0.73$), and fears regarding the CTA ($OR = 0.67$), were less likely to adopt the CTA. Those with a higher trust in the technology ($OR = 1.16$), a higher feeling of data safety ($OR = 0.62$), and those with more positive societal beliefs ($OR = 2.18$) were more likely to adopt the CTA. Model fit indices for the separate models can be found in Supplement C.

5. Discussion

As a consequence of COVID-19, many countries devoted time and effort to the development of a CTA, with the main goal to reduce the spread of the coronavirus. Studying the variables that explain CTA adoption is important from both a societal as well as a scientific perspective, allowing to adjust policy based on these studies, as well as taking advantage of this unique case in which widespread app adoption can be investigated in the context of a global crisis. CTAs distinguish themselves from apps that have been studied previously in the realm of app adoption, such that CTAs are passively used and mainly used for protection of others. Considering the society-wide scope of CTA adoption, this study employed a holistic approach by integrating three perspectives (i.e., technology-, health- and context-related) relevant for CTA adoption. Thereby, theoretical knowledge about well-known models (i.e., UTAUT and HBM) is expanded by applying them to this new phenomenon, and variables specifically related to the context were examined to gather new insights into what defines CTA adoption. This study distinguishes itself from other studies investigating CTA adoption, by using actual adoption as an outcome measure in combination with a representative sample, including those with low digital literacy.

The current study showed that 27.2% of the sample used the CTA. This is in line with a study that predicted CTA uptake in the Netherlands, whereby 33.7% of the respondents chose to install a least preferred

² The effect of the age category 35–54 becomes non-significant when excluding outliers ($n = 185$), $p = .120$.

³ The effect of gender becomes significant when excluding outliers ($n = 186$), $p = .007$.

⁴ The effect of medium education level becomes significant when excluding outliers ($n = 185$), $p = .034$.

⁵ The effect of medium education level becomes significant when excluding outliers ($n = 191$), $p = .038$.

⁶ The effect of medium education level becomes significant when excluding outliers ($n = 186$), $p = .028$.

⁷ The effect of perceived severity becomes significant when excluding outliers ($n = 186$), $p < .001$.

⁸ The effect of self-efficacy becomes non-significant when excluding outliers ($n = 186$), $p = .414$.

⁹ The effect of conspiracy beliefs becomes non-significant when excluding outliers ($n = 186$), $p = .097$.

¹⁰ The effect of data safety beliefs becomes non-significant when excluding outliers ($n = 186$), $p = .295$.

Table 2
Fit indices.

	Hosmer and Lemeshow test ^a		Pseudo R ²	Likelihood Ratio Test ^b			
	χ^2 (df = 8)	p	McFadden	Df	Residual deviance	Deviance	p
Model 1 ^c (vs. intercept only)	7.91	.44	0.02	6	2186.58	33.35	<.001
Model 2 ^d (vs. model 1)	13.57	.09	0.48	4	1149.40	1019.10	<.001
Model 3 ^e (vs. model 2)	4.73	.79	0.51	5	1080.90	68.47	<.001
Model 4 ^f (vs. model 3)	4.53	.81	0.55	9	1020.40	60.54	<.001

^a Hosmer and Lemeshow test statistics are reported under $g = 10$.

^b The comparison between models for each row apply only to Likelihood Ratio Test.

^c Model 1 = demographics.

^d Model 2 = demographics + UTAUT.

^e Model 3 = demographics + UTAUT + HBM.

^f Model 4 = demographics + UTAUT + HBM + context-related.

version of the CTA over not installing a CTA at all. This percentage resembles the moment when the uptake was highest in the Netherlands even better, which was 32% according to a later wave of this study [8]. Another study employed a discrete choice experiment and found that a much higher percentage (51%) preferred a CTA with the least preferred specifications over no CTA at all [46]. This study was conducted first (March 2020), which could be a reason for the relatively high adoption found in this study (i.e., concerns regarding CTAs might not have been that prevalent in media at that time, while in a later stadium, this gained more attention).

Two important things should be taken into account when interpreting the results. First, CTA adoption was measured only one and a half week after the launch of the CTA. This should be considered when interpreting the results, as motivations of early adopters to install the app might not equal motivations of late adopters. For example, a study found that with the acceptance of a new learning management system at universities, social influence might play a larger role in the early adoption stage, while facilitating conditions could be a major reason to start using a new technology in a later stage [70].

Second, as the study was cross-sectional, we cannot draw strong conclusions about the direction of the causality. From a cognitive dissonance perspective, it is also possible that attitudes follow from behavior. For example, one downloads the CTA simply out of curiosity, and then positive attitudes follow to be able to rationalize the decision to install the app. The mutual relationship between attitudes and behavior has been demonstrated in a study towards computer use [71], and travelling behavior [72], whereby in the latter study, the relationship from behaviors to attitude was larger than vice versa. Although the results will be discussed using CTA adoption as the outcome measure, this does not imply that the existence of the relationship in the other direction is ruled out.

5.1. Main findings research questions

The first overarching goal of this study was to examine whether integrating three perspectives (i.e., technology-related, health-related and context-related) led to a better-explaining model than each of the models separately. The UTAUT, HBM, and context-related variables all played a role in the CTA adoption, as all specified models had a good model fit. To answer RQ1 'To what extent do UTAUT variables explain CTA adoption', the data showed that the UTAUT already had a good model fit, whereby all UTAUT constructs significantly explained CTA adoption. Extending the model with HBM outperformed the model with UTAUT variables only (RQ2). Lastly, extending the model with context-related variables resulted as well in a better model (RQ3). In other words, and taken all RQs together, the integrative model with all three perspectives outperformed the more parsimonious models in terms of model fit, indicating that the integrative model fitted the data best.

It is common practice to expand well-founded theoretical frameworks with new variables to get a more nuanced view on how real-world

phenomena occur (e.g. Refs. [17,18]). This has previously been done in the field of (e-)health, although with a variety of analysis methods. For instance, by merging two complete models (e.g., integrating UTAUT and protection motivation theory to explain personal health record use [73]), by adding a selected group of variables of one model to another model (e.g., using several UTAUT variables to expand the HBM to explain fitness app usage [74]), or by adding a group of variables that specifically relates to the examined population (e.g., the addition of technology anxiety and resistance to change to UTAUT when investigating mHealth adoption among elderly [75]). Lastly, some scholars hierarchically compared the extended model to the original model, for example, when adding contextual factors to UTAUT when explaining remote mobile payment [24]. However, the studies mentioned did not examine whether model extension significantly adds to the explained variance of the more parsimonious (original) model, leading to uncertainty about whether adding these variables led to a better-explaining model. Only a study that extended HBM with peer norms and social sexualization to explain condom use reported a significant improvement of model fit for the extended model [25]. The current study also hierarchically compared model fit to be able to actually expand theoretical knowledge about the models.

In the context of COVID-19 and CTAs, only one other study used a similar integrative approach, whereby TPB, UTAUT, and contextual variables were taken into account to explain CTA adoption intention and CTA usage frequency [15]. In that study, in the first step of the hierarchical analysis, the predictive value of TPB and UTAUT combined was compared to the predictive value of demographics, and as a second step, context-related variables were added to the model, leading to a slightly better model fit for both intentions ($R^2_{diff} = 0.01$) and usage frequency ($R^2_{diff} = 0.02$). As outlined previously, in this study we found that adding the context-related variables led to a significantly better model fit. Similar to Tomczyk et al. [15], the model fit in this study increased only slightly after adding the context-related variables ($R^2_{diff} = 0.04$). Thus, our study extends these findings by showing that a technological perspective on CTA adoption already accounts for a large contribution to model fit, but that integrating the health- and context perspective is still valuable, supporting the holistic approach that was proposed by this study.

5.2. UTAUT hypotheses

This study provides evidence for the application of the UTAUT to a new domain, namely to the adoption of *passive* health apps that are mainly useful for the health of others, and only useful when installed by others. Previous studies have shown that the UTAUT is a good model when explaining *active* use of apps that are mainly installed for one's own benefit (e.g., physical activity apps: [74,76]; mobile banking apps: [12,37]; online shopping apps [77,78]). This study contributed to the literature by showing that the UTAUT is also a well-predictive model in the context of CTAs that have these unique features, given that all

Table 3
Model statistics.

	Model 1: demographics			Model 2: demographics + UTAUT			Model 3: demographics + UTAUT + HBM			Model 4: demographics + UTAUT + HBM + context		
	β (SE)	<i>p</i>	OR	β (SE)	<i>p</i>	OR	β (SE)	<i>p</i>	OR	β (SE)	<i>p</i>	OR
Intercept	−1.30 (0.24)	<.001	NA	−14.65 (0.80)	<.001	NA	−13.99 (0.97)	<.001	NA	−12.92 (1.17)	<.001	NA
Age (ref = 17–34)												
35–54	−0.04 (0.15)	.779	1.29	0.42 (0.21)	.050 ²	1.52	0.45 (0.22)	.043	1.57	0.33 (0.23)	.158	1.39
55–64	0.39 (0.15)	.011	1.99	0.88 (0.22)	<.001	2.41	0.82 (0.24)	.001	2.27	0.68 (0.25)	.008	1.97
65–96	0.21 (0.15)	.162	1.67	0.79 (0.24)	<.001	2.21	0.68 (0.26)	.010	1.98	0.57 (0.28)	.042	1.77
Gender (ref = male)												
Female	−0.12 (0.11)	.270	1.09	0.08 (0.15)	.581	1.09	0.03 (0.16)	.831	1.03	0.32 (0.17)	.057 ³	1.38
Education level (ref = low)												
Medium	0.31 (0.14)	.033	1.83	0.01 (0.21)	.979 ⁴	1.01	0.01 (0.22)	.972 ⁵	1.01	0.02 (0.23)	.946 ⁶	1.02
High	0.65 (0.15)	<.001	2.54	0.22 (0.21)	.294	1.25	0.27 (0.22)	.224	1.31	0.29 (0.24)	.219	1.34
UTAUT variables												
Performance expectancy				0.85 (0.08)	<.001	2.34	0.60 (0.08)	<.001	1.82	0.65 (0.10)	<.001	1.92
Effort expectancy				0.62 (0.08)	<.001	1.86	0.54 (0.09)	<.001	1.71	0.47 (0.09)	<.001	1.60
Social influence				0.74 (0.07)	<.001	2.08	0.72 (0.07)	<.001	2.05	0.71 (0.08)	<.001	2.04
Facilitating conditions				0.43 (0.08)	<.001	1.54	0.37 (0.09)	<.001	1.45	0.45 (0.10)	<.001	1.57
HBM variables												
Perceived susceptibility							0.03 (0.07)	.623	1.04	0.07 (0.08)	.419	1.07
Perceived severity							−0.01 (0.07)	.842	0.99	0.15 (0.08)	.059 ⁷	1.16
Self-efficacy							0.19 (0.09)	.039	1.21	0.21 (0.10)	.035 ⁸	1.23
Perceived barriers							−0.26 (0.06)	<.001	0.77	−0.25 (0.06)	<.001	0.78
Perceived benefits							0.26 (0.06)	<.001	1.30	0.26 (0.06)	<.001	1.29
Context-related variables												
Monitoring beliefs										−0.29 (0.07)	<.001	0.75
Conspiracy beliefs										0.24 (0.10)	.023 ⁹	1.27
Fear beliefs										−0.15 (0.07)	.039	0.86
Societal beliefs										−0.18 (0.10)	.091	0.84
Data safety										0.26 (0.10)	.006 ¹⁰	1.77
Perceived susceptibility (others)										0.03 (0.07)	.663	1.03
Perceived severity (others)										−0.40 (0.10)	<.001	0.68
Technology performance										0.04 (0.08)	.578	1.05
Corona infection other										0.05 (0.17)	.782	1.05

Note. OR = odds ratio. Cells highlighted in grey represent significant log odds at the 0.05 significance level.

Table 4
Model statistics for the separate models.

	HBM ^{a,b}			Context		
	β (SE)	<i>p</i>	OR	β (SE)	<i>p</i>	OR
Intercept	−6.13 (0.66)	<.001	NA	−2.30 (0.63)	<.001	NA
Age (ref = 17–34)						
35–54	0.17 (0.19)	.37	1.19	0.14 (0.19)	.44	1.16
55–64	0.44 (0.20) ^c	.03	1.55	0.22 (0.19)	.24	1.25
65–96	0.32 (0.21)	.14	1.37	−0.14 (0.19)	.46	0.87
Gender (ref = male)						
Female	−0.11 (0.13)	.41	0.90	0.32 (0.17)	.06	1.14
Education level (ref = low)						
Medium	0.08 (0.18)	.66	1.08	0.01 (0.23)	.97	0.08
High	0.42 (0.18)	.02	1.52	0.27 (0.24)	.25	1.27
HBM variables						
Perceived susceptibility	−0.01 (0.06)	.93	0.99			
Perceived severity	0.01 (0.06)	.92	1.01			
Self-efficacy	0.61 (0.07)	<.001	1.84			
Perceived barriers	−0.39 (0.05)	<.001	0.68			
Perceived benefits	0.57 (0.05)	<.001	1.76			
Context-related variables						
Monitoring beliefs				−0.31 (0.06)	<.001	0.73
Conspiracy beliefs				0.07 (0.08)	.40	1.07
Fear beliefs				−0.36 (0.05)	<.001	0.67
Societal beliefs				0.78 (0.07)	<.001	2.18
Data safety				0.48 (0.08)	<.001	1.61
Perceived susceptibility (others)				0.02 (0.07)	.73	1.01
Perceived severity (others)				−0.03 (0.07)	.07	0.97
Technology performance				0.15 (0.06)	.02	1.16
Corona infection other				0.18 (0.13)	.98 ^d	1.19

^a When removing influential outliers (n = 183) from the HBM model, no differences in results (i.e., significance levels) appeared from the analysis, compared to the results reported in the table.

^b See Table 3 for the model including UTAUT variables and demographics.

^c Cells highlighted in grey represent significant log odds at the .05 significance level.

^d The effect of others' corona infection becomes significant when excluding outliers (n = 185), *p* = .007.

UTAUT variables significantly explained CTA adoption in the expected directions, and thus confirming the hypotheses (H1 to H4).

Prior research has already demonstrated the applicability of UTAUT to this context by explaining adoption intention, however, with slightly different outcomes. In contrast to the current study, in which we found that effort expectancy was related to adoption (H2), Tomczyk et al. [15] and Walrave et al. [14] found that effort expectancy was not predictive of CTA adoption intention. However, in both studies, the CTA was not yet launched when the data collection took place, and at this point in time respondents might not have had a clear idea of the effort it would take to use the app. Besides that, both studies explained intentions instead of adoption behavior.

5.3. HBM hypotheses

Several, but not all HBM constructs were significantly related to CTA adoption, indicating that the HBM can partly be applied to app adoption behavior that primarily benefits the others' instead of own health. In this study, self-efficacy appeared to relate most strongly to CTA adoption, confirming H9. This is in line with previous studies in the realm of mobile health [56,79], and also more specifically for CTA adoption intention [15,23]. Furthermore, significant relationships were found between both perceived benefits (positive) and CTA adoption (H7), and perceived benefits (negative) and CTA adoption (H8), but not for perceived susceptibility and perceived severity (H5 & H6). There are mixed findings regarding the relationship of these trait appraisals [15, 23,46,47], and it is yet unknown what causes this variation. CTA adoption is merely helpful to detect possible COVID-19 cases after they have occurred, meaning that the CTA is not directly affecting your own health. In line with this, governments of countries worldwide emphasize the responsibility towards others in promoting CTAs (e.g., 'For whom do you download the CoronaMelder [80]'). People therefore might feel that it does not matter how susceptible they are or how badly the illness will unfold for them, as they will not experience direct health benefits from using the CTA. However, this line of reasoning does not apply to the studies that found support for the relationship between perceived severity/susceptibility and CTA adoption intentions, which emphasizes the need for future research. For instance, Jonker and colleagues [46] found that as general health status worsened, the proportion of respondents that always wanted to use a COVID-19 app increased.

5.4. Research questions contextual variables

A research question was formulated to explore which contextual factors could influence personal beliefs and attitudes towards CTAs, which eventually lead to (the inhibition of) CTA adoption. To illustrate, discussions that arose with regard to privacy issues [26], conspiracy theories that gained public support [27], and the emphasis on the societal responsibility to protect vulnerable others [28], are specifically applicable to the COVID-19 pandemic, and could be indicative for CTA adoption. No previous studies have aimed to incorporate these factors into well-founded theoretical models, and therefore the third aim of this study is to explore the contribution of context-related factors to explain CTA adoption.

First, societal beliefs were most strongly, and positively related to CTA adoption. This is in line with previous studies in which respondents were asked to give their motivations why to adopt a CTA, whereby reasons such as governmental trust, collective responsibility, economic benefit, and protecting the vulnerable were often mentioned (e.g. Refs. [29,41,51]). In the Netherlands, other scholars found that societal effects (i.e., the decrease in the number of deaths; the decrease in the number of household facing long-term financial problems; the number of people quarantined at home as a result of an incorrect notification by the app) had a negative effect on CTA adoption intention [16]. Second, feelings of fear were negatively related to CTA adoption. Although no prior studies have investigated the relationship between fears and CTA

adoption, studies have asked respondents about their main barriers to use an app, in which fear and distress were identified [29,51]. Third, as also argued by several scholars (e.g. Refs. [30,59]), privacy concerns played a part in this study, in a way that those believing that the app monitors location and personal information were less likely to install the app. Similar to this finding, trust that data will be treated confidentially was positively associated with CTA adoption. Lastly, those with more trust in the functionality of the technology were more likely to adopt the CTA.

5.5. Limitations

It should be noted that, due to the lack of existing measurement instruments for the COVID-19 context-related variables, these items were retrieved from studies that asked respondents about their main barriers and motivations of CTA adoption. Validity was assessed through a factor analysis, and even though this is a commonly used procedure for scale development, a more elaborate study could be conducted to assure construct- and content validity.

Also, the results of this study need to be placed in the cultural and political context in which the CTA was implemented, which makes it generalizable to countries that have similar, decentralized CTAs and CTA policies (e.g., Germany), but less generalizable to countries that have much stricter policy (e.g., obligatory use in China [81]). For instance, the adoption rates were much higher in China, but it is likely that policy-related variables such as the mandatory use are the main drivers for differences in adoption rates, which makes the current framework less applicable. Additionally, research investigating new technology adoption rate across countries shows that country-specific characteristics such as enhanced cybersecurity, a low level of political violence, and high competitiveness are factors that drive the adoption of various technologies [82]. This should be taken into account when comparing studies.

5.6. Implications

This study has important implications for practice, with regard to the stimulation of CTA adoption in the Netherlands. Knowing for example that variables in the UTAUT are strongly associated with CTA adoption, the government could focus on increasing performance expectancy, effort expectancy, facilitating conditions and social influence. Performance expectancy and effort expectancy could easily be addressed in government communication about the CTA, for example by emphasizing the added value of the CTA, and the little effort that people have to make to increase this added value. If effort expectancy is high within a certain population, a financial incentive could be a feasible solution, for example in the form of free credit on app stores, to compensate for the burden to install the app [83]. Norm-based persuasive strategies could be applied to strengthen the social norms regarding CTA adoption, and utilize the social influence. For example, the encouragement from important others to install a CTA can be highlighted in intervention messages, together with showing that these important others expect that the CTA is being installed [84].

6. Conclusion

To the best of our knowledge, this study is the first to provide a holistic approach to explain actual CTA adoption instead of adoption intentions, by taking into account technology-related, health-related, and context-related factors. Although the UTAUT already provided a good fit with the data, adding the health-related and context-related variables significantly improved model fit. Furthermore, it appeared that both health-related and context-related variables could explain CTA adoption, emphasizing the importance of this integrative approach. This study gained knowledge on the variables associated with CTA adoption, which could support policy makers and app developers with identifying

factors that should be focused on when promoting the increase of CTA adoption. This is not only relevant for the current COVID-19 pandemic, but also for possible future pandemics, enabling to adequately react on health threats with technology.

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Author statement

Nadine Elisa van der Waal: Methodology, Formal Analysis, Writing – Original Draft, Visualization **Jan de Wit:** Writing – Methodology,

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Declaration of competing interest

The authors do not have any competing interests to declare.

Data availability

Data will be made available on request.

Supplement A.

Items of the questionnaire that were related to technology and health predictors were adopted from the UTAUT [10] and the HBM [19]. The items that were included as contextual variables were retrieved from other studies in which these predictors were prevalent. A rapid review was conducted to gain an overview of the current literature and the important contextual factors that could play a role in CTA uptake. The items retrieved from this literature review are listed below. A factor analysis was performed to discover whether items could be merged into one variable.

Item	Factor 1	Factor 2	Factor 3	Factor 4
The CoronaMelder helps to protect vulnerable people against the coronavirus	0.80	−0.08	0.01	−0.03
Using the CoronaMelder will help the Dutch economy	0.78	−0.03	−0.07	0.06
Using the CoronaMelder will make you a good citizen	0.76	−0.02	−0.08	−0.01
I trust the way in which the Dutch government is trying to control the coronavirus	0.60	−0.17	−0.04	−0.04
The coronavirus is a biological weapon that is created in a lab	−0.10	0.59	0.16	0.15
The coronavirus outbreak is related to the construction of the 5G-network	0.00	0.79	0.06	0.11
The CoronaMelder tracks my location	−0.16	0.06	0.75	0.05
The CoronaMelder stores my name or other personal details	−0.27	0.23	0.63	0.15
I am afraid of the CoronaMelder	−0.28	0.22	0.11	0.72
I am afraid of receiving notifications from the CoronaMelder	0.09	0.05	0.04	0.64
If I get infected with the coronavirus, chances are high that I will infect others	0.14	−0.10	0.14	0.11
I think it is severe when I infect others with the coronavirus	0.27	−0.32	0.13	0.10
The information I provide in the CoronaMelder is treated confidentially	−0.56	0.18	0.21	0.16
The technology (Bluetooth) that is being used in the CoronaMelder app indicates who has been close to someone infected with the coronavirus	0.13	−0.20	0.21	−0.05

Supplement B

Construct	Item
UTAUT variables	
Performance expectancy	Door de CoronaMelder app te gebruiken help ik mee bij de bestrijding van het coronavirus De CoronaMelder app is nuttig om ervoor te zorgen dat het coronavirus zich minder verspreidt
Effort expectancy	Het kost(te) mij veel tijd en energie om de CoronaMelder app te gebruiken/De CoronaMelder app is makkelijk te gebruiken Ik denk dat het mij veel tijd en energie kost om de CoronaMelder app te gebruiken/Ik denk dat de CoronaMelder app makkelijk te gebruiken is
Social influence	Veel mensen in mijn omgeving gebruiken de CoronaMelder app Mensen in mijn directe omgeving vinden dat ik de CoronaMelder app moet gebruiken
Facilitating conditions	Ik heb een smartphone tot mijn beschikking met toegang tot het internet waarmee ik de CoronaMelder app kan gebruiken Ik heb genoeg (technische) kennis om de CoronaMelder app te gebruiken
HBM variables	
Perceived susceptibility	Ik loop in de komende twee maanden risico op een besmetting met het coronavirus Er is een grote kans dat ik in de komende twee maanden besmet raak met het coronavirus
Perceived severity	Ik vind het erg om besmet te raken met het coronavirus Een besmetting met het coronavirus heeft voor mij grote lichamelijke, psychische of economische gevolgen
Self-efficacy	Ik ben in staat om de CoronaMelder app te gebruiken
Perceived barriers	Het heeft voor mij persoonlijke nadelen om de CoronaMelder app te gebruiken
Perceived benefits	Het heeft voor mij persoonlijke voordelen om de CoronaMelder app te gebruiken
Context-related variables	
Monitoring beliefs	De CoronaMelder app houdt mijn locatie bij De CoronaMelder app slaat mijn naam of persoonsgegevens op
Conspiracy beliefs	Het coronavirus is een biologisch wapen dat in een laboratorium is gemaakt De uitbraak van het coronavirus heeft te maken met (de aanleg van) het 5G netwerk
Fear beliefs	Ik vind de CoronaMelder app eng Ik zou angstig worden als ik een melding ontvang van de CoronaMelder app
Societal beliefs	Het gebruiken van de CoronaMelder app maakt je een goede burger

(continued on next page)

(continued)

Construct	Item
Data safety	Het gebruiken van de CoronaMelder app helpt de Nederlandse economie
Perceived susceptibility (others)	De CoronaMelder app helpt om mensen met een kwetsbare gezondheid te beschermen tegen het coronavirus
Perceived severity (others)	Ik heb vertrouwen in de manier waarop de Nederlandse overheid probeert het coronavirus onder controle te houden
Technology performance	Alle informatie die ik geef in de CoronaMelder app wordt vertrouwelijk behandeld
Corona infection other	Als ik besmet raak met het coronavirus is de kans groot dat ik anderen zal besmetten
	Ik vind het erg als ik andere mensen besmet met het coronavirus
	De techniek (bluetooth) die wordt gebruikt in de CoronaMelder app geeft aan wie er in de buurt is geweest van een persoon die besmet is met het coronavirus
	Zijn er mensen in uw directe omgeving besmet (geweest) met het coronavirus?

Supplement C

	Hosmer and Lemeshow test		Pseudo R ²
	χ^2 (df = 8)	p	Mcfadden
UTAUT	13.57	.09	0.48
HBM	5.94	.65	0.32
Context	5.63	.69	0.29

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