CoronaMelder: A longitudinal data analysis on perceived privacy risks and perceived health risks on CTA use

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Abstract

Traditional forms of contact tracing alone were not sufficient to keep up with the rising number of COVID-19 infections in the Netherlands. Contact tracing apps (CTAs) provided a more efficient method of contact tracing. However, the impact of CTAs depends on the adoption rate. The risk-risk tradeoff is typically used to examine an individual's decision-making process when behavior to solve a risk involves creating a new risk and can be used to examine the influence of risks on CTA use. Previous studies have shown perceived privacy risks (PPR) negatively influences CTA use. Studies focused on the influence of perceived health risk on CTA use found ambiguous results (i.e. a positive relationship and no relationship). However, little is known about the risk-risk tradeoff between PPR and perceived health risk on CTA use over time after the introduction of a novel technology. A longitudinal study by the Dutch LISS survey panel followed the adoption of the Dutch CoronaMelder during a 17-month period. Participants who completed all questionnaires were included in this study (n = 1220). The analyses showed that PPR about CTA use decreases over time after launch of the CTA. CTA use at each time point remained negatively associated with PPR. At each measurement, perceived severity of the disease for others positively affected CTA use. No clear evidence was found of a moderating effect of perceived health risk for oneself or others on the relationship between PPR and CTA use. The results have several practical and theoretical implications. The Dutch government should focus on PPR and perceived severity of the disease for others in communication about technology adoption throughout a future pandemic since the results suggest that both PPR and perceived severity of the disease for others influence CTA use at each measurement. In addition, the results contribute to the literature and research on technology adoption by showing for the first time that perceived severity of the disease for others positively influences CTA use, demonstrating that technology adoption theory should not focus solely on risks influencing oneself.

Keywords: CoronaMelder, COVID-19, contact tracing apps, risk-risk tradeoff, health belief model, privacy calculus theory, longitudinal

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As a measure against COVID-19, governments have used both traditional, manual forms of contact tracing and novel, digital ones, i.e. contact tracing apps (CTAs). Traditional contact tracing alone was too labor intensive and time consuming to keep up with the rising number of infections. CTAs have the potential to overcome these limitations (Kleinman & Merkel, 2020). This potential is important because COVID-19, among others, negatively affects people's health, disrupts social activity and weakens the economy (WHO, 2020). Along with other measures, the use of CTAs can result in control over the virus by lowering the number of infections, thereby indirectly reducing its mortality rate and mitigating its impact on society. However, the impact of CTAs depends on their adoption rate. The more people use CTAs, the greater the reduction in infections and the indirect effect on mortality (Jenniskens et al., 2021). The World Health Organization (WHO) has started a Health Emergencies Programme to prepare countries for future pandemics (WHO, n.d.). Pandemics have occurred in the past and are likely to occur in the future (Behl et al., 2022). Investigating what factors influence CTA use could help increase the adoption rate of CTAs in a future pandemic.

An individual's decision-making process, more specifically, deciding whether to use a CTA, can be assessed using the risk-risk tradeoff, i.e. the tradeoff between creating new risks for oneself while eliminating other risks (Kip Viscusi et al., 1991). This tradeoff is used in the privacy calculus theory (PCT) to examine the tradeoff between perceived risks and anticipated benefits for oneself in deciding whether to disclose personal information (Kokolakis, 2017). In the context of CTA use, there exists perceived privacy risk (PPR), i.e. the expectation of privacy loss associated with disclosing private information, can be perceived as a risk of CTA use. For example, a common misconception is that CTAs track their users' locations and store their users' personal data (Ebbers et al., 2021). Individuals may perceive that by using a CTA, they are sharing personal information with the risk of this information being exposed. This risk can be viewed as the cost of CTA use. In addition, individuals may perceive CTA use as protecting themselves and others against health risks associated with COVID-19. The perceived health risk of a disease is an individuals' evaluation of the likelihood that an unfavorable outcome will occur from a hazard. Protecting the health of oneself or others can be viewed as the anticipated benefits of CTA use. An individual may weigh this anticipated benefit against the perceived risk (i.e. PPR) in deciding whether to use a CTA.

However, this risk-risk tradeoff has not been studied often. To the best of my knowledge, only the studies of Chopdar (2022) and Tran and Nguyen (2021) have examined the risk-risk tradeoff. Their studies found evidence for the moderating influences of perceived severity and perceived susceptibility of the disease for oneself on the relationship between PPR and CTA use. Individuals who perceive the severity and susceptibility of the disease to be high, demonstrate a weaker negative relationship between PPR and CTA use. These studies used cross-sectional data. My research indicates that the variables have not yet been examined using longitudinal data. Ariely and Zakay (2001) state that in the decision-making process, time plays a prominent role. Weighing risks to decide whether to use a CTA is unlikely to be intuitive, which could result in the decision-making process may take more time than when it would be an intuitive decision. This means that individuals may change their behavior over time while their PPR and perceived health risk remain constant. Based on this understanding, it can be expected that over time, after the launch of a CTA, the moderating effects of perceived severity and perceived susceptibility of a disease for oneself on the relationship between PPR and CTA use could remain the same but perhaps grow more evident after more time has passed following the launch of a CTA because it is likely an individual making the decision to use a CTA would take more time.

Several studies have examined the direct influence of PPR on CTA use and found a significant negative relationship between them (Carlsson Hauff & Nilsson, 2021; Chan & Saqib, 2021; Li et al., 2021; Tran & Nguyen, 2021; Walrave et al., 2020). These studies used cross-sectional data and found that individuals who demonstrate a high PPR towards CTAs were less likely to use one. Again, I believe this relationship has only been examined cross-sectional. According to Rogers's diffusion of innovation theory (Sahin, 2006), individuals who adopted the CTA at a later time point after the launch of a CTA are more likely to have done so because of a decrease in perceived risks. As such, the relationship between PPR and CTA use after more time has passed following the launch of a CTA is expected to remain negative because a change in behavior is likely to be preceded by a decrease in PPR.

In addition to PPR, researchers also investigated the direct influence of perceived health risk for oneself on CTA use. Perceived health risk is included in the health belief model (HBM) as a predictor of behavior. The perceived health risk is divided into perceived severity of the disease, i.e. beliefs about how serious a given disease and its consequences are, and perceived susceptibility of the disease, i.e. beliefs about the likelihood of being infected by a disease (Glanz et al., 2008; Tran & Nguyen, 2021). Results from studies investigating these factors were ambiguous: whereas one study found a significant positive relationship between perceived severity and perceived susceptibility of the disease for oneself and CTA use (Geber & Ho, 2022), other studies found no significant relationship (van der Waal et al., 2022; Walrave et al., 2020). A possible explanation for these ambiguous results is that CTA use is mainly beneficial for others and thereby may be perceived as not directly affecting one's own health. A CTA informs a person whether they may be infected with a disease. Knowing this, one can take measures to prevent infecting others (van der Waal et al., 2022). However, this explanation does not account for the significant positive association found by Geber and Ho (2022). Their findings could perhaps be explained by the studies' differing periods of data collection: Walrave et al. (2020) and van der Waal et al. (2022) collected data before or right after the launch of a CTA, while Geber and Ho (2022) collected data at a later time point. This could result in a change in relationship between perceived health risk for oneself and CTA use after more time has passed following the launch of a CTA. However, as stated by Carpenter (2010), an individual's perceived health risk and consequently the behavior based on these beliefs can change over time. Therefore, the relationship between perceived health risk and CTA use over time following the launch of a CTA is expected to remain positive because a change in behavior is likely to be preceded by a change in the perceived health risk. An analysis including multiple points in time could provide more insight into the effect of time after the launch of a CTA on the relationship between perceived health risk and CTA use.

Furthermore, based on the reasoning that CTA use mainly protects the health of others rather than one's own health, studies have also examined the influence of altruistic motives (i.e. the desire to increase the well-being of others at a loss to oneself) on CTA use (Elster, 2006). To the best of my knowledge, van der Waal et al. (2022) performed the only study to examine the influence of perceived severity of a disease for others, i.e. beliefs about how serious infecting others is, and perceived susceptibility of a disease for others, i.e. the beliefs on the likelihood of infecting others, on CTA use. Contrary to expectations based on the literature, this study did not find a significant relationship between perceived severity and perceived susceptibility of the disease for others and CTA use. In contrast, several studies found that risk to others was an important predictor of CTA use. Jones and Thompson (2021) found that reducing such risk was one of the main reasons for adoption. Furthermore, Caserotti et al. (2022) found that intention to take measures against a disease is higher when people intend to do so for others. However, it is important to note that the data of the study of van der Waal et al. (2022) was collected one and a half weeks after the launch of the CTA and is part of the longitudinal dataset that will be used in this paper. No earlier studies examined the influence of perceived health risk of the disease for others on CTA use at a time point longer after launch. Since protecting others has been found to be one of the main reasons to adopt a CTA, and a change in behavior is likely to have been preceded by a change in the perceived health risk for others (Carpenter, 2010), the relationship between perceived health risk for others and CTA use is expected to be positive after more time has passed following the launch of a CTA.

Although researchers have examined the direct effect of altruistic motives on CTA use, to the best of my knowledge, no studies have focused on the risk-risk tradeoff between perceived risks for oneself and perceived risks for others. Unlike the perceived health risk for oneself, the perceived health risk for others have not been examined as moderators on the relationship between PPR and CTA use. Based on the reasoning that CTA use mainly protects the health of others rather than one's own health, on earlier research that shows protecting others is one of the main reasons to use a CTA (Caserotti et al., 2022; Jones & Thompson, 2021) and on the fact that no research has yet been conducted on the risk-risk tradeoff between risks for oneself and risks for others, it could be beneficial to examine whether perceived severity and perceived susceptibility of the disease for others moderates the relationship between an individual's PPR and CTA use after the launch of a CTA.

This study uses longitudinal data collected in a 17-month period after the introduction of a novel technology to research changes over time and gain insight into the cause-and-effect relationships. Longitudinal data enables researchers to investigate how variables change over time (Hedeker & Gibbons, 2006). Little investigation has been done into the previously mentioned variables and their development over time after the launch of a CTA. Analysis of longitudinal data will provide insights into how influential the variables after more time has passed following the launch of a CTA. In addition, as mentioned before, previous studies have mainly focused on cross-sectional- or cross-national data. Longitudinal data can enrich the current knowledge by focusing on CTA use as a process. Individuals may stop using, start re-using, or begin using a CTA at a later point in time after the launch of the technology. By examining the influence of a variable on CTA use at multiple points in time, a more precise understanding of the influence in different phases after the launch of a CTA, can be gained (Verpaalen et al., 2022).

This study examines the moderating influences of perceived health risk variables (i.e. perceived health risk of the disease for oneself and others) on the relationship between PPR and CTA use and the direct influence of PPR and perceived health risk on CTA use. The following research questions have been formulated:

RQ1**.** How does PPR about CTA use develop in a 17-month period after launch?
RQ2. How does the relationship between CTA use and PPR (RQ2a), and between CTA use and perceived health risk (RQ2b) develop in a 17-month period after launch?
RQ3. Do perceived severity of the disease and perceived susceptibility of the disease for oneself and others moderate the relationship between PPR and CTA use in a 17-month period after launch?

Theoretical framework

CoronaMelder

The Dutch government introduced the CTA *CoronaMelder* in October 2020 (Ebbers et al., 2021) and deactivated the CTA in September 2022 (Rijksoverheid, n.d.). The CTA caused a phone to periodically send Bluetooth messages that could be received by nearby devices that also had the CTA. If a CoronaMelder user tested positive for the virus, they could report it anonymously through the CTA. Individuals who were nearby during the infectious period received a message about the possible exposure to the virus and advice on testing and quarantine (Boncz, 2021). The purpose of this message and the CoronaMelder was to complement traditional, manual forms of contact tracing by reaching more contacts more quickly after a positive test result was detected and to provide advice after a notification was received from the CTA (Ebbers et al., 2021).

However, the impact of the CoronaMelder depended on its adoption rate. The more people used the CTA, the greater the reduction in infections and the indirect effect on mortality (Jenniskens et al., 2021). In May 2021, the CTA was evaluated on multiple key figures. This evaluation showed that a mere 4.9 million people (28% of the population) had downloaded the CoronaMelder. It was also estimated that of these people only 2.9 million people (approximately 17% of the population) used the CTA (Ebbers et al., 2021). The adoption rate of the CoronaMelder in May 2021 was low, and it can be concluded that the direct and indirect effects on infection and mortality were lower than they would have been if there was a higher adoption rate.

Technology adoption

The low adoption rate and slow diffusion of the CoronaMelder is not exceptional for new technologies. In contrast to the rate at which new technologies can be invented, the diffusion and adoption of these new technologies are ongoing and slow processes. However, this diffusion, i.e. the result of multiple individuals weighing the costs and benefits of adopting a new technology, and adoption, i.e. the result of a single individual weighing the costs and benefits of adopting a new technology, determines the productivity of a technology

(Hall & Khan, 2003). The weighing of costs and benefits is similar to the technology acceptance model (TAM). According to the TAM (Surendran, 2012), the perceived usefulness (i.e. an individual's perception of the probability that the use of a technology will enhance their life) and the perceived ease of use of a new technology are weighted to determine whether to use it. To ultimately increase the adoption rate, the benefits of using the new technology should outweigh the costs of use. In the context of CTA use, PPR is one such cost.

Perceived privacy risk

Privacy has been an important concern during the development of the CoronaMelder. Since the launch of the CTA, there have been several misconceptions about data storage. The CoronaMelder was believed to track its users' locations and store its users' personal data (Ebbers et al., 2021). Although this is a misconception, an individual may still equate use of a CTA with sharing private information.

These concerns about data storage could influence the PPR towards CTA use. PPR refers to the expectation of privacy loss associated with disclosing private information at the risk of this information being exposed or misused (Tran & Nguyen, 2021; Xu et al., 2008). Based on the misconceptions about data storage of the CoronaMelder, it is possible that individuals have privacy concerns about CTA use. These concerns could result in individuals having high PPR about CTA use.

However, an individual's PPR towards a new technology can change over time. As stated by the study of Nilsen et al. (2016), individuals who show initial ethical resistance (e.g. privacy concern) towards a new technology can decrease after more time has passed following the launch as their familiarity and experience with that technology grows, altering their perceptions of it. Importantly, this may suggests that the PPR towards a new technology may decrease over time after launch. In addition, anxieties about a new technology are expected to decrease over time after launch because the technology becomes more publicly visible and familiar (Mueller et al., 2011). Based on these studies, PPR towards CTA use after launch may decrease over time.

However, to the best of my knowledge, this change that Mueller et al. (2011) found has not been empirically charted throughout the process of implementing a new technology. The study by Nilsen et al. (2016) examined resistance toward a new technology during its implementation over a 14-month period. This study showed initial evidence for the change in PPR over time after launch. Based on the misconception about data storage, as well as the studies of Nilsen et al. (2016) and Mueller et al. (2011), it can be expected that the PPR about

CTA use will decrease in the 17-month period after the launch of the CTA. For this reason, the following hypothesis was established:

H_1 The perceived privacy risk about contact tracing app use will decrease in the 17-month period after the launch of the CTA.

PPR can also be used in the PCT. The PCT can be used to examine the tradeoff between expected risks (i.e. expectation of loss associated with disclosing private information) and anticipated benefits (i.e. expectations of value added by disclosing private information) for oneself in deciding whether to disclose private information. It is expected that an individual will disclose personal information when the anticipated benefits surpass the expected risks (Kokolakis, 2017). In the context of CTA use, PPR can be perceived as an expected risk of using a CTA. Based on the misconception about data storage of the CoronaMelder, it is possible that the expected risks of using the CoronaMelder outweigh the anticipated benefits. This could result in a negative relationship between PPR and CTA use.

Furthermore, privacy concerns directly influence the adoption of a new technology. Individuals who have privacy concerns about a new technology are more cautious about using it. Privacy concern is a strong predictor of privacy-related behavior. Failure to address the privacy concerns of potential adopters may negatively affect behavior toward the new technology (Dhagarra et al., 2020). Based on this theory, individuals who have privacy concerns about a CTA could be less likely to use the CTA. This could result in a negative relationship between PPR and CTA use.

The influence of PPR on the use of or intention to use a CTA has been examined cross-sectionally, revealing a negative relationship between them (Carlsson Hauff & Nilsson, 2021; Chan & Saqib, 2021; Li et al., 2021; Tran & Nguyen, 2021; Walrave et al., 2020). Individuals who have a high PPR towards a CTA are less likely to use or intend to use one. It is important to note that the studies of Walrave et al. (2020), Chan and Saqib (2021) and Li et al. (2021) investigated the use of or intention to use a CTA when the CTA was not yet developed. Participants indicated their willingness to use a CTA based on the fictional existence of one. Only the study of Tran and Nguyen (2021) focused on CTA use of an existing CTA. The results showed a negative relationship between PPR and CTA use. Individuals who had a high PPR were less likely to use a CTA. Based on these studies, I could expect to find a negative relationship between PPR and CTA use.

However, the decision to use a CTA can be revised and changed at a later point in time. Rogers's diffusion of innovation theory (Sahin, 2006) can provide insight into this change. By applying this theory, one can divide users of a new technology into adopter categories based on their innovativeness (i.e. the degree to which an individual relatively early or late adopts a new system). These adopter categories are innovators, early adopters, early majority, late majority, and laggards. Each category has its own defining set of characteristics (Sahin, 2006). For example, individuals that belong in the category of innovators are more prepared to deal with the potential risks of privacy loss, while individuals who are part of the late majority are more skeptical towards a new technology and they will wait to adopt until the potential risks are reduced. Individuals who adopt the CTA at a later time point after launch are more likely to do so because their PPR has decreased. This could result in the relationship between PPR and CTA remaining negative after the launch of the CTA because a change in behavior is likely to be preceded by a decrease in PPR.

To the best of my knowledge, no research has been done to examine the relationship between PPR and CTA use at a time point longer after the launch of the technology. The earlier mentioned studies focused on use of or intention to use a CTA before the launch or in the first months after the launch and found a negative relationship between PPR and use of or the intention to use a CTA. Considering Rogers's diffusion of innovation theory (Sahin, 2006), adopting the CTA at a later time point is likely to be preceded by a decrease in PPR. This could result in the same relationship between the variables after more time has passed following the launch of the CTA. One would expect to find a negative relationship between PPR and CTA use throughout a 17-month period after the launch of the CTA. For this reason, the following hypothesis was established:

H_2 The perceived privacy risk is negatively associated with contact tracing app usage at each time point.

Perceived health risk

Perceived health risk for oneself

The perceived health risk is an individual's evaluation of the likelihood that a disease will cause an unfavorable outcome. Perceived health risk is a predictor of behavior according to the HBM. This predictor of behavior is divided into the perceived severity and perceived susceptibility of a disease. The perceived severity of a disease is an individual's beliefs about how serious the disease and its consequences are. The perceived susceptibility of a disease is an individual's beliefs about the likelihood of being infected by a disease (Glanz et al., 2008). In the context of CTA use, CTA use could protect oneself and others from infection and thereby prevent an unfavorable outcome.

HBM states that an individual determines their behavior in response to a threat based on the assessment of the consequences of that threat and the efficiency and achievability of the protective behavior. According to the HBM, individuals who perceive a disease as a serious threat and perceive themselves as likely to be infected are more likely to undertake action that they believe will reduce these risks (Glanz et al., 2008). CTAs inform a person whether they are at risk of being infected with a disease. Knowing this, one can take measures to prevent infecting others (van der Waal et al., 2022). In addition, by protecting others from getting infected, an individual indirectly protects themselves by slowing the pandemic and thereby reducing the likelihood of a new infection. Based on HBM, it is likely that individuals who perceive the severity and susceptibility of the disease as high are more likely to use a CTA. This assumption could result in a positive relationship between perceived severity of the disease and CTA use and a positive relationship between perceived susceptibility of the disease and CTA use.

However, results from studies investigating these relationships, were ambiguous (Geber & Ho, 2022; van der Waal et al., 2022; Walrave et al., 2020). The study of Geber and Ho (2022) was the only study to find a significant positive effect of perceived susceptibility and perceived severity of the disease for oneself on CTA use. This study examined the association in two countries (i.e. Singapore and Switzerland) but only found a significant effect in one country (i.e. Singapore). This difference may be explained by the differences in development of the pandemic between these countries. While Singapore had few new infections per day, Switzerland faced a high number of new infections daily. This could have resulted in a significant relationship between perceived health risk and CTA use at time points with low infection rates, and no significant relationship at points in time with high infection rates. The studies of van der Waal et al. (2022) and Walrave et al. (2020) found no significant relationship between perceived health risk and use of or the intention to use CTA. The study of Walrave et al. (2020) used a fictional CTA to analyze the relationship between perceived susceptibility and perceived severity of the disease and the intention to use CTA. It is possible that after the launch of a CTA, this relationship could change. Furthermore, the study of van der Waal et al. (2022) examined the relationship between perceived susceptibility and perceived severity of the disease and CTA use one and a half weeks after launch of the CTA. Geber and Ho (2022) examined this relationship after more time had passed between the launch and data collection (i.e. five and eight months). This could have resulted in the significant relationship between perceived health risk and CTA use that they found since more time has passed following the launch of the CTA.

In addition, an individual's perceived health risk and consequent behavior can change over time. Based on the results of Geber and Ho (2022) and the meta-analysis of Carpenter

(2010), someone who does not perceived the severity and susceptibility of a disease to be high at the beginning of an outbreak may adopt prevention behavior over time due to a change in health beliefs. Over time, individuals interact with each other, read more information about a subject or gain new insights into certain risks. These changes could result in adopting a CTA at a later time point, likely after a change in the perceived health risk. Consequently, the relationship between perceived susceptibility and perceived severity of the disease for oneself and CTA use may remain positive after more time has passed following the launch of the CTA.

To the best of my knowledge, no research has been done to examine the relationship between perceived health risk for oneself and CTA use at a time later than after eight months of the launch of the technology. Based on the significant positive relationship found by Geber and Ho (2022) and HBM (Glanz et al., 2008), it can be expected that individuals who perceive a disease as a serious threat and perceive themselves as likely to be infected are more likely to undertake action that they believe to reduce these risks. Since adoption of the CTA at a later time point is likely to have been preceded by a change in perceived health risk (Carpenter, 2010), the relationship between these variables can be expected to remain the same. One would expect to find a positive relationship between perceived health risk for oneself and CTA use throughout a 17-month period after the launch of the CTA. Based on these expectations, the following hypothesis was established:

H_3 The perceived severity (H_{3a}) and perceived susceptibility (H_{3b}) of the disease for oneself is positively associated with contact tracing app usage at each time point.

Perceived health risk for others

The perceived health risk can also be assessed as an influence of an individual's behavior on others. Perceived severity for others refers to an individual's beliefs about how serious infecting others is. Perceived susceptibility of the disease for others refers to the beliefs of an individual about the likelihood of infecting others (van der Waal et al., 2022). CTA use could protect others from getting infected with a disease and thereby prevent an unfavorable outcome.

HBM focuses on behavior protecting oneself from the consequences of a threat. However, CTAs are mainly effective in protecting others from being infected. CTA use may be perceived as not directly affecting one's own health (van der Waal et al., 2022). Knowing this raises the question of whether the perceived health risk for others could influence CTA use since one of the most common reasons to use or be willing to use a CTA is to protect others (Caserotti et al., 2022; Jones & Thompson, 2021). Based on this reasoning, it is likely that individuals who perceive the severity and susceptibility of a disease for others as high are more likely to use a CTA. This could result in a positive relationship between the perceived health risk for others and CTA use.

The study by van der Waal et al. (2022) investigated the relationship between perceived health risk for others and CTA use. The researchers did not find a significant effect of the perceived severity and perceived susceptibility of the disease for others on CTA use. The study only focused on adoption one and a half weeks after the launch of the CTA. Several studies that focused on the motivation of individuals to use a CTA found reducing risk for others to be one of the main reasons to use a CTA. The study by Jones and Thompson (2021) examined the intentions of citizens in Wales to use a CTA and the reasons they were willing to do so. One of the main reasons to use a CTA was to reduce risks for others. In addition, the study by Caserotti et al. (2022) focused on exploring factors that influenced the likelihood to adopt preventive measures against the disease and found that intention to take such measures was higher when people intended to do so for others. Based on these results, a positive relationship between perceived health risk for others and CTA use is likely.

Furthermore, an individual's perceived health risk and consequent behavior can change over time (Carpenter, 2010). Just as the perceived health risk for oneself can change, the perceived health risk for others can do the same. Such change could result in adopting a CTA at a later time point. The relationship between perceived susceptibility and perceived severity of a disease for others on CTA use may therefore remain positive after more time has passed following the launch of the CTA.

Based on the reasoning that CTA use mainly protects the health of others and that protecting others is one of the main reasons to use or be willing to use a CTA (Caserotti et al., 2022; Jones & Thompson, 2021), it can be expected that an individual who perceives health risks of a disease for others to be high is more likely to use a CTA. Furthermore, since adoption of the CTA at a later time point is likely to be preceded by a change in perceived health risk for others (Carpenter, 2010), the same relationship between the variables after more time has passed following the launch of the CTA may hold true. One would expect to find a positive relationship between perceived health risk for others and CTA use throughout a 17-month period after the launch of the CTA. For this reason, the following hypothesis was established:

H_4 The perceived severity (H_{4a}) and perceived susceptibility (H_{4b}) of the disease for others is positively associated with contact tracing app usage at each time point.

Risk-risk tradeoff

In the risk-risk tradeoff individuals weigh whether resolving one risk is worth creating new risks with a given behavior. The risk an individual is focused on reducing is called the primary risk. The new risk created by the activity undertaken to reduce the primary risk is called the countervailing risk. The countervailing risk can affect the individual undertaking the behavior, or it can affect others, and it can be, but is not necessarily, the same type of risk as the primary risk (Graham et al., 1995; Hansen et al., 2008). In context of CTA use, individuals can weigh perceived health risk for themselves or others as the primary risks against PPR for themselves as the countervailing risks in deciding whether to use a CTA. Based on this risk-risk tradeoff, individuals can decide whether to use a CTA.

Perceived health risk for oneself

Individuals can use the risk-risk tradeoff to weigh perceived health risk and PPR for themselves in deciding whether to use a CTA. As stated by HBM, individuals who perceive a disease as a serious threat and perceive themselves as likely to be infected are more likely to undertake action that they believe to reduce these risks (Glanz et al., 2008). Individual could start using the CTA to protect one's health because they perceive the disease as a serious threat and perceive themselves as likely to be infected and thereby accepting possible PPR. This could result in high perceived health risk for oneself predicting a weaker negative relationship between PPR and CTA use.

Several studies have examined the risk-risk tradeoff between perceived health risk and PPR on use of or intention to use a CTA (Chopdar, 2022; Tran & Nguyen, 2021). The study by Tran and Nguyen (2021) found that individuals for whom the perceived health risk outweighed PPR were more likely to use a CTA. In addition, the study by Chopdar (2022) showed that individuals who perceived the severity and susceptibility of the disease as high demonstrated a weaker negative association between PPR and intention to use a CTA. These studies provide supporting evidence of the risk-risk tradeoff between PPR and perceived health risk.

In this risk-risk tradeoff the decision-making process is likely to take more time because weighing risks to decide whether to use a CTA is unlikely to be intuitive, which could result in the decision may take more time than when it would be an intuitive decision. In a decision-making process an individual can come to a decision fast and intuitive, while other decisions require a more analytic approach which will likely take more time (Ariely & Zakay, 2001). In context to CTA use, an individual could assess whether solving perceived health risk for oneself its worth creating PPR. This decision is unlikely to be intuitive, which could result in the decision-making process taking more time. Individual may decide to use a

CTA at a later time point after launch because the decision to do so require a more analytic approach. It is possible that the perceived health risk for oneself and PPR over time after launch would remain the same; the decision of whether to use a CTA will simply come at a later point. The moderating effect could become more evident after more time has passed following the launch of a CTA. However, because the perceived health risk for oneself and PPR for oneself would remain constant over time after launch, the moderating effect would not otherwise change.

Based on the results by Chopdar (2022) and Tran and Nguyen (2021), it can be expected that individuals who perceived the severity and susceptibility of a disease for themselves to be high will demonstrate a weaker negative relationship between PPR and CTA use than individuals who perceive the severity and susceptibility of a disease for themselves to be low. Furthermore, because individuals can change their behavior at a later time point while retaining the same perceived health risk and PPR for themselves (Ariely & Zakay, 2001), it is possible that the moderating effect will become more evident after more time has passed following the launch of a CTA. However, because the perceived health risk for oneself and PPR would stay the same, the moderating effect is not likely to change. Therefore, one would expect to find that a high perceived severity and high perceived susceptibility of the disease for an individual predicts a weaker negative relationship between PPR and CTA use throughout a 17-month period following the launch of the CTA. For this reason, the following hypothesis was established:

H_5 High perceived severity (H_{5a}) and high perceived susceptibility (H_{5b}) of the disease for oneself predicts a weaker negative association of perceived privacy risk on contact tracing app use at each time point.

Perceived health risk for others

Individuals can also use the risk-risk tradeoff to weigh perceived health risk for others against PPR for themselves in deciding whether to use a CTA. Perceived health risk for others can be assessed as an influence of an individual's behavior on others. In this risk-risk tradeoff, risks for an individual and risks for others are weighed against each other to decide whether to use a CTA. In context of CTA use, individuals could weigh perceived health risk for others as the primary risks against PPR for the individual as the countervailing risk in deciding whether to use a CTA.

To the best of my knowledge, the moderating effect of perceived health risk for others on the relationship between PPR for themselves and CTA use has not been researched. Studies have, however, found protecting others to be one of the main reasons to use or be willing to use a CTA (Caserotti et al., 2022; Jones & Thompson, 2021). In addition, Chopdar (2022) did find a significant moderating effect of perceived health risk for oneself on the relationship between PPR and CTA use. As protecting others is one of the main reasons to use or be willing to use a CTA, and initial evidence has been found of the influence of health risks on the relationship between PPR and CTA use, an analysis of the moderating influence of perceived health risk for others could show that a high perceived severity and susceptibility of a disease for others to predicts a weaker negative relationship between PPR and CTA use

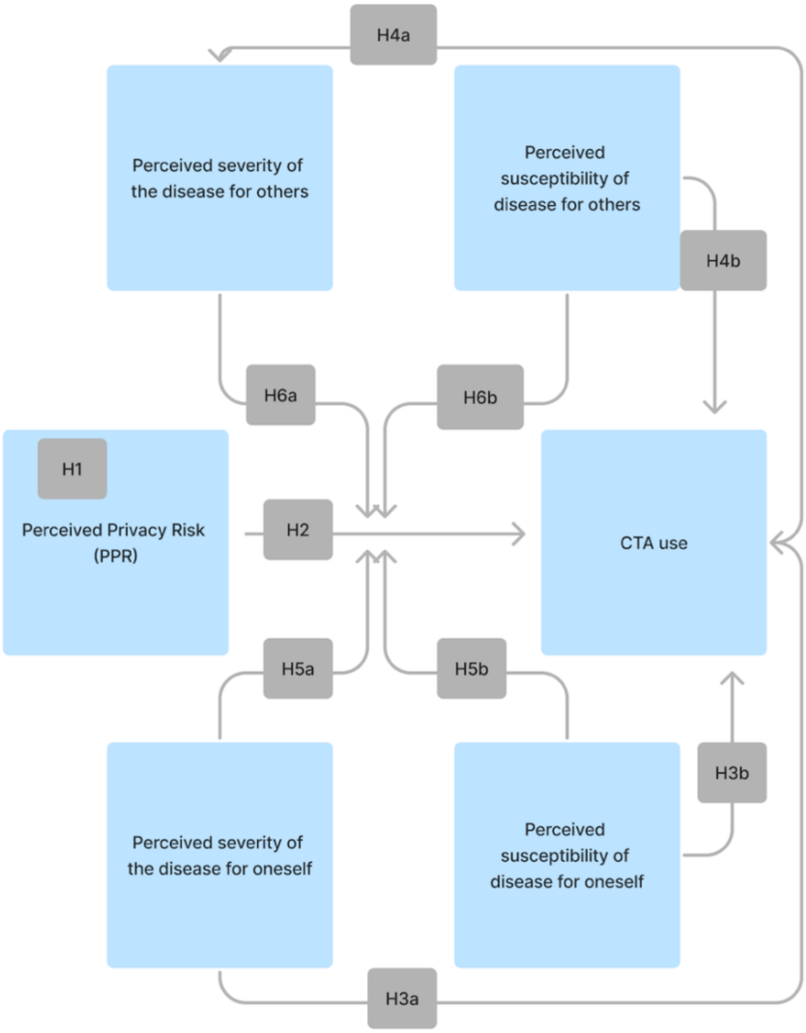
Furthermore, in the decision-making process the risk-risk tradeoff is unlikely to be intuitive, which may lead to the process taking more time than when it would be an intuitive decision (Ariely & Zakay, 2001). To decide whether to use a CTA, an individual could assess whether resolving a certain risk for others is worth creating another risk for oneself. This assessment process could result in a change in behavior over time after launch due to the fact that the decision of whether to use a CTA would arrive at a later time point after launch. This means that individuals may change their behavior while their perceived health risk for others and PPR stay the same. This could result in the moderating effect becoming more evident after more time has passed following the launch of a CTA. However, because the perceived health risk for others and PPR would remain constant over time after launch, the moderating effect would not change.

Based on the studies of Jones and Thompson (2021) and Caserotti et al. (2022) it can be expected that individuals who perceive the severity and susceptibility of a disease for others to be high likely to demonstrate a weaker negative relationship between PPR and CTA use. Furthermore, because individuals can change their behavior at a later time point while perceiving the same health risks for others and retaining their own PPR (Ariely & Zakay, 2001), it is possible that the moderating effect will become more evident after more time has passed following the launch of the technology. However, because the perceived health risk for others and PPR would stay same, the moderating effect would not change. Therefore, one would expect to find that a high perceived severity and high perceived susceptibility of the disease for others predict a weaker negative relationship between PPR and CTA use throughout a 17-month period after the launch of the CTA. For this reason, the following hypothesis was established:

H_6 High perceived severity (H_{6a}) and high perceived susceptibility (H_{6b}) of the disease for others predicts a weaker negative association of perceived privacy risk on contact tracing app use at each time point.

Figure 1

The research framework



Note. Figure 1 shows the hypotheses described in the theoretical framework.

Materials and Methods

Data collection

The data used in this study had already been collected. The data was collected in six waves over a 17-month period after the launch of the CTA by the Dutch LISS survey panel. It is important to note that the time intervals between each measurement were not equal. For each measurement, respondents completed a questionnaire focused on CTA adoption, CTA message compliance and general COVID-19 countermeasures. Questions on CTA adoption were included here because this study attempts to determine the influence of certain variables on CTA use. By using this data, it was possible to examine the development of the variables that can influence CTA over a long period of time after the launch of a CTA.

Sampling procedure

Participants were selected by a random sampling procedure from the Dutch LISS survey panel. Participants received an invitation by mail or home visit. To be eligible for the study, participants had to be at least 16 years old and had to have participated in the health and coronavirus questionnaires. Respondents were reminded twice per assessment to complete the questionnaire. After completing each questionnaire, respondents received a cash reward for each completed questionnaire (van der Laan et al., 2022).

Participants

The participants of this study completed six questionnaires in a time period of 17-months after the launch of the CTA. Participants who did not complete all six questionnaires were excluded from this study. These participants were excluded to ensure that any discrepancy in results at different time points was not caused by a difference in the data sample. After exclusion, a total of 1220 participants were included, 647 women (53%) and 573 men (47%) with a mean age of 55 years (*SD* = 17.3).

Attrition

Of the 1900 participants who completed the first questionnaire, 680 (35.80%) participants were excluded from this study because they did not complete all six questionnaires. To examine differences between participants who completed all questionnaires and those who did not and to assess whether the exclusion of participants could have influenced the results, a chi-square test for independence was performed. The variables included in this study and the demographic data were compared. The results of this analysis are shown in the result section.

Materials

Dependent measures

CTA use. CTA use was measured at all time points by the item “Which situation is applicable to you?” Respondents were given the following options: “I am currently using the CoronaMelder app”, “I have used the CoronaMelder app in the past but currently no longer use it” and “I have never used the CoronaMelder app” (users CTA range = 20.33% - 31.88%). Based on this question, participants were divided into users and non-users of the CoronaMelder app. Participants who indicated that they were former users were included in the non-user group because they were no longer currently using the CTA. Appendix A shows how this question was recoded.

Independent measures

PPR. PPR was measured at all time points by three items on a 5-point Likert scale (i.e. 1 *definitely not true - maybe not true – do not know - maybe true - definitely true* 5). Earlier studies also used the 5-point Likert scale to measure PPR (Tran & Nguyen, 2021; Walrave et al., 2020). The three PPR assessment items were as follows: "All information I provide in the CoronaMelder app is handled confidentially", "The CoronaMelder app tracks my location" and "The CoronaMelder app stores my name or personal information" (*M* range = 2.93 – 3.06; *SD* range = 1.02 – 1.06). Before calculating the Cronbach's alpha to measure the reliability of these assessments, the items were recoded. The item "All information I provide in the CoronaMelder app is handled confidentially" was reverse coded because unlike the other items the phrase was stated in a positive way. The items "The CoronaMelder app tracks my location" and "The CoronaMelder app stores my name or personal information" were recoded to put the "do not know" option in the middle of the Likert scale. Appendix A shows how the items were recoded. The PPR items as a scale had a questionable reliability in all measurements (Cronbach's α range = .66 – .68). Appendix B shows the Cronbach's alpha for all time points.

Perceived health risk for oneself. Perceived severity and perceived susceptibility of the disease for oneself were both measured at all time points by two items on a 7-point Likert scale (i.e. 1 *totally disagree – disagree – somewhat disagree – neutral – somewhat agree – agree – totally agree* 7). The 7-point Likert scale is typically used to measure variables of the HBM (Cummings et al., 1978). Perceived severity of the disease was measured by two items: "I mind getting infected with the coronavirus" and "Being infected with the coronavirus would have major physical, psychological or economic consequences for me" (*M* range = 4.01 – 4.95; *SD* range = 1.33 – 1.48). Perceived susceptibility of the disease was measured by: "I am at risk of a coronavirus infection in the next two months" and "There is a high probability that in the next two months I will be infected with the coronavirus" (*M* range = 3.50 – 4.27; *SD* range = 1.18 – 1.44). The perceived severity of the disease items as a scale had an acceptable reliability in all measurements (Cronbach's α range = .71 – .76). The perceived susceptibility of the disease items as a scale had a good or acceptable reliability in all measurements (Cronbach's α range = .76 – .87). Appendix B shows the Cronbach's alpha for all time points.

Perceived health risk for others. Perceived severity and perceived susceptibility of the disease for others were both measured at all time points by one item on a 7-point Likert scale (i.e. 1 *totally disagree – disagree – somewhat disagree – neutral – somewhat agree –*

agree – *totally agree* 7). Perceived severity of the disease for others was measured by: "I mind if I infect other people with the coronavirus" (*M* range = 5.45 – 6.07; *SD* range = 1.06 – 1.33). The items had a good reliability (Cronbach's α = .83). Perceived susceptibility of the disease for others was measured by one item: "If I become infected with the coronavirus there is a good probability I will infect others" (*M* range = 4.14 – 4.45; *SD* range = 1.40 – 1.47). The items had a good reliability (Cronbach's α = .80).

Data analyses

The collected longitudinal data was analyzed in RStudio (Advanced Statistics Using R[2], n.d.). All analyses are described below per hypothesis.

Hypothesis 1. The perceived privacy risk about contact tracing app use will decrease in the 17-month period after the launch of the CTA.

Hypothesis 1 was tested using the growth curve model from the lavaan package (Advanced Statistics Using R[1], n.d.). The growth curve model was developed to analyze the change in one or more variables over time (Oravecz & Muth, 2017). In this analysis, one model was used with PPR from each time point. The growth curve model shows development over time as a whole and at each time point. Because I used multiple tests to examine this hypothesis, I applied the Bonferroni correction method to ensure that significant relationships in the analyses were not due to chance (Bland & Altman, 1995). I have divided the *p*-value by the number of time points in the analysis. For this hypothesis, the *p*-value was significant at $\leq$ .008 or lower.

Hypothesis 2. The perceived privacy risk is negatively associated with contact tracing app usage at each time point.

Hypothesis 2 was tested using the growth curve model from the lavaan package (Advanced Statistics Using R[1], n.d.). In this analysis, one model was used with PPR as the predictor variable and CTA use as the dependent variable. The predictor and dependent variables for this analysis were taken from the same time point and each time point was analyzed. The growth curve model shows development over time as a whole and at each time point. Because I used multiple tests to examine this hypothesis, I applied the Bonferroni correction method to ensure that significant relationships in the analyses were not due to chance (Bland & Altman, 1995). I have divided the *p*-value by the number of time points in the analysis. For this hypothesis, the *p*-value was significant at $\leq$ .008 or lower.

Hypothesis 3. The perceived severity (H_{3a}) and perceived susceptibility (H_{3b}) of the disease for oneself is positively associated with contact tracing app usage at each time point.

Hypothesis 3 was tested using the growth curve model from the lavaan package (Advanced Statistics Using R[1], n.d.). In this analysis, two models were used with either perceived severity of the disease for oneself or perceived susceptibility of the disease for oneself as the predictor variable and CTA use as the dependent variable. The perceived severity and perceived susceptibility of the disease for oneself were examined separately to be able to assess the influence of one variable separately from the other. The predictor and dependent variables for the analysis were taken from the same time point, and each time point was analyzed. The growth curve model shows development over time as a whole and at each time point. Because I used multiple tests to examine this hypothesis, I applied the Bonferroni correction method to ensure that significant relationships in the analyses were not due to chance (Bland & Altman, 1995). I have divided the *p*-value by the number of time points in the analysis. For this hypothesis, the *p*-value was significant at $\leq .008$ or lower.

Hypothesis 4. The perceived severity (H_{4a}) and perceived susceptibility (H_{4b}) of the disease for others is positively associated with contact tracing app usage at each time point.

Hypothesis 4 was tested using the growth curve model from the lavaan package (Advanced Statistics Using R[1], n.d.). Two models were used in which either perceived severity of the disease for others or perceived susceptibility of the disease for others was the predictor variable and CTA use was the dependent variable. The perceived severity and perceived susceptibility of the disease for others were examined separately to be able to assess the influence of one variable separately from the other. The predictor and dependent variables were taken from the same time point, and each time point was analyzed. The growth curve model shows the development over time as a whole and at each time point. Because I used multiple tests to examine this hypothesis, I applied the Bonferroni correction method to ensure that significant relationships in the analyses were not due to chance (Bland & Altman, 1995). I have divided the *p*-value by the number of time points in the analysis. For this hypothesis, the *p*-value was significant at $\leq .008$ or lower.

Hypothesis 5. High perceived severity (H_{5a}) and high perceived susceptibility (H_{5b}) of the disease for oneself predicts a weaker negative association of perceived privacy risk on contact tracing app use at each time point.

Hypothesis 5 was tested using PROCESS model 2 (Hayes, 2017). Five models were used to test the moderating effects of perceived severity and perceived susceptibility of the disease for oneself on the relationship between PPR and CTA use. In the models, the predictor variable was PPR, the dependent variable was CTA use and the moderator variables were perceived severity and perceived susceptibility of the disease for oneself. By using

PROCESS model 2, two moderators could be examined simultaneously and their respective influences assessed separately. To assess whether the dependent variable could be predicted by the predictor and moderator variables, the model was analyzed with predictor and moderator measured at T1 and CTA use at T2, predictor and moderator measured at T2 and CTA use at T3, predictor and moderator measured at T3 and CTA use at T4, predictor and moderator measured at T4 and CTA use at T5 and predictor and moderator measured at T5 and CTA use at T6. By using data from different time points in the analyses, the differences between the time points are shown. In addition, the predictor and moderator were measured at the same time point to ensure that the influence of the moderator was analyzed. Finally, the dependent variable was taken from a later time point to assess whether the dependent variable could be predicted by the other variables. Because I used multiple tests to examine this hypothesis, I applied the Bonferroni correction method to ensure that significant relationships in the analyses were not due to chance (Bland & Altman, 1995). I have divided the *p*-value by the number of time points in the analysis. For this hypothesis, the *p*-value was significant at $\leq$ .01 or lower.

Hypothesis 6. High perceived severity (H_{6a}) and high perceived susceptibility (H_{6b}) of the disease for others predicts a weaker negative association of perceived privacy risk on contact tracing app use at each time point.

Hypothesis 6 was tested PROCESS model 2 (Hayes, 2017). Five models were used to test the moderating effects of perceived severity and perceived susceptibility of the disease for others on the relationship between PPR and CTA use. In the models, the predictor variable was PPR, the dependent variable was CTA use and the moderating variables were perceived severity and perceived susceptibility of the disease for others. By using PROCESS model 2, two moderators could be examined simultaneously and their respective influences assessed separately. To assess whether the dependent variable can be predicted by the predictor and moderator variables, the model was analyzed with predictor and moderator measured at T1 and CTA use at T2, predictor and moderator measured at T2 and CTA use at T3, predictor and moderator measured at T3 and CTA use at T4, predictor and moderator measured at T4 and CTA use at T5 and predictor and moderator measured at T5 and CTA use at T6. By using the data from different time points in the analyses, the differences between the time points are shown. In addition, the predictor and moderator were measured at the same time point to ensure that the influence on the moderator was analyzed. Finally, the dependent variable was included from a later time point to assess if the dependent variable could be predicted by the predictor and moderator. Because I used multiple tests to examine this hypothesis, I applied the Bonferroni correction method to ensure that significant relationships in the analyses were not due to chance (Bland & Altman, 1995). I have divided the *p*-value by the number of time points in the analysis. For this hypothesis, the *p*-value was significant at $\leq$ .01 or lower.

Results

Descriptive results

To show the variables and participants included in the analyses and their development over time, a few characteristics of the variables and participants will be discussed and shown. The characteristics of the measured variables included in the analyses are reported per wave in Table 1. Table 2 shows the characteristics of the participants who completed all questionnaires.

Table 1

The description of variables included in the analyses to depict an overall image of each variable at each time point and its development

Variables	mean (*SD*)	mean (*SD*)	mean (*SD*)	mean (*SD*)	mean (*SD*)	mean (*SD*)
	T1	T2	T3	T4	T5	T6
CTA use %	28.03%	31.47%	31.88%	30.82%	25.57%	20.33%
Perceived susceptibility oneself *	4.27 (1.22)	4.09 (1.18)	4.21 (1.20)	3.99 (1.23)	3.50 (1.26)	4.06 (1.44)
Perceived susceptibility others *	4.40 (1.40)	4.30 (1.47)	4.40 (1.46)	4.36 (1.46)	4.14 (1.45)	4.45 (1.46)
Perceived severity oneself *	4.95 (1.33)	4.87 (1.34)	4.86 (1.34)	4.70 (1.37)	4.50 (1.41)	4.01 (1.48)
Perceived severity others *	6.07 (1.08)	5.95 (1.08)	6.05 (1.06)	5.91 (1.16)	5.70 (1.28)	5.45 (1.33)
Perceived privacy risk **	3.06 (1.06)	3.03 (1.02)	3.01 (1.02)	3.06 (1.04)	2.97 (1.03)	2.93 (1.03)

Note. * Scores on a Likert scale from 1 to 7 (i.e. 1 totally disagree - totally agree 7).

Note. ** Scores on a Likert scale from 1 to 5 (i.e. 1 definitely not true - definitely true 5).

Table 2

The characteristics of participants included in this study to depict the composition of the participants

Characteristic	Study sample (*n* = 1220)
Gender, *n* (%)	
Male	573 (46.97%)
Female	647 (53.03%)
Age, *n* (%)	
17 – 34 years	217 (17.79%)
35 – 54 years	276 (22.62%)
55 years or older	727 (59.59%)
Educational level, *n* (%)	
Primary education or lower secondary education diploma	337 (27.62%)
Secondary education diploma	407 (33.36%)
Higher education diploma	473 (38.77%)
Unknown	3 (0.25%)

The number of participants who reported using CoronaMelder at each time point differed between a minimum of 248 participants (i.e. 20.33%) and a maximum of 389 participants (i.e. 31.88%). No significant differences were found between males (*n* = 573, 46.97%) and females (*n* = 647, 53.03%) in their use of the CoronaMelder (see Appendix C). Among the different age groups, a significant difference was found between the participants who used the CTA and the participants who did not. There were significantly more older participants in the group of respondents that used the CoronaMelder at T2 (*n* = 247, 63.50%) than in the group of participants who did not use CoronaMelder at T2 (*n* = 480, 57.76%). In addition, a significant difference was found between the education categories of primary education or lower secondary education diploma, secondary education diploma and higher education diploma and their use of the CoronaMelder at each time point (see Appendix C). There were significantly more participants with a high education diploma in the group of respondents that used the CoronaMelder (T1: *n* = 156, 45.61%; T2: *n* = 173, 45.05%; T3: *n* = 172, 44.22%; T4: *n* = 167, 44.41%; T5: *n* = 137, 43.91%; T6: *n* = 108, 43.55%) than in the group of participants who did not use the CoronaMelder (T1: *n* = 317, 36.23%; T2: *n* = 300, 36.01%; T3: *n* = 301, 31.04%; T4: *n* = 306, 36.39%; T5: *n* = 336, 37.13%; T6: *n* = 365, 37.67%; see Appendix C). Summarizing, the participants included in this study differed between user and non-users in age and education categories.

Attrition analysis

Participants who did not complete all questionnaires were excluded from this study. Chi-square tests were performed to ensure that the exclusion of these participants did not affect the results of the analyses. One of the findings from these chi-square tests was that participants who completed all questionnaires and participants who did not complete all questionnaires differed in age. Among participants who completed all questionnaires, there were significantly fewer young participants (between 17 and 34 years of age) and more older participants (55 years of age or older; see Table 3), $X^2(2, n = 1900) = 23.66, p < .001$. In addition, the group of participants who completed all questionnaires included significantly more participants with a low (between zero and one) or average (between two and three) numbers of members in their households and fewer high (four or more) numbers of members in their households (see Table 3), $X^2(2, n = 1900) = 13.65, p =.001$. This group also included more participants with significantly lower numbers of children in their households (zero or one) and fewer participants with an average number of children in their households (two or three; see Table 3), $X^2(2, n = 1900) = 19.01, p < .001$. Finally, among participants who completed all questionnaires, there were significantly more married participants and divorced participants (see Table 3), $X^2(3, n = 1900) = 804.44, p < .001$. For the variables included in the analyses (i.e. PPR, CTA use and perceived health risk for oneself and others), no significant differences were found. These results showed that there are demographic differences between the participants who completed all questionnaires and the participants who did not complete all questionnaires, but no differences are shown between these groups in PPR, CTA use and perceived health risk. All the results of the attrition analysis can be found in Appendix D.

Table 3

The characteristics that deviated significantly between the participants who completed all questionnaires and the participants who only completed the first questionnaire to depict differences between the participants

Variables	Participants who completed questionnaire from T1 (*N* = 1900)	Participants who completed all questionnaires (*N* = 1220)

Age, *n* (%)		
17 – 34 years	443 (23.32%) *	217 (17.79%) *
35 – 54 years	488 (25.68%) *	276 (22.62%) *
55 years or older	969 (51%) *	727 (59.59%) *
Members in household, *n* (%)		
Low number of members	664 (34.95%) *	444 (36.39%) *
Middle number of members	912 (48%) *	627 (51.39%) *
High number of members	324 (17.05%) *	149 (12.21%) *
Children in household, *n* (%)		
Low number of children	1564 (82.32%) *	1073 (87.95%) *
Middle number of children	319 (16.79%) *	136 (11.15%) *
High number of children	17 (0.89%) *	11 (0.90%) *
Marital status, *n* (%)		
Married	803 (42.26%) *	730 (59.84%) *
Divorced	258 (13.58%) *	490 (40.16%) *
Widowed or widower	129 (6.79%) *	0 (0.00%) *
Never married	710 (37.37%) *	0 (0.00%) *

Note. * = significant $p \leq .05$.

Hypothesis tests

Hypothesis 1. The perceived privacy risk about contact tracing app use will decrease in the 17-month period after the launch of the CTA.

To test the hypothesis, a growth curve model was used to show the development of the perception of PPR about CTA use over time after launch of the technology. The model includes all time points. The model showed that participants at T1 on average started with a PPR of 3.07 (SE = .028, z = 108.696, p < .001), and on average their PPR decreased by 0.022 (SE = .005, z = -4.425, p < .001) with every time point. Table 1 shows the mean and standard deviation of PPR at each time point. These results support hypothesis 1.

Hypothesis 2. The perceived privacy risk is negatively associated with contact tracing app usage at each time point.

To test the hypothesis, a growth curve model was used to show the development of the relationship between PPR and CTA use at each time point. One model was used to assess the relationship for each time point. The model showed that at each time point, PPR and CTA use had a significant negative relationship (see Table 4). The model overall had a good fit, X2(46)

= 193.632, RMSEA = .051, CFI = .973, SRMR = .128, $p < .001$. These results support hypothesis 2.

Table 4

The results of the growth curve model to test the relationship between PPR and CTA use at each time point

Covariances				
Variables	Estimate	Std.Err	z-value	$p(>\|z\|)$
Perceived privacy risk T1 ~~ CTA use T1	-.517 *	.047	-10.959	< .001
Perceived privacy risk T2 ~~ CTA use T2	-.394 *	.040	-9.825	< .001
Perceived privacy risk T3 ~~ CTA use T3	-.384 *	.038	-10.250	< .001
Perceived privacy risk T4 ~~ CTA use T4	-.271 *	.039	-6.985	< .001
Perceived privacy risk T5 ~~ CTA use T5	-.317 *	.044	-7.234	< .001
Perceived privacy risk T6 ~~ CTA use T6	-.294 *	.051	-5.731	< .001

Note. * = significant $p \leq .008$.

Hypothesis 3. The perceived severity (H_{3a}) and perceived susceptibility (H_{3b}) of the disease for oneself is positively associated with contact tracing app usage at each time point.

To test the hypothesis, two growth curve models were used to separately assess the association of perceived severity of the disease for oneself on CTA use and perceived susceptibility of the disease for oneself on CTA use at each time point. The model showed that participants at T1 on average started with a perceived severity of 5.010 (*SE* = .037, *z* = 139.904, $p < .001$), and on average their perceived severity decreased by 0.130 (*SE* = .007, *z* = -19.449, $p < .001$) with every time point. The model also showed that at T3, T4 and T5, perceived severity for oneself and CTA use had a significant positive association (see Table 5). The model overall had an acceptable fit, X2(46) = 220.123, RMSEA = .056, CFI = .962, SRMR = .034, $p < .001$. These results partially support hypothesis 3a.

For perceived susceptibility of the disease, the model showed that participants at T1 on average started with a perceived susceptibility of 4.224 (*SE* = .035, *z* = 120.520, $p < .001$), and on average their perceived susceptibility decreased by 0.100 (*SE* = .008, z = -12.697, p < .001) with every time point. The model also showed that at T3, T4 and T6, perceived susceptibility for oneself and CTA use had a significant positive association. At T5, the model showed a significant negative relationship between perceived susceptibility for oneself and CTA use (see Table 5). The model overall had an acceptable fit, X2(64) = 293.730, RMSEA = .066, CFI = .908, SRMR = .063, p < .001. These results partially support hypothesis 3b.

Table 5

The results of the growth curve model to test the relationship between perceived severity (H_{3a}) and perceived susceptibility (H_{3b}) of the disease *for oneself and CTA use at each time point*

Covariances				
Variables of hypothesis 3a	Estimate	Std.Err	z-value	p (>|z|)
Beliefs perceived severity self T1 ~~ CTA use T1	.036	.062	0.581	.561
Beliefs perceived severity self T2 ~~ CTA use T2	.045	.055	0.820	.412
Beliefs perceived severity self T3 ~~ CTA use T3	.176*	.053	3.341	.001
Beliefs perceived severity self T4 ~~ CTA use T4	.212 *	.055	3.889	< .001
Beliefs perceived severity self T5 ~~ CTA use T5	.188 *	.064	2.927	.003
Beliefs perceived severity self T6 ~~ CTA use T6	-.152	.079	-1.913	.056
Variables of hypothesis 3b	Estimate	Std.Err	z-value	p (>|z|)
Beliefs perceived susceptibility self T1 ~~ CTA use T1	.058	.063	0.914	.360
Beliefs perceived susceptibility self T2 ~~ CTA use T2	.070	.056	1.240	.215
Beliefs perceived susceptibility self T3 ~~ CTA use T3	.347 *	.054	6.417	< .001
Beliefs perceived susceptibility self T4 ~~ CTA use T4	.185 *	.055	3.371	.001

Variables of hypothesis 3b	Estimate	Std.Err	z-value	*p* (>|z|)
Beliefs perceived susceptibility self T5 ~~ CTA use T5	-.225 *	.072	-3.119	.002
Beliefs perceived susceptibility self T6 ~~ CTA use T6	.662 *	.086	7.694	< .001

Note. * = significant $p \leq .008$.

Hypothesis 4. The perceived severity (H_{4a}) and perceived susceptibility (H_{4b}) of the disease for others is positively associated with contact tracing app usage at each time point.

To test the hypothesis, two growth curve models were used to separately assess the association of perceived severity of the disease for others on CTA use and perceived susceptibility of the disease for others on CTA use at each time point. The model showed that participants at T1 on average started with a perceived severity for others of 2.795 (SE = .011, z = 253.559, p < .001), and on average their perceived severity of others decreased by 0.043 (SE = .003, z = -15.523, p < .001) with every time point. The model also showed that at almost each time point, perceived severity of the disease for others and CTA use had a significant positive association (see Table 6). Only at T1 no significant relationship was found between perceived severity of the disease for others and CTA use. The model overall had an acceptable fit, X2(67) = 10214.950, RMSEA = .352, CFI = .000, SRMR = .364, p < .001. These results partially support hypothesis 4a.

For perceived susceptibility of the disease for others, the model showed that participants at T1 on average started with a perceived susceptibility of 4.224 (SE = .035, z = 120.520, p < .001), and on average their perceived susceptibility for others decreased by 0.100 (SE = .008, z = -12.697, p < .001) with every time point. The model also showed that at T6, perceived susceptibility for others and CTA use had a significant positive association (see Table 6). The model overall had an acceptable fit, X2(67) = 10161.200, RMSEA = .351, CFI = .000, SRMR = .359, p < .001. These results partially support hypothesis 4b.

Table 6

The results of the growth curve model to test the relationship between perceived severity (H_{4a}) and perceived susceptibility (H_{4b}) of the disease for others and CTA use at each time point

Covariances				
Variables of hypothesis 4a	Estimate	Std.Err	z-value	*p*(>|z|)

Beliefs perceived severity others T1 ~~ CTA use T1	.042	.021	2.006	.045
Beliefs perceived severity others T2 ~~ CTA use T2	.061 *	.018	3.421	.001
Beliefs perceived severity others T3 ~~ CTA use T3	.119 *	.016	7.269	< .001
Beliefs perceived severity others T4 ~~ CTA use T4	.145 *	.018	8.232	< .001
Beliefs perceived severity others T5 ~~ CTA use T5	.138 *	.022	6.396	< .001
Beliefs perceived severity others T6 ~~ CTA use T6	.113 *	.027	4.165	< .001
Variables of hypothesis 4b	Estimate	Std.Err	z-value	*p*(>|z|)
Beliefs perceived susceptibility others T1 ~~ CTA use T1	.015	.029	0.534	.594
Beliefs perceived susceptibility others T2 ~~ CTA use T2	.006	.024	0.266	.791
Beliefs perceived susceptibility others T3 ~~ CTA use T3	.051	.022	3.480	.020
Beliefs perceived susceptibility others T4 ~~ CTA use T4	.025	.022	1.122	.262
Beliefs perceived susceptibility others T5 ~~ CTA use T5	-.016	.025	-0.645	.519
Beliefs perceived susceptibility others T6 ~~ CTA use T6	.084 *	.031	2.722	.006

Note. * = significant $p \leq .008$.

Hypothesis 5. High perceived severity (H_{5a}) and high perceived susceptibility (H_{5b}) of the disease for oneself predicts a weaker negative association of perceived privacy risk on contact tracing app use at each time point.

To test the hypothesis, PROCESS model 2 was used to separately assess the moderating effects of perceived severity and perceived susceptibility of the disease for oneself on the relationship between PPR and CTA use at each time point. Five models were used with the predictor (i.e. PPR) and moderator (i.e. perceived severity and perceived susceptibility of the disease for oneself) variables taken from the same time point and the dependent (i.e. CTA use) variable from one time point later to assess whether the dependent variable could be predicted by the predictor and moderator. Each model's summary showed that the combined variables significantly predicted CTA use (see Appendix E). The models also showed a significant relationship between PPR and CTA use (see Table 7). Most models did not find a significant moderating effect of perceived severity of the disease for oneself (see Table 7). However, model two (see Table 7) showed a significant moderating effect of perceived severity of the disease for oneself on the relationship between PPR and CTA use (n = 1220, Nagelkerke's $R2N$ = 0.183, p < .001, 95% CI = -.04; -.23). Finally, the models showed that perceived severity for oneself significantly predicted CTA use in model five (see Table 7). These results partially support hypothesis 5a.

Furthermore, models two and three showed significant relationships between perceived susceptibility of the disease for oneself and CTA use (see Table 7). However, no significant interaction effect was found between perceived susceptibility of the disease for oneself, PPR and CTA use (see Table 7). These results do not support hypothesis 5b.

Table 7

The result of the analyses to test the moderating effect of perceived health risk for oneself on the relationship between PPR and CTA use at different time points

Moderation analyses										
Models	Model 1		Model 2		Model 3		Model 4		Model 5	
Variables	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI
Perceived severity self	-.11	.001; .21	.11	.005; .21	.05	-.06; .15	.11	.002; .22	.17 *	.05; .28
Perceived susceptibility self	.14	.02; .27	.19 *	.07; .31	.26*	.14; .39	.07	-.05; .19	.14	.01; .27
PPR	-.80 *	-.93; -.67	-.80 *	-.93; -.66	-.79 *	-.92; -.65	-.63 *	-.77; -.50	-.68 *	-.81; -.53
Perceived severity self X PPR	-.02	-.12; .09	.14 *	.04; .23	.01	-.08; .12	.04	-.06; .13	.05	-.05; .15

Models	Model 1		Model 2		Model 3		Model 4		Model 5	
Variables	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI
Perceived susceptibility self X PPR	.03	-.08; .14	-.02	-.12; .08	-.02	-.15; .10	-.11	-.22; .001	-.06	-.18; .06

Note. Model 1 with predictor and moderator at T1 and the dependent at T2.

Note. Model 2 with predictor and moderator at T2 and the dependent at T3.

Note. Model 3 with predictor and moderator at T3 and the dependent at T4.

Note. Model 4 with predictor and moderator at T4 and the dependent at T5.

Note. Model 5 with predictor and moderator at T5 and the dependent at T6.

Note. * = significant $p \leq .01$.

Hypothesis 6. High perceived severity (H_{6a}) and high perceived susceptibility (H_{6b}) of the disease for others predicts a weaker negative association of perceived privacy risk on contact tracing app use at each time point.

To test the hypothesis, PROCESS model 2 was used to separately assess the moderating effect of perceived severity and perceived susceptibility of the disease for others on the relationship between PPR and CTA use at each time point. Five models were used with the predictor (i.e. PPR) and moderator (i.e. perceived severity and perceived susceptibility of the disease for others) variables taken from the same time point and the dependent (i.e. CTA use) variable from one time point later to assess whether the dependent variable could be predicted by the predictor and moderator. Each model's summary showed that the combined variables significantly predicted CTA use (see Appendix E). The models also showed a significant relationship between PPR and CTA use (see Table 8). Models two and three showed a significant relationship between perceived severity of the disease for others and CTA use (see Table 8). All models showed no significant relationship between perceived susceptibility of the disease for others and CTA use (see Table 8). Furthermore, no significant interaction effect was found between perceived severity of the disease for others, PPR and CTA use, or between perceived susceptibility of the disease for others, PPR and CTA use (see Table 8). These results do not support hypothesis 6a and hypothesis 6b.

Table 8

The result of the analyses to test the moderating effect of perceived health risk for others on the relationship between PPR and CTA use at different time points

Moderation analyses										
Models	Model 1		Model 2		Model 3		Model 4		Model 5	
Variables	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI	Coeff	95% CI
Perceived severity for others	.28	-.06; .62	.55 *	.23; .89	.48 *	.14; .82	.31	.01; .62	.40	.07; .71
Perceived susceptibility for others	.01	-.23; .24	.19	-.03; .40	.16	-.08; .39	-.002	-.22; .22	.03	-.24; .28
PPR	-.79 *	-.91; -.66	-.77 *	-.90; -.64	-.77 *	-.90; -.63	-.62 *	-.75; -.49	-.63 *	-.77; -.48
Perceived severity for others X PPR	-.17	-.50; .19	.05	-.28; .41	-.27	-.57; .06	-.16	-.44; .13	-.26	-.54; .03
Perceived susceptibility for others X PPR	.03	-.17; .23	.05	-.14; .24	.12	-.10; .32	.07	-.14; .26	.04	-.19; .26

Note. Model 1 with predictor and moderator at T1 and the dependent at T2.
Note. Model 2 with predictor and moderator at T2 and the dependent at T3.
Note. Model 3 with predictor and moderator at T3 and the dependent at T4.
Note. Model 4 with predictor and moderator at T4 and the dependent at T5.
Note. Model 5 with predictor and moderator at T5 and the dependent at T6.
Note. * = significant $p \leq .01$.

Discussion

The overarching goal of this study was to examine the influence of PPR and perceived health risk for oneself and others on CTA use during a pandemic using longitudinal data. In this section, the main results for each research question will be discussed followed by the limitations, implications and suggestions for future research and the overall conclusion.

Main findings for research questions

RQ1. How does PPR about CTA use develop in a 17-month period after launch?

RQ 1 focuses on the development of PPR about CTA use in a 17-month period after launch of the CTA. The results support hypothesis 1 and showed that PPR about CTA use decreased over time after launch. There are several explanations for these findings. For example, as mentioned by Ebbers et al. (2021), there was a misconception that the CTA tracked users' locations and stored users' personal information. It is likely that these misconceptions have been disproven over time. This could explain the high PPR about CTA use shortly after the launch of the CTA and the decrease in PPR about CTA use over time afterward. Furthermore, as stated by Mueller et al. (2011), anxiety about a new technology is expected to decrease over time after launch because the technology becomes more visible and familiar to people, and Nilsen et al. (2016) similarly showed that initial ethical resistance (e.g. privacy concerns) toward a new technology can decrease after the launch of the technology as individuals grow more familiar and experienced with it. The Dutch population was inexperienced with the use of CTAs. The technology was new and unfamiliar, which could explain why individuals at the launch of the app had high PPR about CTA use. After more time had passed following the launch of the CTA, individuals were likely to have more experience with the technology and therefore have a lower PPR about CTA use. This could explain the decrease in PPR about CTA use found in the results. In summary, the results of this study showed a decrease in PPR about CTA use over a 17-month period after the launch of a CTA, thereby extending current knowledge of the development of PPR about a new technology over time after launch and providing new insights into PPR about CTA use and its development after the launch of a CTA.

RQ2. How does the relationship between CTA use and PPR (RQ2a), and between CTA use and perceived health risk (RQ2b) develop in a 17-month period after launch?

RQ2 focuses on the relationship between CTA use and PPR (RQ2a), and between CTA use and perceived health risk (RQ2b) over a 17-month period after launch of the CTA. The results support hypothesis 2 and showed that for each time point, individuals with high PPR were less likely to use a CTA. These results are in line with earlier studies that found a significant negative relationship between PPR and use of or the intention to use a CTA (Carlsson Hauff & Nilsson, 2021; Chan & Saqib, 2021; Li et al., 2021; Tran & Nguyen, 2021; Walrave et al., 2020). In addition, Dhagarra et al. (2020) states that individuals who experience privacy concerns about a technology are more cautious about using that technology. Individuals with high privacy concerns are less likely to use a CTA, which could explain the negative relationship found between PPR and CTA use. In addition, the diffusion of innovation theory may explain why the relationship between PPR and CTA use remained the same after more time had passed following the launch of the CTA. Individuals who adopt a new technology can be categorized according to their relative times of adoption, each group having its own set of characteristics (Sahin, 2006). Adopters at a later time point are more likely to have adopted the CTA because of a decrease in PPR because unlike early adopters they are not willing to deal with possible risks. This means that the relationship between PPR and CTA use over time after launch would remain the same, and individuals change their behavior due to a change in PPR. The results of this study showed a negative relationship between PPR and CTA use at each time point in a 17-month period after the launch of a CTA, thereby extending current knowledge of the relationship between PPR and CTA use and providing new insights into the development of this relationship after the launch of a CTA.

Regarding perceived health risk for oneself, the results partially support hypothesis 3a and hypothesis 3b. The results showed no significant relationship between perceived health risk for oneself and CTA use early after the launch of the CTA. After more time had passed following the launch of the CTA, significant positive relationships were found between perceived severity of the disease for oneself and CTA use and between perceived susceptibility of the disease for oneself and CTA use. However, longer after the CTA was launched, the results also showed a negative relationship (i.e. for perceived susceptibility of the disease for oneself and CTA use at T5). This result can perhaps be explained by the time period during which data was collected. Similar to the results of van der Waal et al. (2022), no significant association was found when data was collected soon after the launch of the CTA. After more time had passed, like in the study of Geber and Ho (2022), a significant positive association was found between perceived health risk for oneself and CTA use. The results by van der Waal et al. (2022) and Geber and Ho (2022) are similar to the results found in this study. This change in relationship may be explained by the overall progress of technology adoption. The diffusion and adoption of new technologies are ongoing and slow processes (Hall & Khan, 2003). These processes could result in individuals adopting the CTA at a later point in time after launch because deciding whether to adopt the CTA can take time which could explain why no relationship was found at the time points of measurement taken early after the launch of the CTA. Furthermore, as HBM states, individuals who perceive the disease as a serious threat or perceive themselves as likely to get infected, are more likely to undertake action that they believe will reduce these risks (Glanz et al., 2008). HBM could explain the positive relationship found in the results. However, no earlier studies showed a negative relationship between perceived health risk and CTA use. This negative relationship could perhaps be explained by the knowledge individuals have about the coronavirus. At the beginning of the pandemic, COVID-19 was an uncommon risk, which could have led to higher perceptions of health risks (Cori et al., 2020). To deal with these high perceptions of health risks, individuals could eventually show protective behavior against the virus. After more time has passed, individuals are likely to gain more knowledge about the virus, the virus could become less of an uncommon risk and the perceived health risk would therefore diminish. However, these individuals already adopted protective behavior, and it is possible that they would continue this behavior. This could explain the negative relationship found between perceived health risk and CTA use at a later time point. The results of this study showed no significant relationship early after launch of the CTA and positive and negative relationships between perceived health risk for oneself and CTA use after more time had passed in a 17-month period following the launch of the CTA, thereby extending current knowledge on the relationship between perceived health risk for oneself and CTA use and providing new insights into the development of this relationship after the launch of a CTA.

Finally, regarding perceived health risk for others, the results partially support hypothesis 4a and showed a significant positive relationship at almost each time point between perceived severity of the disease for others and CTA use. Only at T1 no significant relationship was found between the perceived severity of the disease for others and CTA use. These results are partially in line with the results of van der Waal et al. (2022), who did not find a significant relationship between perceived severity of the disease for others and CTA use shortly after the launch of the CTA. The results of this study confirm that early after the launch of the CTA no significant relationship was found between the perceived severity of the disease for others and CTA use. However, after more time had passed following the launch of the CTA, the results showed significant positive relationships between perceived severity of the disease for others and CTA use. This could be explained the diffusion and adoption of new technologies being ongoing and slow processes (Hall & Khan, 2003). This could result in individuals adopting the CTA at a later time point despite their perceived health risk remaining the same because deciding whether to adopt the CTA can take time. This could explain why no relationship was found at T1. Furthermore, the positive relationships found between perceived severity of the disease for others and CTA use could be explained by the fact that the CoronaMelder is mainly focused on protecting others. If an individual would perceive the severity for others as high and would see the use of the CTA as protecting others, they could start using the CTA to protect others. This could result in a positive relationship between perceived severity of the disease for others and CTA use. In addition, studies by Jones and Thompson (2021) and Caserotti et al. (2022) showed that protecting others was one of the main reasons to adopt or be willing to adopt a CTA, which may explain the positive association I found. The results of this study showed a positive relationship between perceived severity of the disease for others and CTA use in a 17-month period after the launch of a CTA, thereby providing new insights into this relationship and its development after the launch of a CTA and demonstrated that theory on technology adoption should also focus on risks of others influencing an individual's behavior.

Furthermore, the results partially support hypothesis 4b. The results only showed a positive relationship at the last measurement (i.e. T6). Similar to the results of van der Waal et al. (2022), no significant relationship was found when data was collected soon after the launch of the CTA. However, no earlier studies examined the relationship between perceived susceptibility of the disease for others and CTA use after more time had passed following the launch of a CTA. An earlier study by El-Toukhy (2015) showed that the perceived susceptibility and perceived severity of a disease are different concepts. This could explain the different results found in the relationship between perceived severity of the disease and CTA use and between perceived susceptibility of the disease and CTA use. The study showed that when the perceived severity of the disease is undeniable, individuals downplay the perceived susceptibility of the disease (El-Toukhy, 2015). It is possible that at most time points the perceived severity of the disease was indeed undeniable, causing individuals to downplay their perceived susceptibility of the disease. After more time had passed, individuals were likely to be more experienced with the disease and its severity and therefore no longer downplay their perceived susceptibility to it. This could explain why at most time points no significant relationship was found. The results of this study overall showed no significant relationship between perceived susceptibility of the disease and CTA use except at T6, thereby extending current knowledge of the differences between perceived severity and perceived susceptibility of the disease and the relationship between perceived susceptibility of the disease and CTA use in a 17-month period after the launch of a CTA and the development of that relationship after the launch of a CTA.

RQ3. Do perceived severity of the disease and perceived susceptibility of the disease for oneself and others moderate the relationship between PPR and CTA use in a 17-month period after launch?

RQ3 focuses on the moderating influences of perceived health risk for oneself and others on the relationship between PPR and CTA use. The results partially support hypothesis 5a and showed in model two (i.e. with predictor and moderator at T2 and the dependent at T3) a significant moderating influence of perceived severity of the disease for oneself on the relationship between PPR and CTA use. A high perceived severity of the disease for oneself at T2 predicts a weaker negative relationship between PPR at T2 and CTA use at T3. These results are partially in line with those of Chopdar (2022) and Tran and Nguyen (2021), who found that individuals who perceive the severity of the disease for oneself as high, have a weaker negative relationship between PPR and CTA use. These results are partially in line with the results found in this study. Furthermore, the moderating influence found may be explained by the HBM. As stated by HBM, individuals who perceive the disease as a serious threat and perceive themselves as likely to get infected, are more likely to undertake action that they believe to reduce these risks (Glanz et al., 2008). Individuals with a high perceived severity of the disease for oneself are more likely to undertake action to protect one's health at the cost of others risks than individuals with a lower perceived severity of the disease for oneself. This could explain why a high perceived severity of the disease for oneself could predict a weaker negative relationship between PPR and CTA use. However, this does not explain why the moderating effect was only found at model two. Furthermore, the results do not support hypothesis 5b and showed no evidence of a significant moderating influence of perceived susceptibility of the disease for oneself on the relationship between PPR and CTA use. These results are not in line with the results of Chopdar (2022) and Tran and Nguyen (2021). However, differences between the studies of Chopdar (2022) and Tran and Nguyen (2021) and this study could perhaps explain the differences found in results for hypothesis 5a and hypothesis 5b. For instance, the studies of Chopdar (2022) and Tran and Nguyen (2021) examined the moderating effect of the perceived severity and perceived susceptibility of the disease as one variable, unlike this study, which examined these variables separately. El-Toukhy (2015) stated that the perceived susceptibility and perceived severity of the disease are different concepts. Examining the influence of these variables as one variable could influence the results because of the differences between the perceived susceptibility and perceived severity of the disease. This could possibly explain why unlike the studies of Chopdar (2022) and Tran and Nguyen (2021), this study did not find a moderating effect for both the perceived severity and perceived susceptibility of the disease for others on the relationship between PPR and CTA use. Furthermore, the study of Chopdar (2022) analyzed data of participants from India and the study of Tran and Nguyen (2021) analyzed data of participants from the United States of America. It is possible that the difference between the participants could have led to differences in the results. As shown in the results of Dryhurst et al. (2020), the perceived health risk of COVID-19 for oneself are strongly correlated with socio-cultural factors across countries. For example, a person with a more individualistic worldview is more likely to perceive a risk as lower. Conversely, an individual who believes acting for society's benefit is important is more likely to perceive the risk as high (Dryhurst et al., 2020). These socio-cultural differences could result in differences in perception of health risks for oneself between countries, which could explain why Chopdar (2022) and Tran and Nguyen (2021) found a moderating effect that I did not. The results of this study showed a moderating effect of perceived severity of the disease for oneself on the relationship between PPR and CTA at one time point and no moderating effect of perceived susceptibility of the disease for oneself on the relationship between PPR and CTA in a 17-month period following the launch of a CTA, thereby providing new insights into the risk-risk tradeoff between perceived health risk and PPR and its development after the launch of a CTA.

Finally, the results do not support hypothesis 6 and showed no evidence for a moderating influence of perceived health risk of the disease for others on the relationship between PPR and CTA use. To the best of my knowledge, no earlier research had been done examining the tradeoff between PPR for oneself and perceived health risk for others. A moderating effect was expected based on the fact that protecting others is one of the main reasons for use of or intention to use a CTA (Caserotti et al., 2022; Jones & Thompson, 2021). However, in this analysis, risks for others are weighed against risks for oneself. It is possible that risks for others constitute one of the main reasons to use a CTA but that is consideration is not judged important enough to overcome risks for oneself. This could explain why I found no significant moderating effect of risks for others on risks for oneself. Summarizing, the results of this study showed no moderating effect of perceived health risk of the disease for others on the relationship between PPR and CTA use in a 17-month period after the launch of a CTA, thereby providing new insights into the risk-risk tradeoff between risks for oneself and risks for others and its development after the launch of a CTA.

Limitations

This study has limitations that should be addressed. First, the decision to exclude participants who did not complete all questionnaires. The attrition analysis showed that the group of participants who were excluded from this study significantly deviated in multiple demographic characteristics from the group of participants who were included in this study (see Table 3). For example, the group that was excluded from this study had significantly more young participants (between 17 and 34 years of age) than the group of participants that was included. The differences in these demographic characteristics could have caused the results to reflect only a certain group of individuals. However, the participants excluded from this study did not significantly deviate from the participants who were included in this study with respect to the variables that were used in the analyses (i.e. PPR, CTA use, perceived health risk for oneself and for others). Because these variables did not differ, it is unlikely that the results from the analyses would have been affected greatly if all participants had been included in this study.

Furthermore, the results of this study are only generalizable for the Netherlands or countries with a similar cultural and political environment because only data from Dutch participants was used. By doing so, the results of this study are less generalizable to countries with a different cultural and political environment. As mentioned by Dryhurst et al. (2020), the perceived health risk of COVID-19 for oneself and others are strongly correlated with socio-cultural factors across countries. This correlation could lead to different results when similar studies are conducted in different countries.

Finally, the PPR items were calculated to be of questionable reliability scale. This calculation could indicate a problem with their internal consistency of the items used to measure PPR. The questionable reliability indicates an inconsistency in the answers, which could have influenced the results.

Implications

The results of this study have implications for practice with regard to technology adoption during a future pandemic in the Netherlands. For example, the results showed that for each time point, PPR was negatively associated with CTA use. Earlier studies already confirmed this negative association; however, whether this association would differ or remain the same over time was not examined. Based on these results, the government should focus in their communication about technology adoption in a future pandemic on reducing PPR throughout the event since the association remains negative between PPR and technology adoption over time. However, the PPR about CTA does decrease over time. This indicates that it may be more important to emphasize PPR in communication about the CTA at the launch of the technology.

In addition, the results showed, in contrast to an earlier study, a significant positive association between perceived severity of the disease for others and CTA use. Knowing of this association and its development over time, the government should focus in their communication about technology adoption in a future pandemic on perceived severity of the disease for others throughout the event. For example, officials might focus on how technology adoption during a pandemic can protect others in an individual's area who are likely to suffer severe consequences if infected. Similar to PPR, perceived severity of the disease for others decreases over time. To ensure a high perceived severity of the disease for others throughout the pandemic, the Dutch government should further emphasize the importance of protecting the health of others in its communication about the CTA more as more time passes after the launch of a CTA.

The results also have theoretical implications. This study contributes to the literature and research on technology adoption during a pandemic by verifying earlier found results and offering new knowledge about the relationship between PPR and CTA use and between perceived health risk for oneself and others and CTA use with longitudinal data. The results verify the relationship cross-sectionally found between PPR and CTA use and showed for the first time that this relationship over time after the launch of a CTA remains negative. Furthermore, the results showed for the first time a significant positive relationship between perceived severity of the disease for others and CTA use and also showed that this relationship remained the same over time after the launch of a CTA. This study is the first to examine the risk-risk tradeoff with a focus on risks for others and gained knowledge by showing no clear evidence of perceived health risk for others moderating the relationship between PPR and CTA use. Finally, this study also revealed new information about the risk-risk tradeoff with a focus on risks for oneself and its development over time following the launch of a CTA by showing no clear evidence of perceived health risk for oneself moderating the relationship between PPR and CTA use.

These new insights are valuable for future research on CTAs and technology adoption during a pandemic in general.

Future research

In the future, it may be of interest to explore how the perceived risk influencing CTA use are formed. This study focuses on the influence of certain perceived risks on CTA use. However, these perceived risks are formed based on unknown reasonings. This study and the data employed mainly focus on quantitative results. The quantitative nature of this study does not permit a deeper examination of the participants' formation of risks perceptions. As stated by Ferrer and Klein (2015), much is already known about the formation of deliberative health-related risk perceptions; in contrast, little research has been done examining the formation of experiential and affective health-related risk perceptions. Examining the formation of deliberative, experiential and affective health-related risk perceptions of CTA use can verify earlier results and provide new insights into the formation of risk perceptions. A possible research question for this type of investigation could be “How are the deliberative, experiential and affective health-related risk perceptions of CTA use formed after the launch of a CTA?”

Furthermore, it may be of interest for future research to further examine the risk-risk tradeoff. The results in this study do not show clear evidence for the risk-risk tradeoff between PPR and perceived health risk for oneself on CTA use. The results of the study by Dryhurst et al. (2020) showed that experiential and socio-cultural factors explain most of the differences in risk perceptions of COVID-19 between countries. This may explain the differences found in the results between this study and the studies of Chopdar (2022) and Tran and Nguyen (2021). It could be of interest to examine whether differences in experiential and socio-cultural factors affect the moderating influence of perceived health risk for oneself on the relationship between PPR and CTA use. This is important because as stated by the HBM, the perceived health risk is a predictor of behavior, and by gaining more understanding of how these perceived risks are influenced, governments can better understand the determinants of people to engage in preventive behavior. Countries of Europe, America, and Asia could be included in this study to ensure cultural and geographic differences are accounted for (Dryhurst et al., 2020). A possible research question for this type of investigation could be “How do experiential and socio-cultural factors affect the risk-risk tradeoff between perceived health risk and PPR on CTA use in countries across Europe, America and Asia?”

Conclusion

To the best of my knowledge, this is the first study to examine the tradeoff between perceived health risk for others to moderate the relationship between PPR and CTA use. From the results, I cannot conclude that there is a tradeoff between perceived health risk for others, PPR and CTA use. However, I can conclude that PPR remains a driver of resistance to CTA use over time after launch. In addition, the findings that perceived severity of the disease for others is related to CTA use provides suggestions for governmental communication about technology adoption during a pandemic and confirms the influence of risk for others on individuals’ behavior. Overall, this study deepened understanding of the development of PPR about CTA use and on the relationships between PPR and CTA use and between perceived health risk for oneself and others and CTA use during a 17-month period after the launch of a CTA. Furthermore, this study verified previously obtained knowledge about the relationship between PPR and CTA use and between perceived health risk for oneself and CTA use. This knowledge can help to understand the adoption rate of the former CTA. In addition, this knowledge can support governments in their development of CTAs and communication about the use of technology in future pandemics to ensure a higher adoption rate, which could result in a greater reduction in infections and, indirectly, a lower mortality rate (Jenniskens et al., 2021).

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Appendix A

The recoded variables of CTA use, beliefs identity monitoring, beliefs location monitoring and beliefs data safety

Variables	Recoded from	Recoded to	New variables
CTA use	1 = 1; 2 = 2; 3 = 3	1 = 2; 2 = 0; 3 = 0	Behavior_UTAUT_R
Beliefs identity monitoring	1 = 1; 2 = 2; 3 = 3; 4 = 4; 99 = 99	1 = 1; 2 = 2; 3 = 4; 4 = 5; 99 = 3	Beliefs_identitymonitoring_R
Beliefs location monitoring	1 = 1; 2 = 2; 3 = 3; 4 = 4; 99 = 99	1 = 1; 2 = 2; 3 = 4; 4 = 5; 99 = 3	Beliefs_locationmonitoring_R
Beliefs data safety	1 = 1; 2 = 2; 3 = 3; 4 = 4; 99 = 99	1 = 5; 2 = 4; 3 = 2; 4 = 1; 99 = 3	Beliefs_datasafety_R

Appendix B

The results of the Cronbach's alpha for the measures that consist of multiple items

Variables	T1	T2	T3	T4	T5	T6
Perceived privacy risk	.68	.66	.67	.70	.67	.68
Perceived severity for oneself	.72	.74	.71	.71	.73	.76
Perceived susceptibility for oneself	.81	.76	.79	.78	.80	.87

Appendix C

The characteristics of CTA users and non-users of CTA to depict differences between the participants in this study

Users CTA						
Variables	T1 (*n* = 342)	T2 (*n* = 384)	T3 (*n* = 389)	T4 (*n* = 376)	T5 (*n* = 312)	T6 (*n* = 248)
Gender, *n* (%)						
Male	165 (48.25%)	79 (46.61%)	188 (48.33%)	181 (48.14%)	150 (48.08%)	125 (50.40%)
Female	177 (51.75%)	205 (53.39%)	201 (51.67%)	195 (51.86%)	162 (51.92)	123 (49.60%)
Age, *n* (%)						
17 – 34 years	55 (16.08%)	65* (16.93%)	70 (17.99%)	62 (16.49%)	55 (17.63%)	39 (15.73%)
35 – 54 years	69 (20.18%)	72* (18.75%)	72 (18.51%)	74 (19.68%)	64 (20.51%)	50 (20.16%)
55 years or older	218 (63.74%)	247* (64.32%)	247 (63.50%)	240 (63.83%)	193 (61.86%)	159 (64.11%)
Education, *n* (%)						
Primary education or lower secondary education diploma	73* (21.35%)	77 * (20.05%)	80* (20.57%)	81* (21.54%)	67* (21.47%)	51* (20.56%)

Variables	T1 (*n* = 342)	T2 (*n* = 384)	T3 (*n* = 389)	T4 (*n* = 376)	T5 (*n* = 312)	T6 (*n* = 248)
Secondary education diploma	113* (33.04%)	134* (34.90%)	137* (35.22%)	128* (34.04%)	108* (34.62%)	89* (35.89%)
Higher education diploma	156* (45.61%)	173* (45.05%)	172* (44.22%)	167* (44.41%)	137* (43.91%)	108* (43.55%)
Non-users CTA						
Variables	T1 (*n* = 878)	T2 (*n* = 836)	T3 (*n* = 831)	T4 (*n* = 844)	T5 (*n* = 908)	T6 (*n* = 972)
Gender, *n* (%)						
Male	408 (46.67%)	394 (47.13%)	385 (46.33%)	392 (46.45%)	423 (46.59%)	448 (46.09%)
Female	470 (53.53%)	442 (52.87%)	446 (53.67%)	452 (53.55%)	485 (53.41%)	524 (53.91%)
Age, *n* (%)						
17 – 34 years	162 (18.45%)	152* (18.18%)	147 (17.69%)	155 (18.36%)	162 (17.84%)	178 (18.31%)
35 – 54 years	207 (23.58%)	204* (24.40%)	204 (24.55%)	202 (23.93%)	212 (23.35%)	226 (23.35%)
55 years or older	509 (57.97%)	480* (57.42%)	480 (57.76%)	487 (57.70%)	534 (58.81%)	568 (58.44%)
Education, *n* (%)						

Variables	T1 (*n* = 878)	T2 (*n* = 836)	T3 (*n* = 831)	T4 (*n* = 844)	T5 (*n* = 908)	T6 (*n* = 972)
Primary education or lower secondary education diploma	264* (30.07%)	260* (31.30%)	257* (30.93%)	256* (30.33%)	270* (29.74%)	286* (29.42%)
Secondary education diploma	294* (33.49%)	273* (32.66%)	270* (32.49%)	279* (33.06%)	299* (32.93%)	318* (32.72%)
Higher education diploma	317* (36.10%)	300* (35.89%)	301* (36.22%)	306* (36.26%)	336* (37%)	365* (37.55%)

Note. This table demonstrate the results of the chi-square analysis between the participants who completed all questionnaires and either used a CTA or did not use a CTA.

Note. Numbers with * means the numbers significantly ($p \leq .05$) differs between users and non-users CTA.

Appendix D

The results of the attrition analyses between the participants who completed all questionnaires and the participants who only completed the first questionnaire

Variables	X-squared	df	*p*
Age	23.66 *	2	< .001
Marital status	804.44 *	3	< .001
Personal net monthly income	0.44	3	.932
Number of members in the household	13.65 *	2	.001
Number of children in the household	19.01 *	2	< .001
Gender	1.08	1	.299
Urbanity residence	0.05	2	.974
Education	1.13	2	.567
Partner	0.02	1	.897
CTA use	0.21	1	.645
Beliefs data safety	1.76	3	.623
Beliefs location monitoring	1.31	3	.726
Beliefs identity monitoring	2.80	3	.423
Beliefs perceived susceptibility self1	2.95	2	.228
Beliefs perceived susceptibility self2	1.11	2	.574
Beliefs perceived susceptibility others	0.72	2	.698
Beliefs perceived severity self 1	5.74	2	.057
Beliefs perceived severity self 2	5.25	2	.072
Beliefs perceived severity others	2.49	2	.287

Note. This table demonstrate the results of the chi-square analysis between the participants who completed all questionnaire and the participants who only completed the questionnaire at T1.

Note. * = significant $p \leq .05$.

Appendix E

The model summary of the moderation analyses for hypothesis 5 and hypothesis 6

Moderation analyses perceived health risk for oneself			
Models	Nagelkrk	df	*p*-value
Model 1	0.188 *	5	< .001
Model 2	1.83 *	5	< .001
Model 3	0.191 *	5	< .001
Model 4	0.128 *	5	< .001
Model 5	0.129 *	5	< .001
Moderation analyses perceived health risk for others			
Models	Nagelkrk	df	*p*-value
Model 1	.181 *	5	< .001
Model 2	.178 *	5	< .001
Model 3	.183 *	5	< .001
Model 4	.122 *	5	< .001
Model 5	.124 *	5	< .001

Note. Model 1 is the analysis with predictor and moderator at T1 and the dependent at T2.

Note. Model 2 is the analysis with predictor and moderator at T2 and the dependent at T3.

Note. Model 3 is the analysis with predictor and moderator at T3 and the dependent at T4.

Note. Model 4 is the analysis with predictor and moderator at T4 and the dependent at T5.

Note. Model 5 is the analysis with predictor and moderator at T5 and the dependent at T6.

Note. * = significant $p \leq .01$.