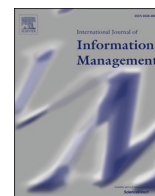




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Research Article

Explaining citizens' resistance to use digital contact tracing apps: A mixed-methods study

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ABSTRACT

Governments worldwide are using digital contact tracing (DCT) apps as a critical element in their COVID-19 pandemic lockdown exit strategy. Despite substantial investment in research and development, the public's acceptance of DCT apps has been phenomenally low, signaling resistance among potential users. Little is known about why people would resist using the DCT app, a useful innovation that can potentially save millions of human lives. This study explores the determinants and consequences of citizens' resistance to use DCT apps using a sequential two-stage mixed-methods approach. The preliminary qualitative study analyzed interviews of 24 Indian smartphone users who chose not to use or discontinued the DCT app after an initial trial. In the quantitative stage, an integrated model based on innovation resistance theory and distrust theory was tested using the survey data collected from 194 non-adopters of the DCT app from India. The findings revealed that the factors, distrust, value barrier, information privacy concerns, and usage barrier predicted the resistance to the DCT app, and resistance, in turn, predicted intention to use. Additionally, distrust was found to be a key mediator between innovation barriers and resistance. The insights from this study could help the developers and policymakers formulate strategies for implementing DCT interventions during future disease outbreaks.

1. Introduction

The COVID-19 pandemic is by far the most severe public health emergency in a century, and the biggest threat humankind has faced since World War II (UNDP, 2020). In the absence of known treatment methods or preventive vaccines, the global public health response was limited to non-pharmaceutical interventions like social distancing, case isolation, and manual contact tracing (Ferguson et al., 2020). However, these traditional methods did not sufficiently contain the pandemic's rapid spread due to the asymptomatic transmission of COVID-19 (Altmann et al., 2020). Hence, countries had to resort to more stringent measures like lockdown. Although effective in controlling the spread, it comes with severe economic and social consequences (Bonaccorsi et al., 2020; Coibion, Gorodnichenko, & Weber, 2020).

There seems to be a growing consensus that returning to a pre-pandemic status quo can only be possible with the help of a vaccine (which requires more than two years for development and administration). In its effort to loosen restrictions without an intolerable surge in COVID-19 cases, the governments are looking at using data-driven technologies as a critical component in their lockdown exit strategy

(Dwivedi et al., 2020; He, Zhang, & Li, 2021; Kind, 2020). Researchers have proposed using digital contact tracing (DCT) apps as a potentially valuable alternative to restrictive measures (Ferretti et al., 2020). The idea is to harness the Bluetooth technology in smartphones to monitor similar devices' proximity and use this as a proxy measure of interaction between two individuals. DCT is touted to be superior to manual tracing methods because of its ability to provide instantaneous notifications and overcome the information loss caused by the patient's recall bias/imperfect knowledge (Altmann et al., 2020). A recent study on the epidemiological impact of the DCT app found that cases between 284,000–594,000, that is, 4200–8700 deaths, were averted in the UK alone (Wymant et al., 2021). As per the study, with every percentage rise in app users, nearly 0.8–2.3% of cases can be reduced.

Despite the advantages and emerging evidence of efficacy (Wymant et al., 2021), significant technical limitations and socio-ethical risks are associated with implementing the DCT app (He et al., 2021; Kind, 2020). As the DCT apps rely on Bluetooth technology to ascertain the distance, these measurements could often be imprecise and can lead to a significant number of false positives (Hegde & Masthi, 2020; Pandl, Thiebes, Schmidt-Kraepelin, & Sunyaev, 2021). Additionally, to be effective, it

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requires a high level of data accuracy regarding the community's infection rates, which depend heavily on the testing. Besides that, such applications have an unpleasant effect on personal privacy, which democratic countries would typically deem unacceptable (Bengio et al., 2020; Fahey & Hino, 2020). Moreover, modeling studies suggest that at least 60% of the population would need to adopt it before it could stop the pandemic from escalating (Braithwaite, Callender, Bullock, & Aldridge, 2020; Hinch et al., 2020). Without extensive adoption, these systems run the risk of being useless or even dangerous, that is, by lulling users into a false sense of safety (Farronato et al., 2020).

One approach to drive adoption is to make it mandatory, as done by China (Bi et al., 2020). However, most countries planned to introduce it voluntarily (He et al., 2021); and in places where the uptake was kept voluntary, the adoption rates have been very low, for example, Singapore (35%), Australia (21%), Germany (14%), India (12%), Italy (7%), Japan (5%), France (3%), Thailand (0.7%), and so on (Statista, 2020). The argument that the much-hyped DCT apps will fail without adequate adoption despite the initial enthusiasm is gaining momentum among the policy experts, researchers, and observers (Bradshaw, 2020; Braithwaite et al., 2020; Moscovici, 2020). Evidently, the slow pace of adoption is a matter of great concern for the developers. Thus, understanding why people resist using DCT apps is vital from a managerial perspective to ensure this health innovation's success.

Despite a recent surge in interest in DCT applications, the literature on the subject is still sparse. Some gaps have been observed in the literature. First, prior studies have focused heavily on predicting adoption intention among potential users and continued use among current users but not on deliberate resistance behavior (postponement and opposition/rejection) among the non-users. Second, from a theoretical perspective, most of the available studies take an adoption or diffusion perspective; however, they remain insufficient in explaining the individual's oppositional reactions. Specifically, studies have not yet examined why individuals would develop resistance towards using DCT apps. Third, in terms of methodology, qualitative studies are very few, and more comprehensive studies that combine qualitative and quantitative insights using a mixed-methods approach are not present in the literature. Thus, it has become necessary to probe deep into the factors contributing to the individual's resistance to using DCT apps. Therefore, the following research questions are the focus of this study:

RQ1. What factors determine citizens' resistance to use DCT app?

RQ2. What is the impact of citizens' resistance on their intention to use the DCT app?

To this end, a study was conducted in India among the nonadopter population to identify and examine the determinants of resistance and its effect on intentions to use the DCT app. This study's contributions are three folds; firstly, it throws light into nonadopters' perception about DCT apps currently overlooked in the literature. Secondly, the study gives empirical evidence on the factors that determine the resistance to use DCT apps. Finally, insights provided by this study could guide potential improvements, help frame communication strategies and effective policy decisions to facilitate its diffusion during future disease outbreaks.

The remaining part of the paper is organized as follows: The following section examines the associated literature. Sections 3 and 4 presents the hypotheses development and methodology. The data analysis and the result are presented in Section 5. Following this, there is a discussion of the major findings and their implication on theory and practice. The study concludes by acknowledging the limitations and suggesting directions for future research.

2. Literature review

2.1. Digital Contact tracing

Contact tracing is a public health intervention aimed at controlling infectious disease outbreaks. It is typically done manually by identifying the infected people, obtaining information about people with whom they have had contact while infectious, identifying and quarantining all such contacts to avoid the disease's further spread (Ferretti et al., 2020). Nevertheless, the manual method has several limitations, such as error proneness, time-labor intensity, and privacy invasion, limiting its effectiveness during a fast-spreading disease like COVID-19 (Ferretti et al., 2020). DCT can potentially alleviate some/all of these limitations and enhance the tracing efforts' effectiveness (Ferretti et al., 2020; Wymant et al., 2021). DCT apps use a proximity tracing approach wherein proximity-based data is collected as and when the contact occurs instead of doing it retrospectively. It uses Bluetooth technology in smartphones to follow up on a recently diagnosed patient's infection period contacts (Li & Guo, 2020).

Following the footsteps of Singapore and China, India launched a DCT app, "Aarogya Setu," in early April 2020 (Clarance, 2020; Dwivedi et al., 2020). It was made available in the 11 regional languages in the country. This app relies on a proximity tracing technique using Bluetooth and GPS technologies to monitor contagion time contacts of a recently diagnosed patient (Dwivedi et al., 2020). This app also shows how many positive cases are probable within a variable radius of the users, which aids people in understanding the virus's propagation in the surrounding area. It became very popular, with a total of 100 million-plus downloads in Google Playstore within a few months of its launch (Dwivedi et al., 2020). However, it was soon met with opposition from several spheres owing to concerns regarding the privacy and efficacy of the app (PTI, 2020).

2.2. Prior research on DCT app use

There has been renewed interest in studies relating to DCT apps in the literature owing to the scientific community's response to the COVID-19 pandemic (Anglemyer et al., 2020). Researchers have examined several topics such as the effectiveness of the app (Pandl et al., 2021; Wymant et al., 2021), ethical issues (Klenk & Duijf, 2020; Lanzing, 2020; Morley, Cows, Taddeo, & Floridi, 2020; Roche, 2020), IT governance issues (Riemer, Ciriello, Peter, & Schlagwein, 2020), privacy issues (Bengio et al., 2020; Fahey & Hino, 2020; Martinez-Martin, Wieten, Magnus, & Cho, 2020; Rowe, 2020; Sharon, 2020) and surveillance & resultant social inequalities (Madianou, 2020; Rowe, Ngwenyama, & Richet, 2020). It is observed that studies that examined factors influencing the adoption and use of DCT apps by the public represent the largest cluster in the literature (Villius Zetterholm, Lin, & Jokela, 2021). The studies related to the adoption/use of DCT apps are summarized in the following table.

It can be observed from Table 1 that extant studies related to the use of DCT apps have investigated a few closely tied issues. The majority of the studies examined the pre-adoption intention to use DCT apps among non-users. A few studies (Prakash, Das, & Pillai, 2021; Saw, Tan, Liu, & Liu, 2021; Tretiakov & Hunter, 2021) focused on current users and user experience/factors driving the use of the app. Tomczyk, Barth, Schmidt, and Muehlan (2021) examined the frequency of use among current app users ($n = 67$) in addition to examining adoption intentions among nonusers ($n = 282$). Fox, Clohessy, van der Werff, Rosati, and Lynn (2021), which adopted a longitudinal design to investigate pre-launch adoption intention and post-launch usage intention/continuance, is another exception.

In terms of methodological approaches, most of the studies were cross-sectional in nature except for Fox et al. (2021), which adopted a longitudinal approach. Similarly, most of the studies (see Table 1) adopted a survey-based quantitative approach, using SEM, SEM-ANN, or

Table 1
Summary of related literature.

Author (year)	Objective/Context	Methodology	Theory	Results/Findings
Altmann et al. (2020)	Potential user's acceptance of DCT app	Quantitative – Survey, Multivariate regression analysis	NIL	The main impediments to adoption are concerns about security and privacy and a lack of trust in the government.
Walrave, Waeterloos, and Ponnet (2020)	Factors influencing DCT app usage intention among potential users	Quantitative – Survey, SEM	HBM	Perceived benefits, self-efficacy, perceived barriers, and cues to action predicted app use intention. Perceived severity and perceived susceptibility were not related to use intention.
Trang, Trenz, Weiger, Tarafdar, and Cheung (2020)	To examine how app specifications influence DCT app installation intention.	Experimental, OLS, and Quantile regression	Prosocial behavior, privacy, and usability	Self-benefit appeal, self-societal-benefit appeal, high privacy design, high convenience design influence DCT app installation intention.
Sharma et al. (2020)	Factors that influence DCT app use intention among potential users	Quantitative – Survey, SEM	DC theory, PFT, PMT, TPB, and CDT	Attitude, subjective norms, and privacy self-efficacy predict DCT app use intention. Privacy concerns, expected personal and community-related outcomes of sharing information determine attitude towards the DCT app.
Hassandoust, Akhlaghpour, and Johnston (2021)	To develop a model for explaining potential users' privacy concerns and intention to install a DCT app	Quantitative – Survey, SEM	PCT, Risk beliefs	Risk beliefs, contact tracing benefits (individual and societal), personal innovativeness, voluntariness, perceived effort, social influence, and age influences intention to install a DCT app
Saw et al. (2021)	To identify the factors associated with the voluntary download of a DCT app	Quantitative – Survey, Logistic regression	NIL	Using hand sanitizers, avoiding public transportation, and preferring outdoor over indoor settings during pandemic were related to DCT app download. However, neither demographic nor situational factors were significantly associated with app downloads.
Kaspar (2020)	To examine factors determining the motivation for using the DCT app	Quantitative – Survey, Multiple regression	PMT and Social trust	Self-efficacy, response efficacy, response cost, severity and vulnerability of data miss-use, and trust in the app were associated with motivation for using the DCT app.
Walrave, Waeterloos, and Ponnet (2021)	Factors that influence DCT app use intention among potential users	Quantitative – Survey, SEM	Extended UTAUT	Performance expectancy, facilitating conditions, social influence, innovativeness, and privacy concerns predicted use intentions. Effort expectancy was not related to intention.
Blom et al. (2021)	To investigate barriers to the adoption of the DCT app	Qualitative – Survey, Descriptive	NIL	Inability to install apps/activate Bluetooth, lack of access (to a smartphone, compatible OS), and lack of willingness (to use, to go into quarantine, to test or report results etc.) were identified as the major barriers
Lin, Carter, and Liu (2021)	Factors influencing willingness to download a DCT app	Quantitative – Survey, SEM	DOI theory	Relative advantage, compatibility, and trusting beliefs increase adoption intentions.
O'Callaghan et al. (2021)	To examine barriers and drivers to the use of a DCT app	Qualitative – Survey, Descriptive	NIL	Protection of family and friends, responsibility to the community, knowing the risk, reducing the deaths, etc. were the reasons for and concerns about surveillance, risk of hacking, concerns about disclosing information about location/people in contact, difficulty in installation, etc. were reasons against the use of DCT app
Tomczyk et al. (2021)	To test and compare the validity of technology acceptance models in predicting DCT app adoption intention and use	Quantitative – Survey, Hierarchical regression	TPB and UTAUT2, Privacy	Adoption intentions ($R^2 = 56\text{--}63\%$) and frequency of current app use ($R^2 = 33\text{--}37\%$) were predicted by the TPB and UTAUT2 models. A combined model including privacy concerns and anticipatory anxiety improved the predictive value by around 5%.
Fox et al. (2021)	To investigate the impact of privacy, social, and benefit perceptions on DCT app acceptance.	Quantitative – longitudinal two-stage survey, SEM	PCT and SET	Social influence, reciprocal benefits, health benefits predict pre-launch adoption intention. Privacy concerns, reciprocal benefits, and pre-launch adoption intention predict post-launch usage intention.
Duan and Deng (2021)	Investigates the factors influencing adoption of DCT app	Quantitative – Survey, SEM, and ANN	UTAUT and PCT	Effort expectancy, the value of information disclosure, and social influence predict adoption intention. Performance expectancy and privacy risks indirectly influence the adoption via the value of information disclosure. The effect of facilitating conditions on adoption intention is insignificant.
Touzani et al. (2021)	Evaluate the acceptability of the DCT app and investigate the barriers to use	Quantitative – Survey, Multinomial logistic regression analysis	NIL	Only 19.2% supported the app use. Lower financial deprivation, perceived usefulness, trust in political representatives, concern about the pandemic situation, knowledge about the COVID-19 transmission, and age were associated with the willingness to use the DCT app.
Tretiakov and Hunter (2021)	Investigate factors driving the use of the DCT app and the experience of using it	Qualitative – interviews, Thematic analysis	NIL	Identified five major themes perceived benefits, patterns of use, privacy, social influence, and need for collective action.
Trkman, Popović, and Trkman (2021)	To examine the influence of perceived crisis severity and perceived benefits on intention to use DCT apps	Quantitative – Survey, SEM	CDT	The findings support the impact of perceived crisis severity on DCT app use intention and the mediating impacts of personal and social benefits on this relationship.
Prakash et al. (2021)	To explore the factors that determine individuals' intentions to continue using the DCT app.	Quantitative – Survey, SEM	ECM	User satisfaction, trust in government, and trust in technology are all major determinants of individuals' intention to continue using the DCT app. User satisfaction is influenced by perceived security and privacy and trust in technology.

Notes: SEM, Structural Equations Modeling; OLS, Ordinary least squares regression; UTAUT, Unified Theory of Acceptance and Use of Technology; PFT, procedural fairness theory; PMT, protection motivation theory; DC, dual calculus; TPB, theory of planned behavior; CDT, cultural dimension theory; DOI, Diffusion of Innovation; HBM, health belief model; PCT, privacy calculus theory; SET, social exchange theory; ANN, artificial neural networks; CDT, crisis decision theory; ECM, expectation confirmation model of IS continuance.

various regression methods for analysis. Only one study (Trang et al., 2020) had used experimental methods to examine app specifications' influence on DCT app installation intention. Qualitative studies (Blom et al., 2021; O'Callaghan et al., 2021; Tretiakov & Hunter, 2021) were few, used thematic analysis of interviews or descriptive analysis of survey data.

In terms of the theoretical paradigms, the majority of the studies have used technology acceptance models such as TPB, DOI, TAM, UTAUT, or its adaptations/extensions for modeling the adoption behavior/intentions. Several psycho-social theories from other disciplines such as PMT, DC theory, PCT, HBM, CDT, SET, PFT, ECM have been brought in to explain the intricate issue of individuals' adoption/use of DCT apps. It is also to be noted that many studies do not have any theoretical foundations (Altmann et al., 2020; Blom et al., 2021; O'Callaghan et al., 2021; Saw et al., 2021; Touzani et al., 2021; Tretiakov & Hunter, 2021).

The results of the extant studies have reported several drivers and barriers for DCT app adoption/use intentions. The main barriers/inhibitors reported are concerns/risks about security and privacy of the app, lack of trust in the government, response cost, perceived effort, severity and vulnerability of data miss-use, inability to install apps/activate Bluetooth, lack of access (to smartphone and compatible OS) and lack of willingness (to use, to go into quarantine, to test or report results, etc.), concerns about surveillance, concerns about disclosing private information, financial deprivation, and so on. The drivers/motivations are perceived benefits (personal and societal), relative advantage, perceived usefulness, self-efficacy, privacy self-efficacy, cues to action, high privacy design, high convenience design, attitude, subjective norms, voluntariness, innovativeness, performance expectancy, effort expectancy, social influence, facilitating conditions, compatibility, response efficacy, the value of information disclosure, trust in the app, trust in political representatives, knowledge about the COVID-19 transmission, concern about the pandemic situation/perceived crisis severity and age.

From a thorough review of the related literature, it is observed that: 1) prior studies have focused heavily on predicting adoption intention among potential users and continued use among current users but not on deliberate resistance behavior (postponement and opposition/rejection) among the non-users. 2) Theoretically, prior studies have taken an adoption or diffusion perspective and not an innovation resistance perspective; that is, they have not investigated the drivers of non-adopter's resistance behavior. This perspective is significant because the IS literature has argued that antecedents of user acceptance and resistance behavior are distinct and different from each other (Heidenreich & Spieth, 2013; Huang, Jin, & Coghlan, 2021; Talwar, Talwar, Kaur, & Dhir, 2020). 3) In terms of methodological approaches, qualitative studies are very few, and more comprehensive studies that combine qualitative and quantitative insights using a mixed-methods approach are not present in the literature. Given the gaps mentioned above in the literature, it is deemed essential to investigate the drivers of resistance behavior among the non-users (postponer, rejectors/opposers) using the theoretical perspective of consumer resistance to innovation and following a comprehensive mixed-methods approach.

3. Theoretical background and hypotheses development

3.1. Theoretical background

3.1.1. Theory of innovation resistance

The innovation diffusion literature has two distinct streams: the first one seeks out to comprehend the determinants of adoption, builds on the

theories like the theory of diffusion of innovation (DOI), the theory of reasoned action (TRA), and the technology acceptance model (TAM). The second stream focuses on consumer resistance to innovation (Ram & Sheth, 1989; Ram, 1987). Prior studies have shown a high rate of innovation failure (50–90%), implying that many technologies stall due to consumer resistance (Heidenreich & Kraemer, 2016; Talke & Heidenreich, 2014; Talwar et al., 2020). Thus, while the study of adoption is helpful in comprehending the diffusion of innovation, exploring innovation resistance is crucial to identifying why individuals are unwilling to adopt a possibly useful new technology (Huang et al., 2021; Talwar et al., 2020). Several studies have used the innovation resistance approach to investigate the drivers of non-adoption of novel technologies in a wide variety of settings like internet banking (Kuisma, Laukkanen, & Hiltunen, 2007; Laukkanen, 2016; Laukkanen, Sinkkonen, & Laukkanen, 2009), mobile apps (Chen, Lu, Gong, & Tang, 2019; Leong, Hew, Ooi, & Wei, 2020), smart devices/services (Chouk & Mani, 2019; Mani & Chouk, 2019), and so on.

Innovation resistance is described as opposition to any innovation that emerges from possible challenges to the status quo and current consumer belief systems (Ram & Sheth, 1989; Ram, 1987). Ram (1987) proposed a model of innovation resistance that illustrates that the degree of innovation resistance is determined by attributes of innovation, consumer characteristics, and propagation mechanisms. Later Ram and Sheth (1989) integrated those components into functional barriers and psychological barriers, which formed the sources of resistance. Functional barriers comprise usage, value, and risk barriers. The usage barrier occurs when innovation is thought to be difficult to comprehend and use. The value barrier stems from the "performance or monetary value of innovation" in relation to the alternatives. The risk barrier denotes the degree of risk involved in the use of innovation. On the other hand, tradition and image are psychological barriers. The tradition barrier emerges when the innovation is conflicting with current beliefs, previous experiences, and social norms. Finally, the image barrier refers to an unfavorable image arising from the country of origin, brand, and product category.

Kleijnen, Lee, and Wetzels (2009) proposed that resistance behavior manifests along a hierarchy starting with the postponement, followed by the rejection of the product or service, and finally, opposition. Postponement is a temporary stage in which an individual passively denies deciding on adoption decisions. A rejection requires an active consumer assessment, resulting in a clear refusal to adopt the innovation. The opposition is the highest form of resistance in which the individual engages in actions or attacks against adoption (e.g., negative word of mouth). Another prominent classification categorizes innovation resistance into passive and active (Ali, Zhou, Miller, & Ieromonachou, 2016; Heidenreich & Spieth, 2013). Passive innovation resistance is a result of a person's predisposition to resist innovation. Active resistance, by comparison, is a negative attitude that follows a new product evaluation driven by product-specific barriers (Heidenreich & Spieth, 2013). Previous research has revealed that active innovation resistance decreases adoption and results in negative word of mouth (WoM) and boycott (Heidenreich & Spieth, 2013; Kleijnen et al., 2009). This study specifically looks at the factors that contribute to 'active innovation resistance' in the context of DCT apps.

3.1.2. Theory of distrust

Distrust generally refers to the absence of trust or suspicion, or wariness, and is commonly viewed as a functional opposite of trust (McKnight & Chervany, 2001a, 2001b). However, a growing body of evidence suggests distrust as a conceptually and empirically distinct construct from the trust (Dimoka, 2010; McKnight & Chervany, 2001a;

McKnight & Choudhury, 2006). According to McKnight & Chervany (2001a), distrust is often characterized by intense negative emotions, that is, it makes one feel “insecure, worried, and suspicious” as against trust, which makes one feel “safe, secure, and comfortable.” Thus, distrust is more than a lack of trust; it is a belief that the other person will act in a way that endangers one’s security and welfare (Cho, 2006). Although it was initially applied in interpersonal relationships among humans, distrust was later extended to human relationships with non-human entities such as IT artifacts/technology (Chau, Ho, Ho, & Yao, 2013; McKnight & Choudhury, 2006).

Like trust, distrust also comprises distrusting beliefs and intentions (McKnight & Chervany, 2001a, 2001b). Distrusting belief is defined as “the degree to which one believes, with feelings of relative certainty, that the other person or entity does not have characteristics beneficial to one” (McKnight & Chervany, 2001). While distrusting intentions refer to the trustor’s unwillingness to depend on the other party (McKnight, Kacmar, & Choudhury, 2004). Research confirms that distrusting beliefs impact distrusting intentions, and distrusting intentions lead to distrust-related behaviors like unwillingness to purchase/share information/follow advice (McKnight & Choudhury, 2006). Distrust thus alters/influences the trustor’s behavior with the trustee (Chau et al., 2013). Specifically, in terms of its consequences, distrust inactivates the consumer; that is, it “blocks, inhibits and restrains business transactions and changes customers from being active to passive or keeps them passive” (Lee, Lee, & Tan, 2015, p. 162).

Also, taking a cue from the recent surveys conducted in the USA, which point to widespread distrust of DCT programs among the citizens (Kreps, 2020; Kreps, Zhang, & McMurry, 2020; Ropek, 2020), it is reasonable to believe the individual’s distrust in the DCT app could affect his subsequent usage behavior. Prior research in IS has also argued that user cynicism/distrust could lead to active forms of user resistance during IT implementation in organizations (Ali et al., 2016; Selander & Henfridsson, 2012). Extending this to the context, distrust in the DCT app could influence citizens’ resistance to use the DCT app.

3.2. Preliminary qualitative study on drivers of resistance

A preliminary qualitative study was conducted to seek answers for RQ1. Accordingly, 24 semi-structured interviews were conducted with citizens familiar with the functionality and features of the ‘Aarogya Setu’ (DCT) app launched by the government of India (Dwivedi et al., 2020) to explore the drivers of citizens’ resistance to use the DCT app. As the study was targeted at the nonadopter population, that is, (compatible) smartphone owners who are aware and have not yet used the DCT app (postponers) or discontinued using DCT app after the initial trial (rejectors/opposers), three screening questions were used to select the participants. Thus, the participants were chosen using a combination of convenience and purposive sampling strategies (see Appendix A for sample profile). The theoretical saturation principle was used to calculate the number of participants (Corbin & Strauss, 1990). A semi-structured form of the interview was used to explore the drivers of their resistance to use DCT apps. For further analysis, the interviews were voice captured and transcribed.

Further, a thematic analysis (Braun & Clarke, 2006) based on deductive and inductive coding approaches was used to analyze the qualitative data collected from the interviews. A QSR NVivo v.10 software package was used for conducting the thematic analysis. In line with the objectives, the study focused on finding probable drivers of resistance and identified seven factors, namely, information privacy concern, government surveillance concern, security risk, distrust, usage barrier, complexity barrier, and value barrier that could lead to the formation of resistance to use DCT apps. The results are also in line with Ram and Sheth (1989) categorization of resistance drivers. A summary of the results of the thematic analysis (factors, sample verbatim comments by the informants, relationship with dependent variable, and corresponding theories) is provided in Appendix B. The factors and relationships

identified in the qualitative study were then used in combination with the insights gained from the literature review to conceptualize the research model evaluated in the quantitative stage of this study.

3.3. Hypotheses development

Our hypotheses are formulated based on relevant empirical literature as well as on the evidence from the preliminary qualitative study. Specifically, we followed a three-layered approach (Wunderlich, Veit, & Sarker, 2019) in developing our contextualized research model. 1) Use of innovation resistance theory (IRT) as the foundational model to understand the primary variables that would affect the formation of citizen’s resistance to DCT app. 2) Use of qualitative data to identify context-specific factors that might have an effect on resistance to DCT app. 3) Combining insights from the qualitative data and literature to develop the hypotheses.

We chose the IRT as the foundational model because, according to the literature (Huang et al., 2021; Talwar et al., 2020), most of the prior studies that examined innovation failure have used IRT (Ram & Sheth, 1989) to investigate why consumers reject innovations. These prior studies have investigated consumer resistance to a variety of technologies such as smartwatches (Ghazali, Mutum, Pua, & Ramayah, 2020), smart meters (Chamaret, Steyer, & Mayer, 2020), mobile payment solutions (Kaur, Dhir, Singh, Sahu, & Almotairi, 2020), e-books (Kim, Seo, Zo, & Lee, 2021), mobile wallet (Leong, Hew, Ooi, & Wei, 2020), Internet of things (Chouk & Mani, 2019; Mani & Chouk, 2018), a set of product and service innovations (Joachim, Spieth, & Heidenreich, 2018), Internet banking (Laukkanen et al., 2009), online shopping (Lian & Yen, 2013) etc. Further, in accordance with the objective, the main dependent variable in this model is citizen’s resistance to the DCT app, which is conceptualized as an active innovation resistance, i.e., a negative attitude that follows a new product evaluation driven by product-specific barriers (Heidenreich & Spieth, 2013). Intention to use DCT app was included as a behavioral outcome/consequence of active innovation resistance (Heidenreich & Spieth, 2013; Huang et al., 2021; Talwar et al., 2020). Further, as suggested by the theory and empirical literature (Huang et al., 2021; Talwar et al., 2020), we included the value, usage, complexity, and risk barriers as antecedents to resistance.

The preliminary qualitative study helped in two ways: 1) It provided validity to the factors identified through literature review and helped operationalize (adapt) existing scales to suit the context, 2) It identified new contextual determinants of resistance and corresponding theory (theory of distrust in technology) that would help explain the contextual phenomenon in a better way. With respect to the risk barrier in our qualitative study, we found evidence for three distinct types of risks associated with DCT app usage (see Appendix B), i.e., information privacy concern, government surveillance concern, and security risk. Further, the other original constructs in the IRT framework (Heidenreich & Spieth, 2013; Huang et al., 2021), the usage, complexity, and value barrier, were also supported by the qualitative study.

In addition to the constructs in IRT, we found another barrier, i.e., distrust in the DCT app (technology) as a prominent factor driving citizens’ resistance (see Appendix B). Thus, as indicated by Appendix B, the evidence from qualitative study pointed towards the necessity of incorporating the theoretical paradigm of distrust in technology (McKnight & Chervany, 2001a; McKnight & Choudhury, 2006; McKnight et al., 2004) in addition to the IRT (Ram & Sheth, 1989) to explain the phenomenon of citizens’ resistance to use DCT apps. Furthermore, a recent empirical study on customer resistance to digital-only banks (Nel & Boshoff, 2021) suggested that combining the theoretical concepts of innovation resistance and distrust and incorporating distrust as a mediator between innovation barriers and resistance would contribute to a more comprehensive explanation of the resistance phenomena. Finally, the evidence from qualitative data (excerpts) in combination with the insights from literature was used to develop the hypotheses. Thus, the following integrated research framework (Fig. 1)

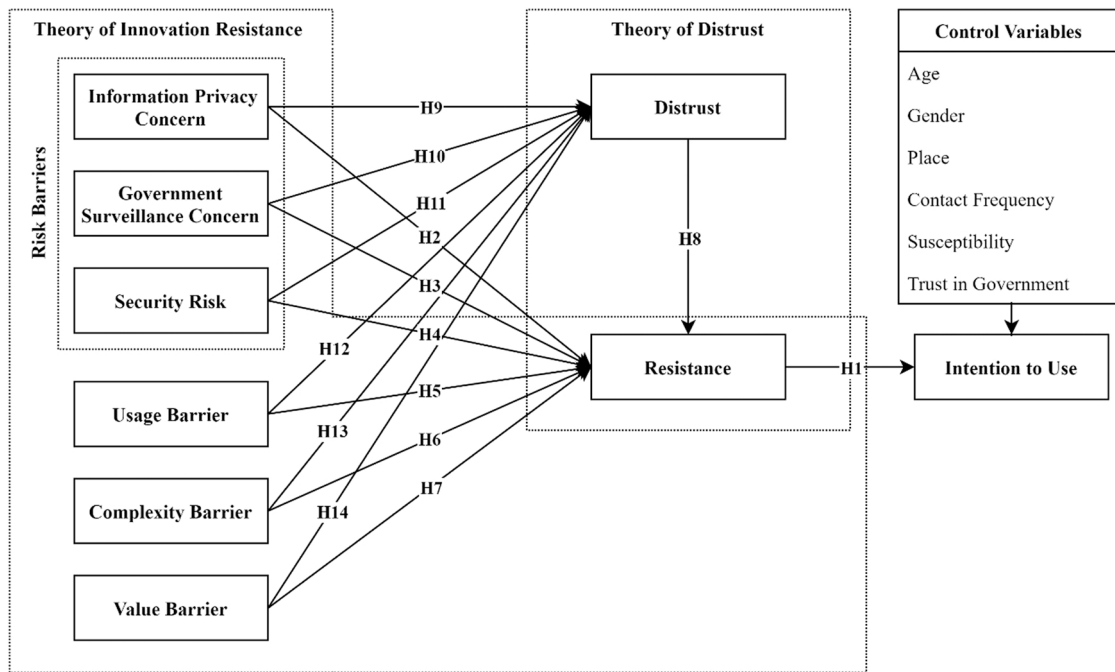


Fig. 1. Proposed theoretical framework.

Source: Derived based on the theory of innovation resistance (Heidenreich & Spieth, 2013; Ram & Sheth, 1989), theory of distrust in technology (McKnight & Choudhury, 2006; McKnight et al., 2004; Nel & Boshoff, 2021), and insights from the preliminary qualitative study (Appendix B).

was developed to explain the phenomena of citizens' resistance to the DCT app and its behavioral consequence.

3.3.1. Resistance to the DCT app

The variable resistance to the DCT app is conceptualized as active innovation resistance (Heidenreich & Spieth, 2013). The characteristics of innovation are the primary drivers of active innovation resistance (Heidenreich & Spieth, 2013). As per Heidenreich and Spieth (2013), active innovation resistance represents "a negative attitude formation driven by product-specific barriers that follow new product evaluation." It is the degree to which an individual has an unfavorable evaluation of the behavior to adopt the novel product under consideration. Here, it represents the degree of unfavorable evaluation towards adopting the DCT app. From the qualitative study, it was evident that many citizens oppose or resist using the DCT app soon after evaluating its features, which was expressed variedly by the respondents, for example: "I'm not going to use this for sure" [P4], "I would better not install and invite trouble" [P7], "I would rather pay the 1000 rupees as fine (for not using)." [P9], "I uninstalled the app due to this." [P11]. Moreover, prior research in innovation resistance has established that active innovation resistance can lead to a reduced intention to adopt the innovation in question (Heidenreich & Spieth, 2013; Kleijnen et al., 2009). In the light of evidence from the qualitative study as well as the recent literature on innovation resistance, the current study proposes the following hypothesis:

H1. Individual's resistance to DCT app is negatively related to citizens' intention to use DCT app.

3.3.2. Perceived information privacy concern

Since using the DCT app necessitates disclosing sensitive private information such as name, phone number, health status, location data, and details of contacts with others, this can trigger concern about privacy among the potential users (Dwivedi et al., 2020; Fox et al., 2021; Sharma et al., 2020; Walrave et al., 2020). Prior research has identified that individuals who attach considerable significance to preserving their privacy would inevitably resist using IoT-based smart services (Chouk &

Mani, 2019; Mani & Chouk, 2019). Since DCT apps use smart technologies (Bluetooth, GPS etc.) for contact tracing, the feeling of invasion of privacy associated with the use of these apps could trigger resistance. Further, the evidence reported from our qualitative study also points to the possible causal relationship between privacy concerns and citizens' resistance to use DCT apps. For example, when asked about the reason for not using the DCT app, one of the interview respondents (P4) gave this reason "Look, the app is even collecting real-time location info of the users, in addition to all the other personal data. They will get to know who is where and doing what in real-time. It is like being completely naked; tell me, what is left? user's privacy is a huge concern." In fact, many respondents (e.g., P13, P15, P19, etc.) mentioned privacy concerns as one of the major reasons for the non-usage of the DCT app. Thus, based on the theoretical paradigm of IRT (Chouk & Mani, 2019) and the phenomenological relationship identified from the preliminary qualitative study, the current study proposes the following hypothesis,

H2. Perceived information privacy concern is positively related to citizens' resistance to use DCT app.

3.3.3. Perceived government surveillance concern

One of the most alarming concerns raised about the use of the DCT app in the preliminary qualitative study is about the government's ability to monitor users' activities through the app. Many respondents pointed to this as the reason for their resistance to using DCT apps. For example, one of the respondents (P7) said, "I am worried if this would be misused by the government agencies to track and abuse people, [...] I would better not install and invite trouble." In the literature, Dinev, Hart, and Mullen (2008) refer to this specific concern as "government intrusion concerns," which is defined as "a negative belief about the proactive gathering and processing of personal information and monitoring online behavior by the government." Similarly, recent literature on smart services reports 'perceived government surveillance concern' as an important driver of consumer resistance to smart services (Chouk & Mani, 2019; Mani & Chouk, 2019). Recent opinion papers by experts also point to the rising concerns about the potential of state surveillance through the DCT apps (De, Pandey, & Pal, 2020; Dwivedi et al., 2020).

Additionally, recent studies (Altmann et al., 2020; O'Callaghan et al., 2021) cited government monitoring as one of the reasons for not installing the DCT app. Thus, in this case, based on the evidence from qualitative study and related literature, it is reasonable to assume that the citizens' concerns about the ability of the government to track their personal data (location, social contacts, and health status) via the app might increase their resistance to use the app. Accordingly, the study proposes the following hypothesis,

H3. Perceived government surveillance concern is positively related to citizens' resistance to use DCT app.

3.3.4. Perceived security risk

According to IRT, the use of an innovation is associated with several perceived risks (Laukkanen, 2016; Ram & Sheth, 1989). Security risk generally refers to "concerns related to the loss of control over personal and private information after an attack by a potentially malicious individual or through the fraudulent behavior of organizations" (Miyazaki & Fernandez, 2001). Security risk concerns reported by the respondents in the qualitative study include a general concern about the risk of data theft and concerns specific to the security vulnerabilities due use of Bluetooth technology for contract tracing. For example, a respondent (P13) voiced a general concern over data theft "How secure are these systems and servers? It is a goldmine and will be a target to hackers. There have been instances in the past where similar security flags were raised against government apps." While another respondent (P10) was anxious about the vulnerabilities of using Bluetooth for tracing mechanism "Keeping the Bluetooth always on would make my phone visible to hackers and viruses. Can't they use some other mechanisms?". Several earlier studies have reported the negative effect of security risk perceptions on attitudes toward e-services (Curran & Meuter, 2005; Schierz, Schilke, & Wirtz, 2010). Likewise, other studies have found a positive relationship between security risk and resistance in smart services (Chouk & Mani, 2019; Mani & Chouk, 2019). A recent qualitative study on DCT apps (O'Callaghan et al., 2021) also mentioned security risk as a key barrier to DCT app adoption. Therefore, it is highly likely that individuals who perceive high security risks related to the use of DCT apps may tend to develop resistance towards using it. Accordingly, the following hypothesis is proposed,

H4. Perceived security risk is positively related to citizens' resistance to use DCT app.

3.3.5. Perceived usage barrier

The usage barrier refers to the perception that using innovation necessitates an unpleasant disruption to existing usage habits and routines (Heidenreich & Spieth, 2013). Conceptually the meaning of the usage barrier is related to the compatibility concept of Rogers (1995). Here, in this case, the qualitative study revealed that a major usage-related barrier is a concern about whether using this app would require frequent battery recharging. This was primarily because the DCT app requires the phone's Bluetooth and location services to be always on. The users were concerned that this might discharge the battery faster, and they might have to limit their smartphone usage to conserve battery power during routine use. For example, one of the respondents (P11) remarked, "It was keeping my Bluetooth and location sharing always on. I found that my device was getting heated up, and the battery was draining very fast. I uninstalled the app due to this." Additionally, a recent study related to DCT app in the UK found that the majority of citizens (46%) are less likely to use the app if it depletes their battery life even moderately (Nolsoe, 2020). It is known from the IRT that the users who cannot adjust to the possible disruption in the established usage patterns associated with the adoption may develop a negative attitude towards the innovation (Heidenreich & Spieth, 2013). Several empirical studies have identified a negative relationship between usage barriers and attitude related to the use of innovation (Joachim et al., 2018; Laukkanen, 2016). Usage barrier has also been identified as a key determinant of

active innovation resistance based on the theoretical perspective of IRT (Heidenreich & Spieth, 2013; Joachim et al., 2018; Kleijnen et al., 2009). Thus, from the preliminary qualitative study and the theoretical perspective of IRT, it can be assumed that perceived usage barriers may increase citizens' resistance to use the DCT app. Hence the study proposes the following hypothesis,

H5. Perceive usage barrier is positively related to citizens' resistance to use DCT app.

3.3.6. Perceived complexity barrier

The complexity barrier occurs as people find innovation to be difficult to grasp "complexity of idea" or to use "complexity of execution" (Heidenreich & Spieth, 2013; Laukkanen, 2016). The preliminary qualitative study revealed that some of the users might find the DCT app complex/difficult to use (see Appendix B). For example, "The app looks complicated to use. Need to be more simple and less cluttered" [P18]. Further, prior research has found perceived complexity to be negatively related to an individual's attitude about using an innovation (Heidenreich & Spieth, 2013). Moreover, perceived complexity was identified as a barrier that negatively influences user adoption of smart services (Joachim et al., 2018; Laukkanen, 2016). More recent literature on innovation resistance has identified complexity as an antecedent of resistance to smart services (Mani & Chouk, 2018, 2019). Therefore, in the light of the evidence from the qualitative study as well as the related literature, it is likely that the individuals who perceive the DCT app as highly complex to understand or use may develop resistance towards using it. Hence, the study proposes the following hypothesis,

H6. Perceived complexity barrier is positively related to citizens' resistance to use DCT app.

3.3.7. Perceived value barrier

Value barrier refers to "the performance or monetary value of the innovation in comparison with its alternatives" (Ram & Sheth, 1989). It occurs where innovation does not provide greater benefits to existing alternatives or simply due to a perception of a lack of benefits resulting from the innovation (Laukkanen, 2016). The concept of value barrier in IRT (Ram & Sheth, 1989) is related to the concepts of perceived usefulness and relative advantage in the innovation diffusion literature (Venkatesh, Morris, Davis, & Davis, 2003). In this case, the preliminary qualitative study indicated that citizens doubted the benefits/usefulness of the DCT app over other available alternatives. For example, participant 11 stated, "I uninstalled the app [...] I find it pretty much useless; it does not update positive cases regularly and always shows that I am safe. The other information available on this app is similar to what I get on Google or health ministry website." According to the theoretical perspectives of IRT, the value barrier is one of the most important causes of user resistance (Kleijnen et al., 2009; Ram & Sheth, 1989; Talke & Heidenreich, 2014). Empirical studies also suggest that perceived dearth of value in the adoption of an innovation can negatively affect the adoption behavior (Joachim et al., 2018; Kleijnen et al., 2009; Laukkanen, 2016). Further, the value barrier was found as a key driver of resistance to smart products (Mani & Chouk, 2017) and smart services (Mani & Chouk, 2018). Therefore, it is expected that if the citizen does not find any value in using the DCT app, they are more likely to resist it. Hence, the following hypothesis is proposed,

H7. Perceived value barrier is positively related to citizens' resistance to use DCT app.

3.3.8. Distrust in the DCT app

Though trust is a critical aspect in technology acceptance, distrust could assume an even more vital role in consumer decisions to use new technologies (Ou & Sia, 2010). Novelty theory (Kaplan, 1976) and Prospect Theory (Tversky & Kahneman, 1989) also emphasize the substantial influence of distrust in human decision-making. According to

these theories, negative information is more influential in decision-making than positive information. The preliminary qualitative study of this research revealed citizens' distrust towards the DCT app (i. e., skepticism/suspicion towards the efficacy and reliability of the app). For example, participant 24 remarked, "*The efficacy of the app is yet to be proven, the accuracy of the algorithm is questionable, e.g., Bluetooth may travel across physical barriers [...] and hence could give a lot of false positives [...] I don't think I can trust this app.*" Similarly, another participant observed, "*Does not give accurate data. In my building, there are six patients. They are not listed in a 500 m radius. Not foolproof. Not reliable.*" [P20].

In the literature, distrusting belief is defined as a person's belief in the other entity's unfavorable attributes (McKnight & Chervany, 2001). According to the theory of distrust, when the trustor distrusts the trustee's competence and/or integrity, they will tend to respond cautiously with the trustee (McKnight & Chervany, 2001a). The trustor may even try to guard themselves by reducing their reliance on the trustee (McKnight & Chervany, 2001a, 2001b). Thus, distrusting beliefs cause psychological discomfort and may lead to strong distrust-related behaviors such as lack of cooperation, non-acceptance of influence, or avoidance of business transactions with the trustee, and so on (McKnight & Chervany, 2001a, 2001b; Ou & Sia, 2010). The trustee could be a person or an IT artifact/technology (Chau et al., 2013; McKnight & Choudhury, 2006).

In other words, individuals who believe that the other person or entity lacks qualities that are beneficial to them will tend to reduce dependence on them, in extreme cases, totally avoid transactions with them (Nel & Boshoff, 2021). Therefore, in this case, distrust in DCT apps may result in the formation of an intense negative attitude (active innovation resistance) and subsequent nonuse of the DCT app. Moreover, the prior literature strongly supports the notion that distrust in technology could be a barrier to adoption (Carpenter, Young, Barrett, & McLeod, 2019). A recent study on digital-only banks has also empirically validated the positive relationship between customers' distrusting beliefs and their resistance to use (Nel & Boshoff, 2021). Hence, in the light of this evidence, the study suggests the following hypothesis,

H8. Distrust in the DCT app is positively related to citizens' resistance to use DCT app.

3.3.9. Mediating role of distrust

In terms of its consequences, a stream of studies has shown that distrust can increase negative attitudes (Nel & Boshoff, 2021), reduce purchase intentions (Xie, Madrigal, & Boush, 2015), and increase negative word of mouth (Riquelme, Román, & Iacobucci, 2016). Additionally, distrust has been reported to play mediating roles in determining customer loyalty (Lee et al., 2015), resistance to use (Nel & Boshoff, 2021), and unwillingness to purchase (McKnight & Chervany, 2001). Extending this to the present context, distrust could act as a mediator between the innovation barriers and citizens' intention to use the DCT app. Prior research on consumer resistance to smart services (Mani & Chouk, 2018) and digital-only banks (Nel & Boshoff, 2021) have also argued for exploring the relationship between innovation barriers and consumer distrust. Hence in this case, in addition to the direct effect, innovation barriers could indirectly influence resistance through distrust. The related hypotheses are discussed in detail below.

Information privacy concern was one of the most prominent concerns reported in the qualitative stage. For example, one of the respondents (P4), "*Look, the app is even collecting real-time location info of the users, in addition to all the other personal data. [...] tell me what is left? user's privacy is a huge concern.*" The same person expressed his lack of trust in the DCT app further in the interview: "*This is kind of scary rather than useful. Seriously, why would I trust this app?*" Thus, it gives a cue that information privacy concerns might lead to distrust in the DCT app. Additionally, literature related to electronic health also points out the link between information privacy concerns and distrust (Stablein, Hall, Pervis, & Anthony, 2015). Thus, the individuals who have concerns

about information privacy may start doubting the integrity aspect of the technology (DCT app) and consequently develop a suspicion about the technology (Stablein et al., 2015). Since lack of integrity is a key dimension of distrust (McKnight & Chervany, 2001a, 2001b), it implies that the higher the information privacy concern, the higher could be the distrust in the DCT app. This leads the authors to hypothesize,

H9. Perceived information privacy concern is positively related to citizens' distrust in the DCT app.

It was evident from the qualitative study that citizen's concerns about government surveillance would lead to distrust; for example, one of the participants (P4) mentioned that "*I am worried my data will be used against me; this is kind of scary rather than useful. Seriously, why would I trust this app? I'm not going to use this for sure.*" The possibility of government surveillance through the app without their knowledge or consent could be seen by the individual as an undesirable intrusion into their private life (Dinev et al., 2008). The possibility of such intrusions could negatively affect the integrity notion associated with the DCT app (Kreps et al., 2020). According to the theory of distrust, when an individual has doubts regarding the integrity (a critical dimension of distrust) of the trustee (here DCT app), the trustor may tend to respond cautiously, for example, by showing reluctance to provide the information required for the transaction (Dinev et al., 2008) or, in extreme cases, totally avoid transactions with the trustee (McKnight & Chervany, 2001a, 2001b). Thus, based on the theory of distrust and evidence from the qualitative study, it can be assumed that the higher the perceived government surveillance, the higher could be the distrust towards the DCT app. Hence, the following hypothesis is proposed,

H10. Perceived government surveillance concern is positively related to citizens' distrust in the DCT app.

Like government surveillance concerns, another reported risk perception is related to the security of the app. The vulnerability of the DCT app to hacking and the probable loss of private information was a serious concern among the respondents in the qualitative stage (see Appendix B). For example, one of the respondents (P20) said, "*I am doubtful about the security of the app. I heard that there are many flaws and that it is vulnerable to hacking.*" Further, the same person exclaimed in the interview that the app is not reliable. This gives a cue that security risk perception could lead to distrust formation in the DCT app. Further, the poor security of the system can negatively affect the potential user's confidence in the technology (Ben-David et al., 2011). The security risk perception could lead to the development of suspicion/doubt towards the integrity of the system (Nel & Boshoff, 2021). Additionally, the lack of adequate security features may also affect the perceptions of competence of the system, as it would imply that the app is a poorly developed piece of software and is not reliable (Nel & Boshoff, 2021; Talke & Heidenreich, 2014). Furthermore, the positive relationship between security risk perceptions and distrusting beliefs was validated in the context of digital-only banks (Nel & Boshoff, 2021). Therefore, based on the findings from qualitative study and the theoretical paradigms of distrust and IRT, it is reasonable to assume that individuals with higher security risk perception may develop higher distrust in the system. Hence, the following hypothesis is proposed,

H11. Perceived security risk is positively related to citizens' distrust in the DCT app.

The participants in the qualitative study had expressed concerns about likely disruption in their established smartphone usage patterns due to the installation of the DCT app that drains the battery at a faster rate. For example, "*...keeping app setting as location sharing always is going to kill my battery life. I would need to either carry a power bank or limit my phone usage*" [P21]. Given their use expectations, such usage barriers would cause a user to conclude that the innovation is dysfunctional or ineffective (Kuisma et al., 2007; Talke & Heidenreich, 2014). In this case, an app that causes their phone to discharge/heat up faster may be

perceived with suspicion by the users, thus resulting in distrust for the app and non-use (Nolsoe, 2020; Reuters, 2020). Thus, from the related literature, it is evident that usage barriers could lead to the formation of distrust in the DCT app. Additionally, recent research has empirically validated the positive relationship between the usage barrier and distrusting beliefs (Nel & Boshoff, 2021) in the context of digital-only banks. Thus, based on the above-mentioned arguments, the following hypothesis is proposed,

H12. Perceived usage barrier is positively related to citizens' distrust in the DCT app.

The preliminary qualitative study has pointed out that some individuals (e.g., older age groups) may perceive the DCT app as difficult to understand and operate (see Appendix B). Perceived complexity from IRT is related to the notion of ease of use or usability in the technology adoption/use models (Heidenreich & Spieth, 2013). If a technology or system is perceived as less user-friendly/complex, the users may attribute it to the lack of competence and benevolence of the system (Kuisma et al., 2007; Nel & Boshoff, 2021). Moreover, research on data exchange systems has found that system quality (usability and accessibility) has a significant negative influence on distrust (McKnight, Lankton, Nicolaou, & Price, 2017), implying that improving usability (ease of use) can alleviate distrust. Taking these cues to the current context, the complexity of the DCT app may result in the formation of distrust in the system. Thus, based on IRT and the theory of distrust in combination with the cues obtained from the qualitative study, it can be assumed that the higher the perception of complexity, the higher could be the distrust in the system. Thus, the following hypothesis is proposed,

H13. Perceived complexity barrier is positively related to citizens' distrust in the DCT app.

The preliminary qualitative study suggested the presence of a value barrier among the citizens concerning the adoption of the DCT app (See Appendix B). One of the respondents of this study (P12) stated, "And then it is useless there were at least ten positive cases nearby but no updates in the app. I can get better information about cases from local media. What is the purpose of using this app?" If a system is perceived as having low benefits, it will, in turn, affect user's perception about competence/functionality (trust-related beliefs) of the system (McKnight & Chervany, 2001) and lead people to believe that the innovation is inadequate/ineffective (Nel & Boshoff, 2021; Talke & Heidenreich, 2014). Lack of competence/functionality is a key dimension of distrusting beliefs (McKnight & Chervany, 2001a, 2001b). Thus, value barriers may add to citizens' perceptions that DCT apps do not have adequate functionality to monitor/inform about their risk of infection in comparison with manual contact tracing or other alternatives, contributing to distrusting beliefs. Consequently, in the context of this research, increased perceptions of value barriers may increase distrust in the DCT app. Hence, the following hypothesis is proposed,

H14. Perceived value barrier is positively related to citizens' distrust in the DCT app.

4. Methodology

The current study used a sequential mixed-method (Venkatesh, Brown, & Bala, 2013) approach to qualitatively identify factors that drive citizens' resistance to use the DCT app, followed by a quantitative survey-based study that empirically examined the identified relationships. The mixed-methods approach helps to explain the phenomenon in more depth and detail by leveraging the complementary capabilities of qualitative and quantitative methods (Venkatesh et al., 2013). Following the recommendations by Venkatesh et al. (2013), we first conducted a preliminary qualitative study based on semi-structured interviews and formulated a research model using insights gained from the qualitative study and literature review. This was immediately

followed by a survey-based quantitative study to evaluate the research model.

4.1. Study design, procedure, and participants

A quantitative survey was used to assess the relationship proposed in the theoretical model. Participants were invited (Indian citizens currently residing in India) to respond to the survey using social media handles (Twitter, LinkedIn, and Facebook) of a premier public university in India and some India-based Facebook groups. As this survey was targeted at the nonadopter population, that is, smartphone owners who are aware and have not yet used the Arogya Setu DCT app (postponers) or discontinued using the app after the initial trial (rejectors/opposers), three sequential screening questions were used to select the respondents. The first question was whether they were aware of the Arogya Setu DCT app launched by the government of India (Dwivedi et al., 2020). The second question was whether they had a compatible smartphone. The third question was whether they were currently using the app. Only the people who are yet to use the Aarogya Setu app or who tried it earlier but uninstalled it after some time could fill the questionnaire (the current users were filtered out). Completed responses were received from 194 participants from 24 (out of 36) states/union territories of India. Table 2 displays the demographic characteristics of the survey respondents.

4.2. Survey instrument

The data collected using a structured questionnaire was used to validate the hypothesized model. All items were measured on a five-point Likert scale, where "1 = Strongly disagree" and "5 = Strongly agree". All the items were adapted versions of preexisting scales. The content validity of the instrument was assessed by a panel consisting of two professors from the management discipline and two doctoral students. The measures and sources are presented in Appendix C. In addition to the primary constructs, few control variables were used to rule out the confounding effects of respondents' characteristics on the outcome variable. The control variables were gender, age, place (urban/rural), contact frequency, perceived susceptibility, and trust in government (see Appendix C).

Table 2
Sample profile.

Respondent characteristics		Frequency	Percentage
Gender	Female	83	42.78
	Male	111	57.22
Age	18–27	98	50.52
	28–37	59	30.41
	38–47	22	11.34
	48–57	12	6.19
	58–67	2	1.03
	68–77	1	0.52
Education	Doctorate	5	2.58
	Postgraduate	99	51.03
	Graduate	73	37.63
	Higher Secondary	12	6.19
	Professional Diploma	5	2.58
Employment	Private sector	78	40.21
	Public sector	17	8.76
	Other (e.g.: Retired)	3	1.55
	Self Employed	13	6.70
	Student	73	37.63
Place	Unemployed	10	5.15
	Rural	60	30.93
	Urban	134	69.07

5. Results

5.1. Structural equations modeling analysis

A partial least square structural equation modeling (PLS-SEM) approach was used to examine the hypotheses. Since PLS-SEM is a prediction-oriented tool, it is well suited for modeling adoption behavior (Hair, Risher, Sarstedt, & Ringle, 2019). Additionally, it works well with small data samples and even under the case of non-normality (Hair et al., 2019). Hence PLS-SEM was found appropriate for this study.

5.1.1. Measurement model

Following the guidelines set by Hair et al. (2019), the instrument's validity and reliability were tested using the measurement model. The scale reliability of all the constructs was assessed by means of indicator loadings and composite reliability (CR). As per the guidelines, indicator loadings must be greater than 0.708 to meet the acceptable item reliability (Hair et al., 2019). For indicator CB3 the loading was found to be 0.681, which is slightly short of the conservative cut-off value of 0.708. However, an item of a multi-item reflective construct can be retained even if the loading value is between 0.4 or 0.7 if the average variance extracted (AVE) and composite reliability (CR) of the construct is above the threshold value (Hair, Hult, Ringle, & Sarstedt, 2016). Accordingly, we chose to retain CB3 on the grounds of content validity with support of PLS-SEM guidelines (Hair et al., 2016). The internal consistency reliability was assessed using CR, and as the values in Table 3 indicate, all the values were observed to be greater than the cut-off of 0.7 (Hair et al., 2019). Following this, convergent and discriminant validities of the constructs were assessed to establish construct validity. Convergent validity was established as all the average variance extracted (AVE) was greater than the cut-off 0.5 (Hair et al., 2019). Discriminant validity was evaluated using both heterotrait-monotrait ratio of correlations (HTMT) criteria (Hair et al., 2019) and the traditional Fornell-Larcker criteria (Hair et al., 2019). It was established as all the HTMT values (see Table 4) were found less than the conservative threshold of 0.85 (Hair

Table 3
Reliability and validity statistics.

Construct	Mean	Standard Deviation	Item	Loading	Composite Reliability	AVE
Behavioral Intention to Use (BI)	2.137	1.088	BI1	0.965	0.976	0.931
			BI2	0.959		
			BI3	0.971		
Complexity Barrier (CB)	1.687	0.768	CB1	0.948	0.895	0.743
			CB2	0.931		
			CB3	0.681		
Distrust (DT)	3.818	0.923	DT1	0.887	0.925	0.755
			DT2	0.907		
			DT3	0.887		
			DT4	0.789		
Government Surveillance Concern (GS)	3.764	1.057	GS1	0.930	0.944	0.850
			GS2	0.929		
			GS3	0.907		
Information Privacy Concern (IP)	3.748	1.023	IP1	0.905	0.946	0.777
			IP2	0.890		
			IP3	0.918		
			IP4	0.784		
Resistance (RE)	3.517	1.176	IP5	0.904	0.957	0.881
			RE1	0.939		
			RE2	0.950		
			RE3	0.926		
Security Risk (SR)	3.484	1.008	SR1	0.943	0.950	0.862
			SR2	0.919		
			SR3	0.924		
Usage Barrier (UB)	3.507	0.962	UB1	0.849	0.896	0.741
			UB2	0.880		
			UB3	0.854		
Value Barrier (VB)	2.848	1.016	VB1	0.962	0.960	0.923
			VB2	0.960		

et al., 2019). Similarly, the inter-construct correlations were found less than the square root of AVE (see Table 5), satisfying the Fornell-Larcker criteria (Hair et al., 2019).

5.1.2. Assessing potential common method bias

The common method bias (CMB) was assessed using two methods. First, Harman's single-factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) revealed that no single factor explained most of the variance. The largest single factor that emerged from the test accounted for 36.029% of the variance, which is way less than the cut-off value of 50% (Podsakoff et al., 2003). Second, we used a marker variable approach by using a theoretically unrelated marker variable in the study model (Lindell & Whitney, 2001). The maximum shared variance with other factors was estimated to be 0.0151 (1.51%), which is very low (Johnson, Rosen, & Djurdjevic, 2011). Thus, based on this evidence, it can be inferred that no significant CMB is present.

5.1.3. Structural model

The model was first assessed for multicollinearity issues using the variance inflation factor (VIF) values of the latent constructs (Hair et al., 2019). All the constructs' VIF values were smaller than the conservative threshold of 3, indicating that the results did not have multicollinearity issues (Hair et al., 2019). Table 6 summarizes the VIF values.

A PLS bootstrapping process with 5000 subsamples was performed to evaluate the magnitude and significance of the path coefficients in the model (Hair et al., 2019). Tables 7 and 8 summarizes the results of hypothesis testing, and Fig. 2 illustrates the empirical findings. Firstly, the impact of the control variables on the outcome variable intention to use was tested. The results reveals that the impact of the control variables that is, age ($\beta = -0.001$, $t = 0.015$), gender ($\beta = -0.033$, $t = 0.587$), place ($\beta = -0.033$, $t = 0.659$), contact frequency ($\beta = -0.136$, $t = 1.685$), perceived susceptibility ($\beta = 0.065$, $t = 0.901$), Trust in government ($\beta = 0.099$, $t = 1.320$) were not statistically significant at $p < 0.05$. However, contact frequency is significant at $p < 0.1$ (90% confidence). Hence the role of control variables other than 'contact frequency' is negligible in the model.

Supporting results were obtained for the proposed hypotheses H1, H2, H5, H7, H8, H10, and H14, while the other hypotheses H3, H4, H6, H9, H11, H12, H13 turns out to be statistically insignificant at $p < 0.05$. It is to be noted that H4 and H12 are significant at $p < 0.1$ (90% confidence). Among the empirically significant predictors of resistance, DT ($\beta = 0.315$, $t = 4.399$) turns out to be the strongest determinant, followed by VB ($\beta = 0.249$, $t = 4.257$), IP ($\beta = 0.205$, $t = 3.360$), and UB ($\beta = 0.119$, $t = 2.072$). Similarly, among the factors that influence distrust, VB ($\beta = 0.444$, $t = 6.143$) has the most substantial influence, followed by GS ($\beta = 0.212$, $t = 2.901$). Furthermore, citizens' resistance to contact tracing apps registered a strong negative impact ($\beta = -0.564$, $t = 6.718$) on their behavioral intention to use the app.

Finally, the endogenous constructs' R² and Stone-Geisser's Q² values explain the model's explanatory power and predictive relevance, respectively (Hair et al., 2019). The R² values (see Table 7) indicate satisfactory explanatory power of the model. The R² value of intention to use reveals that 45.1% of the variance in the intention to use is accounted for by its predictors. Similarly, the R² value of resistance indicates that its predictors explain approximately 67.6% of its variance. Finally, 58.3% of the variance of distrust is attributed to its predictors in the empirical model. Furthermore, all the Q² values were found to be higher than zero (see Table 7), implying the high predictive relevance of the empirical model (Hair et al., 2019).

5.2. Mediation analysis

A mediation analysis was performed to evaluate the mediating impact of distrust on the relationships between innovation barriers and resistance. A PLS-SEM-based mediation analysis was performed using the bootstrapping method (Nitzl, 2016). The significance of the direct

Table 4
Discriminant validity (HTMT criteria).

	BI	CB	DT	GS	IP	RE	SR	UB	VB
BI									
CB	0.155								
DT	0.504	0.101							
GS	0.418	0.081	0.676						
IP	0.416	0.095	0.624	0.733					
RE	0.690	0.093	0.792	0.647	0.678				
SR	0.286	0.168	0.484	0.466	0.412	0.522			
UB	0.339	0.162	0.546	0.499	0.439	0.572	0.544		
VB	0.736	0.107	0.764	0.619	0.633	0.766	0.441	0.463	

Notes: As per HTMT criteria, all the HTMT values should be less than 0.85 for confirming discriminant validity.

Table 5
Discriminant validity (Fornell-Larcker criteria).

	BI	CB	DT	GS	IP	RE	SR	UB	VB
BI	0.965								
CB	0.174	0.862							
DT	-0.473	-0.008	0.869						
GS	-0.395	-0.006	0.613	0.922					
IP	-0.405	-0.063	0.572	0.675	0.882				
RE	-0.655	-0.107	0.728	0.600	0.644	0.939			
SR	-0.272	0.134	0.448	0.429	0.383	0.487	0.929		
UB	-0.310	0.082	0.471	0.439	0.388	0.505	0.474	0.861	
VB	-0.692	-0.118	0.696	0.569	0.592	0.708	0.409	0.408	0.961

Notes: As per Fornell-Larcker criteria, the inter-construct correlations should be less than the square root of AVE (diagonal values in bold italics font in the table) for confirming discriminant validity.

Table 6
VIF values.

	BI	DT	RE
BI			
CB		1.066	1.069
DT			2.399
GS		2.130	2.238
IP		2.105	2.124
RE	1.000		
SR		1.477	1.492
UB		1.457	1.493
VB		1.813	2.286

Table 7
Predictive validity and predictive relevance.

	R ²	R ² Adjusted	Q ²
BI	0.451	0.430	0.403
DT	0.583	0.570	0.427
RE	0.676	0.664	0.585

Notes: R² denotes the explanatory power of the model; R² Adjusted is the adjusted value of R²; Q² represents the predictive relevance of the model.

and indirect effects and the sign of the product of effects were examined to find out the type and magnitude of the mediation effect. Table 9 summarizes the findings of the mediation analysis. The results revealed that the indirect effects were significant for the variables GS and VB. Hence it can be concluded that there is no mediating effect of distrust between the other innovation barriers (CB, SR, IP, and UB) and RE. Then the direct effects were analyzed to assess the nature and magnitude of the mediation for the variables GS and VB. The direct effect was not significant for GS, implying that there is full mediation, while the direct effect was significant for VB, implying a partial mediation. The VAF value and the signs of direct and indirect effects of the VB (VAF = 35.98%) and indicate that the mediation effect of distrust is complementary partial mediation for the variable VB (Nitzl, 2016).

Table 8
Hypothesis testing.

Hypothesis	Path	B	t Statistics	p-value	Supported?
H1	RE → BI	-0.564	6.718	0.000	Yes***
H2	IP → RE	0.205	3.360	0.001	Yes**
H3	GS → RE	0.028	0.398	0.691	No
H4	SR → RE	0.108	1.699	0.089	No
H5	UB → RE	0.119	2.072	0.038	Yes*
H6	CB → RE	-0.086	1.401	0.161	No
H7	VB → RE	0.249	4.257	0.000	Yes***
H8	DT → RE	0.315	4.399	0.000	Yes***
H9	IP → DT	0.089	1.144	0.253	No
H10	GS → DT	0.212	2.901	0.004	Yes**
H11	SR → DT	0.079	1.304	0.192	No
H12	UB → DT	0.122	1.846	0.065	No
H13	CB → DT	0.031	0.689	0.491	No
H14	VB → DT	0.444	6.143	0.000	Yes***

Notes: β denotes the path coefficient; t denotes two-tailed t-test values; p-value stands for the significance level; Path significances: ***p < 0.001; **p < 0.01; *p < 0.05.

Source: PLS-SEM analysis.

6. Discussion

The aim of this research was to identify and examine the determinants of citizens' resistance to use DCT apps using a mixed-methods approach. Quantitative validation of the proposed model confirmed that distrust, value barrier, information privacy concern, and usage barrier were the direct determinants of citizens' resistance to the DCT app. Additionally, the mediation analysis revealed that factors, namely value barrier and government surveillance concern, have a significant indirect effect on resistance through distrust. We discuss the findings in greater detail below.

First, this research confirms the positive relationship between distrust (distrusting beliefs about the DCT app) and resistance to use the DCT app. It means that people who have high distrust in the DCT app are likely to resist using it. Distrust registered the strongest impact among the direct predictors of resistance. This study empirically validates the

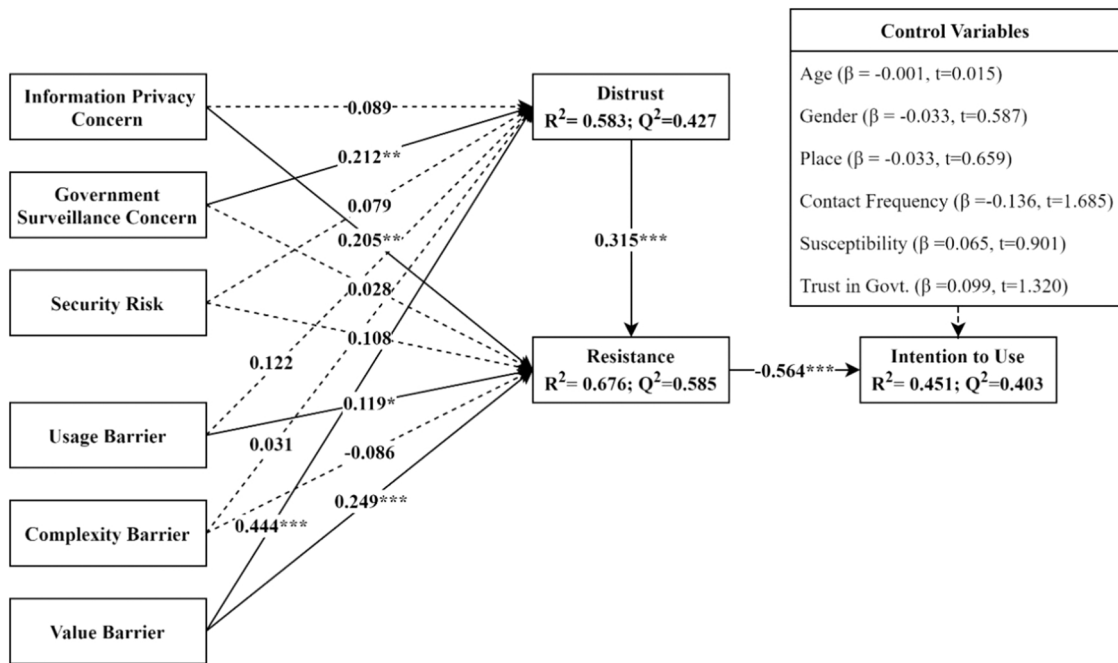


Fig. 2. Results of structural model assessment. Notes: Continuous line indicates an empirically significant relationship, and a dotted line indicates a statistically non-significant relationship; Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 9
Mediation analysis.

Relationship	Indirect Effect	t	p	Direct Effect	t	p	Mediation type	VAF (%)
<i>Mediation Effect of Distrust</i>								
CB → DT → RE	0.010	0.655	0.512	-0.086	1.401	0.161	NM	NA
GS → DT → RE	0.067	2.192	0.028	0.028	0.398	0.691	FM	NA
SR → DT → RE	0.025	1.148	0.251	0.108	1.699	0.089	NM	NA
IP → DT → RE	0.028	1.119	0.263	0.205	3.360	0.001	NM	NA
UB → DT → RE	0.038	1.686	0.092	0.119	2.072	0.038	NM	NA
VB → DT → RE	0.140	3.876	0.000	0.249	4.257	0.000	CPM	35.98%

Note: t, represents two-tailed t-test values; p denotes significance level; VAF, Variance Accounted For; FM, Full Mediation; CPM, Complementary Partial Mediation; NA, Not Applicable; NM, No Mediation.

argument that most citizens distrust the idea of DCT apps (Kreps, 2020; Muoio, 2020) and establishes that this belief could well be the prime deterrent to its widespread adoption. The findings are also in line with the surveys conducted in the USA, which point to widespread distrust of the DCT program among the citizens (Kreps et al., 2020; Ropek, 2020).

Second, the proposed relationship between value barrier and resistance is found significant. Empirically, it is found to be the second strongest determinant of resistance in the model. It implies that people who perceive that the DCT app does not offer superior benefits over the alternatives (or a perception of lack of benefits) are more likely to develop resistance towards using it. The results are in line with the earlier literature on smart products (Mani & Chouk, 2017) and smart services (Chouk & Mani, 2019). This finding is also similar to the findings reported by DCT app adoption studies in which related constructs such as perceived benefits (personal and societal), relative advantage, perceived usefulness/performance expectancy were identified as the determinants of adoption of DCT apps (Duan & Deng, 2021; Fox et al., 2021; Hassandoust et al., 2021; Lin et al., 2021; Sharma et al., 2020; Tomczyk et al., 2021; Touzani et al., 2021; Trkman et al., 2021;).

Third, this study also confirms the positive relationship between information privacy concerns and resistance to use DCT apps. This demonstrates that if people are worried about information privacy, they are more likely to avoid using DCT apps (Dwivedi et al., 2020). The finding is in consonance with the previous research on consumer resistance to smart services/devices (Chouk & Mani, 2019; Mani & Chouk,

2018). Several other studies related to DCT apps also have reported the negative impact of privacy concerns on the adoption intentions/behavior (Altmann et al., 2020; Duan & Deng, 2021; Fox et al., 2021; O’Callaghan et al., 2021; Sharma et al., 2020; Tretiakov & Hunter, 2021; Tomczyk et al., 2021; Walrave et al., 2021).

Finally, the results confirm that the usage barrier has a direct positive impact on the resistance. This implies that the individuals who perceive that using DCT apps can disrupt existing user habits and routines in an undesirable way (e.g., frequent battery charging, limiting the use for conserving battery) are more likely to resist it. This finding is in consonance with earlier research on innovation resistance, which identifies the usage barrier as a cause of negative attitude formation (Joachim et al., 2018; Laukkanen, 2016) and a determinant of active innovation resistance (Heidenreich & Spieth, 2013). This finding corroborates a recent survey (Nolsoe, 2020) which indicated that the majority of citizens are less likely to use the app if it depletes their battery life even moderately.

Unexpectedly, the factors, namely, government surveillance concern, security risk, and complexity barrier, did not significantly influence the resistance as proposed in the model. This result contradicts the findings reported by Chouk and Mani (2019). However, it should be noted that government surveillance concerns (along with value barriers) indirectly influence resistance through distrust. Mediation analysis revealed that the effect of the variable GS on resistance is fully mediated, and the effect of VB on resistance is partially mediated through distrust.

This implies that individuals who perceive a high degree of government surveillance or low value of DCT apps are inclined to develop a high degree of distrust towards DCT apps, which further leads to a high degree of resistance. Thus, the finding resonates with the views of the opinion paper (De et al., 2020) and a qualitative study (O'Callaghan et al., 2021), which suggested that state surveillance concerns could be a deterrent to the adoption of DCT apps. Unlike the previous studies on smart services (Chouk & Mani, 2019), this study, therefore, reveals the important role of distrust as a mediator between innovation barriers and resistance.

Nevertheless, this study did not observe any significant direct or indirect effects of the security risk and complexity barrier on resistance. The non-significant impact of the complexity barrier contradicts the results published in the case of innovation in general (Joachim et al., 2018) and smart services (Mani & Chouk, 2018) in particular. Conflicting evidence about the role of ease of use (effort expectancy) in predicting DCT app adoption also has been reported by earlier studies (Duan & Deng, 2021; O'Callaghan et al., 2021; Walrave et al., 2021). In this case, the relatively large majority of young respondents in the sample (80.93% < 37 years) could have been the reason for the non-significance of the complexity barrier. Young respondents would have perceived the innovation to be easy to learn/use and hence did not perceive any complexity associated with the use. Similarly, the non-significance of security risk on resistance contradicts the findings of Chouk and Mani (2019) and similar studies reported on DCT app adoption (Altmann et al., 2020; O'Callaghan et al., 2021). This implies that the perceived vulnerability of the DCT app to hacking is not a key consideration and does not lead to resistance. This could be because Indians have a tendency to overlook cyber security risks (Thejesh, 2016).

Additionally, among the factors that were proposed to influence distrust, only two factors, namely, government surveillance concerns and value barrier, were statistically significant. The findings indicate that distrust in the DCT app is determined by the degree of perceived value barrier and government surveillance concern (in the order of their relative strength). It is noteworthy that the other innovation barriers did not influence distrust significantly. This implies that distrust/suspicion in the DCT app mainly happens due to concerns about the state surveillance and perception of the lack of benefits from using the app. Further, as proposed, resistance to the DCT app had a strong negative effect on the intention to use, validating the original proposition in the active innovation literature that a negative attitude following a new product evaluation can reliably predict the future use intentions (Heidenreich & Spieth, 2013).

Finally, none of the control variables significantly impacted the intention to use except for contact frequency, which is slightly significant at a 90% confidence interval. Its beta value ($\beta = -0.136$, $t = 1.685$) suggests that as the contact frequency (respondent's self-reported frequency of physical contact with other people) increases, the individual's intention to use DCT apps decreases. One reason could be that as they engage more socially out of their personal or job-related responsibilities, they tend to lose the fear of contracting the virus and thus tends to play down the need to use DCT apps. While people who have the privilege of staying mostly indoors are more likely to be fearful of the disease and its consequences, and thus, they are likely to have positive intentions to use. Another important finding to be noted is the non-significant effect of the factor 'trust in government' on the intention to use, unlike indicated by DCT app adoption studies (Altmann et al., 2020; Touzani et al., 2021). A possible reason for this could be that individuals are more concerned about technology attributes than the government implementing the DCT app.

It is also worth noting that a large proportion of our sample belonged to the emerging adulthood (18–27 years – 50.52%) and young adulthood (27–37 years – 30.41%) age groups and was educated (graduate – 37.63% or postgraduate – 51.03%). This could have shaped the results of this study. Previous research has linked age to adoption or rejection

decisions (Laukkanen, 2016), with younger users more likely to accept technology than their older counterparts (Ferreira, da Rocha, & da Silva, 2014). Further, Laukkanen, Sinkkonen, Laukkanen, and Kivijarvi (2008) confirmed that demographics such as age could explain customers' resistance to mobile banking. Studies related to self-service checkouts (Lee, Jeong Cho, Xu, & Fairhurst, 2010) and internet voting (Bélanger & Carter, 2010) has also found a negative influence of age on intentions to use technology. Accordingly, we believe the barriers and resistance would have less among the younger age group, who is the major share of our respondents. However recent study on m-wallets could not establish the negative influence of age on m-wallet resistance (Leong et al., 2020).

Similarly, an individual's education level is related to technology usage behavior (Gunawardana & Ekanayaka, 2009). According to Laukkanen et al. (2008), customer resistance to mobile banking can be explained by education. Similarly, Leong et al. (2020) was of the opinion that consumers who are well-educated are more critical and cautious when determining whether or not to use an m-wallet, and hence are more wary of its adoption. In line with this, prior literature on social media suggests that younger age and educated individuals are more knowledgeable and concerned about the risk of online privacy and are more likely to engage in privacy protection behavior (Kezer, Sevi, Cemalcilar, & Baruh, 2016; Park, 2011; Van den Broeck, Poels, & Walrave, 2015). Thus, in this case, the perceived barriers and the resulting resistance would have been relatively high among the educated respondents, who constitute a major share of our respondents.

Examining the model's explanatory power, the values for the endogenous constructs, namely resistance (67.6%), distrust (58.3%), and intention to use (45.1%), are greater than the suggested value of 40% (Straub, Boudreau, & Gefen, 2004). This suggests the satisfactory performance of the model in terms of its predictive power.

6.1. Theoretical contributions and implications

Based on the results, this study has five theoretical contributions to the IS literature. First, to our knowledge, this study is the first to integrate the theories of innovation resistance and distrust to explain an innovation resistance phenomenon in the health IT setting. The only earlier study to have used theories of innovation resistance and distrust in combination is Nel and Boshoff (2021) to study consumer resistance to digital-only banks. Thus, this study has addressed the limited understanding of what factors contribute to the resistance towards DCT apps using a rare combination of theories. Additionally, the study has examined these influences during the COVID-19 pandemic, an incredibly rare global disruption, which provided a new research background for making contributions (Sein, 2020).

Second, since the DCT app is a newly introduced technology, studies on individuals' resistance to the DCT app are completely missing from the literature. Although the phenomenon was noted by the observers (Kreps et al., 2020; Kreps, 2020; Ropek, 2020), no study had examined why and how it occurs. This research provides a comprehensive empirically validated insight into the phenomenon of citizens' resistance to DCT apps among the nonadopter population using a mixed-methods approach.

Third, in terms of novel associations between the constructs, the relationship between distrust and resistance to DCT apps was strongly positive and statistically significant. This is a novel contribution to the innovation resistance literature (Heidenreich & Spieth, 2013; Kleijnen et al., 2009; Ram & Sheth, 1989) as well as the literature on technology distrust (McKnight & Chervany, 2001a, 2001b; McKnight et al., 2004). The relationships reported between innovation barriers and distrusting beliefs further validate the findings of an earlier study (in the context of digital banking) (Nel & Boshoff, 2021). This research has also empirically validated the role of distrust as a mediator between innovation barriers and innovation resistance in the context of a health technology, which is again an original addition to the literature on innovation resistance and resistance to health IT (Ali et al., 2016; Kumar, Singh,

Chandwani, & Gupta, 2020).

Fourth, although trust in technology has received considerable attention from the research fraternity, the phenomenon of distrust is severely under-researched (Nel & Boshoff, 2021). This study helps in addressing the dearth of empirical research related to distrust in the context of innovation resistance to a health IT. A specific contribution is that this study has identified the antecedents of distrusting beliefs in DCT apps and empirically validates its impact, which is a novel addition to the literature on distrust in technology (McKnight & Chervany, 2001a, 2001b; McKnight et al., 2004).

Finally, the contradictory findings (in comparison with prior literature) reported by this research, such as the non-significant impact of complexity barrier and security risk on resistance (Chouk & Mani, 2019; Heidenreich & Spieth, 2013; Joachim et al., 2018) and non-significance of control variables like trust in government, perceived susceptibility, age, on intention to use (Altmann et al., 2020; Touzani et al., 2021) calls for a more elaborate study incorporating a larger representative sample.

6.2. Implications for practice

This paper has significant practical implications that can aid decision-makers in the development and deployment of DCT apps, particularly in developing countries. Firstly, it has drawn out the factors that act as inhibitors to the acceptance of DCT apps. Addressing these factors could be key to improving the diffusion of this novel technology.

The results strongly suggest that the general public's distrust in the DCT app is the foremost deterrent to its adoption. Developers and healthcare policymakers in charge of implementation should primarily focus on the public's skepticism about the app's efficacy and reliability and prioritize trust-building efforts to improve its acceptance. Primarily, the efficacy of the DCT apps needs to be tested using scientific studies. The findings on key indicators such as false positivity rate must be communicated to the public to boost trust and facilitate improvements (Pandl et al., 2021). A recent paper on the efficacy of the UK government's DCT app is a good step in this direction (Wymant et al., 2021).

Furthermore, this research has provided insights to address distrust by finding the important determinants of distrusting beliefs. As per the finding of this study, distrust in the DCT app significantly depends on the innovation barriers, that is, perceptions about government surveillance and value barrier. Hence reducing the perceptions related to these innovation barriers is the key to potentially alleviating distrust in DCT apps. Communication strategies to overcome resistance in Internet banking recommended by Laukkanen et al. (2009) would be helpful in this case too.

Substantial performance value over alternatives must be provided to lower the perceived value barrier (Ram & Sheth, 1989). The benefits of using the DCT app must be made clear through adequate awareness programs. As stated above, the efficacy and usefulness of the app must be studied scientifically and communicated to the public to boost the perceived benefits. Additional information regarding the number of recent contacts, number of infections in an area, risk-prone areas, and so on should be provided to increase the perceived value. In addition, some value-added services like doctors on video/chat, online booking of tests, vaccination can also boost value perceptions.

Addressing government surveillance concerns could be much more challenging. Providing the user the ability to control when they want to pause tracking could help reduce the perception that they are always being tracked. Although this might reduce the effectiveness to some degree, this privacy control option can provide a sense of control and improve acceptance. Additionally, an independent agency constituted under the supervision of a trusted legal body (judiciary) which is at arm's length from the government to implement the DCT app program, could also be helpful.

The second most pressing factor that affects citizens' resistance is the value barrier. Measures for improving the value perceptions have been suggested in the earlier paragraph. The third most potent factor

influencing resistance is information privacy concerns, which imply that the best chance for improving tool adoption mainly lies in privacy-preserving settings and effectively communicating these measures to the community. Privacy concerns could be eased by preserving the anonymity of stored data, automatic deletion of data after a fixed period, and ensuring privacy-preserving settings/safeguards, such as using privacy seals & certificates by trusted third-party agencies like TRUSTe and VeriSign. Using a decentralized architecture for the DCT app, that is, one in which the proximity details are locally stored in the users' device rather than centralized servers (Sadeghi, Miettinen, & Nguyen, 2021), could help reduce privacy concerns. Even though Aarogya Setu is using a decentralized design, lack of proper awareness might be the reason for the persisting concern. Communication strategies should focus on highlighting this unique aspect of the app to reduce privacy concerns (Laukkanen et al., 2009). Additionally, having a well-crafted privacy policy that clearly addresses all nuances of data collection, usage and protection will help in reducing the uncertainty related to privacy (Chang, Wong, Libaque-Saenz, & Lee, 2018).

The fourth significant factor affecting resistance is usage barriers. Battery drainage issue and resulting disruption in the smartphone usage pattern is clearly a bottleneck in the adoption (Nolsoe, 2020). Unless the app is compatible with the past routines and lifestyles of the user, adoption is going to suffer. Addressing the usage barrier would require novel technological interventions in terms of finding more efficient schemes for Bluetooth-based tracking, which is not very easy to achieve given the variations in the architecture/specifications of smartphones/devices. However, other alternative technologies such as GPS, Bluetooth Low Energy and so on could be explored (Pandl et al., 2021).

The complexity barrier did not register a significant impact on either resistance or distrust in this study. This could be due to two reasons: 1) a higher proportion of young respondents in our sample, or 2) a simple and user-friendly design of the DCT app. Similarly, the impact of security risk on distrust and resistance is non-significant at a 95% confidence interval. However, the effect of security risk on resistance is significant at a 90% confidence interval ($\beta = 0.108$, $t = 1.699$). Security risk could be addressed by using measures like third-party seals/certificates and by opening the app source code for scrutiny by security experts and incorporating the crowdsourced recommendations.

Furthermore, the data suggest that people who have higher contact frequencies, that is, people who engage more with others out of personal or job-related responsibilities, are less likely to use DCT apps. This can arise majorly due to two reasons: 1) As they engage more with others, they tend to lose their fear of the disease and hence play down the need to use the app. 2) They could be fearful of being quarantined if they use the app as their chances of interacting with positive cases are more. In either way, one important implication is that to control the spread of the disease, it is important to track the people who have higher contact frequencies. So, the government should mandate the usage of DCT apps among the working class, commuters, and travelers to compensate for their reduced intention to use.

Another important implication is with respect to the trust in the government. The findings suggest that the intention to use DCT app is not associated with trust in (central) government. This implies that individuals' decision to use DCT app depends on their evaluation of the app's attributes rather than their trust in the central government implementing the app. This result is significant in a diverse and heterogeneous country like India, where there are people of different political ideologies (both supporting and against the central government). The result implies that the government cannot capitalize just on its goodwill and support among citizens for the success of the DCT app-based pandemic control program. Instead, it should rather focus on improving the technical features of the app and citizens' perception about the same.

6.3. Limitations and future research directions

Notwithstanding the findings, this study has certain shortcomings, some of which may be explored in future studies. First, by choosing India as a study location, the results of this study can be found particularly applicable to related countries (developing countries). Acknowledging that national culture influences the acceptance of new technology like the DCT app (Sharma et al., 2020), further studies are required to apply the observations to other countries. Therefore, it is suggested that researchers could examine the hypotheses in other settings and explore the influence of cultural factors on resistance behavior.

Second, pertaining to the sampling and demographic profile of the respondents, we observe that the sample was slightly skewed towards young age (18–27 years – 50.52%) and educated (graduate – 37.63% or postgraduate – 51.03%) individuals. Although we tried to target all demographic groups, the individuals who were aware of the DCT app at the time of the survey (3 months since the launch of the DCT app in India) could have been predominantly from this tech-savvy young age group. Another reason could be that since we used the online survey mode circulated mainly via social media channels to recruit the respondents, educated, young respondents who are a clear majority on these platforms might have responded in a relatively higher ratio. Also, since the study was kept voluntary, we could not get adequate responses from the other groups despite our efforts. Further, the use of a convenience sample and the relatively limited sample size restrict the results’ generalizability. Corroboration of the findings through a larger, representative sample (covering all demographic groups) will add credibility to the observations of this study. In line with this, the moderating impact of demographic variables like age, gender, education, income, personality type, and political affiliations on innovation resistance and its behavioral outcomes could be explored to understand the complexity of this phenomenon further. Similarly, we have only considered one mediator (distrust in the DCT app) between barriers and resistance. In the future, researchers could explore the role of other relevant mediators.

Third, in terms of the outcome of the active innovation resistance, i.e., “a negative attitude formation driven by product-specific barriers that follow new product evaluation.” (Heidenreich & Spieth, 2013) in this study, we have only considered one outcome, i.e., “intention to use.” as per the literature there could be other outcomes such as dissatisfaction and negative word-of-mouth (Huang et al., 2021). It would be worthy of exploring the other outcomes of active innovation resistance to DCT apps.

Fourth, our research was cross-sectional in nature and did not

evaluate how the innovation resistance developed and manifested over a period of time. Further modification and validation of the model in similar settings, perhaps with other relevant variables, using a longitudinal study methodology, is thus recommended. Finally, this study did not distinguish between different forms of resistance (e.g., passive, active). It would be interesting to investigate the impact of the established influences on passive (e.g., postponement) and active (e.g., rejection, opposition) forms of resistance. Also, the current study did not distinguish between pre-adoption and post-adoption (e.g., discontinuance) phases. Hence the manifestation of resistance behavior in the pre-adoption and post-adoption phases is an important topic for future research (Huang et al., 2021).

7. Conclusions

This study looked at the very recent phenomena of citizens’ resistance to DCT apps and its determinants among the nonadopter population using a mixed-methods approach. The findings of this research reveal that the public’s distrust in the DCT app, perceived lack of value/benefits, concerns about information privacy, and usage barriers are the primary drivers of resistance. Further, concerns about government surveillance through the app and the value barrier results in the formation of distrust in the DCT app. The practical insights provided by this study could guide potential improvements and aid the formulation of effective communication strategies and policy decisions to facilitate better diffusion of DCT apps during the present and future disease outbreaks.

CRedit authorship contribution statement

Ashish Viswanath Prakash: Conceptualization, Investigation, Methodology, Software, Data curation, Formal analysis, Visualization, Writing – original draft. **Saini Das:** Methodology, Writing – original draft, Writing – review & editing, Supervision, Validation.

Declarations of interest

None.

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Appendix A. Overview of interview data sources

Participant #	Age	Gender	Education	Job	Place
P1	29	Male	Postgraduate	Deputy Engineer	Bangalore
P2	53	Female	Postgraduate	Kindergarten Teacher	Kharagpur
P3	45	Male	Postgraduate	Material expert	Bangalore
P4	26	Male	Postgraduate	PG Student	Chennai
P5	28	Male	Graduate	Engineer	Trivandrum
P6	32	Male	Doctorate	Assistant Professor	Roorkee
P7	30	Male	Postgraduate	Researcher	Dhanbad
P8	31	Male	Postgraduate	Researcher	Ranchi
P9	30	Male	Postgraduate	Documentation Engineer	Hyderabad
P10	28	Female	Graduate	Systems Engineer	Indore
P11	25	Female	Postgraduate	Design Engineer	Hyderabad
P12	36	Male	Graduate	Electrical Engineer	Mysore
P13	25	Female	Postgraduate	Software Engineer	Kochi
P14	26	Female	Graduate	Student	Mangalore
P15	28	Male	Postgraduate	Associate Manager	Bangalore
P16	27	Male	Graduate	Consultant	Chennai
P17	26	Female	Graduate	Senior Product Engineer	Trivandrum
P18	37	Female	Doctorate	Assistant Professor	Manipal

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Participant #	Age	Gender	Education	Job	Place
P19	26	Female	Postgraduate	Student	Lucknow
P20	26	Male	Doctorate	Researcher	Delhi
P21	35	Female	Graduate	Consultant	Kolkata
P22	40	Male	Doctorate	Assistant Professor	Kharagpur
P23	30	Female	Postgraduate	Data Analyst	Chandigarh
P24	32	Male	Postgraduate	Regional Sales Manager	Surat

Appendix B. Findings of the preliminary qualitative study

Factor	Sample excerpts from semi-structured interviews	Potential relationship of the factor with the dependent variable RE	Supporting theory & empirical research from the literature
Information Privacy Concern (IP)	<p>“Look, the app is even collecting real-time location info of the users, in addition to all the other personal data. They will get to know who is where and doing what in real-time. It is like being completely naked; tell me what is left? user’s privacy is a huge concern.” [P4]</p> <p>“My concern is privacy. Post-pandemic, the data collected need to be kept safe or need to be wiped out. We have already witnessed the data mismanagement with respect to the Aadhaar database.” [P15]</p> <p>“Concern is regarding how secure is the app, is our data protected? Is the data analyzed by the government or some third-party companies?” [P19]</p>	Positively influence RE	IRT (Ram & Sheth, 1989) (Chouk & Mani, 2019; Mani & Chouk, 2019)
Government Surveillance Concern (GS)	<p>“I wouldn’t like to be tracked everywhere by the government.” [P23]</p> <p>“I am afraid of the fact that I could be identified and tracked by the government agencies. I’m afraid if it is the beginning of a new surveillance state” [P5]</p> <p>“I am worried if this would be misused by the government agencies to track and abuse people, [..]. I would better not install and invite trouble” [P7]</p>	Positively influence RE	IRT (Ram & Sheth, 1989) (Chouk & Mani, 2019; Dinev et al., 2008; Mani & Chouk, 2019)
Distrust in the DCT app (DT)	<p>“Does not give accurate data. In my building, there are six patients. They are not listed in a 500 m radius. Not foolproof. Not reliable.” [P20]</p> <p>“The efficacy of the app is yet to be proven, the accuracy of the algorithm is questionable, e.g., Bluetooth may travel across physical barriers [...] and hence could give a lot of false positives [..] I don’t think I can trust this app” [P24]</p>	Positively influence RE	Theory of distrust in technology (McKnight & Choudhury, 2006; McKnight et al., 2004; Nel & Boshoff, 2021)
Security Risk (SR)	<p>“How secure are these systems and servers? It is a goldmine and will be a target to hackers. There have been instances in the past where similar security flags were raised against government apps”. [P13]</p> <p>“Keeping the Bluetooth always on would make my phone visible to hackers and viruses. Can’t they use some other mechanisms?” [P10]</p> <p>“I am doubtful about the security of the app. I heard that there are many flaws and that it is vulnerable to hacking” [P20]</p>	Positively influence RE	IRT (Ram & Sheth, 1989) (Chouk & Mani, 2019; Mani & Chouk, 2019)
Usage Barrier (UB)	<p>“...keeping app setting as location sharing always is going to kill my battery life. I would need to either carry a power bank or limit my phone usage” [P21]</p> <p>“It was keeping my Bluetooth and location sharing always on. I found that my device was getting heated up, and the battery was draining very fast. I uninstalled the app due to this.” [P11]</p>	Positively influence RE	IRT (Ram & Sheth, 1989) (Heidenreich & Spieth, 2013; Joachim et al., 2018; Kleijnen et al., 2009)
Complexity Barrier (CB)	<p>“The app looks complicated to use. Need to be more simple and less cluttered” [P18]</p> <p>“although the youngsters might find it easy to use, I am afraid using it will be a pain for the aged and elderly. For example, my dad is not very tech-savvy. [...] he might find it difficult and hence not use it” [P7]</p>	Positively influence RE	IRT (Ram & Sheth, 1989) (Mani & Chouk, 2018, 2019)
Value Barrier (VB)	<p>“I don’t think it will be really useful because to be effective it would require a large percentage of people to use it. Many people don’t have smartphones...” [P14]</p> <p>“I uninstalled the app [..] I find it pretty much useless; it does not update positive cases regularly and always shows that I am safe. The other information available on this app is similar to what I get on Google or health ministry website.” [P11]</p> <p>“And then it’s useless there were at least ten positive cases nearby but no updates in the app. I can get better information about cases from local media. What is the purpose of using this app?” [P12]</p>	Positively influence RE	IRT (Ram & Sheth, 1989) (Joachim et al., 2018; Kleijnen et al., 2009; Mani & Chouk, 2018)

Note: P1–P24 refers to participants of semi-structured interviews, RE, Resistance to use DCT app; IRT, Innovation resistance theory.

Appendix C. Measurement scales

Construct	Item Code	Item	Source
Resistance to DCT app	RE1	I have a negative opinion about the Aarogya-Setu app	(Heidenreich & Spieth, 2013; Mani & Chouk, 2018)
	RE2	I am not in favor of the Aarogya-Setu app	
	RE3	I do not like the idea of using the Aarogya-Setu app	
Information Privacy Concerns	IP1	I am concerned if this app is collecting too much personal information about me	(Smith, Milberg, & Burke, 1996)
	IP2	I am concerned if this app uses my personal information for other purposes without getting my authorization	
	IP3	I am concerned if the app databases that contain my personal information are not protected from unauthorized access	
	IP4	I am concerned if this app does not have thorough procedures to prevent errors in my personal information	
Government Surveillance Concern	IP5	I have doubts as to how well my privacy is protected on this app	Adapted from Dinev et al. (2008)
	GS1	I am concerned about the government's ability to monitor my location data (using GPS tracking) through this app	
	GS2	I am concerned about the government's ability to monitor my interaction/contact with other people (using GPS/Bluetooth tracking) through this app	
Distrust in the DCT app	GS3	I am concerned about the government's ability to monitor my COVID-19 infection risk status through this app	Adapted from Chau et al. (2013), McKnight and Choudhury (2006)
	DT1	I feel uncertain about whether this app performs its role of COVID-19 contact tracing very well	
	DT2	I am skeptical about whether this app is reliable	
Perceived Security Risk	DT3	I feel uncertain about whether this app would keep its commitments	Adapted from Jun, Lee, and Kim (2016)
	DT4	If I required help, I feel apprehensive about whether this app would do its best to help me	
	SR1	I believe the risk of my phone getting hacked via Bluetooth is high	
	SR2	I believe the risk of data theft (from my device) through unauthorized access is high	
Perceived Usage Barrier	SR3	I believe the risk of hackers securing control over the stored personal information (e.g., credit card number, bank account data, pictures) is high	Adapted from Joachim et al. (2018)
	UB1	Using this app will require more frequent battery charging (or carrying a power bank) as the battery would drain much faster	
	UB2	Using this app will require me to limit my usage of the smartphone to conserve the battery power	
Perceived Complexity Barrier	UB3	Using this app is not compatible with my lifestyle/routine	(Heidenreich & Spieth, 2013)
	CB1	Learning to use this app would be difficult for me	(Heidenreich & Spieth, 2013)
	CB2	I believe this app would be difficult to use	
Perceived Value Barrier	CB3	I am worried that this app is cumbersome, and I am unsure about handling it	Adapted from Chaouali and Souiden (2019), Laukkanen (2016)
	VB1	I am quite skeptical about the benefits of using the Aarogya Setu app	
	VB2	In my opinion, the Aarogya Setu app does not offer any advantage compared to manual contact tracing methods or other alternatives	
Intention to use	B1	I intend to use the Aarogya Setu app within the next four weeks (one month)	Adapted from Venkatesh et al. (2003)
	B2	I predict that I will use the Aarogya Setu app in the next four weeks (one month)	
	B3	I plan to use the Aarogya Setu app in the next four weeks (one month)	
Control Variables			
Age	Age (in years)		
Gender	Gender: Male, Female, Other		
Place	Place of residence: Rural, Urban		
Contact Frequency	How often are you currently in close contact with people outside of your household, for example, at work or socially?		(Altmann et al., 2020)
Perceived Susceptibility	Not more than once per week (1) – A few times per week (2) – A few times per day (3) – Many times per day (4)		
	How likely do you think it is that you will contract COVID-19 over the next one month?		(Nan & Kim, 2014)
Trust in Government	Extremely Unlikely (1) – Extremely Likely (7)		
	"I generally trust the government (central) to do what is right." Fully disagree (1) – Fully agree (5)		(Altmann et al., 2020)

References

- Ali, M., Zhou, L., Miller, L., & Ieromonachou, P. (2016). User resistance in IT: A literature review. *International Journal of Information Management*, 36(1), 35–43. <https://doi.org/10.1016/j.ijinfomgt.2015.09.007>
- Altmann, S., Milsom, L., Zillesen, H., Blasone, R., Gerdon, F., Bach, R., ... Abeler, J. (2020). Acceptability of app-based contact tracing for COVID-19: Cross-country survey study. *JMIR MHealth and UHealth*, 8(8), Article e19857. <https://doi.org/10.2196/19857>
- Anglemyer, A., Moore, T. H., Parker, L., Chambers, T., Grady, A., Chiu, K., ... Bero, L. (2020). Digital contact tracing technologies in epidemics: A rapid review. *Cochrane Database of Systematic Reviews*, 8. <https://doi.org/10.1002/14651858.CD013699>
- Bélanger, F., & Carter, L. (2010). The digital divide and internet voting acceptance. In *Proceedings of the 2010 fourth international conference on digital society* (pp. 307–310). <https://doi.org/10.1109/ICDS.2010.54>
- Ben-David, Y., Hasan, S., Pal, J., Vallentin, M., Panjwani, S., Gutheim, P., ... Brewer, E. A. (2011). Computing security in the developing world: a case for multidisciplinary research. In *Proceedings of the 5th ACM workshop on networked systems for developing regions* (pp. 39–44). <https://doi.org/10.1145/1999927.1999939>
- Bengio, Y., Janda, R., Yu, Y. W., Ippolito, D., Jarvie, M., Pilat, D., ... Sharma, A. (2020). The need for privacy with public digital contact tracing during the COVID-19 pandemic. *The Lancet Digital Health*, 2(7), e342–e344. [https://doi.org/10.1016/S2589-7500\(20\)30133-3](https://doi.org/10.1016/S2589-7500(20)30133-3)
- Bi, Q., Wu, Y., Mei, S., Ye, C., Zou, X., Zhang, Z., ... Feng, T. (2020). Epidemiology and transmission of COVID-19 in 391 cases and 1286 of their close contacts in Shenzhen, China: A retrospective cohort study. *The Lancet Infectious Diseases*, 20(8), 911–919. [https://doi.org/10.1016/S1473-3099\(20\)30287-5](https://doi.org/10.1016/S1473-3099(20)30287-5)
- Blom, A. G., Wenz, A., Cornesse, C., Rettig, T., Fikel, M., Friedel, S., ... Krieger, U. (2021). Barriers to the large-scale adoption of the COVID-19 contact-tracing app in Germany: Survey study. *Journal of Medical Internet Research: JMIR*, 23(3), Article e23362. <https://doi.org/10.1073/pnas.2007658117>
- Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., ... Pammolli, F. (2020). Economic and social consequences of human mobility restrictions under COVID-19. *Proceedings of the National Academy of Sciences*, 117(27), 15530 LP–15515535. <https://doi.org/10.1073/pnas.2007658117>
- Bradshaw, T. (2020). *Warning that contact-tracing apps will fail without high uptake.* (<https://www.ft.com/content/f00483e1-d5f9-4ef4-8dac-01b89cf50ec9>)
- Braithwaite, I., Callender, T., Bullock, M., & Aldridge, R. W. (2020). Automated and partly automated contact tracing: A systematic review to inform the control of COVID-19. *The Lancet Digital Health*, 2(11), e607–e621. [https://doi.org/10.1016/S2589-7500\(20\)30184-9](https://doi.org/10.1016/S2589-7500(20)30184-9)
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp0630a>

- Carpenter, D., Young, D. K., Barrett, P., & McLeod, A. J. (2019). Refining technology threat avoidance theory. *Communications of the Association for Information Systems*, 44. <https://doi.org/10.17705/1CAIS.04422>
- Chamaret, C., Steyer, V., & Mayer, J. C. (2020). "Hands off my meter!" When municipalities resist smart meters: Linking arguments and degrees of resistance. *Energy Policy*, 144, Article 111556. <https://doi.org/10.1016/j.enpol.2020.111556>
- Chang, Y., Wong, S. F., Libaque-Saenz, C. F., & Lee, H. (2018). The role of privacy policy on consumers' perceived privacy. *Government Information Quarterly*, 35(3), 445–459. <https://doi.org/10.1016/j.giq.2018.04.002>
- Chaouali, W., & Souden, N. (2019). The role of cognitive age in explaining mobile banking resistance among elderly people. *Journal of Retailing and Consumer Services*, 50, 342–350. <https://doi.org/10.1016/j.jretconser.2018.07.009>
- Chau, P. Y. K., Ho, S. Y., Ho, K. K. W., & Yao, Y. (2013). Examining the effects of malfunctioning personalized services on online users' distrust and behaviors. *Decision Support Systems*, 56, 180–191. <https://doi.org/10.1016/j.dss.2013.05.023>
- Chen, Q., Lu, Y., Gong, Y.(Y.), & Tang, Q. (2019). Why do users resist service organization's brand mobile apps? The force of barriers versus cross-channel synergy. *International Journal of Information Management*, 47, 274–282. <https://doi.org/10.1016/j.ijinfomgt.2018.07.012>
- Cho, J. (2006). The mechanism of trust and distrust formation and their relational outcomes. *Journal of Retailing*, 82(1), 25–35. <https://doi.org/10.1016/j.jretai.2005.11.002>
- Chouk, I., & Mani, Z. (2019). Factors for and against resistance to smart services: Role of consumer lifestyle and ecosystem related variables. *Journal of Services Marketing*, 33, 449–462. <https://doi.org/10.1108/JSM-01-2018-0046>
- Clarance, A. (2020, May 15). *Aarogya setu: Why India's covid-19 contact tracing app is controversial*. BBC News. (<https://www.bbc.com/news/world-asia-india-52659520>)
- Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). *The cost of the Covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending*. National Bureau of Economic Research Working Paper Series, No. 27141. (<https://doi.org/10.3386/w27141>)
- Corbin, J. M., & Strauss, A. (1990). Grounded theory research: Procedures, canons, and evaluative criteria. *Qualitative Sociology*, 13(1), 3–21. <https://doi.org/10.1007/BF00988593>
- Curran, J. M., & Meuter, M. L. (2005). Self-service technology adoption: Comparing three technologies. *Journal of Services Marketing*, 19, 103–113. <https://doi.org/10.1108/08876040510591411>
- De, R., Pandey, N., & Pal, A. (2020). Impact of digital surge during Covid-19 pandemic: A viewpoint on research and practice. *International Journal of Information Management*, 55, Article 102171. <https://doi.org/10.1016/j.ijinfomgt.2020.102171>
- Dimoka, A. (2010). What does the brain tell us about trust and distrust? Evidence from a functional neuroimaging study. *MIS Quarterly*, 34(2), 373–396. <https://doi.org/10.2307/20721433>
- Dinev, T., Hart, P., & Mullen, M. R. (2008). Internet privacy concerns and beliefs about government surveillance—An empirical investigation. *The Journal of Strategic Information Systems*, 17(3), 214–233. <https://doi.org/10.1016/j.jsis.2007.09.002>
- Duan, S. X., & Deng, H. (2021). Hybrid analysis for understanding contact tracing apps adoption. *Industrial Management & Data Systems*, 121(7), 1599–1616. <https://doi.org/10.1108/IMDS-12-2020-0697>
- Dwivedi, Y. K., Hughes, D. L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., ... Upadhyay, N. (2020). Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life. *International Journal of Information Management*, 55, Article 102211. <https://doi.org/10.1016/j.ijinfomgt.2020.102211>
- Fahey, R. A., & Hino, A. (2020). COVID-19, digital privacy, and the social limits on data-focused public health responses. *International Journal of Information Management*, 55, Article 102181. <https://doi.org/10.1016/j.ijinfomgt.2020.102181>
- Farronato, C., Iansiti, M., Bartosiak, M., Denicolai, S., Ferretti, L., & Fontana, R. (2020). *How to get people to actually use contact-tracing apps*. (<https://hbr.org/2020/07/how-to-get-people-to-actually-use-contact-tracing-apps>)
- Ferguson, N. M., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., ... Cuomo-Dannenburg, G. (2020). *Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand*. (<https://doi.org/10.2020.77482>)
- Ferreira, J. B., da Rocha, A., & da Silva, J. F. (2014). Impacts of technology readiness on emotions and cognition in Brazil. *Journal of Business Research*, 67(5), 865–873. <https://doi.org/10.1016/j.jbusres.2013.07.005>
- Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., ... Fraser, C. (2020). Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science*, 368(6491), eabb6936. <https://doi.org/10.1126/science.abb6936>
- Fox, G., Clohessy, T., van der Werff, L., Rosati, P., & Lynn, T. (2021). Exploring the competing influences of privacy concerns and positive beliefs on citizen acceptance of contact tracing mobile applications. *Computers in Human Behavior*, 121, Article 106806. <https://doi.org/10.1016/j.chb.2021.106806>
- Ghazali, E. M., Mutum, D. S., Pua, M. H.-J., & Ramayah, T. (2020). Status-quo satisfaction and smartwatch adoption: A multi-group analysis. *Industrial Management & Data Systems*, 120(12), 2319–2347. <https://doi.org/10.1108/IMDS-10-2019-0576>
- Gunawardana, K., & Ekanayaka, S. (2009). An empirical study of the factors that impact medical representatives' attitude toward the intention to use m-learning for career development. *Sasin Journal of Management*, 15(1), 1–26.
- Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. SAGE Publications.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hassandoust, F., Akhlaghpour, S., & Johnston, A. C. (2021). Individuals' privacy concerns and adoption of contact tracing mobile applications in a pandemic: A situational privacy calculus perspective. *Journal of the American Medical Informatics Association*, 28(3), 463–471. <https://doi.org/10.1093/jamia/ocaa240>
- He, W., Zhang, Z.(J.), & Li, W. (2021). Information technology solutions, challenges, and suggestions for tackling the COVID-19 pandemic. *International Journal of Information Management*, 57, Article 102287. <https://doi.org/10.1016/j.ijinfomgt.2020.102287>
- Hegde, A., & Masthi, R. (2020). Digital contact tracing in the COVID-19 pandemic: A tool far from reality. *Digital Health*, 6. <https://doi.org/10.1177/2055207620946193> (2055207620946193).
- Heidenreich, S., & Kraemer, T. (2016). Innovations—Doomed to fail? Investigating strategies to overcome passive innovation resistance. *Journal of Product Innovation Management*, 33(3), 277–297. <https://doi.org/10.1111/jpim.12273>
- Heidenreich, S., & Spieth, P. (2013). Why innovations fail — The case of passive and active innovation resistance. *International Journal of Innovation Management*, 17(05), Article 1350021. <https://doi.org/10.1142/S1363991613500217>
- Hinch, R., Probert, W., Nurtay, A., Kendall, M., Wymant, C., Hall, M., & Fraser, C. (2020). *Effective configurations of a digital contact tracing app: A report to NHSX*. Retrieved from (<https://www.pepp-pt.org>).
- Huang, D., Jin, X., & Coghlan, A. (2021). Advances in consumer innovation resistance research: A review and research agenda. *Technological Forecasting and Social Change*, 166, Article 120594. <https://doi.org/10.1016/j.techfore.2021.120594>
- Joachim, V., Spieth, P., & Heidenreich, S. (2018). Active innovation resistance: An empirical study on functional and psychological barriers to innovation adoption in different contexts. *Industrial Marketing Management*, 71, 95–107. <https://doi.org/10.1016/j.indmarman.2017.12.011>
- Johnson, R. E., Rosen, C. C., & Djurdjevic, E. (2011). Assessing the impact of common method variance on higher order multidimensional constructs. *The Journal of Applied Psychology*, 96(4), 744–761. <https://doi.org/10.1037/a0021504>
- Jun, J., Lee, K. J., & Kim, B. G. (2016). Factors affecting user acceptance of mobile commerce services. *Asia Pacific Journal of Information Systems*, 26(4), 489–508. <https://doi.org/10.14329/apjis.2016.26.4.489>
- Kaplan, M. F. (1976). Measurement and generality of response dispositions in person perception. *Journal of Personality*, 44(2), 179–194. <https://doi.org/10.1111/j.1467-6494.1976.tb00117.x>
- Kaspar, K. (2020). Motivations for social distancing and app use as complementary measures to combat the COVID-19 pandemic: Quantitative survey study. *Journal of Medical Internet Research*, 22(8), Article e21613.
- Kaur, P., Dhir, A., Singh, N., Sahu, G., & Almotairi, M. (2020). An innovation resistance theory perspective on mobile payment solutions. *Journal of Retailing and Consumer Services*, 55, Article 102059. <https://doi.org/10.1016/j.jretconser.2020.102059>
- Kezer, M., Sevi, B., Cemalcilar, Z., & Baruh, L. (2016). Age differences in privacy attitudes, literacy and privacy management on Facebook. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, 10(1), Article 2. <https://doi.org/10.5817/CP2016-1-2>
- Kim, J., Seo, J., Zo, H., & Lee, H. (2021). Why digital goods have not replaced traditional goods: The case of e-books. *Journal of Enterprise Information Management*, 34(3), 793–810. <https://doi.org/10.1108/JEIM-05-2019-0129>
- Kind, C. (2020). Exit through the app store? *Patterns*, 1(3), Article 100054. <https://doi.org/10.1016/j.patter.2020.100054>
- Kleijnen, M., Lee, N., & Wetzels, M. (2009). An exploration of consumer resistance to innovation and its antecedents. *Journal of Economic Psychology*, 30(3), 344–357. <https://doi.org/10.1016/j.joep.2009.02.004>
- Klenk, M., & Duijff, H. (2020). *Ethics of digital contact tracing and COVID-19: Who is (not) free to go?* Ethics and Information Technology. (<https://doi.org/10.1007/s10676-020-09544-0>)
- Kreps, S. (2020). *New Apple iOS supports contact tracing — But is meaningless without government adoption*. (<https://news.cornell.edu/media-relations/tip-sheets/new-apple-ios-supports-contact-tracing-meaningless-without-government>)
- Kreps, S., Zhang, B., & McMurry, N. (2020). *Contact-tracing apps face serious adoption obstacles*. (<https://www.brookings.edu/techstream/contact-tracing-apps-face-serious-adoption-obstacles/>)
- Kuisma, T., Laukkanen, T., & Hiltunen, M. (2007). Mapping the reasons for resistance to internet banking: A means-end approach. *International Journal of Information Management*, 27(2), 75–85. <https://doi.org/10.1016/j.ijinfomgt.2006.08.006>
- Kumar, M., Singh, J. B., Chandwani, R., & Gupta, A. (2020). "Context" in healthcare information technology resistance: A systematic review of extant literature and agenda for future research. *International Journal of Information Management*, 51, Article 102044. <https://doi.org/10.1016/j.ijinfomgt.2019.102044>
- Lanzing, M. (2020). *Contact tracing apps: An ethical roadmap*. Ethics and Information Technology. (<https://doi.org/10.1007/s10676-020-09548-w>)
- Laukkanen, T. (2016). Consumer adoption versus rejection decisions in seemingly similar service innovations: The case of the internet and mobile banking. *Journal of Business Research*, 69(7), 2432–2439. <https://doi.org/10.1016/j.jbusres.2016.01.013>
- Laukkanen, T., Sinkkonen, S., & Laukkanen, P. (2009). Communication strategies to overcome functional and psychological resistance to Internet banking. *International Journal of Information Management*, 29(2), 111–118. <https://doi.org/10.1016/j.ijinfomgt.2008.05.008>
- Laukkanen, T., Sinkkonen, S., Laukkanen, P., & Kivijarvi, M. (2008). Segmenting bank customers by resistance to mobile banking. *International Journal of Mobile Communications*, 6(3), 309–320.
- Lee, H., Jeong Cho, H., Xu, W., & Fairhurst, A. (2010). The influence of consumer traits and demographics on intention to use retail self-service checkouts. *Marketing Intelligence & Planning*, 28(1), 46–58. <https://doi.org/10.1108/02634501011014606>

- Lee, J., Lee, J.-N., & Tan, B. C. Y. (2015). Antecedents of cognitive trust and affective distrust and their mediating roles in building customer loyalty. *Information Systems Frontiers*, 17(1), 159–175. <https://doi.org/10.1007/s10796-012-9392-7>
- Leong, L.-Y., Hew, T.-S., Ooi, K.-B., & Wei, J. (2020). Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management*, 51, Article 102047. <https://doi.org/10.1016/j.ijinfomgt.2019.102047>
- Li, J., & Guo, X. (2020). COVID-19 contact-tracing apps: A survey on the global deployment and challenges. In *arXiv e-prints* (p. arXiv:2005.03599). (<https://ui.adsabs.harvard.edu/abs/2020arXiv200503599L>).
- Lian, J.-W., & Yen, D. C. (2013). To buy or not to buy experience goods online: Perspective of innovation adoption barriers. *Computers in Human Behavior*, 29(3), 665–672. <https://doi.org/10.1016/j.chb.2012.10.009>
- Lin, J., Carter, L., & Liu, D. (2021). Privacy concerns and digital government: Exploring citizen willingness to adopt the COVIDSafe app. *European Journal of Information Systems*, 30(4), 389–402. <https://doi.org/10.1080/0960085X.2021.1920857>
- Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *The Journal of Applied Psychology*, 86(1), 114–121. <https://doi.org/10.1037/0021-9010.86.1.114>
- Madianou, M. (2020). A second-order disaster? Digital technologies during the COVID-19 pandemic. *Social Media + Society*, 6(3). <https://doi.org/10.1177/2056305120948168>
- Mani, Z., & Chouk, I. (2017). Drivers of consumers' resistance to smart products. *Journal of Marketing Management*, 33(1–2), 76–97. <https://doi.org/10.1080/0267257X.2016.1245212>
- Mani, Z., & Chouk, I. (2018). Consumer resistance to innovation in services: Challenges and barriers in the internet of things era. *Journal of Product Innovation Management*, 35(5), 780–807. <https://doi.org/10.1111/jpim.12463>
- Mani, Z., & Chouk, I. (2019). Impact of privacy concerns on resistance to smart services: Does the 'Big Brother effect' matter? *Journal of Marketing Management*, 35(15–16), 1460–1479. <https://doi.org/10.1080/0267257X.2019.1667856>
- Martinez-Martin, N., Wieten, S., Magnus, D., & Cho, M. K. (2020). Digital contact tracing, privacy, and public health. *Hastings Center Report*, 50(3), 43–46. <https://doi.org/10.1002/hast.1131>
- McKnight, D. H., & Chervany, N. (2001a). While trust is cool and collected, distrust is fiery and frenzied: A model of distrust concepts. In *AMCIS 2001 proceedings*, 171.
- McKnight, D. H., & Chervany, N. L. (2001b). Trust and distrust definitions: One bite at a time. In *Trust in cyber-societies* (pp. 27–54). Berlin, Heidelberg: Springer.
- McKnight, D. H., & Choudhury, V. (2006). Distrust and trust in B2C e-commerce: Do they differ? In *Proceedings of the 8th international conference on electronic commerce: the new e-commerce: innovations for conquering current barriers, obstacles and limitations to conducting successful business on the internet* (pp. 482–491).
- McKnight, D. H., Kacmar, C. J., & Choudhury, V. (2004). Dispositional trust and distrust distinctions in predicting high- and low-risk internet expert advice site perceptions. *E-Service Journal*, 3(2), 35–58. <https://doi.org/10.2979/esj.2004.3.2.35>
- McKnight, D. H., Lankton, N. K., Nicolau, A., & Price, J. (2017). Distinguishing the effects of B2B information quality, system quality, and service outcome quality on trust and distrust. *The Journal of Strategic Information Systems*, 26(2), 118–141. <https://doi.org/10.1016/j.jsis.2017.01.001>
- Miyazaki, A. D., & Fernandez, A. (2001). Consumer perceptions of privacy and security risks for online shopping. *Journal of Consumer Affairs*, 35(1), 27–44. <https://doi.org/10.1111/j.1745-6606.2001.tb00101.x>
- Morley, J., Cowsils, J., Taddeo, M., & Floridi, L. (2020). Ethical guidelines for COVID-19 tracing apps. *Nature*, 582(7810), 29–31. <https://doi.org/10.1038/d41586-020-01578-0>
- Moscovici, U. (2020). COVID-19 digital contact tracing is failing miserably. (<https://www.neweurope.eu/article/covid-19-digital-contact-tracing-is-failing-miserably/>).
- Muoio, D. (2020). COVID-19 tracking tech – Weighing personal and public health benefits against privacy. (<https://www.mobilhealthnews.com/news/covid-19-tracking-tech-weighing-personal-and-public-health-benefits-against-privacy>).
- Nan, X., & Kim, J. (2014). Predicting H1N1 vaccine uptake and H1N1-related health beliefs: The role of individual difference in consideration of future consequences. *Journal of Health Communication*, 19(3), 376–388. <https://doi.org/10.1080/10810730.2013.821552>
- Nel, J., & Boshoff, C. (2021). Traditional-bank customers' digital-only bank resistance: Evidence from South Africa. *International Journal of Bank Marketing*. <https://doi.org/10.1108/IJBM-07-2020-0380> (ahead-of-print(ahead-of-print)).
- Nitzl, C. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems*, 116(9), 1849–1864. <https://doi.org/10.1108/IMDS-07-2015-0302>
- Nolsoe, E. (2020). NHS COVID-19 app success hinges on battery life. (<https://yougov.co.uk/topics/technology/articles-reports/2020/05/14/nhs-covid-19-app-success-hinges-battery-life>).
- O'Callaghan, M. E., Buckley, J., Fitzgerald, B., Johnson, K., Laffey, J., McNicholas, B., ... Glynn, L. (2021). A national survey of attitudes to COVID-19 digital contact tracing in the Republic of Ireland. *Irish Journal of Medical Science*, 190(3), 863–887. <https://doi.org/10.1007/s11845-020-02389-y>
- Ou, C. X., & Sia, C. L. (2010). Consumer trust and distrust: An issue of website design. *International Journal of Human-Computer Studies*, 68(12), 913–934. <https://doi.org/10.1016/j.ijhcs.2010.08.003>
- Pandl, K. D., Thiebess, S., Schmidt-Kraepelin, M., & Sunyaev, A. (2021). How detection ranges and usage stops impact digital contact tracing effectiveness for COVID-19. *Scientific Reports*, 11(1), 1–11.
- Park, Y. J. (2011). Digital literacy and privacy behavior online. *Communication Research*, 40(2), 215–236. <https://doi.org/10.1177/0093650211418338>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879. <https://doi.org/10.1037/0021-9010.88.5.879>
- Prakash, A. V., Das, S., & Pillai, K. R. (2021). Understanding digital contact tracing app continuance: Insights from India. *Health Policy and Technology*, 10(4), Article 100573. <https://doi.org/10.1016/j.hlpt.2021.100573>
- Press Trust of India. (2020). *Rahul Gandhi raises security, privacy concerns over Aarogya Setu app*. The Times of India. (<https://timesofindia.indiatimes.com/india/rahul-gandhi-raises-security-privacy-concerns-over-aarogya-setu-app/articleshow/75508824.cms>).
- Ram, S. (1987). *A model of innovation resistance*. ACR North American Advances. (<https://www.acrwebsite.org/volumes/6688>).
- Ram, S., & Sheth, J. N. (1989). Consumer resistance to innovations: The marketing problem and its solutions. *Journal of Consumer Marketing*, 6, 5–14. <https://doi.org/10.1108/EUM000000000002542>
- Reuters. (2020). *Active Irish COVID-19 tracing app users drop on battery problem – HSE*. Reuters. (<https://www.reuters.com/article/us-health-coronavirus-ireland-apps-idUSKBN25N1PA>).
- Riemer, K., Ciriello, R., Peter, S., & Schlagwein, D. (2020). Digital contact-tracing adoption in the COVID-19 pandemic: IT governance for collective action at the societal level. *European Journal of Information Systems*, 1–15. <https://doi.org/10.1080/0960085X.2020.1819898>
- Riquelme, I. P., Román, S., & Iacobucci, D. (2016). Consumers' perceptions of online and offline retailer deception: A moderated mediation analysis. *Journal of Interactive Marketing*, 35, 16–26. <https://doi.org/10.1016/j.jintmar.2016.01.002>
- Roche, S. (2020). Smile, you're being traced! Some thoughts about the ethical issues of digital contact tracing applications. *Journal of Location Based Services*, 14(2), 71–91. <https://doi.org/10.1080/17489725.2020.1811409>
- Rogers, E. V. (1995). *Diffusion of innovations* (4th ed.). The Free Press.
- Ropek, L. (2020). For successful contact tracing, consider the demographics. (<https://www.governing.com/community/For-Successful-Contact-Tracing-Consider-the-Demographics.html>).
- Rowe, F. (2020). Contact tracing apps and values dilemmas: A privacy paradox in a neoliberal world. *International Journal of Information Management*, Article 102178. <https://doi.org/10.1016/j.ijinfomgt.2020.102178>
- Rowe, F., Ngwenyama, O., & Richet, J. L. (2020). Contact tracing apps and alienation in the age of COVID-19. *European Journal of Information Systems*, 1–18. <https://doi.org/10.1080/0960085X.2020.1803155>
- Saw, Y. E., Tan, E. Y.-Q., Liu, J. S., & Liu, J. C. (2021). Predicting public uptake of digital contact tracing during the COVID-19 pandemic: Results from a nationwide survey in Singapore. *Journal of Medical Internet Research*, 23(2), Article e24730. <https://doi.org/10.2196/24730>
- Schierz, P. G., Schilke, O., & Wirtz, B. W. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic Commerce Research and Applications*, 9(3), 209–216. <https://doi.org/10.1016/j.elerap.2009.07.005>
- Sein, M. K. (2020). The serendipitous impact of COVID-19 pandemic: A rare opportunity for research and practice. *International Journal of Information Management*, 55, Article 102164. <https://doi.org/10.1016/j.ijinfomgt.2020.102164>
- Selander, L., & Henfridsson, O. (2012). Cynicism as user resistance in IT implementation. *Information Systems Journal*, 22(4), 289–312. <https://doi.org/10.1111/j.1365-2575.2011.00386.x>
- Sharma, S., Singh, G., Sharma, R., Jones, P., Kraus, S., & Dwivedi, Y. K. (2020). Digital health innovation: Exploring adoption of COVID-19 digital contact tracing apps. In *IEEE Transactions on Engineering Management*. <https://doi.org/10.1109/TEM.2020.3019033>
- Sharon, T. (2020). Blind-sided by privacy? Digital contact tracing, the Apple/Google API and big tech's newfound role as global health policy makers. *Ethics and Information Technology*. <https://doi.org/10.1007/s10676-020-09547-x>
- Smith, H. J., Milberg, S. J., & Burke, S. J. (1996). Information privacy: Measuring individuals' concerns about organizational practices. *MIS Quarterly*, 20(2), 167–196. <https://doi.org/10.2307/249477>
- Stablein, T., Hall, J. L., Pervis, C., & Anthony, D. L. (2015). Negotiating stigma in health care: Disclosure and the role of electronic health records. *Health Sociology Review*, 24(3), 227–241. <https://doi.org/10.1080/14461242.2015.1078218>
- Statista. (2020). *Coronavirus: Adoption of government endorsed COVID-19 contact tracing apps in selected countries*. (<https://www.statista.com/statistics/1134669/share-pollutions-adopted-covid-contact-tracing-apps-countries/>).
- Straub, D., Boudreau, M. C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information Systems*, 13(1), 24.
- Talke, K., & Heidenreich, S. (2014). How to overcome pro-change bias: Incorporating passive and active innovation resistance in innovation decision models. *Journal of Product Innovation Management*, 31(5), 894–907. <https://doi.org/10.1111/jpim.12130>
- Talwar, S., Talwar, M., Kaur, P., & Dhir, A. (2020). Consumers' resistance to digital innovations: A systematic review and framework development. *Australasian Marketing Journal (AMJ)*. <https://doi.org/10.1016/j.ausmj.2020.06.014>
- Thejesh, G. N. (2016). *Why are Indian users so vulnerable to cyberattacks?* Factor Daily. (<https://archive.factoraily.com/why-is-india-vulnerable-to-cyberattacks-bug-bounty-programs-cybersecurity/>).
- Tomczyk, S., Barth, S., Schmidt, S., & Muehlan, H. (2021). Utilizing health behavior change and technology acceptance models to predict the adoption of COVID-19 contact tracing apps: Cross-sectional survey study. *Journal of Medical Internet Research*, 23(5), Article e25447.
- Touzani, R., Schultz, E., Holmes, S. M., Vandentorren, S., Arwidson, P., Guillemin, F., ... Mancini, J. (2021). Early acceptability of a mobile app for contact tracing during the

- COVID-19 pandemic in France: National web-based survey. *JMIR MHealth and UHealth*, 9(7), Article e27768. <https://doi.org/10.2196/27768>
- Trang, S., Trenz, M., Weiger, W. H., Tarafdar, M., & Cheung, C. M. K. (2020). One app to trace them all? Examining app specifications for mass acceptance of contact-tracing apps. *European Journal of Information Systems*, 29(4), 415–428. <https://doi.org/10.1080/0960085X.2020.1784046>
- Tretiakov, A., & Hunter, I. (2021). User experiences of the NZ COVID tracer app in New Zealand: Thematic analysis of interviews. *JMIR Mhealth Uhealth*, 9(9), Article e26318. <https://doi.org/10.2196/26318>
- Trkman, M., Popović, A., & Trkman, P. (2021). The impact of perceived crisis severity on intention to use voluntary proximity tracing applications. *International Journal of Information Management*, 61, Article 102395. <https://doi.org/10.1016/j.ijinfomgt.2021.102395>
- Tversky, A., & Kahneman, D. (1989). In B. Karpak, & S. Zions (Eds.), *Rational choice and the framing of decisions BT – Multiple criteria decision making and risk analysis using microcomputers* (pp. 81–126). Springer Berlin Heidelberg.
- UNDP. (2020). *COVID-19 pandemic: Humanity needs leadership and solidarity to defeat the coronavirus pandemic*. (<https://www.undp.org/content/undp/en/home/coronavirus.html#:~:text=The%20coronavirus%20COVID%2D19%20pandemic,to%20every%20continent%20except%20Antarctica>).
- Van den Broeck, E., Poels, K., & Walrave, M. (2015). Older and wiser? Facebook use, privacy concern, and privacy protection in the life stages of emerging, young, and middle adulthood. *Social Media + Society*, 1(2). <https://doi.org/10.1177/2056305115616149> (2056305115616149).
- Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, 37, 21–54. (<http://www.jstor.org/stable/43825936>).
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Villius Zetterholm, M., Lin, Y., & Jokela, P. (2021). Digital contact tracing applications during COVID-19: A scoping review about public acceptance. *Informatics*, 8(3), 48. <https://doi.org/10.3390/informatics8030048>
- Walrave, M., Waeterloos, C., & Ponnet, K. (2020). Adoption of a contact tracing app for containing COVID-19: A health belief model approach. *JMIR Public Health Surveillance*, 6(3), Article e20572. <https://doi.org/10.2196/20572>
- Walrave, M., Waeterloos, C., & Ponnet, K. (2021). Ready or not for contact tracing? Investigating the adoption intention of COVID-19 contact-tracing technology using an extended unified theory of acceptance and use of technology model. *Cyberpsychology, Behavior, and Social Networking*, 24(6), 377–383.
- Wunderlich, P., Veit, D. J., & Sarker, S. (2019). Adoption of sustainable technologies: A mixed-methods study of German households. *MIS Quarterly*, 43(2), 673–692.
- Wymant, C., Ferretti, L., Tsallis, D., Charalambides, M., Abeler-Dörner, L., Bonsall, D., ... Fraser, C. (2021). The epidemiological impact of the NHS COVID-19 App. *Nature*. <https://doi.org/10.1038/s41586-021-03606-z>
- Xie, G.-X., Madrigal, R., & Boush, D. M. (2015). Disentangling the effects of perceived deception and anticipated harm on consumer responses to deceptive advertising. *Journal of Business Ethics*, 129(2), 281–293. <https://doi.org/10.1007/s10551-014-2155-2>
- Sadeghi, A. R., Miettinen, M., & Nguyen, T. D. (2021). *The stony road to privacy-preserving and secure contact tracing schemes: Summary of a comparative analysis* (CYSEC Report No. v.1.1) Cybersecurity Research Centre CYSEC, TU Darmstadt. <https://tracecorona.net/wp-content/uploads/2020/04/Pandemic-tracing-comparison-v.1.1.1.pdf>.